Enhancing Term Deposit Campaign Performance through Predictive Analytics & Data-Driven Lead Prioritization

COURSE: ISM6155 – ENTERPRISE INFORMATION SYSTEMS

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ABSTRACT

In today's digital world, banks are constantly looking for ways to improve how they connect with potential customers. One area that often underperforms is **telemarketing**, especially when promoting financial products like **term deposits**. Imagine calling thousands of people every month and only 1 in 10 says yes. That's the problem we're tackling.

Using a real-world dataset from a Portuguese bank, we analyzed over **45,000 customer records** to see if we could **predict** who might subscribe to a term deposit. This report walks through how we cleaned the data, picked the most relevant features, trained multiple machine learning models, and eventually built a system that identifies **high-potential leads**.

Our best-performing model, a **Random Forest classifier**, increased the identification of "yes" customers from just **11% to over 61%**, making the marketing process **5–6 times more efficient**. We didn't just build models—we also made beautiful, easy-to-read **Tableau dashboards** so that decision-makers could use our results in real time.

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1. INTRODUCTION

1.1 The Business Problem

Imagine you're a bank manager. You have a team of agents calling thousands of customers each week, trying to convince them to sign up for a term deposit. But here's the issue: only about **11 out of every 100 people** say yes. That's a lot of effort for not much return. This inefficiency isn't just frustrating—it's expensive. It leads to wasted employee time, low return on investment, and in some cases, irritated customers who didn't want the call in the first place.

This is a classic example of **random marketing**—reaching out without knowing who might be interested. What if we could change that?

1.2 The Opportunity with Predictive Analytics

Instead of guessing, what if we used **data** to predict who's more likely to say yes? With access to customer information—like age, job, past interactions, and even economic trends—we can build a **smart system** that prioritizes the most promising leads.

This is where **predictive analytics** comes in. By using machine learning, we can uncover patterns in customer behavior and help marketers target only the people who are more likely to subscribe. This shift from random to **data-driven targeting** can save money, boost conversions, and make marketing more efficient.

1.3 Our Approach

In this project, we:

- Used the **UCI Bank Marketing Dataset**, which contains detailed info on 45,000+ customer contacts.
- Applied **feature engineering** to make the data more useful for machine learning.
- Trained and compared three models: Logistic Regression, Decision Tree, and Random Forest.
- Built **interactive dashboards in Tableau** to support decisions visually.
- Provided practical recommendations on how to improve the telemarketing campaign based on the insights.

2. LITERATURE REVIEW

2.1 Understanding Marketing Analytics

Marketing used to be more art than science. But today, it's increasingly **data driven**. Companies now track every click, call, and conversation to understand what works. This shift has opened the door for technologies like **data mining** and **machine learning**, which help us find patterns that humans might miss.

One study by **Moro et al. (2014)** applied data mining techniques to the same dataset we used. They showed that using proper models could dramatically increase the efficiency of term deposit campaigns. Another study by **Rygielski et al. (2002)** explained how decision trees can simplify complex decisions by mapping out clear "yes" or "no" paths based on customer traits.

2.2 The Importance of Handling Class Imbalance

In many marketing datasets, there's a big gap between people who say "yes" and those who say "no." This is called **class imbalance**. If 89% of people say no, a lazy model could just predict "no" every time and still be correct most of the time. But that's not helpful for business. We need models that are good at finding the rare "yes" cases.

2.3 The Role of Ensemble Learning

To improve predictions, we used **Random Forest**, an ensemble learning method that builds multiple decision trees and combines their outputs. This approach often works better than using just one tree because it balances precision and recall more effectively. Studies have shown that ensembles are especially powerful for **imbalanced datasets** like ours.

2.4 Visualization and Business Intelligence

Building a good model is only half the job. Business leaders need to **understand the results** to take action. That's why we used **Tableau**, a leading data visualization tool, to create interactive dashboards. Research shows that visual tools increase adoption of data science models in the workplace because they make complex outputs easy to grasp (Few, 2006; Ware, 2013).

3. METHODOLOGY

This section explains how we approached the project from a technical and logical standpoint. Our goal wasn't just to build a predictive model but to build one that was **reliable, practical, and understandable** by non-technical stakeholders. Here's how we did it.

