NOVA IMS Information Management School

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Master Degree Program in
Data Science and Advanced Analytics

FOLLOW THE MONEY OF FIXED – INCOME ASSET MATURITIES

A REINVESTMENT ANALYSIS AND RECOMMENDATION SYSTEM FOR POST MATURITIES

Daniel Bayerl Vieira

Project Work

presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

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Project Work presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Business Analytics

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Daniel Bayerl Vieira

Lisbon, July 2024

DEDICATION

I would like to dedicate this work, first and foremost, to my father, Willians Vieira; my stepmother, Ana Lucia da Silva; my brother, Bernardo Vieira; and my mother, Sônia Maria Alves, with whom I grew up. They provided all the familial support needed to overcome the challenges I faced. I also dedicate this to my friends Phelipe Darc, Nathan Macedo, Fernando Crelier, Lucas Caldas, and Enzo Pereira, who have always supported and encouraged me throughout this journey. To the other members of my family, thank you for providing all the necessary support throughout my life, allowing me to grow and pursue my goals. A special dedication goes to my grandparents, Franz Vieira and Cleusa Vieira, who always encouraged and cheered for my development. Although they are no longer with us, their spirit and support have been instrumental in my achievements.

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ABSTRACT

The landscape of investment banking has grown significantly, with these institutions acting as key intermediaries between clients and investments. Investment banks focus on converting client capital into both short and long-term investments, particularly in fixed-income assets. However, the maturation of these assets leads to idle funds in current accounts, posing a challenge in reallocating these resources effectively. This research aims to understand the dynamics following fixed-income asset maturities and to address the gap in knowledge regarding client reinvestment behaviors, preferred assets, and the impact of advisor actions. A quantitative approach using data analytics will be employed to map transactions and identify post-maturity asset destinations. The study will propose a recommendation system to enhance client investment decisions and improve fund allocation strategies. Ultimately, this research contributes to better understanding the role of fixed-income maturities in investment banking and offers actionable insights for optimizing fund retention and client engagement.

KEY-WORDS

Fixed-Income; Investment Banking; Recommendation System; Asset Maturity; Collaborative Filtering; Advisory Impact

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LIST OF ABREVIATIONS AND ACRONYMS

LQ	Liquidity Assets
FI	Fixed - Income
PV	Previdence
FN	Funds
VI	Variable-Income
PC	Private Credit
BC	Bank Credit
ALM	Asset-Liability Management
NBO	Next Best Offer
CDF	Cumulative distribution function
FIFO	First-In-First-Out
CRM	Customer relationship management
SMS	Short message service
APP	Application
PCS	Pearson Correlation Similarity
SRC	Spearman Rank Correlation

1. INTRODUCTION

The landscape of investment banking has experienced substantial growth, positioning these institutions as key intermediaries between clients and investments (Ravi et al., 2023). The fundamental mission of investment banks revolves around skillfully converting client capital into both short and long-term investments, with a particular emphasis on fixed-income assets. In a world where accessibility to investment opportunities has expanded (Bunting, 2021; Ehrsam et al., 2021),these fixed-income investments play a pivotal role. However, the maturation of these assets presents a unique challenge, leading to a significant accumulation of idle funds in current accounts. The crux of the challenge lies in the ability of investment banks to effectively harness and optimize these unallocated resources, redirecting them towards profitable products that mutually benefit the institution and its clients. In this pursuit, "follow-the-money" analyses emerge as a potent tool for tracking transaction destinations and evaluating campaign outcomes.

The motivation behind this research stems from the necessity to comprehend the intricate dynamics ensuing from the maturation of fixed-income assets in the realm of investment banking Drakos (2001) explores the relation between asset maturities time and returns, Goswami (2000) studies the impact of asset quality on debt maturities. As investment opportunities become increasingly accessible mainly in economically underdeveloped regions with the growth of the digital world (Tashtamirov et al., 2021), the efficient allocation of idle funds post-maturity emerges as a critical factor in sustaining the growth and profitability of investment banks. The motivation transitions from this broad understanding to a more particular level, focusing on the specific challenges posed by the maturation of fixed-income assets and the need for effective strategies in redirecting these funds, to achieve this, we will use the "follow the money" principle, which is an expression used to trace the origin and destination of money. Our goal is to apply this principle to separate all the money that comes from fixed-income asset earnings and track where it goes afterward.

The research addresses a crucial gap in the existing knowledge, since the projects on follow the money analysis was focused on bigger scale markets (Hayes, 2002; Reckhow, 2014; Wagner & Rabuy, 2017), aiming to unravel the multifaceted impact of fixed-income asset maturities on the investment banking landscape. Existing literature falls short in providing comprehensive insights into critical aspects such as the time taken by clients to reinvest after maturity, the types of assets favored in reinvestment, the influence of client positions on allocation decisions, and the quality of client service within the banking institution. Additionally, the study identifies a lack of exploration into the significant role played by notifications and actions taken by advisors in influencing fund allocation for the benefit of both the bank and the client. Additionally, the aim of the final project englobes the possibility to implement and evaluate a recommendation system using the knowledge already available in the literature about different types of recommendation system and comparison between them (Burke & Ramezani, 2011; El Abbass, 2018; Fabrizi & Banoub, 2014; Molina, 2018; Pazzani & Billsus, 2007; Schafer et al., 2007).

The overarching objectives of this research encompass the [1] create a table of transactions between each movement in the client’s account, then [2] mapping of investment bank transactions and precise identification of asset destinations post-maturity. [3] The methodology applied adopts a quantitative approach and employs data analytics to uncover patterns and trends related to post-maturity asset allocation. The anticipated results aim to offer insights into optimal fund retention strategies, effective advisor actions, and client communications that generate returns. [4] Additionally, the study seeks to propose product offerings through a recommendation system, that is aligned with client preferences to enhance investment inclination. The contributions of this research lie in enhancing the understanding of the role of fixed-income asset maturities in investment banking and shedding light on the dynamics between investment banks and retail investors. [5] Evaluation of results found in [3] and [4] steps.

2. LITERATURE REVIEW

2.1. Investiment Banking and fixed income

The contemporary landscape of investment banking has witnessed a transformative shift, with banks now acting as vital intermediaries between companies seeking capital and eager investors (Ravi et al., 2023). In this dynamic environment, investment banks play a crucial role in efficiently channeling clients' capital into various short and long-term investments, with a particular emphasis on fixed-income assets. These capitals are divided into two major submarkets: private credits and bank credits, where bank credits aim to allocate clients' capital in banks and receive returns for the allocated capital, or private credit investments that perform a similar role to banking but with non-financial institutions, and the smaller submarkets, public securities or direct treasuries as investments directly in the government. With the existence of investment banks facilitating access for the public and making it increasingly easy to invest from the palm of your hand, with just a few clicks and without the need for a significant amount of available capital, an era with a significant increase in accessibility to investment opportunities was initiated (Bunting, 2021). With this ease, there has been a noticeable increase in investor activity (Ehrsam et al., 2021), highlighting the need for innovative approaches to manage the consequences of the maturity of fixed-income assets, that can increase portfolio risk, depending on the investor's overall asset allocation and how far out the maturities are extended (Swedroe & Grogan, 2009). This literature review synthesizes insights from key articles to establish the foundation for a thesis that employs a follow-the-money analysis to comprehensively evaluate customer behavior and devise an effective recommendation system. Also, we aim to track the advisory contact impact on customer behavior what can lead us to an AI-based advisory in the future (Dietzmann et al., 2023).

2.2. Asset classification

Recent studies on customer preferences for assets and asset classifications generally focus on the type of assets, rates, and terms to define good products but do not take customer behavior into account. Baghai et al. (2024) discuss the use of ratings in fixed-income assets to increase investor reliability and prevent risky investments, which have previously led to various crises. Russell & Weston (2024) provide information on customer preferences regarding rates linked to fixed-income assets, as well as global risk and growth indicators, de Longis & Ellis (2023) study the risk-return relationship that customers are willing to take, specifically how much risk customers are willing to assume in pursuit of higher returns.

We have recent studies on the extensive use of data within the product classification environment. Krabichler & Teichmann (2023) introduces the fundamental concepts of Deep Asset-Liability Management ("Deep ALM"), highlighting its role in revolutionizing the technological management of assets and liabilities across an entire term structure. This innovative approach significantly influences various applications, including optimal decision-making, Bai et al. (2023) studied the importance of data within fixed income and found that the value of data on corporate bonds increases with yield, time-to-maturity, size, callability, liquidity, and uncertainty during normal times.

2.3. Follow the money

The literature on "follow the money" analyses is quite limited and generally linked to much broader scopes than the one used in this work. For instance, Hayes (2002) applied the "follow the money" approach to economic simulation models, simulating transactions within a society and how individuals become richer or poorer. Reckhow (2014) works with the concept of "follow the money" in terms of how foundation dollars have impacted changes in the U.S. public education system. Wagner & Rabuy (2017) conducted a study on "follow the money" within the prison system, tracking all expenses and mapping the destination of funds allocated to maintain this system. These approaches are typically employed to assess movements in the financial markets of countries, meaning that studying individual behavior patterns is far removed from the scope of this work.

