Internship Report

On

Data Science

Submitted by

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**Executive Summary**

This report provides an overview of the work we did during our time at Futurense Technologies from June to September 2024. During this time, we worked on data collection, cleaning, analyzing data analytics (EDA), and developing machine learning models to solve specific business problems. Key benefits include identifying target customers**,** developing effective sales strategies, and providing insight into resource allocation. This report summarizes the methodology used, key findings, and business outcomes of our work.

**1. Introduction**

Futurense Technologies are committed to empowering Indian Tech Talent to achieve Global Job Readiness. By building strategic and historic partnerships with prestigious educational organisations in India and across the globe, they make upskilling and higher education accessible to all deserving candidates.

**Purpose of the Internship**

The main goal of the internship was to apply data science techniques to help Futurense Technologies enhance their business strategies. The goal was to analyze business data, uncover hidden patterns, and build models to help clients improve their performance. We were tasked with working on real-world data, conducting exploratory analysis, and building machine learning models to solve various business problems.

**2. Internship Objectives**

The primary objectives for my internship were:

1. **Data Analysis and Exploration:** Analyze business data to uncover patterns, trends, and insights.
2. **Predictive Modelling:** Develop machine learning models to predict key business outcomes (e.g., customer churn, sales forecasting).
3. **Business Optimization:** Identify actionable insights to help improve operational processes such as resource allocation, sales strategy, and customer retention.
4. **Report Generation:** Present findings through detailed reports and dashboards to aid decision-making.

**3. Methodology & Tools**

-> **Data Collection**

The data provided by **Futurense Technologies** included:

* **Campaign Data:** Amount spent on campaigns, impressions and clicks generated, platforms on which campaigns run.
* **Leads:** Lead details like graduation degree, graduation percentage, work experience, platform.
* **Phone Metrics:** Contact information of the leads including call records of the lead.
* **Candidate Application Tracker:** Lead status and information throughout the whole process.

Data was provided by the Futurense Technologies themselves. The data was then transformed for analysis.

**-> Data Preparation**

Before analysis, the data underwent several preprocessing steps, including:

* **Data Cleaning:** Missing values were handled using imputation methods. Outliers were detected and dealt with through transformations or removal, depending on their nature.
* **Feature Engineering:** New features were created from existing ones, such as calculating customer score (CS) from current status and their behaviour.

**->Analysis & Modelling**

* **Exploratory Data Analysis (EDA):** Initial analysis involved visualizations using tools like Matplotlib and Seaborn in Python. Key insights from this phase included trends in sales data, customer behaviour patterns, and seasonal variations.

**->Machine Learning Models**

**Classification Models** (e.g., Random Forest, SVM) for customer churn prediction.

* **Clustering Techniques** (e.g., K-Means) to segment leads based on lead behaviour.

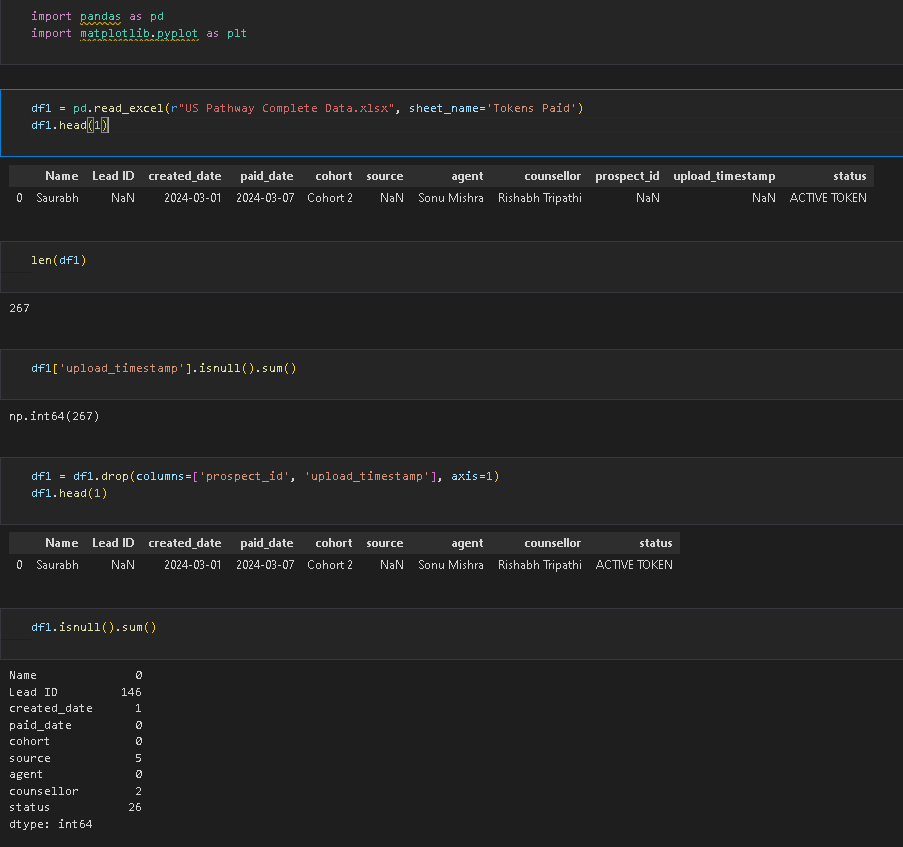
**->Tools & Technologies**

The following tools and technologies were used during the internship:

* **Programming Languages:** Python for data processing.
* **Libraries/Frameworks:** Pandas, NumPy, Scikit-learn, Matplotlib, Seaborn.
* **Data Visualization Tools:** Power BI.
* **Cloud Platforms:** Azure for data storage, compute, and model deployment.