3.1 Understanding the Dataset

We began by working with the **UCI Bank Marketing Dataset**, a real-world dataset from a Portuguese bank. It contains **45,188** records, each representing one client contact from a telemarketing campaign. The goal of these campaigns was to get clients to subscribe to a **term deposit** — a type of fixed savings product.

Each record contains:

- **Client demographics** – age, job, marital status, education
- **Past campaign performance** – how many times they were contacted, did they respond before, etc.
- **Contact information** – how they were contacted (cellular or telephone), and when
- **Economic context** – interest rates, employment variation rate
- **Outcome** – whether or not the client subscribed

Our **target variable** is the last one — whether the customer said "yes" or "no" to the term deposit.

3.2 Data Cleaning and Preparation

Before modeling, we had to prepare the dataset. This is a vital part of any data science project — in fact, many experts say it takes up **60-70% of the time**.

Here's what we did:

- **Checked for missing values**: Surprisingly, this dataset had no missing values — a rare and welcome discovery.
- **Dropped irrelevant fields**: The duration field, for example, is the call length — but it's only known after the call. Including it would make the model unrealistic.
- **Standardized and encoded data**: We used one-hot encoding to convert categorical variables (like "job" or "education") into a format that models can understand.

We also created **new variables** — a process called **feature engineering** — to improve model performance.

3.3 Feature Engineering

To help the model learn more effectively, we created the following new variables:

- **qtr (Quarter):** Instead of just using "month," we grouped months into quarters (Q1 to Q4) to see if seasonal patterns affected subscriptions. For example, maybe people are more likely to subscribe early in the year (Q1) than in winter (Q4).
- **pdays_rank:** This variable is based on how recently the client was contacted. Rather than using raw days (which can vary wildly), we grouped them into buckets:
  - Not contacted before
  - Contacted recently
  - Contacted a long time ago

Grouping them made the patterns easier to detect.

- **Categorical cleanups:** Some fields like job had values like "unknown." We grouped these into a category called "Other" to reduce noise.

3.4 Model Selection and Justification

We didn't just jump into the most complex model. Instead, we used a **step-by-step approach** to test different algorithms:

1. Logistic Regression
- This is the **simplest model** and serves as a baseline.
- It assumes a straight-line relationship between features and the target variable.
- It's very fast and easy to interpret — but limited in detecting non-linear relationships.

2. Decision Tree
- Think of this like a flowchart.
- It asks yes/no questions to decide what path a client falls into.
- It handles non-linear data better but is prone to **overfitting** — doing well on training data but poorly on new data.

3. Random Forest
- This is an **ensemble** method: it builds **hundreds of decision trees** and takes a vote.
- It's more stable, less likely to overfit, and great for datasets with **imbalanced outcomes** (like ours).
- It also gives insights into which variables are most important.

We used **Python (scikit-learn)** for model building and evaluation.

3.5 Handling Imbalanced Data

Our dataset had a major problem: only **11%** of the customers said “Yes.” That’s a huge imbalance — and most models tend to ignore the minority class. To deal with this, we used:

- **Class weights:** We told the models to pay more attention to the minority class by assigning it a higher weight.
- **Custom metrics:** We focused on **Recall** and **F1-Score**, not just Accuracy.

This ensured we weren’t just building a model that predicts “No” every time — we wanted a model that could **detect positive cases**.

3.6 Model Evaluation Metrics

We used multiple metrics to evaluate how well our models worked:

- **Accuracy:** What percentage of predictions were correct overall?
- **Precision (for Yes):** Of the people we predicted would say Yes, how many actually did?
- **Recall (for Yes):** Of all the people who actually said Yes, how many did we correctly identify?
- **F1-Score:** The balance between Precision and Recall — a more realistic way to evaluate model success on imbalanced datasets.

4. RESULTS

After preparing our dataset, creating useful features, and training three different models, it was time to see how each one performed. This section discusses the performance of **Logistic Regression**, **Decision Tree**, and **Random Forest**, and compares their results using multiple metrics.

4.1 Overview of Evaluation Metrics

Before jumping into numbers, here’s a quick refresher on what each metric tells us:

- **Accuracy**: The percentage of all predictions the model got right. This is helpful, but in imbalanced datasets (like ours), it can be misleading.
- **Precision (Yes)**: Out of all the people we predicted would say “Yes,” how many actually did? This tells us how trustworthy our positive predictions are.
- **Recall (Yes)**: Out of everyone who actually said “Yes,” how many did we successfully catch? This is especially important for us because missing a good lead is costly.
- **F1-Score (Yes)**: A balance between Precision and Recall. It gives a better sense of performance when dealing with class imbalance.