2.4. Recommendation Systems

Recommendation systems have been created and improved in recent decades to facilitate people's exposure to large volumes of information, making it easier to choose the next content. This not only optimizes the customers' time but also fosters loyalty to the product, as they tend to consume more. There are five major types of Recommendation Systems: collaborative, content-based, utility-based, demographic, and knowledge-based (Kumar et al., 2023). Also, there are various type of applications for recommendations systems, for example on YouTube, where deep learning significantly improves performance in YouTube recommendations, with a deep candidate generation model and deep ranking model (Covington et al., 2016) and on Netflix, where Molina (2018) created a Recommendation System for Netflix, which was based on using the collaborative filtering recommendation system, Z. He et al. (2024) created a fabric content-based recommendation system with image and text information, Kumar et al. (2023) used the content-based recommendation system to create a movie recommendation system. Also, hybrid models are commonly used, Widayanti (2023) studied hybrid techniques to improve recommendation systems filtering using collaborative and content-based models.

2.4.1. Collaborative Filtering Recommender Systems

Schafer et al. (2007) study contributes valuable insights into recommender systems, specifically collaborative filtering techniques, da Silva et al. (2016) explore an automated and effective approach to combine results from recommendation system techniques, also the use of neural networks in collaborative recommendation system increases in the past years (X. He et al., 2017), Koren et al. (2022) studied the advances in collaborative filtering like matrix factorization and temporal models techniques, however, these more complex methods of collaborative systems depend on a greater depth of data and a larger sample size. These systems play a pivotal role in understanding and predicting customer choices based on user preferences. Collaborative filtering is a key element for a follow-the-money analysis, enabling the evaluation of transaction destinations and client behavior.

The collaborative recommendation system works with customer behavior tracking and correlation, which can be applied to our work since we are seeking behavior patterns that can be used to calculate this correlation. Hassanieh et al. (2018) and Sivaramakrishnan et al. (2018) compared different correlation metrics to identify similarity between two costumers’ behavior and evaluate the difference between this metrics, Herlocker et al. (2002) compare Spearman and Pearson correlation metrics to evaluate which one has better performance, however, the results do not show a significant difference between them. After clustering customers, this system aims to find customers with similar behavior patterns who tend to consume the same content, therefore, if we have two customers with similar behaviors and only one of them has consumed specific content, we can recommend that content to the other customer because they are likely to approve. The image below illustrates how this system functions (Figure 2.1).

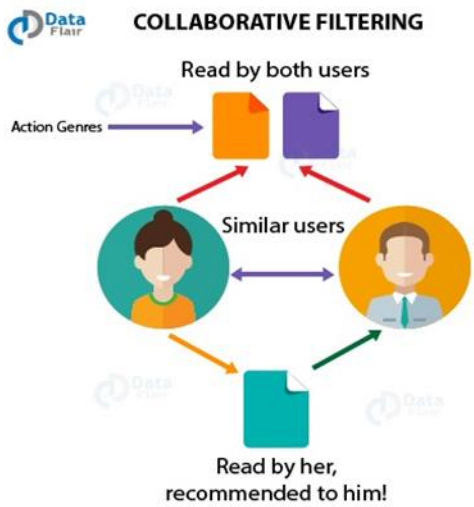

Figure 2.1: Collaborative filtering (DataFlair, 2019)

2.4.2. Content-Based Recommendation Systems

The content-based recommendation systems, that are systems that recommend an item to a user based on item characteristics and a profile of the user's interests. Content-based recommendation systems may be used in a variety of domains ranging from recommending web pages, news articles, restaurants, television programs, and items for sale (Pazzani & Billsus, 2007), this study brings a different dimension to understanding client preferences by considering the attributes of the products themselves. The content-based recommendation system is based on recommending content similar to what the client already consumes. Therefore, the idea of clustering clients is not the focus in this method, which aligns well with the expectations of this article's work since the data used is based on the content consumed by clients (Lops et al., 2011) The image below illustrates how this method works (Figure 2.2).

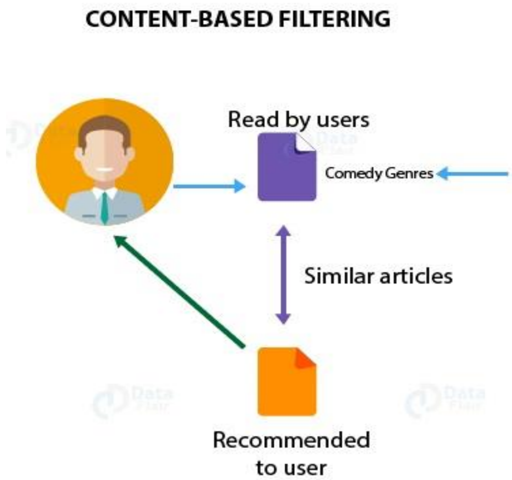

Figure 2.2: Content-Based filtering (DataFlair, 2019)

2.5. Bank Sales Analytics and Predictive Models

Lau et al. (2003) study leads to a 'next product to offer' system, combining data cleansing and fusion, effectively selecting products based on individual customer needs and priorities, improving customer service in the banking industry. El Abbass (2018) study advocates for the strategic integration of analytical solutions into banking operations. The focus on predictive modeling to identify the Next Best Offer (NBO) for clients signals the potential for personalized and targeted marketing strategies based on customer behavior patterns. This article provides a framework for understanding customer preferences. In this work, a collaborative recommendation model was employed, where recommendations are based on finding similar clients and suggesting products that they consume, and their counterparts do not. This type of recommendation system can be applied with follow-the-money analyses, as we aim to map customer behavior in buying and selling assets, thereby identifying their similarities. Furthermore, the article details the importance of data quality, feature engineering, and model evaluation, essential components for creating a robust recommendation system aligned with customer behavior.

2.6. Integration for Follow-the-Money Analysis

The integration of these concepts forms a comprehensive framework for developing a recommendation system based on a "follow the money" analysis of fixed-income assets. Investment banks' pivotal role in channeling capital into fixed-income assets sets the stage for this analysis. By understanding the dynamic landscape of asset classification and leveraging collaborative filtering and content-based recommendation systems, we can predict customer behavior and enhance investment strategies.

The use of collaborative filtering methods allows us to cluster customers based on behavior patterns, identifying those with similar tendencies. This clustering is essential for creating accurate recommendations, ensuring that clients are directed towards investments they are likely to prefer.

By using these methods, we address the limitations of traditional asset classification studies, which often overlook individual behavior patterns. The integration of predictive models and bank sales analytics further enhances the recommendation system, allowing for personalized and targeted investment suggestions based on a comprehensive analysis of customer data.

In conclusion, the synthesis of these elements enables the creation of an effective recommendation system for fixed-income assets. This system not only improves client satisfaction by aligning with their investment preferences but also optimizes portfolio performance by guiding clients towards more profitable long-term investments, ultimately benefiting both the client and the bank.

3. DATA & METHODOLOGY

3.1. Financial markets definition and asset maturities

Before proceeding with our analysis, it is essential to establish certain parameters and concepts that will be utilized in defining our analyses. Firstly, we need to delineate the various markets under consideration. Our markets are categorized into 5 distinct types.

- VI - Variable Income Market: This market is primarily focused on stocks and real estate funds, encompassing all types of variable income derivatives as well. It is tailored for sophisticated investors who are inclined to take risks in pursuit of potentially higher returns.
- OUT - Outflow market: This market is designed for the study encompassing the outflow from accounts through transfers to other banks.
- LQ - The Liquidity Market: This market is devised to consolidate all liquidity assets. Liquidity assets allow for their sale at any time without exposure to market downturns. Within this category, assets include fixed-income assets as bank credits (BC) and funds (FN) that permit withdrawal within 2 days upon request. We have separated this market due to its nature as a secure investment aimed at preventing idle funds in checking accounts, rather than being a direct long-term investment strategy to retain value within the institution. Since this product is similar in thermos of strategy, we will consider all liquidity products inside liquidity market and submarket (LQ).
- FI - Fixed-Income Market without Daily Liquidity: This market primarily consists of private (PC) and bank (BC) credits, supplemented by government bonds and credit notes. It caters more towards conservative investors seeking predefined or minimally variable returns with very low associated risks.
- FN - Funds without Daily Liquidity: Comprised of funds investing in the other listed markets, funds may exhibit diverse investment profiles. However, they tend to be less sophisticated than VI assets owing to their diversified nature.

An important observation is that LQ and FI BC are in the same submarket since all the maturity of LQ comes from liquid bank credit, so we can consider both in the same submarket but not in the same market.

Maturity is a fundamental concept in fixed income investing, referring to the period until the issuer of the security repays the principal amount to the investor. Fixed income securities typically have a specified maturity date, which can range from a few months to several decades.

During the period leading up to maturity, investors receive periodic interest payments, providing a predictable income stream. The maturity date is crucial as it represents the point at which the investor receives the return of the principal investment.

Investors should be aware of the various types of maturities, including short-term, intermediate-term, and long-term. Short-term maturities, such as Treasury bills, have a duration of one year or less, offering quick returns with lower interest rate risk. Intermediate-term and long-term maturities, found in bonds, provide higher yields but come with increased interest rate risk.

3.2. Conceptual Model

Here we present the conceptual model (Figure 3.1) of the project, wherein all the next section will be mentioned in tables (Table 3.1; Table 3.6; Table 3.7; Table 3.8; Table 3.9) are denoted in blue, the model and output tables are denoted in grey. The treatments and processing procedures applied to the data are highlighted in yellow, illustrating the methodological steps taken. Finally, the outcomes and results derived from these processes are depicted in green, signifying the tangible outputs of our efforts. This comprehensive model serves as a visual representation of the project's structure, showcasing the interplay between data representation, processing steps, and the ultimate results.