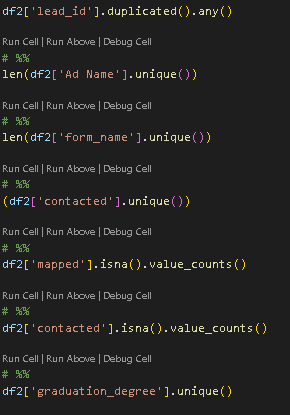
**METHODOLOGY**

**1. Loading Data:**



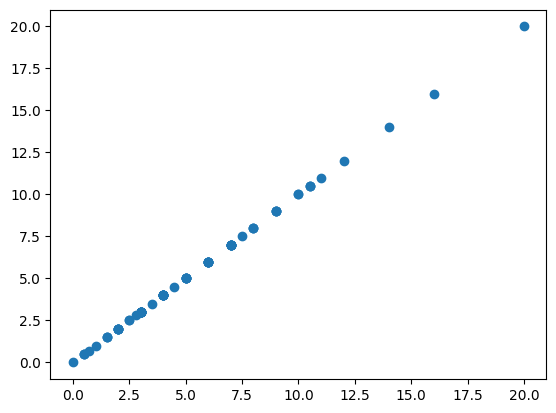
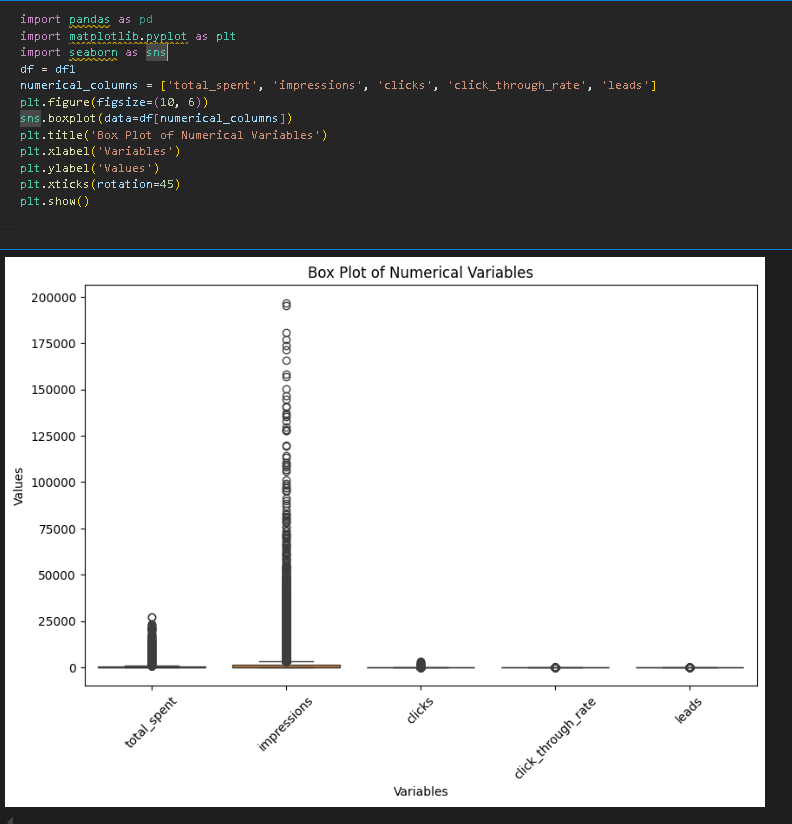
The data was loaded in a ‘.ipynb’ file using Visual Studio Code as IDE.

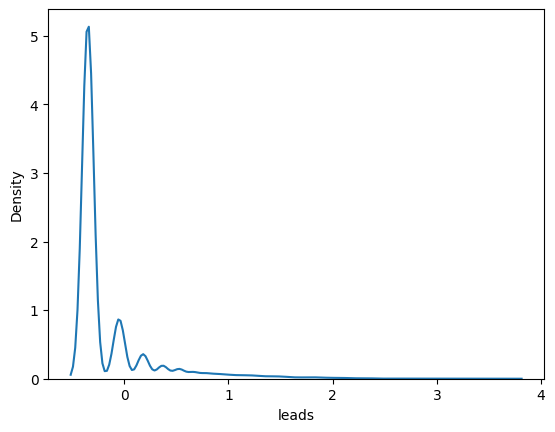
**2. Familiarizing with the data:**



In this step, we try to check null and unique values of various columns.

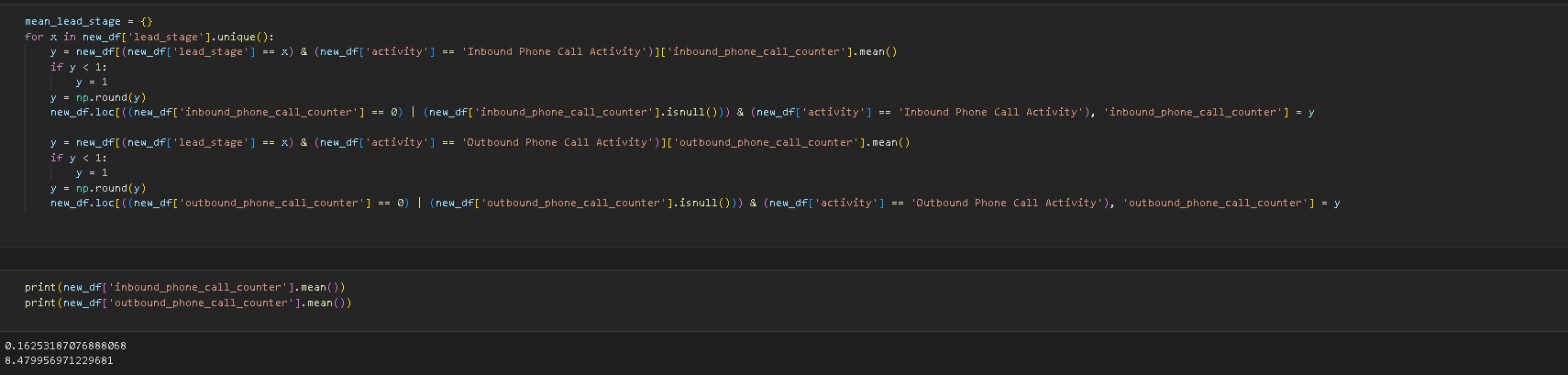
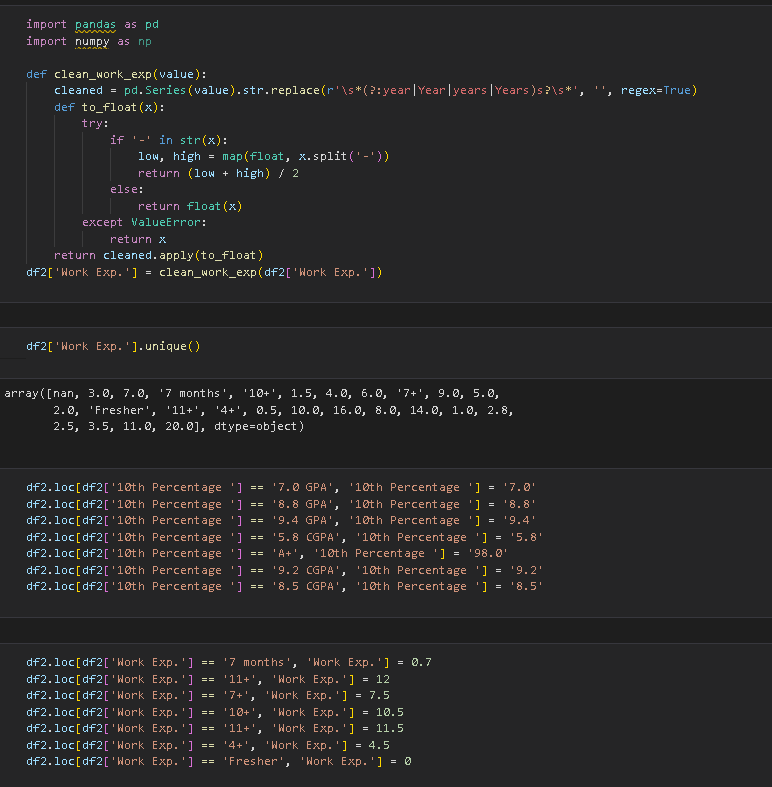
**2. Visualizing with the data:**