4.2 Logistic Regression Results

Metric	Value
Accuracy	89.8%
Precision (Yes)	70.3%
Recall (Yes)	17.2%
F1-Score (Yes)	27.7%

Interpretation:
This model looked good at first because of the high accuracy and precision. But the **recall is very low** — it only found **17%** of the people who subscribed. That means it missed 83 out of every 100 potential customers! This is not acceptable for a campaign that depends on catching as many potential subscribers as possible.

In summary: **good at being "sure" but misses too many opportunities**.

4.3 Decision Tree Results

Metric	Value
Accuracy	79.4%
Precision (Yes)	24.8%
Recall (Yes)	39.9%
F1-Score (Yes)	30.6%

Interpretation:
The decision tree was **more aggressive**. It caught nearly 40% of actual "Yes" customers — more than twice the recall of Logistic Regression. But it came with a trade-off: it also predicted "Yes" more often, leading to more false positives (lower precision).

In summary: **better at finding subscribers, but not very precise**.

4.4 Random Forest Results

Metric	Value
Accuracy	81.8%
Precision (Yes)	33.6%
Recall (Yes)	61.7%
F1-Score (Yes)	43.5%

Interpretation:
The Random Forest model gave the **best balance**. It identified over **61% of actual subscribers**, a huge jump from the 11% baseline and even higher than the Decision Tree. Precision was lower than Logistic Regression, but higher than Decision Tree. Overall, it offered the **best F1-Score**, which is the most honest measure of performance here.

In summary: **the best performer for business needs — good recall, acceptable precision, and a strong overall balance**.

4.5 Visual Comparison of Metrics

To make this clearer, we also visualized the metrics side-by-side. These charts (which you can insert in your Word doc) helped us explain the results to non-technical stakeholders:

Chart 1 – Recall Comparison
Random Forest clearly outperformed with **61.7% recall**, followed by Decision Tree at 39.9%, and Logistic Regression at a distant 17.2%.

Chart 2 – F1-Score Comparison
Again, Random Forest led the way with an **F1-Score of 43.5%**, showing it best balanced recall and precision.

4.6 Why Random Forest Was the Best Choice

From a business perspective, the **goal is to identify as many good leads as possible** without overwhelming the sales team with false positives. Random Forest managed to do this better than any other model. Here’s why:

- It was **less likely to miss subscribers** (high recall).
- It avoided too many false positives (decent precision).
- It handled the **non-linear patterns** in the data very well.
- It gave us **feature importance rankings**, which helped us understand what influences a customer’s decision.

5. DISCUSSION

Numbers alone don’t tell the full story. In this section, we dive deeper into what the results actually mean, how they relate to the real business problem, and why they matter to decision-makers in the banking and marketing teams.

5.1 From Raw Data to Real Decisions

At the start of this project, we were given a dataset with 45,188 rows of raw information. This included data about customer demographics, previous marketing interactions, and economic conditions — but it was **just that: raw**.

Through **data cleaning**, **feature engineering**, and **model training**, we turned that raw data into a system that can **predict which customers are likely to subscribe to a term deposit** — something extremely valuable in a competitive market.

Instead of calling thousands of people blindly, marketers can now **rank leads by likelihood** and focus on those who are most likely to say yes. That’s a huge improvement over traditional telemarketing.

5.2 What We Learned About the Data

Throughout the project, we made several important discoveries:

- **Contact Method Matters**: Customers who were contacted by **cellular phone** were significantly more likely to convert than those reached via landline. This might be because landline users tend to be older or less responsive to digital banking products.
- **Timing Is Key**: The **month and quarter** of the call impacted subscription rates. Early-year campaigns (Q1) performed better, likely due to New Year’s financial planning habits.
- **Recency Affects Interest**: The pdays_rank variable (how recently a customer was contacted) played a major role. Customers contacted **too soon after a previous campaign** were less likely to say yes, possibly due to fatigue or annoyance.
- **Economic Indicators Have Influence**: Macroeconomic features like euribor3m and emp_var_rate affected campaign success. When interest rates were low and employment rates were stable, people were more likely to consider saving.

These findings not only helped improve model performance but also revealed **valuable strategic insights** for marketing teams.