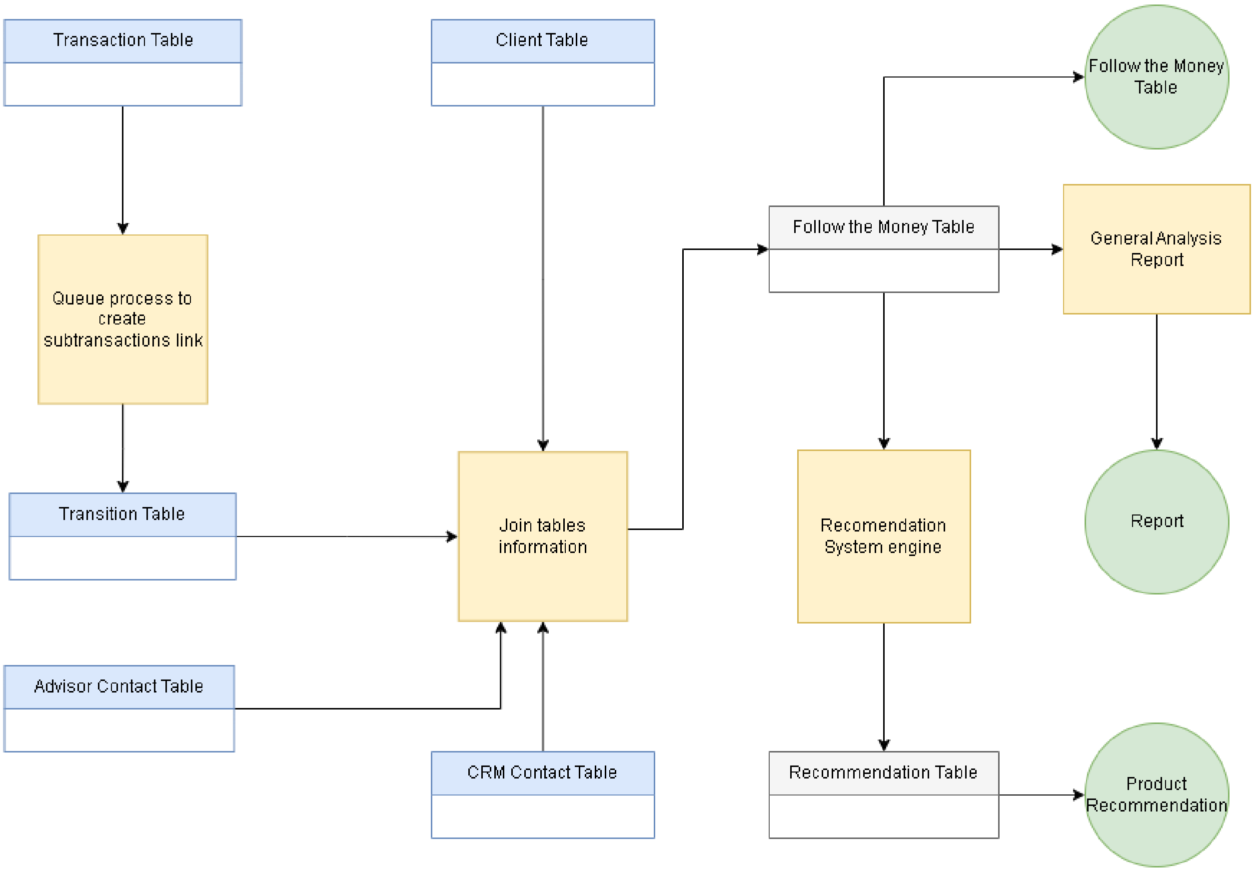

Figure 3.1: Conceptual model

3.3. Data

3.3.1. Transaction table

The database employed is relatively straightforward, comprising a primary dataset that meticulously logs all customer transactions. This foundational dataset encompasses crucial details including the transaction date, market and submarket classifications, specific asset details, transaction type, quantity, and associated value. Through the systematic documentation of this information, we are able to comprehensively trace the entire historical landscape of customer transactions.

This comprehensive dataset serves as the cornerstone for constructing our transition matrix. This matrix is a pivotal analytical tool, designed to establish connections between the various purchases and sales executed within the customer's account. By leveraging this matrix, we gain valuable insights into the intricate patterns and dynamics of the customer's transactional history. This approach facilitates a nuanced understanding of the client's financial activities, enabling us to derive meaningful conclusions and inform strategic decision-making processes. Below is an example of the transaction dataset (Table 3.1) which consists of eight columns: the transaction date, the customer code who performed the transaction, the market, submarket, and the asset involved in the transaction, the transaction type (which can be either a purchase or sale), the quantity, and the negotiated value.

Table 3.1: Table of client transactions

date	client	market	submarket	asset	type	quantity	value
2023-01-01	000000001	A	AA	AAA	sell	40	1000
2023-01-01	000000001	B	BA	BAA	sell	35	1000
2023-01-02	000000001	C	CB	CBC	buy	28	2000
2023-01-03	000000001	A	AA	AAC	sell	63	1500
2023-01-03	000000001	A	AC	ACA	sell	30	2500
2023-01-03	000000001	B	BA	BAA	buy	37	1000
2023-01-04	000000001	B	BB	BBA	buy	68	2500
2023-01-05	000000001	C	CA	CAC	buy	75	500

With the transaction dataset undergoing no prior treatment, except for the omission of inconsequential movements that do not impact the client's account balance, we initiate the construction of our transition matrix. This matrix is to be represented by a dataset that includes date, market, submarket, asset, and both input and output values. To establish links between operations, we employ a First-In-First-Out (FIFO) approach, connecting all inputs to corresponding outputs for each client. This entails organizing the data based on the chronological order of transactions. To facilitate this process, we maintain an input queue, listing all operations depositing funds into the client's account. This queue is continuously updated as we iterate through the transaction dataset to generate the transactional base.

This iterative approach ensures that the order of operations is preserved, allowing us to establish a coherent link between the entries and exits, providing a comprehensive understanding of the financial activities influencing the client's account balance.

To illustrate, consider the example table for inflow (Table 3.2) and outflow (Table 3.3) transactions into the client's account, along with the queue generated from these movements (Table 3.4).

Table 3.2: Table of client inflow

date	client	market	submarket	asset	type	quantity	value
2023-01-01	000000001	A	AB	AAA	sell	40	1000
2023-01-01	000000001	B	BA	BAA	sell	35	1000
2023-01-03	000000001	A	AA	AAC	sell	63	1500
2023-01-03	000000001	A	AC	ACA	sell	30	2500

Table 3.3: Table of client outflow

date	client	market	submarket	asset	type	quantity	value
2023-01-02	000000001	C	CB	CBC	buy	28	2000
2023-01-03	000000001	B	BA	BAA	buy	37	1000
2023-01-04	000000001	B	BB	BBA	buy	68	2500
2023-01-05	000000001	C	CA	CAC	buy	75	500

Table 3.4: Inflow and outflow client queue

income queue			outcome queue		
position	asset	value	position	asset	value
1	AAA	1000	1	CBC	2000
2	BAA	1000	2	BAA	1000
3	AAC	1500	3	BBA	2500
4	ACA	2500	4	CAC	500

With the generated queue, the imperative is to establish connections between input and output transactions. Consequently, we must associate them based on their chronological order, debiting the value of purchase transactions, and generating interconnected sub transactions. In many instances, input transactions can be linked to multiple output transactions, and vice versa. Below is a detailed list of output transactions (Table 3.5), elucidating how they correlate with the pre-existing queues, thereby unveiling matched sequences.

Table 3.5: Sub transaction table

subtransaction	inflow asset	outflow asset	value
1	AAA	CBC	1000
2	BAA	CBC	1000
3	AAC	BAA	1000
4	AAC	BBA	500
5	ACA	BBA	2000
6	ACA	CAC	500

With the linked orders, it's sufficient to create the final relationship table (Table 3.6), which will have the structure shown below.

Table 3.6: Transition table

buy date	sell date	client	sell market	sell submarket	sell asset	buy market	buy submarket	buy asset	value
2023-01-01	2023-01-02	000000001	A	AA	AAA	C	CB	CBC	1000
2023-01-01	2023-01-02	000000001	B	BA	BAA	C	CB	CBC	1000
2023-01-03	2023-01-03	000000001	C	AA	AAC	B	BA	BAA	1000
2023-01-03	2023-01-04	000000001	A	AA	AAC	B	BB	BBA	500
2023-01-03	2023-01-04	000000001	A	AC	ACA	B	BB	BBA	2500
2023-01-03	2023-01-05	000000001	C	AC	ACA	o	CA	CAC	500

This table will serve as the cornerstone of our study, providing a comprehensive and structured foundation for our transaction analysis. Furthermore, this table will play a crucial role in the development of our recommendation model. By offering a reliable and expansive dataset, it will enable us to derive meaningful insights and patterns, which will, in turn, inform the recommendations we generate. The accuracy and integrity of this table are paramount, as it will directly impact the efficacy of our overall study and the reliability of our findings.

3.3.2. Extra data tables

We will use only additional contact data between advisors and clients, including contacts made through WhatsApp or Calls from the client advisor, or email, SMS and notifications in the app collected from the CRM. This way, we can measure the impact of automated contacts and personalized advisor contacts. Our databases include the contact type, client and date columns and the automated ones, we can also track the interactions that the client made with the notification. Down below, we provide examples for advisor contact databases via Calls and WhatsApp (Table 3.7), and CRM contacts that can be made by EMAIL, SMS or APP (Table 3.8).