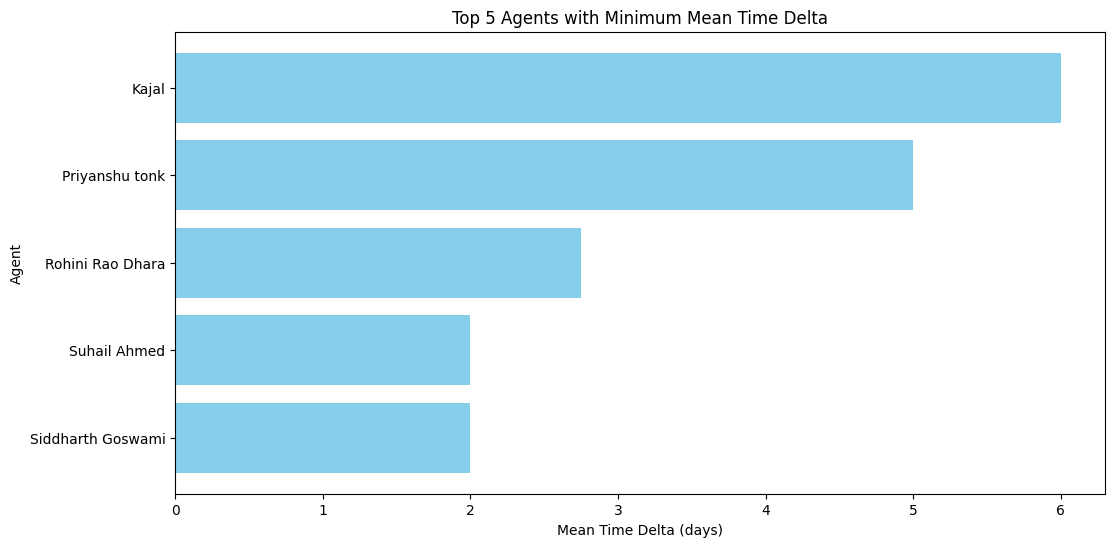


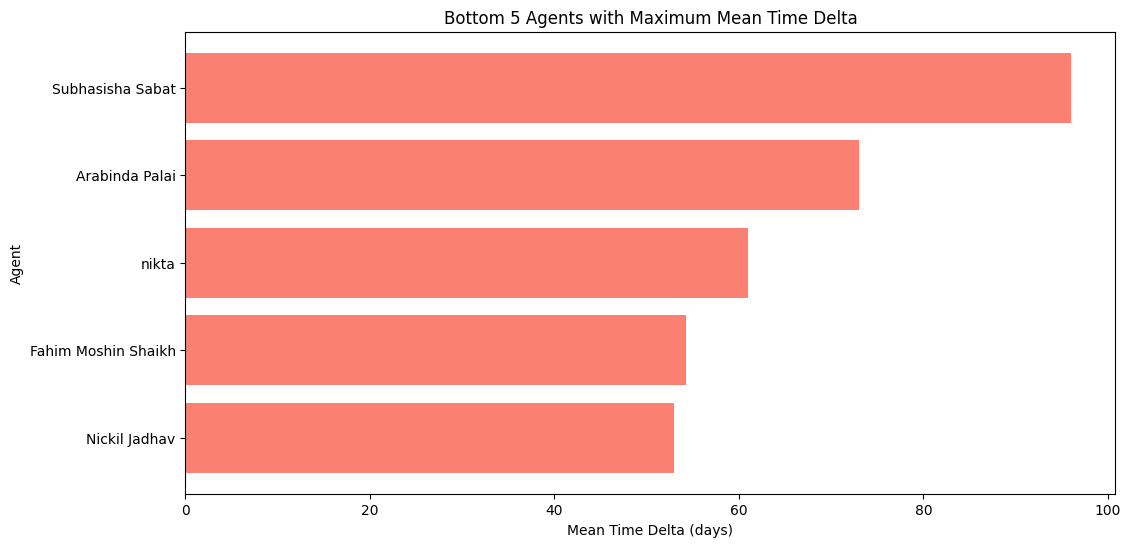
Few plots and graphs are displayed to find how the data is distributed and checking if there are any outliers in the data.

**4. Data Preprocessing & EDA**



Here we did some preprocessing on data like data cleaning and filling null values.

Based on dataset this 5 agents takes least time for join students and 5 of them Agent name Kajal least time as based on performace this 5 agents are best.

Above analysis say that this 5 agents take more time to join students so this 5 agents have lest priority. Based on this 5 agents have low perfomance.