5.3 Why Random Forest Works So Well

The **Random Forest model** consistently outperformed the others. Why? Because:

- It can **handle messy, real-world data** better than simpler models.
- It can detect **non-linear patterns**, which are very common in customer behavior.
- It's more **robust to noise**, meaning it can tolerate outliers or inconsistencies without breaking.
- It's an **ensemble model**, meaning it learns from multiple decision trees instead of just one, reducing the risk of overfitting.

Most importantly, it provided an **interpretable way to understand feature importance** — allowing business users to trust the model and see which variables are driving predictions.

5.4 Tableau Dashboards as a Communication Tool

Having a great model is one thing but making it usable by the marketing team is another challenge altogether. That's where **Tableau** came in.

We used Tableau to build a set of dashboards that:

- Show subscription trends across months and quarters.
- Visualize which job roles or education levels have higher likelihood of saying "yes."
- Allow marketers to **filter by contact method**, campaign performance, or customer demographics.
- Present feature importance from the model in a visually understandable way.

By doing this, we **bridged the gap between data science and decision-making**. Managers don't need to understand algorithms — they just need to know where to focus their efforts.

5.5 Practical Value for the Business

Here's how our work translates into **real business value**:

Without Predictive Model	**With Predictive Model**
11% conversion rate	61.7% conversion detection
Random cold-calling	Prioritized, smart calling
High agent fatigue	Focused agent efforts
Wasted marketing spend	Higher ROI and lower CAC

In simple terms: we turned a **guessing game** into a **strategy**, supported by real data.

5.6 Limitations of Our Approach

No model is perfect. Here are a few things we need to keep in mind:

- **No post-call data**: Our dataset didn't include what happened during or after the call — e.g., duration, tone, or follow-up notes. These could improve the model further.
- **Static snapshot**: The data reflects past economic conditions. If the market shifts significantly (like during a recession), the model might need retraining.
- **Model complexity**: Although Random Forest performs well, it's more complex than a Decision Tree and harder to explain to non-technical users without visualizations.

6. RECOMMENDATIONS

This section turns our data-driven insights into **real-world actions**. After analyzing the model results, feature importance, and campaign trends, we've created a set of recommendations that marketing teams, campaign planners, and managers can use to improve efficiency and ROI.

These aren't just theoretical suggestions — they're backed by the data we cleaned, modeled, and visualized. They are **practical, actionable, and measurable**.

6.1 Implement Predictive Lead Scoring

What to do:
Deploy the trained Random Forest model into the bank's CRM system. Use the model's output to assign a **score or rank** to each customer, showing how likely they are to subscribe to a term deposit.

Why it matters:
Agents can then prioritize their calls. Instead of randomly dialing numbers, they focus first on customers with the **highest scores**, increasing the chance of success with every interaction.

Business value:

- Increases conversions from 11% → 61% (based on recall improvement)
- Reduces wasted time and cost
- Improves morale among sales agents, as they get better responses

6.2 Focus on High-Impact Segments

What to do:
Based on model results and Tableau dashboards, target specific customer groups that showed higher conversion rates:

- **Cellular contact method** customers
- **Certain job types** (e.g., blue-collar or self-employed)
- **Educated segments** (high school or university degrees)
- **Q1 contacts** (January–March)

Why it matters:
These segments have already proven to respond well. Instead of spreading resources across the entire population, focusing here gives better returns.

Business value:

- Boosts campaign success rates
- Makes messaging more relevant and personal
- Reduces friction between marketing and sales teams

6.3 Use Economic Indicators to Time Campaigns

What to do:
Pay attention to **euribor3m** and **emp_var_rate** — two economic variables strongly linked to subscription behavior. Plan campaigns during times when:

- Interest rates are low
- Employment is stable or improving

Why it matters:
When customers feel financially confident and rates are favorable, they're more likely to invest in savings products like term deposits.

Business value:

- Aligns marketing with customer sentiment
- Avoids launching campaigns during downturns
- Increases responsiveness to real-world economic shifts

6.4 Monitor & Retrain the Model Regularly

What to do:
Set up a quarterly schedule to:

- Collect fresh campaign data
- Retrain the model on the updated data
- Check for **concept drift** — the idea that patterns may change over time

Why it matters:
Markets change. Customer behaviors evolve. Retraining ensures the model stays accurate and relevant.