Table 3.7: CRM table

date	client	contact type	interaction
2023-01-01	000000001	EMAIL	None
2023-01-02	000000002	SMS	Visualization
2023-01-03	000000003	APP	Interaction
2023-01-04	000000004	EMAIL	Visualization
2023-01-05	000000005	SMS	Interaction
2023-01-06	000000006	APP	Visualization
2023-01-	000000007	SMS	None

07			
2023-01-08	000000008	EMAIL	None

Table 3.8: Advisor contact table

date	client	contact type
2023-01-01	000000001	CALL
2023-01-02	000000002	WPP
2023-01-03	000000003	WPP
2023-01-04	000000004	CALL
2023-01-05	000000005	WPP
2023-01-06	000000006	CALL
2023-01-07	000000007	WPP
2023-01-08	000000008	WPP

These databases will be cross-referenced with the transaction dataset to map the impact of advisors on customer behavior. Additionally, we will utilize auxiliary tables of client information to determine their segments and to differentiate clients eligible for contact. This approach allows us to distinguish between clients who were eligible but not contacted and those who were contacted. The client database follows the example below (Table 3.9).

Table 3.9: Client table

date	client	business segment	business subsegment	advisor
2023-01-01	000000001	B2B	Partner1	A
2023-01-02	000000002	B2C	Leader1	B
2023-01-03	000000003	WM	Team1	C
2023-01-04	000000004	B2C	Leader2	D
2023-01-05	000000005	B2C	Leader3	E
2023-01-06	000000006	B2B	Partner2	F
2023-01-07	000000007	B2B	Partner3	G
2023-01-08	000000008	WM	Team2	H

3.4. Methodology

3.4.1. General Analysis

The initial approach to the data will involve a comprehensive quantitative exploratory analysis aimed at identifying general trends and basic client behaviors. Among the groupings, we will examine the primary flow of asset movement from sales to purchases, the time taken for expenditures after receiving maturity payments, the impact of automated contacts and advisor interactions on the allocation patterns of maturity payments, as well as the time taken for these allocations. With these groupings, we can observe the overall behavioral patterns and purchasing trends of clients based on the type of asset that has matured in their accounts. In this way, we can already establish an initial version of a potential, more basic recommendation system.

3.4.2. Recommendation System

In this phase, the priority is to leverage transactional data to create a recommendation model that is more flexible and personalized for different client types. This allows for new, more specific clustering that may not be easily observed in general exploratory and quantitative analyses. To achieve this, we will use collaborative-based recommendation models, because they form a vital component of personalized content delivery by leveraging the collective preferences and behaviors of users. Unlike content-based methods that focus on item characteristics, collaborative filtering identifies patterns and similarities in user interactions to make relevant suggestions. This approach operates on two main types: user-based and item-based collaborative filtering. User-based collaborative filtering recommends items to a user based on the preferences of users with similar behaviors (Schafer et al., 2007).

The collaborative filtering recommendation system is based on correlations between customers. Therefore, we first need to build a customer behavior database. Given that we have over 180,000 distinct customers, calculating the individual correlation between each of them would be unfeasible and impractical for day-to-day use. Thus, we will group them into less granular clusters, seeking to group common characteristics among them as is the purpose of a collaborative recommendation system. Moreover, by defining prior groups for customers, we eliminate the "cold start" problem, where new clients lack sufficient historical data for accurate predictions, because we will already directly insert the client in a group based on their own characteristics.

As a basis for grouping customers, we will use the segment, risk profile, and the submarket from the received maturity the combination of these 3 features will determine one client-group. From there, we can develop variations to test the system's performance. Before creating our correlation database, we need a customer behavior database. Now that we have defined the groupings to define the behavior of these groups, we will use the number of operations performed in each submarket to determine their preference. We will normalize these values so that each row will represent a customer-group and the percentage of times they opted for each asset, as shown in the example below (Table 3.10):

Table 3.10: Client-group behavior

Client-Group	FN	LQ	PV	BC	PC	VI
1	4%	30%	0%	60%	4%	2%

2	5%	64%	1%	24%	3%	3%
3	4%	53%	1%	23%	18%	2%
4	6%	31%	0%	50%	7%	5%
5	6%	59%	1%	24%	6%	5%
6	7%	49%	0%	20%	17%	6%
7	3%	13%	0%	76%	3%	4%

After creating the behavior matrix, we need to create a correlation matrix between the customer-groups. Hassanieh et al. (2018) compared various correlation metrics for collaborative filtering systems, and the best methods that fit in our model were Pearson Correlation Similarity in Equation 1 and Spearman Rank Correlation in Equation 2, especially for our dataset where the data is not very sparse since our matrix does not present null values due to customers being grouped and at least one customer from each group having already used some of the products.

$$PCS = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - x)^2}\sqrt{\sum(y_i - \bar{y})^2}} \tag{1}$$

$$SRC = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - x)^2 \sum(y_i - \bar{y})^2}} \tag{2}$$

Where in Equation 1 and Equation 2, x_i and y_i are the values for each client group in the same submarket i, $\bar{x}$ and $\bar{y}$ are the mean rank across the submarkets of each client group.

After applying one of the correlation metrics (PCS or SRC), we have a table like this one below (Table 3.11).

Table 3.11: Client-group correlation

Client-Group	1	2	3	4	5	6	7
1	100%	43%	61%	100%	52%	53%	95%
2	43%	100%	97%	39%	96%	96%	13%
3	61%	97%	100%	58%	26%	50%	33%
4	25%	39%	23%	100%	63%	25%	10%
5	52%	25%	51%	24%	100%	64%	85%
6	53%	96%	21%	84%	52%	100%	25%
7	95%	26%	58%	15%	12%	24%	100%

Now with the correlation matrix created, our model is based on selecting the top "n" customer-groups most similar to the chosen one. After getting the top "n" candidates we take the averages of their behaviors, specifically the average consumption tendencies of the submarkets for these "n" customers. This will give us a ranking of the most likely assets to be consumed by this customer, as shown in the table below (Table 3.12).

Table 3.12: Product ranking

Submarket	Score

LQ	65%
BC	19%
PC	5%
FN	5%
VI	4%
PV	1%

With this base, we just need to select the top “x” submarkets to get the appropriate order of recommendations and the most likely submarkets to be consumed by that customer-group.

To implement the recommendation system, we need to define several variables that will be used for hyperparameter tuning. These variables include the number of similar customer-groups to consider for collecting the average behavior pattern, the minimum correlation to be considered a similar client-group, the correlation method that will be used and the granularity of our client-groups. We can increase the granularity by adding subsegment as an additional variable in the client-group.

In our study, we considered options for the number of similar customer-groups as 5, 10, 15, 20, 25, and 30, minimum correlations of 30%, 50%, or 70% to be considered a similar customer-group and the correlation metric that can be PCS or SRC. Additionally, we divided into two different models: one using customer-groups based on risk profile, segment, and maturity submarket, and a second one using these three features and the subsegment, in this way we have two different client-groups one with subsegment and one without.

Isinkaye et al. (2015) discusses various recommendation methodologies and how evaluation is performed. However, since our recommendation system is categorical, the assertiveness calculation tends to focus more on categorical assertiveness, the score recommended is F1 score (Equation 5) using the following defined rules to calculate precision (Equation 3) and recall (Equation 4) since we do not have true and false positives and negatives.

$$Precision = \frac{\text{Correctly Recommended Itens}}{\text{Total Recommended Itens}} \tag{3}$$

$$Recall = \frac{\text{Correctly Recommended Itens}}{\text{Usefull Recommended Itens}} \tag{4}$$

$$F - measure = \frac{2.Precision.Recall}{Precision + Recall} \tag{5}$$

However, in our study, we consider all recommended products to be useful, even if they are products that the client does not typically consume. Therefore, both precision and recall would be equal (Equation 6), resulting in a standard formula for accuracy (Equation 7) as shown below.

$$Precision = Recall \tag{6}$$

$$F - measure = \frac{2. Precision. Precision}{Precision + Precision} = Precision = \frac{\text{Correctly Recommended Itens}}{\text{Total Recommended Itens}} \quad (7)$$

Accuracy will be used during the hyperparameter tuning stage to define the best model to be used in production.

4. RESULTS & DISCUSSION

4.1. General Analysis

4.1.1. Post maturity flow

During our analysis, we will focus more intensively on the percentage allocations since depending on the breakdown we are conducting, the value does not become very useful to us.

The first point we can observe is the distribution of investments based on what was received from fixed income. In the table below (Table 4.1), we can observe that liquidity assets tend to have a very high reallocation to liquidity, at 64,5%, and a reduced outflow at 12%, with reinvestment into non-liquid fixed income at 18%. Meanwhile, in the BC submarket, we can see that assets tend to have a higher outflow at 17%, an allocation of 30% to liquid assets, and a reinvestment of 45% into fixed income. We also note that unlike other fixed income assets, private credit (PC) has a reinvestment in fixed income well below the expected 19%, which makes sense since private credit asset offerings are not constant and may not always be available for allocation as they are specific and limited offerings in fundraising, so this value tend to be redirected to LQ products while the client is waiting for another PC offer.