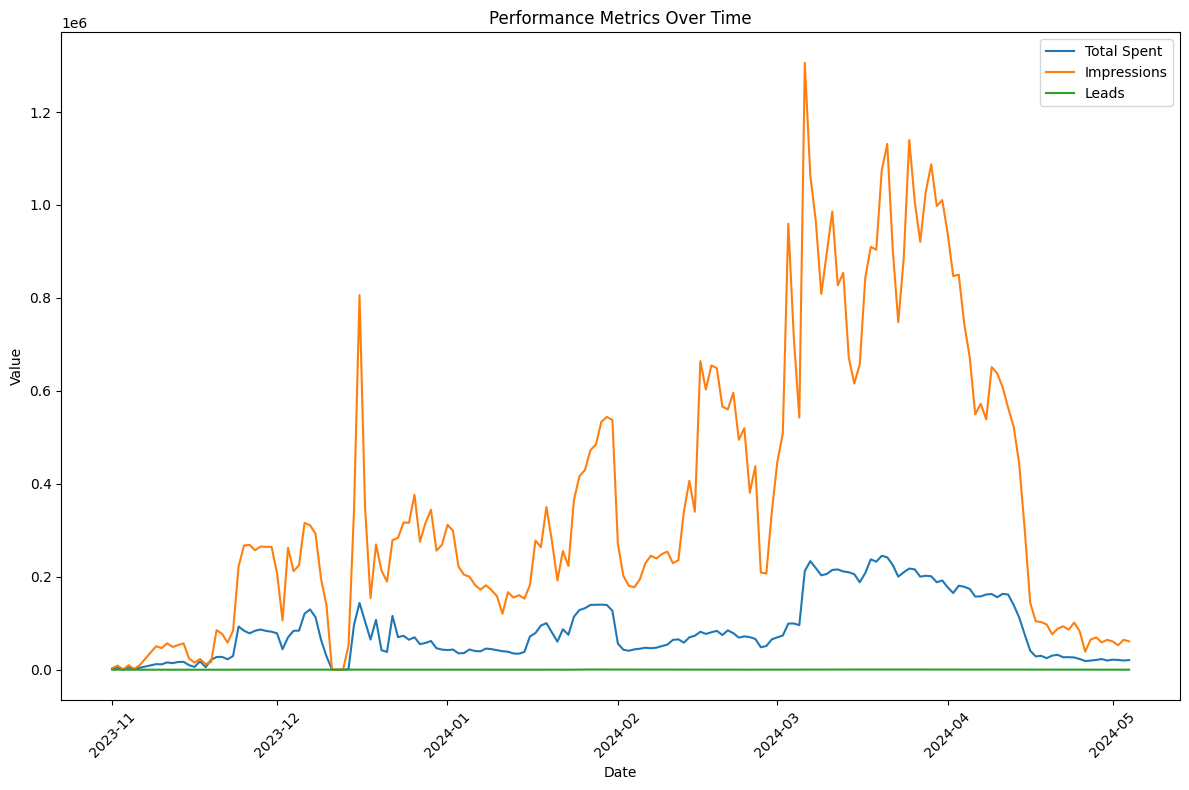


* We are spending 2x Capital on Facebook compared to Google
* But Google has better Click through Rate than Facebook and Linkedin
* Linkedin becomes the Costliest endorsement Platfrom on the basis of CPC,CPL