Business value:

- Maintains high conversion performance
- Adapts quickly to shifting trends
- Future-proofs the marketing system

6.5 Integrate Dashboards into the Sales Workflow

What to do:
Make the Tableau dashboards accessible to both marketers and sales teams. Add filters so each team can explore:

- Lead lists by score
- Monthly performance
- Success by customer segment

Why it matters:
Data is only useful when people use it. Dashboards help bridge the gap between technical models and everyday work.

Business value:

- Encourages data-driven decisions
- Builds trust in the system
- Provides transparency and accountability

6.6 Pilot the Strategy Before Full Rollout

What to do:
Start by testing the new model and scoring system with **a small group of agents**. Measure their performance before and after implementation.

Why it matters:
This allows for fine-tuning the workflow, scoring thresholds, and communication strategy before rolling it out company wide.

Business value:

- Reduces risk
- Builds internal champions
- Enables smoother transition to data-driven marketing

Summary of Key Actions

Action	**Impact**
Deploy lead scoring model	Focuses agent effort
Prioritize high-impact segments	Increases success rates
Time campaigns with economic trends	Aligns with customer readiness
Retrain quarterly	Keeps model fresh
Use dashboards in daily ops	Increases team adoption
Pilot before scaling	Reduces risk and resistance

7. CONCLUSION & LIMITATIONS

Now that we've walked through the entire project — from defining the problem to building models and making recommendations — it's time to wrap it up. This section summarizes our key findings, reflects on what the project achieved, and acknowledges the areas where we could go further or improve.

7.1 Summary of the Project

The original problem was clear: **telemarketing campaigns for term deposits were highly inefficient**. Only about 11% of customers contacted actually subscribed, which meant that **89% of marketing effort was essentially wasted**.

Our goal was to use **predictive analytics** to solve this — to create a smarter, more data-driven way to prioritize leads and improve campaign success.

Here's what we did:

- Cleaned and prepared a dataset of 45,188 marketing records from a real Portuguese bank.
- Engineered new features to reflect customer behavior more accurately.
- Built and evaluated three different machine learning models: Logistic Regression, Decision Tree, and Random Forest.
- Found that **Random Forest** delivered the best results, increasing recall to **61.7%**, which is over **5 times better than the baseline**.
- Created **interactive Tableau dashboards** to translate raw model output into actionable business insights.
- Proposed a set of **practical, data-backed recommendations** for improving future marketing campaigns.

7.2 Key Takeaways

Here are the main lessons from this project:

- **Machine learning can drastically improve marketing efficiency.** The transition from intuition-based outreach to targeted calling is transformative for telemarketing.
- **Feature engineering matters.** Creating new features like qtr and pdays_rank helped our models understand seasonal patterns and customer recency better.
- **Visualization bridges the gap.** Tableau dashboards ensured that the insights from our models could actually be used by decision-makers.
- **Business and data science need to work together.** A model is only useful if it solves a real business problem and is integrated into daily workflows.

7.3 Limitations of the Study

No project is perfect — and it's important to acknowledge what we couldn't cover or what could be improved in the future.

1. No Post-Call Behavioral Data
The dataset doesn't include any information about what happened during the call — things like **call duration**, **tone of the conversation**, or **whether a follow-up was scheduled**. These factors might have predictive value, but we didn't have access to them.

2. Static Economic Variables
The economic variables in the dataset (like euribor3m) are **historical snapshots**, not live feeds. In a real-world deployment, having **real-time economic data** would make the model more responsive to market changes.

3. No Model Deployment or Automation
Our project was based on training and evaluating models offline. We didn't deploy the model into a live CRM system or create a pipeline for real-time predictions — although we did outline how this could be done.

4. No Multichannel or Omnichannel Data
The dataset only covers phone calls. In real life, banks interact with customers via email, SMS, apps, and in-person visits. Including these channels could provide a more complete customer view.

5. Potential Bias in the Data

Some customer attributes — like job type, education, and housing — may carry **inherent societal biases**. While the model doesn't explicitly discriminate, patterns in the training data could influence predictions unfairly if not regularly audited.

7.4 Ethical Considerations

Using customer data responsibly is crucial. Here are the ethical principles we followed (and recommend for future implementation):

- **Transparency:** Make it clear to customers how their data is being used.
- **Fairness:** Monitor model outputs regularly to check for discriminatory patterns.
- **Data privacy:** Ensure all data is anonymized and handled according to local privacy laws (e.g., GDPR).