Table 4.1: Reinvestment by market

Submarket	OUT	FN	LQ	PV	FI	VI
LQ	12%	2%	65%	0%	18%	3%
BC	17%	3%	30%	0%	46%	4%
PC	16%	3%	59%	0%	19%	3%

In the table below (Table 4.2), we broaden our view to see the sub-market as well. We can observe, beyond the market, the sub-market destination of maturities. We can see that, like in the market, the reinvestment trend also extends to the sub-market, once again except for private credit assets, which do indeed have a reallocation in private credit above the average, but well below the average percentage of investment in other assets.

Table 4.2: Reinvestment by submarket

Submarket	OUT	FN	LQ	FI BC	FI PC	VI
LQ	12%	2%	65%	14%	3%	2%
BC	17%	3%	30%	40%	4%	3%
PC	16%	3%	59%	9%	9%	2%

4.1.2. Time

Our analysis of spending behavior will be divided into two parts: pre- and post-maturity. We will begin with the post-maturity analysis.

In the post-maturity phase, we can observe the time it takes for clients to spend the amount received at maturity. With the image below (Figure 4.1), we can see how long clients take to spend a certain percentage of the received amount. We notice that up to 80%, there is a relatively consistent progression, but beyond 90%, there are larger jumps, indicating that clients tend to leave remnants of the maturity amount in their wallets, spending it later. This should not be considered for post-maturity spending, as the extended time frame hinders our ability to infer a connection between the transactions.

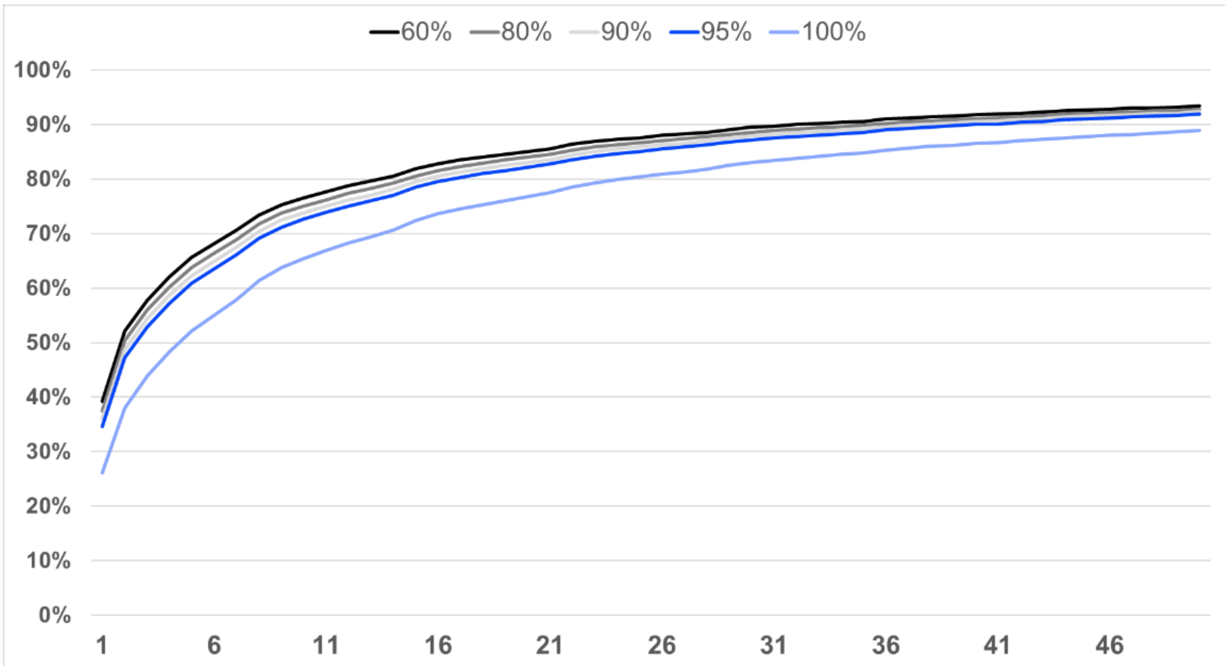

Figure 4.1: Time to reinvest by percentage of allocation

To address issues arising from varying maturity amounts received by different clients, we segmented them into 5 quintiles based on the range of maturity receipts. For each client, we determined the time it took to spend 80% of the received amount, assuming that the amount was almost entirely invested. Through this cumulative distribution function (CDF) (Figure 4.2), we observed that, on average, 80% of clients spend 80% of the maturity amount within 25 days. For higher receipt ranges, this occurs in less than 10 days, while for lower ranges, it takes more than 40 days, demonstrating that the volume received influences the tendency to reallocate the amount more rapidly.

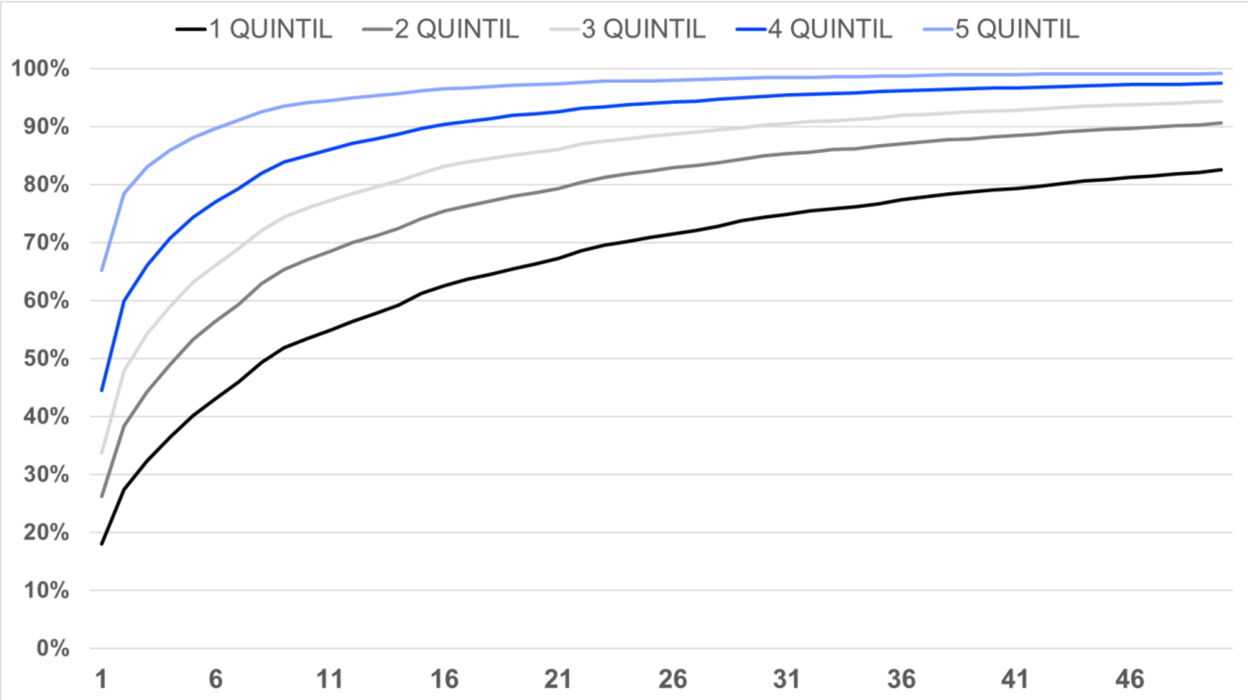

Figure 4.2: Time to reinvest by quintile of received value

In the pre-maturity phase, we need to consider the impact of advisor-client interactions. For this, we accounted for all contacts between advisors and clients, considering the closest contact to the maturity date as the maturity contact for each client-maturity pair. Through this, we observed the distribution of days before maturity when clients are contacted (Figure 4.3). We found that 80% of clients are contacted at least 5 days before maturity, with over 50% being contacted on the maturity date itself.