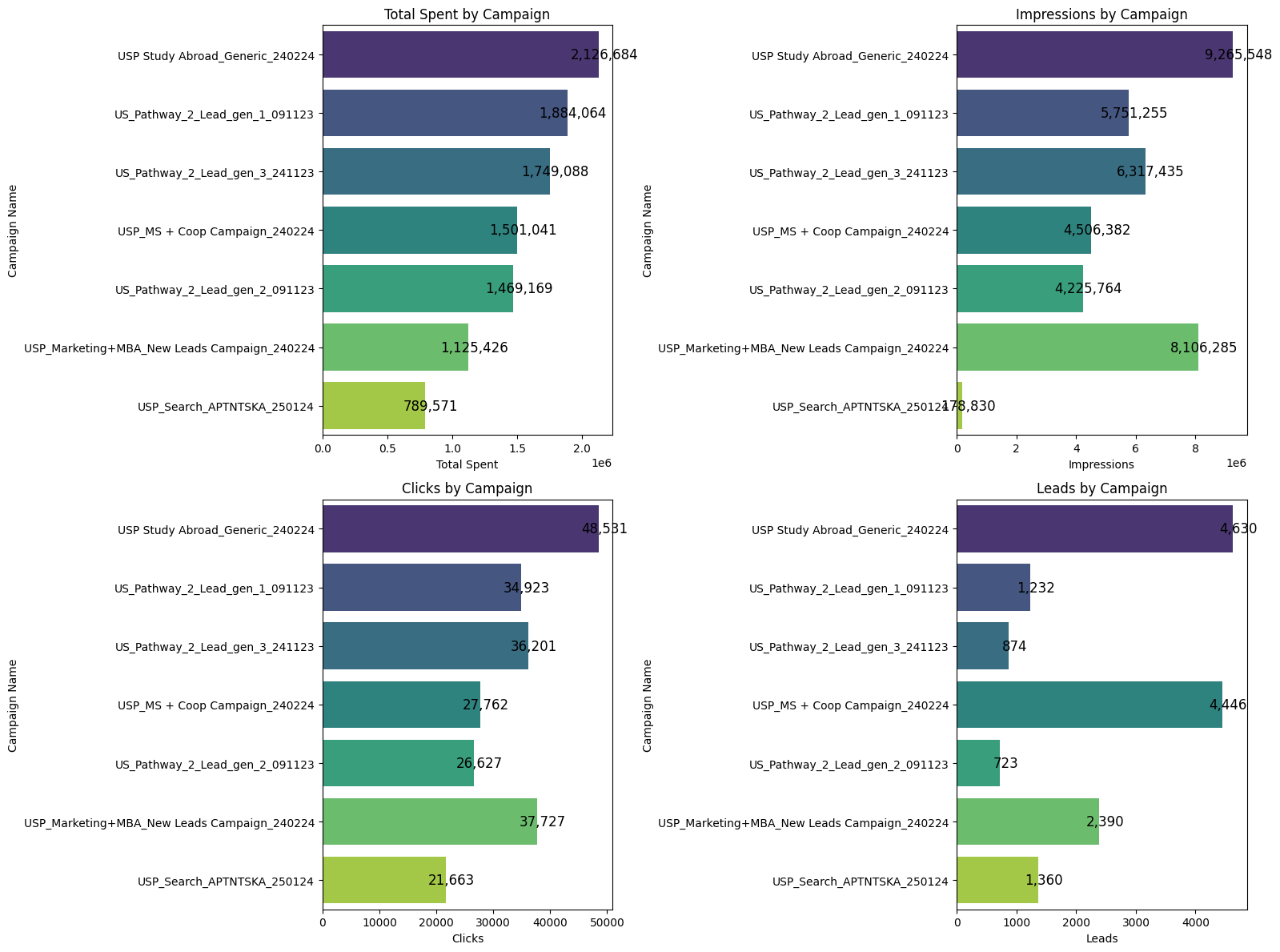


**Key Insights**

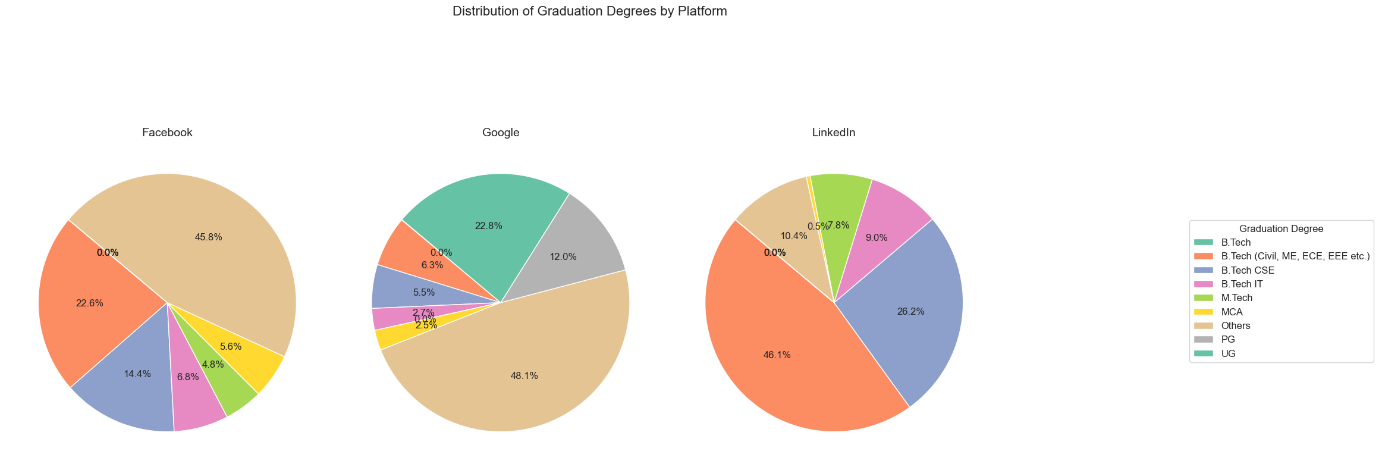
* The CTR mostly remained in the range of 0.005 to 0.01
* The Total spent is being spiked up during the Examination and financial season(March to Mid April)
* As a result of increased spending the conversion rate shown upward trend

**Key Insights::**

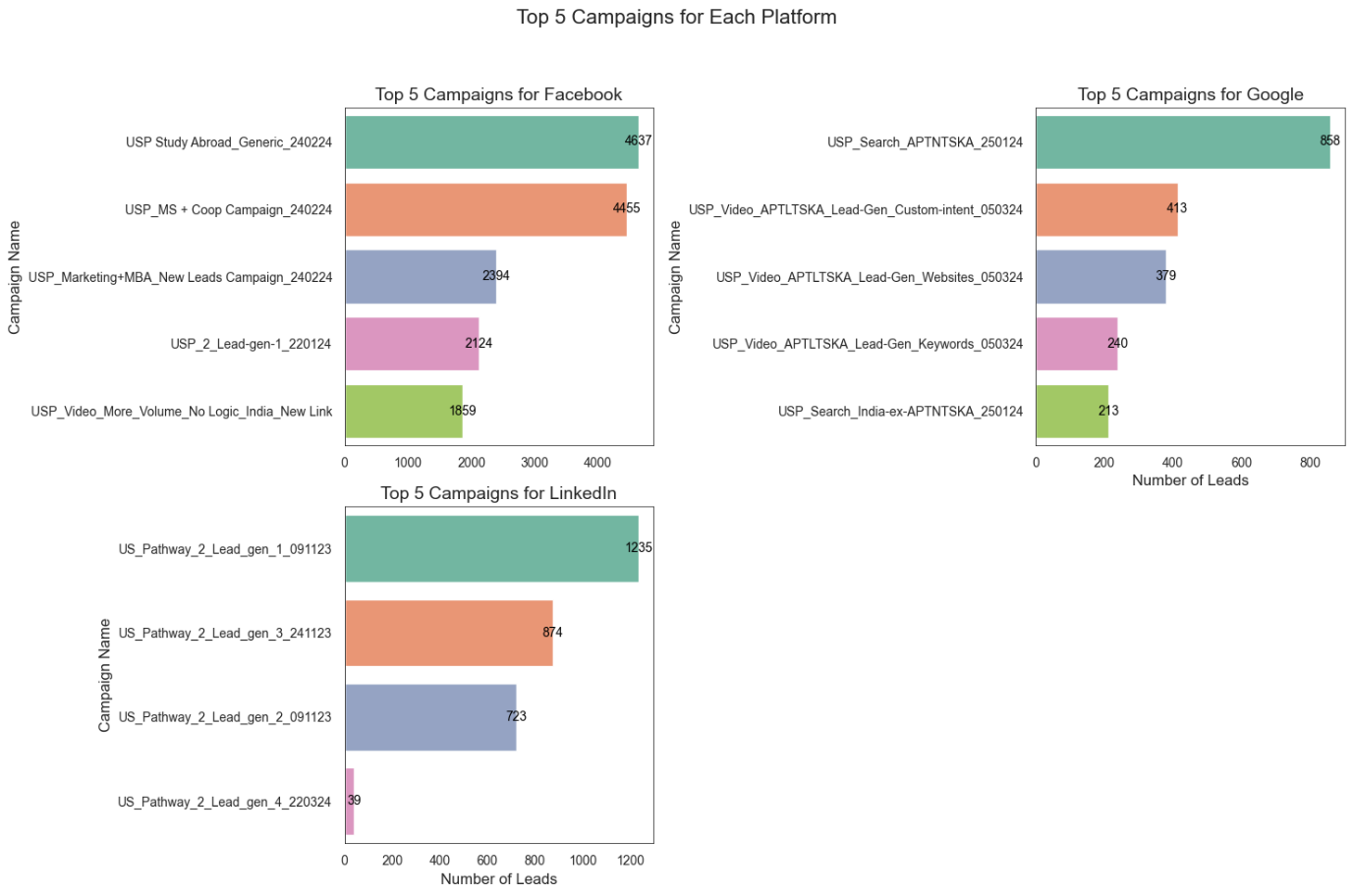
* March to mid April hits the peak in terms of Impressions and Amount Spent