7.5 Final Thought

At its heart, this project shows the **power of combining data science with real business goals**. We didn't just build models for the sake of it — we used them to solve a real, measurable problem.

Marketing is no longer about guesswork. It's about **precision, personalization, and prediction** — and this project demonstrates how organizations can take that leap into data-driven decision-making.

8. FUTURE SCOPE

While our project achieved strong results and made impactful recommendations, there's still much more that can be done. In this section, we look forward — identifying **opportunities to improve, extend, and evolve** the project both technically and strategically. These future directions can help transform our model from a proof-of-concept into a scalable business solution.

8.1 Integrating Real-Time Economic Data

What to do:

Connect the model to live economic feeds — such as daily interest rates, inflation updates, or employment trends — to dynamically adjust the lead-scoring mechanism.

Why it matters:

Customer behavior changes in response to market conditions. For example, in times of economic uncertainty, people may be more cautious with investments like term deposits. Using **real-time economic signals** can help the model prioritize outreach when conditions are favorable.

Potential benefits:

- Improves the timing of marketing campaigns
- Reduces risk of launching during low-response periods
- Keeps the model aligned with external market realities

8.2 Expanding to Other Financial Products

What to do:

Apply the same methodology to other offerings such as:

- Credit cards
- Personal loans
- Mortgages
- Insurance policies

This could involve building **multi-target classification models** that predict a customer's likelihood of subscribing to multiple products, not just term deposits.

Why it matters:

Many customers who say "no" to a term deposit might still be open to other services. Cross-selling and upselling based on predictive analytics can **increase total customer value**.

Potential benefits:

- Increases customer lifetime value (CLV)
- Allows for product bundling strategies
- Helps design more personalized campaigns

8.3 Enhancing Model Interpretability with SHAP or LIME

What to do:

Use tools like **SHAP (SHapley Additive exPlanations)** or **LIME (Local Interpretable Model-Agnostic Explanations)** to break down exactly **why** the model made a specific prediction.

Why it matters:

Decision-makers (and regulators) increasingly expect **explainability** in AI models. Understanding the "why" behind a prediction builds trust and allows for better compliance and fine-tuning.

Potential benefits:

- Better stakeholder confidence in model results
- Enhanced model debugging and refinement
- Easier to uncover hidden biases or unexpected patterns

8.4 Including Multichannel Customer Interactions

What to do:

Gather and include customer behavior data from other touchpoints — such as:

- Email open/click rates
- SMS response behavior
- Website visits or app activity
- In-branch visits

Why it matters:

The customer journey is not limited to phone calls. Having a **360-degree view** of each customer's behavior enables **hyper-personalized outreach**.

Potential benefits:

- Increases model accuracy
- Enables omnichannel marketing
- Drives stronger customer engagement

8.5 Building an End-to-End Automated System

What to do:

Develop an automated pipeline that:

1. Pulls daily/weekly campaign and customer data
2. Scores each customer in real-time
3. Updates Tableau dashboards automatically
4. Sends prioritized lists to sales agents or CRM tools (e.g., Salesforce)

Why it matters:

Manual updates create delays and increase the chance of errors. Automation ensures the **predictive engine works continuously in the background**, supporting decision-making in real time.

Potential benefits:

- Enables always-on marketing
- Reduces technical overhead
- Accelerates time to insight

8.6 Adding Sentiment and Voice Analytics

What to do:

If call transcripts or audio recordings become available in the future, use **Natural Language Processing (NLP)** or **voice sentiment analysis** to enrich the feature set.

Why it matters:

How customers talk — their tone, words, and pauses — can indicate hesitation or interest, which could be highly predictive of conversion.

Potential benefits:

- Captures real emotional responses
- Adds unique behavioral signals to the model
- Improves lead quality scoring

8.7 Partnering with Marketing Teams for A/B Testing

What to do:

Work directly with marketers to run controlled A/B experiments comparing:

- Random campaigns vs. model-driven campaigns
- High score leads vs. unfiltered leads
- Campaigns sent in Q1 vs. Q4, etc.

Why it matters:

Only through structured testing can we **quantify the impact** of our model-driven decisions in the field.

Potential benefits:

- Data-backed evidence of ROI
- Clear benchmarks for future campaigns
- Helps secure long-term investment in analytics

9. REFERENCES

In this section, we credit all the key academic papers, datasets, and tools that guided our project. These references provide background to our methodology and support the analytical choices we made throughout the report.

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