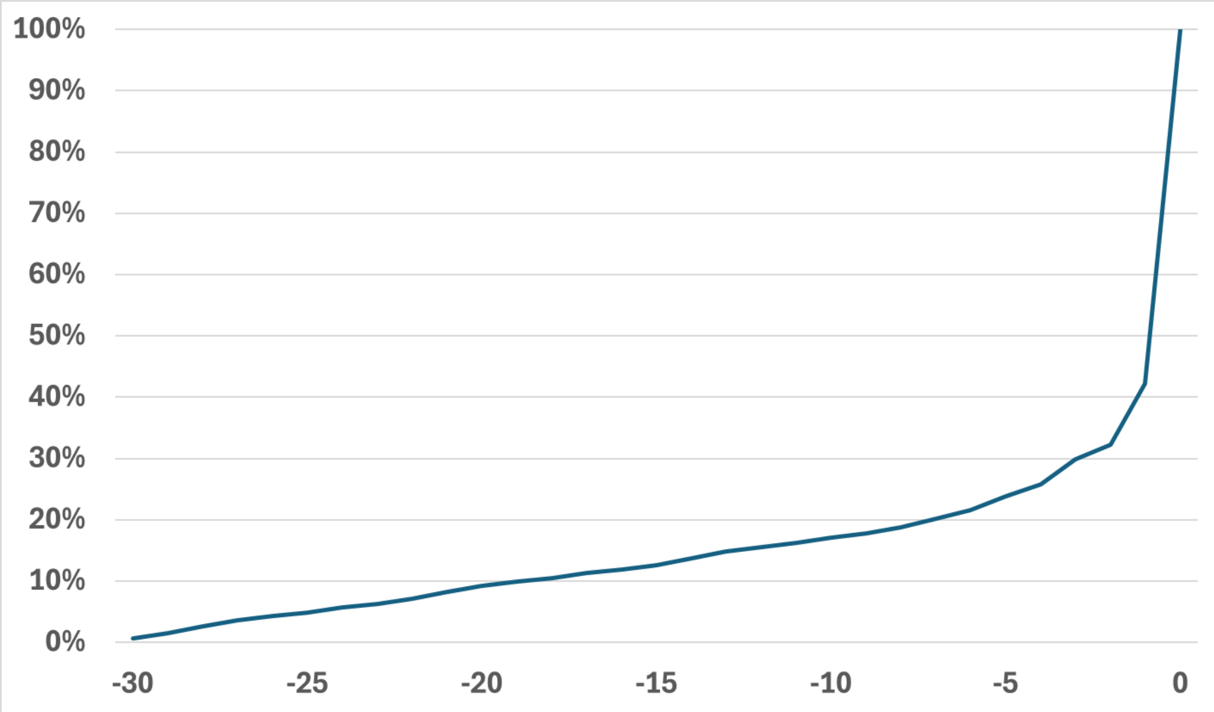

Figure 4.3: Time taken to advisor contact

This allowed us to define a range for considering advisor-client contact to determine its impact on both the maturity and spending behavior of the client. We considered a timeframe from 5 days before maturity to 25 days after maturity, covering both the advisor-client contact period and the time for the client to reinvest the received amount.

4.1.3. Advisory impact

To correlate advisory contact with client reinvestments, we considered whether the client was contacted during the specified period from 5 days before maturity to 25 days after maturity. We then accounted for the highest degree of interaction, whether through advisor contact or automated CRM interactions.

The impact of advisor contacts or automatic CRM pushes is crucial, and we will consistently compare the impact of both processes. The primary indicator of investment improvement is the reduction in outflow generated post-investment, thereby retaining the maximum value possible within the institution. With the image below (Figure 4.4), we can observe the impact of advisor contact segmented by quartiles of client receipts. We note that the impact of advisor contact is most pronounced in lower receipt quartiles and diminishes as receipt quartiles increase. Meanwhile, the impact of CRM contact appears more consistent across receipt quartiles (Figure 4.5). However, the advisor contact in the highest receipt quartile presents challenges regarding the actual impact of advisory services, as clients with higher purchasing power tend to receive closer advisory attention. Our dataset may lack comprehensive data, as contacts may occur through undocumented channels, making evaluation challenging. Therefore, we can more confidently infer the impact on lower receipt quartiles.

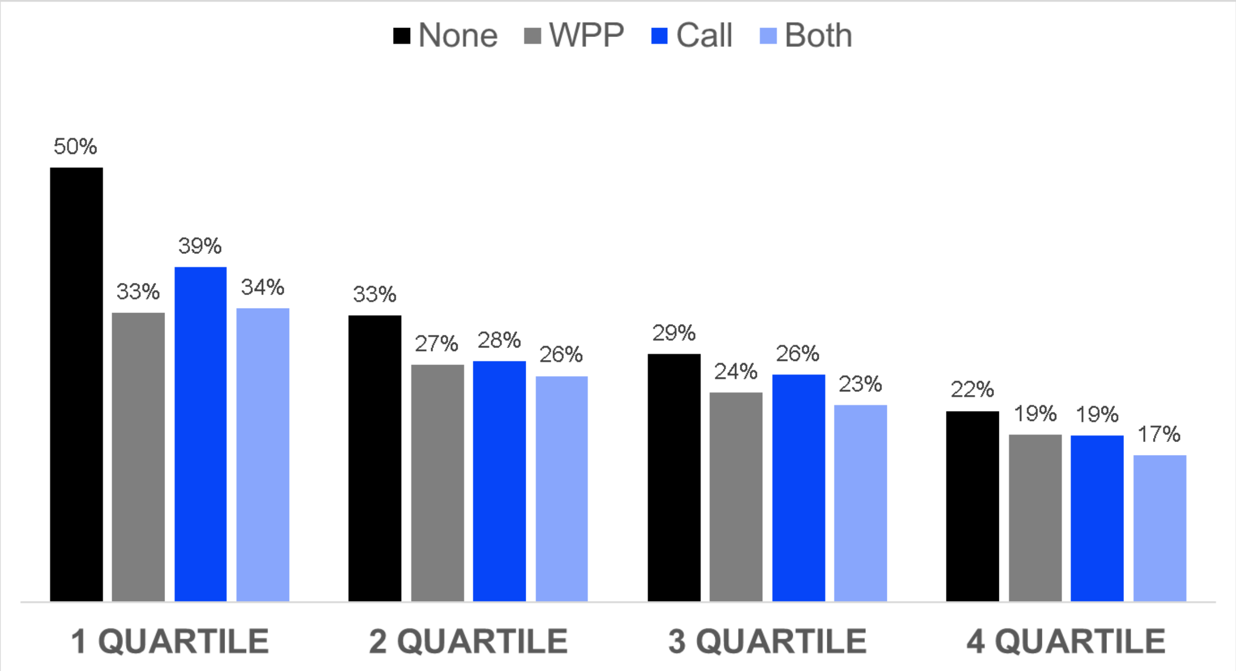

Figure 4.4: Impact of Advisor contact

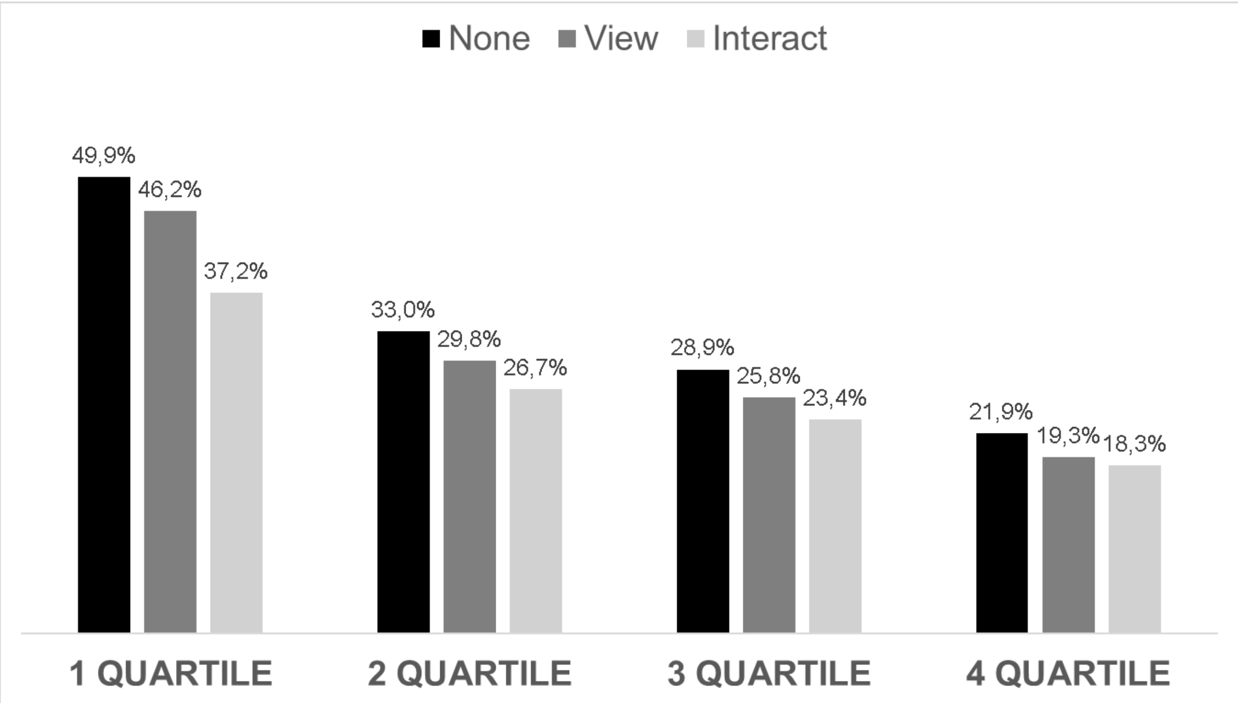

Figure 4.5: Impact of CRM contact

The impact of advisor contact in these lower quartiles not only ensures a lower outflow but also facilitates the reallocation of these funds into illiquid assets, which are more advantageous for the bank, as they cannot be easily sold or withdrawn from the institution and can be retrieved later without significant difficulties. Thus, they become vulnerable capital to the bank to lose.

In the table below (Table 4.3) we can observe the impact of the advisory contact depending on the interaction metric, comparing the client who received none contact and the client that received both, the “both” client has an outflow reduction of 9% that is reinvested in other markets inside the bank, reinforcing that the contact reduces the outflow.

Table 4.3: Impact of Advisor contact in reinvestment

Contact	OUT	FN	LQ	PV	FI
None	35%	3%	18%	0,001	40%
WPP	27%	3%	22%	0,002	40%
Call	29%	3%	19%	0,002	42%
Both	25%	3%	20%	0,001	44%

In the table below (Table 4.4) we can observe the impact of the CRM contact depending on the interaction metric, comparing the client who received none contact and the client that interacted with the push, the “interact” client had a 5% reduction in outflow, also the client reduced the LQ investment and redirected it to FI, as was noticed in advisory contact the CRM contact also reduce the outflow and retains more money inside the bank.