 **Key Insights:**

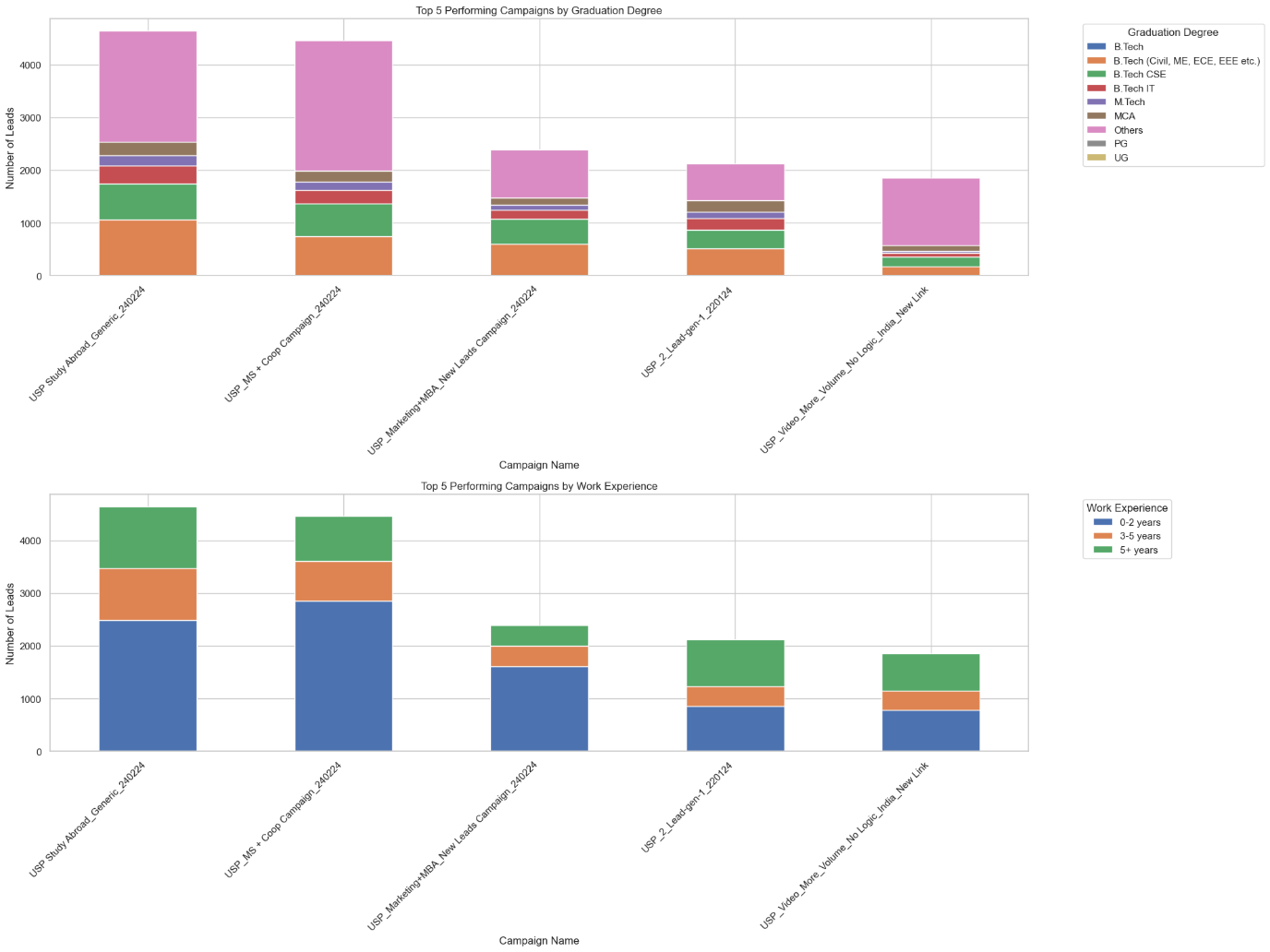
* USP-Marketing+MBA programme’s performance has been truly tremendous in terms of impressions and clicks
* USP\_Pathway+Coop Campaign is attracting a lot of leads offering the best ROI

 **Key Insights:**

* LINKEDIN:Btech(civil,me,ece...etc),GOOGLE:Others,Btech**,**FACEBOOK:Others,Btech(civil,me)are the majority leads from each Platform.
* Leads with PG are mostly fetched from GOOGLE
* Mtech Leads are reluctant with GOOGLE Platform
* Leads with UG are exclusively found from GOOGLE.
* MCA Leads are less likely to found in LINKEDIN