Table 4.4: Impact of CRM contact in reinvestment

Contact	OUT	FN	LQ	PV	FI
None	25%	2%	21%	0%	49%
View	22%	2%	18%	0%	55%
Interact	19%	2%	17%	0%	57%

Based on tables 12 and 13, we can conclude that both advisory and CRM interactions influence client behavior patterns by redirecting their expenditures towards reinvestments within the bank, thereby preventing outflows of funds. This redirection also involves shifting funds from liquid assets to long-term investments, which are more profitable for both the bank and the client.

4.2. Recommendation System

The recommendation system includes the creation of a logic to recommend post-maturity assets to the client. This system leverages the clients' behavioral patterns regarding the sale and purchase of assets to generate an optimal recommendation. Consequently, the idea is to offer products to the client after a maturity, providing the option to diversify the investment among different products or to choose one of them to invest in, to select these products, we will use collaborative based filtering, which will consider what customers with similar profiles tend to consume. We will use this information for customers within the same group. Since our information about the customers is limited, we will use the submarket from the product that matures, their risk profile and the client segment and subsegment as inputs to define what will be recommended, we also will focus on recommend a submarket to be offered to the client, since we do not have enough data to estimate all the assets that will be available to the client now or in a different time.

4.2.1. Client Behavior

Customer behavior patterns are the most important tool when developing the recommendation system. To this end, we begin by evaluating the diversity of customer investments, considering the number of different assets they invest in.

In the images Below, we can see the distribution of the number of markets (Figure 4.6), submarkets (Figure 4.7), and different assets (Figure 4.8) that customers invest in. This analysis shows that customers tend to invest in one market, one submarket, and one, two or three assets. The other values are relatively insignificant. Thus, by offering three assets we can achieve most of the customers' needs.

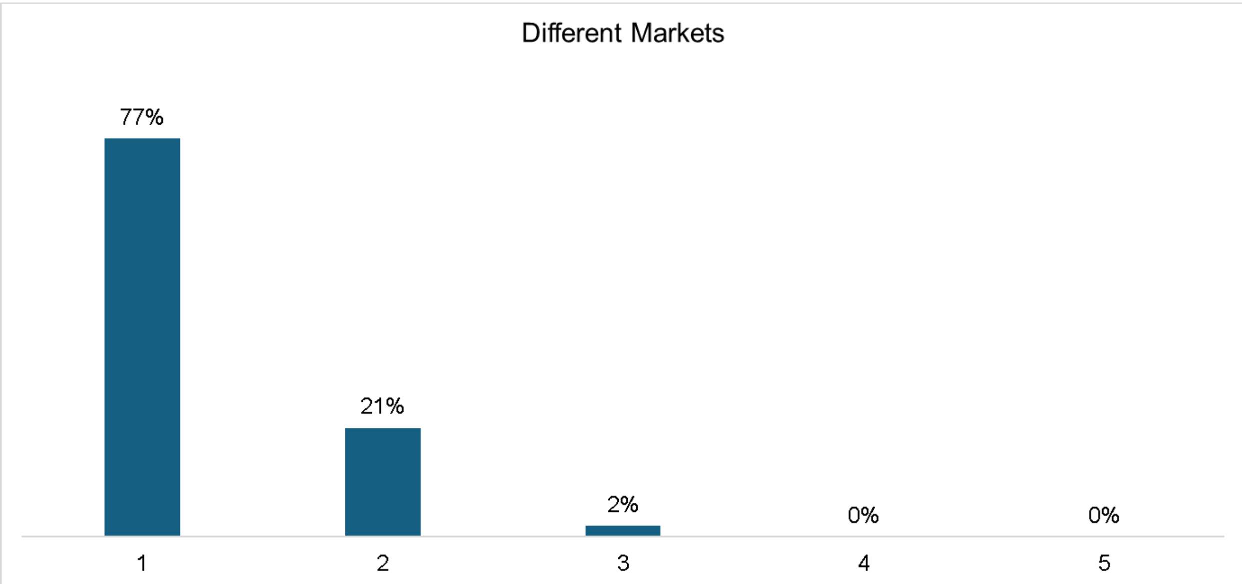

Figure 4.6: Variety of market distribution

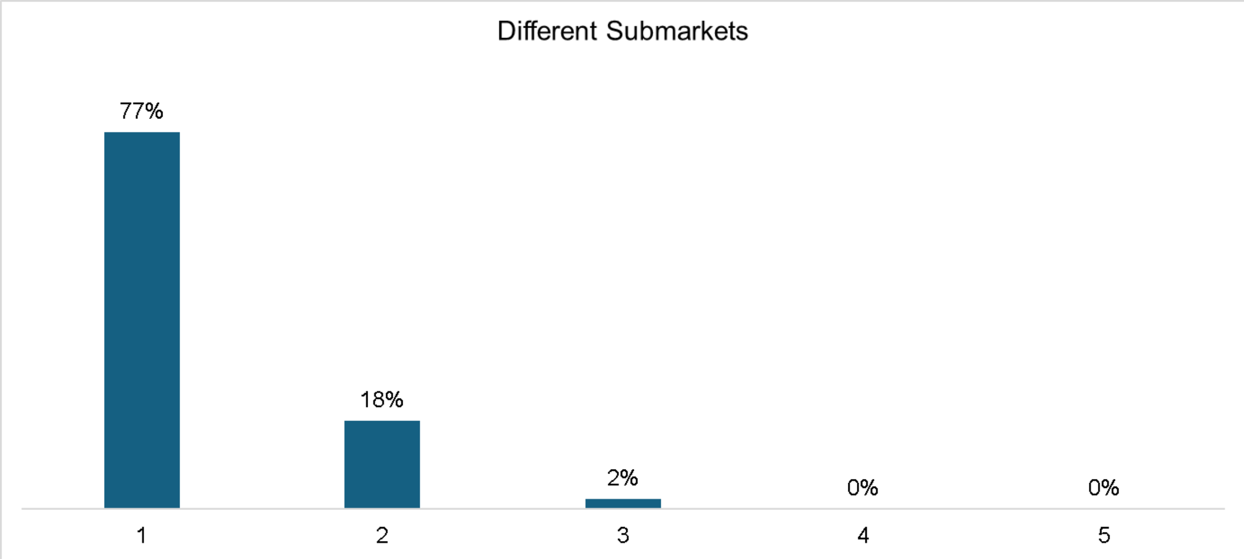

Figure 4.7: Variety of submarket distribution

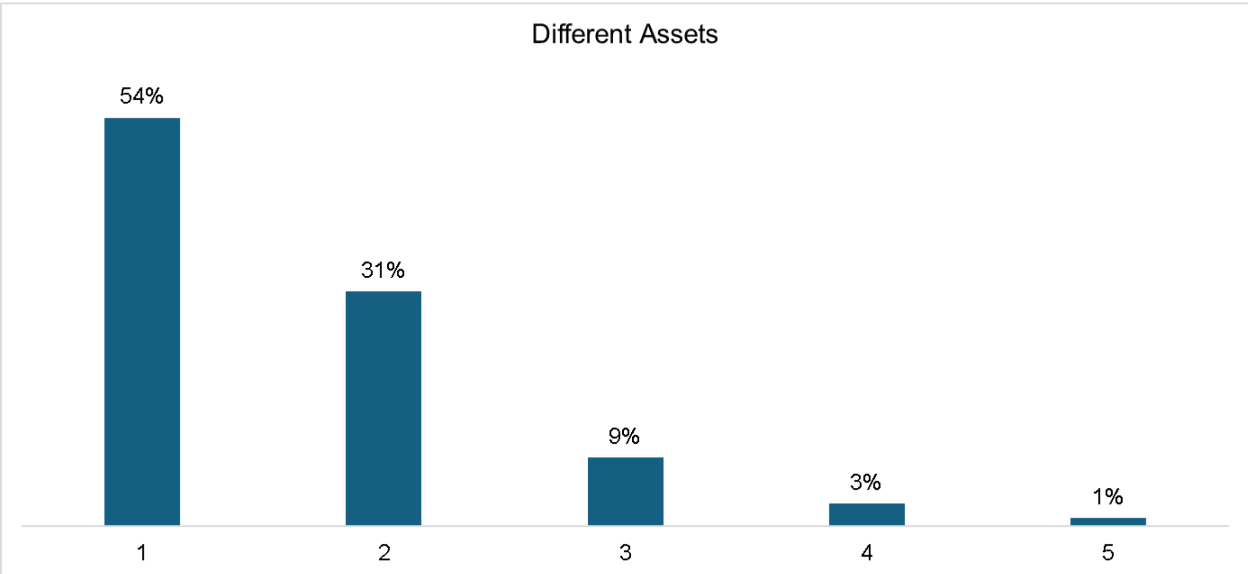

Figure 4.8: Variety of asset distribution

4.2.2. Product Recommendation

Since we have limited information about customer characteristics, we aim to collaborative-based Schafer et al. (2007), recommendation system. The collaborative - based approach considers the assets consumed by the customer, so we will use the client consumes behavior to determine the similar clients and we will use the suitability, segment and the submarket of the asset that matures as additional information to segregate the clients, we will employ a system using the collaborative approach, which uses assets consumed by similar customers to recommend to others. We will focus on recommending submarkets, while the advisor will be responsible for recommending the asset. Since assets are temporarily available, we cannot use historical data to recommend new assets cause the assets consumed one month ago will not be available anymore.