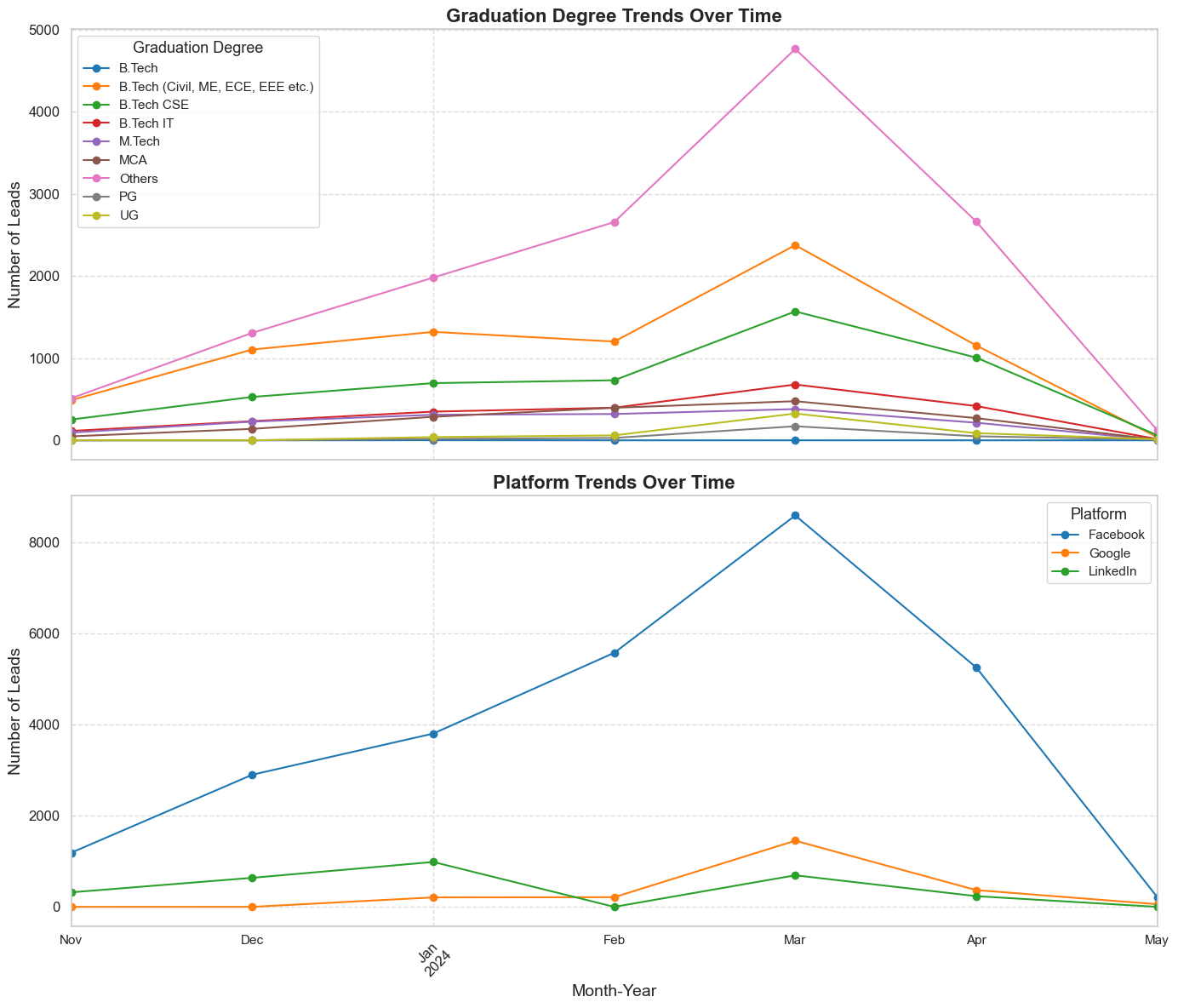
**Key Insights:**

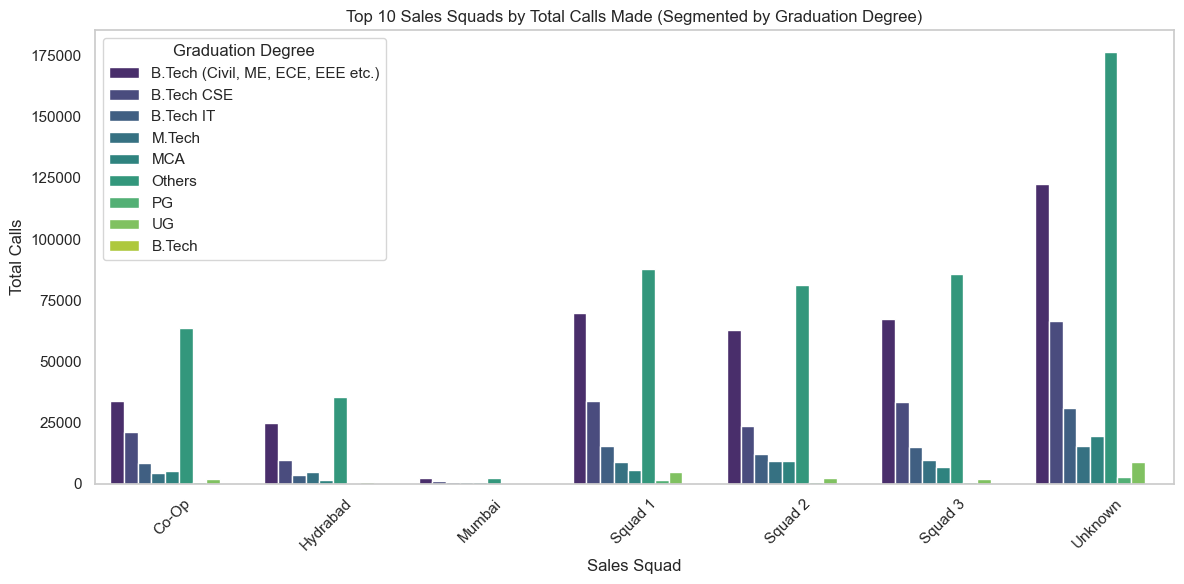
* “USP 220124” is top performer for FB and it has focused on specific location
* USP 250124 is top performer for google,which has Search and Video Campaign’s prominence in top5
* “USP 091123” is the top performer and the performance difference is less pronounced than other platforms