For the generation of the recommendation system, we created a basic recommendation of four assets since we observed in section 4.2.1 that it describes 99% of the invested value.

After applying the recommendation system using the combinations of variables mentioned in subsection 3.4.2, we analyzed the performance metrics to determine the optimal configuration for our client-groups with and without subsegments. Here are the key findings and conclusions drawn from our study:

For client-groups without subsegment, we found using the accuracy measure mentioned in subsection 3.4.2 that using 10 similar client-groups with a minimum correlation of 30%, and the PCS correlation metric yielded the best results. With these parameters, we achieved an impressive 96.7% accuracy in predicting the submarket that clients would choose post-maturity. Furthermore, the recommendation system explained 98.5% of the reinvested value, showcasing its effectiveness in guiding client decisions.

On the other hand, when considering client-groups with the subsegment included, we also identified that using 10 similar client-groups was optimal, but with a higher minimum correlation threshold of 70%, and also PCS correlation metric. Under these conditions, we attained a slightly lower accuracy of 91.0% in predicting post-maturity submarket choices, while still explaining 97.0% of the reinvested value. This indicates that the inclusion of subsegment data adds granularity but requires a stricter correlation threshold to maintain predictive accuracy.

Based on our analysis, the less granular client-group configuration using only risk profile, segment, and maturity submarket, with 10 similar client-groups and a minimum 30% correlation, emerged as the superior option. This setup not only provided high accuracy in predicting client choices but also effectively explained the majority of reinvested values, demonstrating robust performance across different metrics.

We also conducted a longitudinal analysis of accuracy over the best recommendation model found, using data from 2023 as our foundational dataset. (Figure 4.9) and (Figure 4.10) depict the precision in terms of value and offers, respectively, for each month of 2023 and the initial four months of 2024. Notably, the data from the first four months of 2024 served as a separate test set and were not part of our primary analysis dataset. This approach enables us to assess the consistency of accuracy beyond the initial analysis period. Our findings reveal consistent performance across the months, indicating stable accuracy in both value and offers over the extended timeframe.

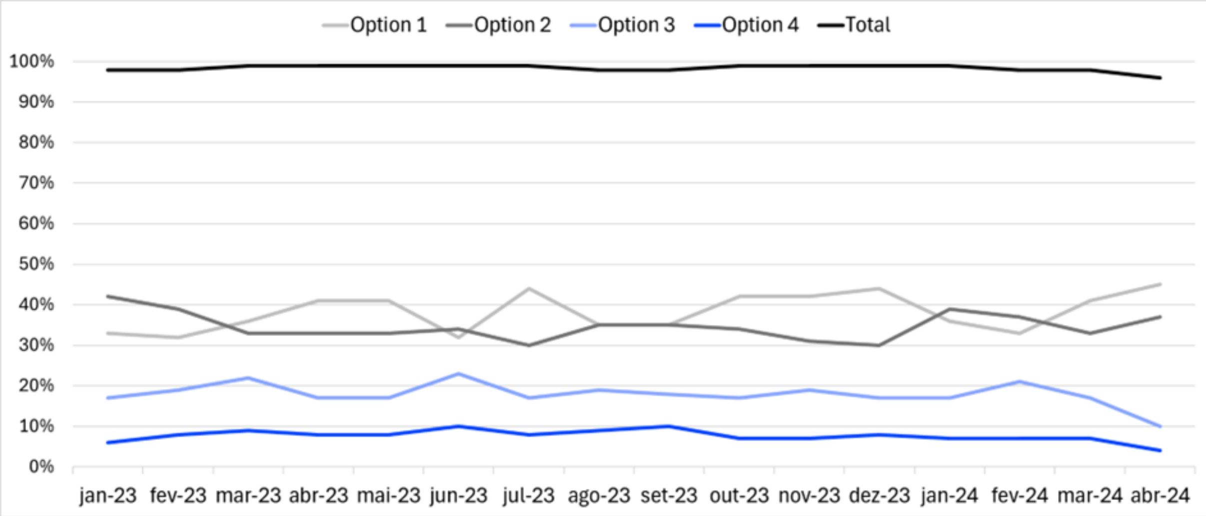

Figure 4.9: Accuracy of value among time

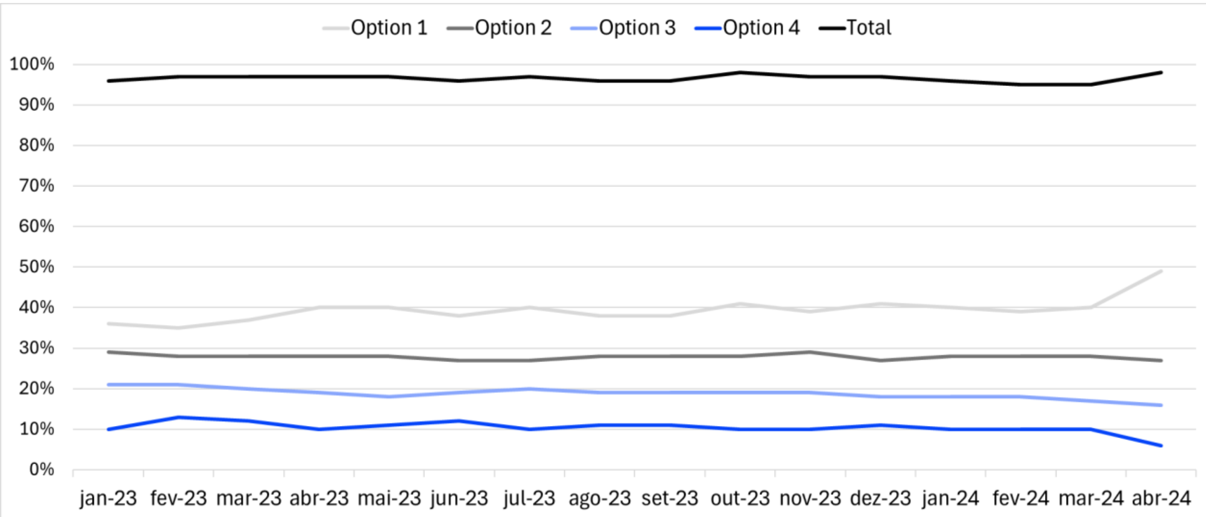

Figure 4.10: Accuracy of offers among time

5. CONCLUSIONS

With this work, we have managed to add significant value to the bank in several ways. We generated an analytical capital flow table, which is already being utilized across various departments within the bank. This table helps explain capital inflows and outflows, as well as map the outcomes of sales or purchases of specific products. This analytical tool has proven essential for understanding and predicting financial movements within the bank. Additionally, we plan to extend its usability to other types of transactions, such as current account movements outside of investment accounts. By expanding its application, we aim to provide a comprehensive view of all financial activities, further enhancing the bank's operational efficiency.

We also delivered a sophisticated dashboard where these results can be tracked and measured daily. This dashboard enables the monitoring of general trends in market movements as well as specific outcomes of buying and selling particular products. It allows for real-time analysis and decision-making, giving the bank an edge in responding promptly to market changes. The dashboard's ability to provide detailed insights and visualizations helps various stakeholders within the bank to make informed decisions based on current data.

The study also quantified the efficiency of advisor contact, demonstrating that they play a crucial role in retaining capital within the bank being able to save almost 10% of outflow and maintain the funds inside the bank. Based on these findings, we suggest implementing a post-maturity asset chatbot to manage large volumes of clients without the need for a substantial increase in the number of advisors.

Finally, the recommendation system, which is currently undergoing preliminary testing, shows strong potential for generating positive results since for client-groups without subsegment, we found that using 10 similar client-groups with a minimum correlation of 30% yielded the best results, leading us to impressive 96.7% accuracy in predicting the submarket that clients would choose post-maturity. Furthermore, the recommendation system explained 98.5% of the reinvested value, showcasing its effectiveness in guiding client decisions. By providing proactive asset recommendations, the objective is to prevent capital outflows from the bank due to a lack of product offerings for clients. As we continue to refine and optimize this system, we anticipate it will play a crucial role in the bank's strategy to enhance customer engagement and increase profitability.

6. LIMITATIONS & FUTURE WORKS

Our primary limitation was the data period, as we only had one year of results to work with. A longer interval would have provided a much larger data sample, which could enhance the robustness and accuracy of our analysis and recommendations, we want to replicate the studies again with a larger date range for analyzing client behavior and consumption patterns of assets post-maturation.

We also faced significant challenges with the contact data between the advisor and the client. We were unable to clearly map the nature of these interactions and differentiate between the types of contact. This lack of clarity makes it difficult to determine which interactions are truly effective in influencing client decisions.

Moreover, many interactions are not recorded in our system because they are conducted through alternative methods. This inconsistency in data recording reduces the reliability of our analysis, particularly for clients with high investment standards who might receive a more personalized advisory approach. Consequently, these data gaps limit our ability to fully understand and optimize the advisor-client relationship, which is crucial for tailoring recommendations that meet the diverse needs of our clients, unfortunately we probably will not be able to cease this lack of information, but we can aim to increase the use of work phones to contact the client using trackable devices.

We also did not have time to implement the recommendation system, so as future work, we plan to implement the system and observe how it impacts customer behavior patterns. Additionally, we aim to evaluate if there are more external variables that affect this decision, which we have not mapped today due to the lack of customer information.

Addressing these limitations will be essential for improving the system's effectiveness and reliability in future iterations.

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