 **All the Top 5 Campaigns show same culmination of leads from**

**1.On the basis of Graduation Degree**

**2.On the basis of Work Experience**

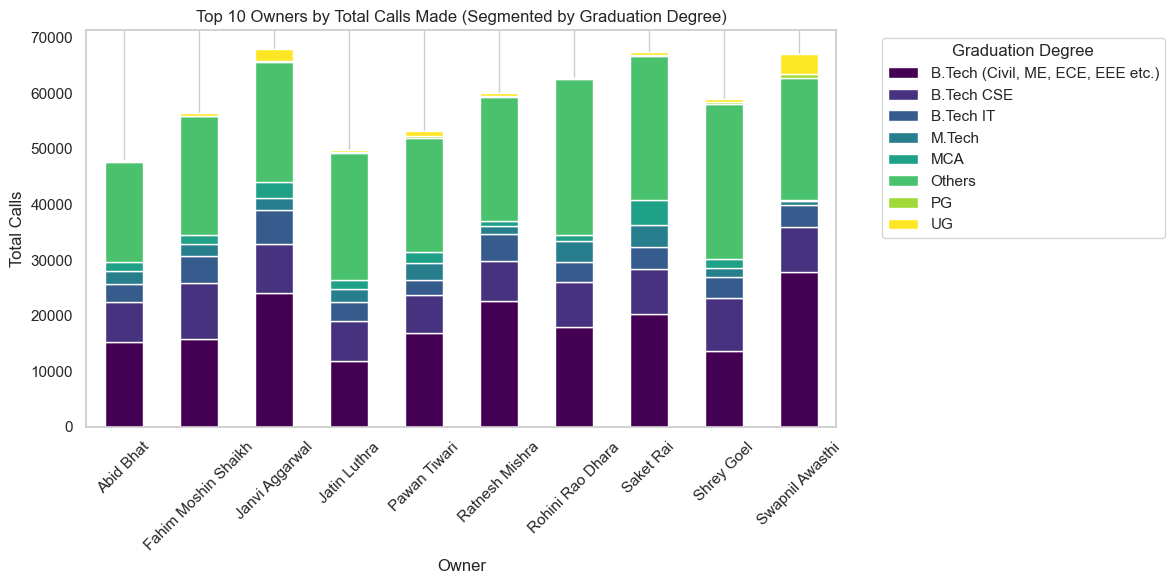


 **B Tech(Civil,ME,ECE,EEE) - Squad 1**

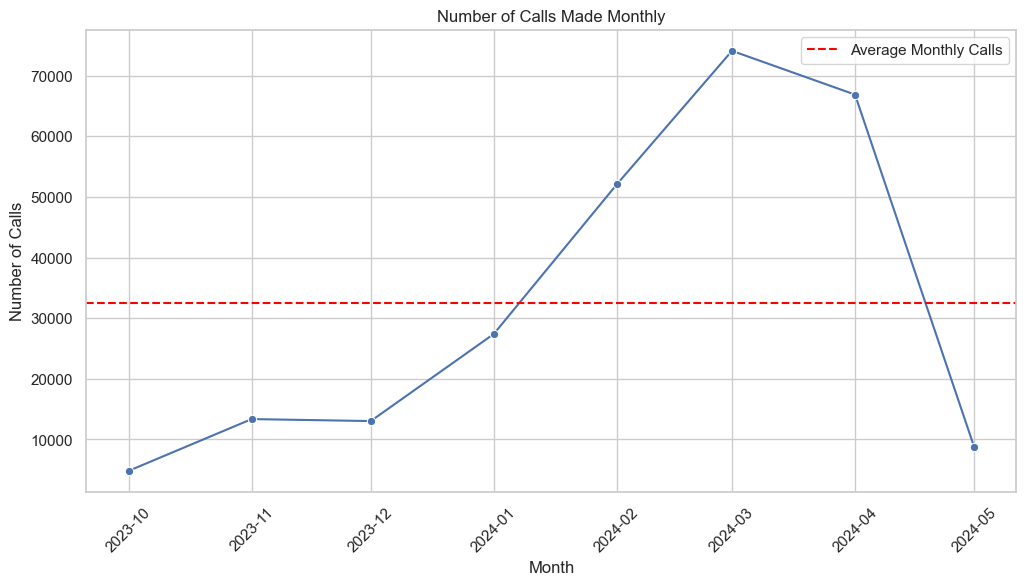
**Btech(CSE) - Squad 3**

**Btech IT ,Mtech,MCA - Squad 1,2**

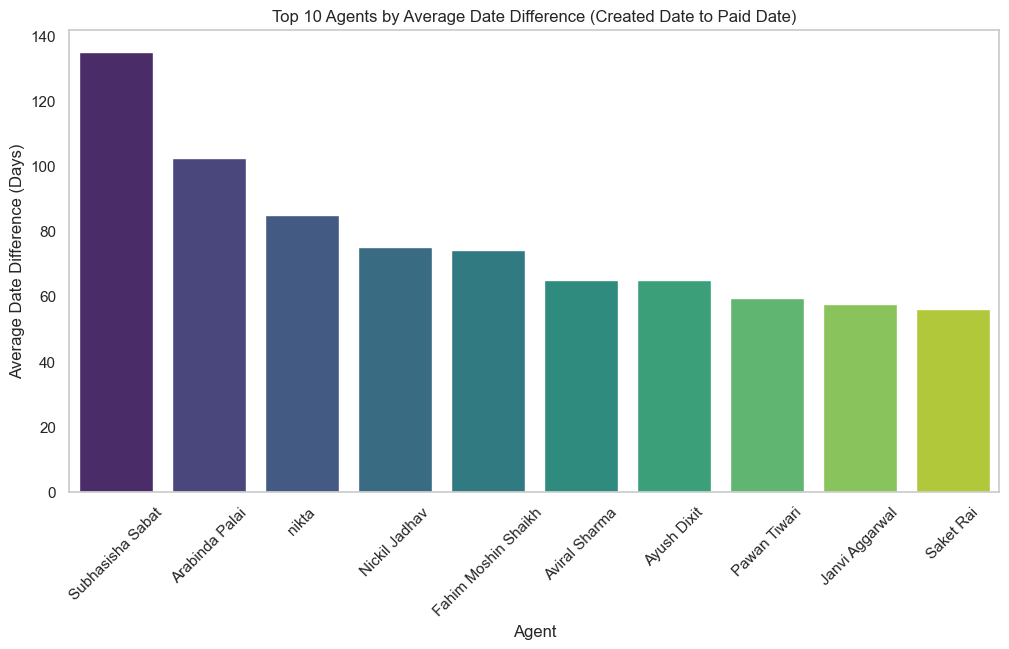
**Squad 1 acts the best appealong for UG students/Holders**

**m1.UG students are better handled by Swapnil avasthi,Janvi Agarwal**

**2.Except the UG chunk everything shows a similar trend for remaining Graduation degree**

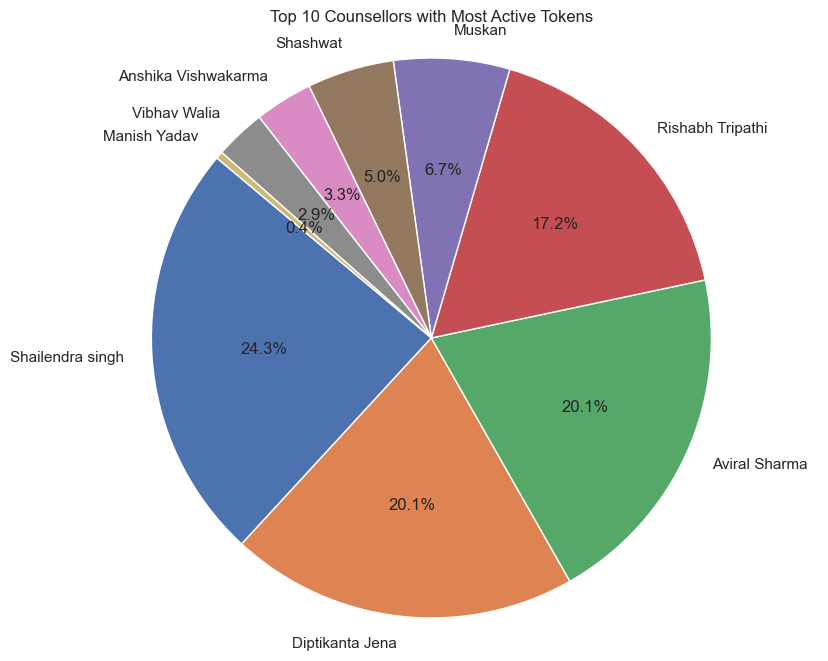
**1.There is an upward trend from the december to march month as on Historical data**

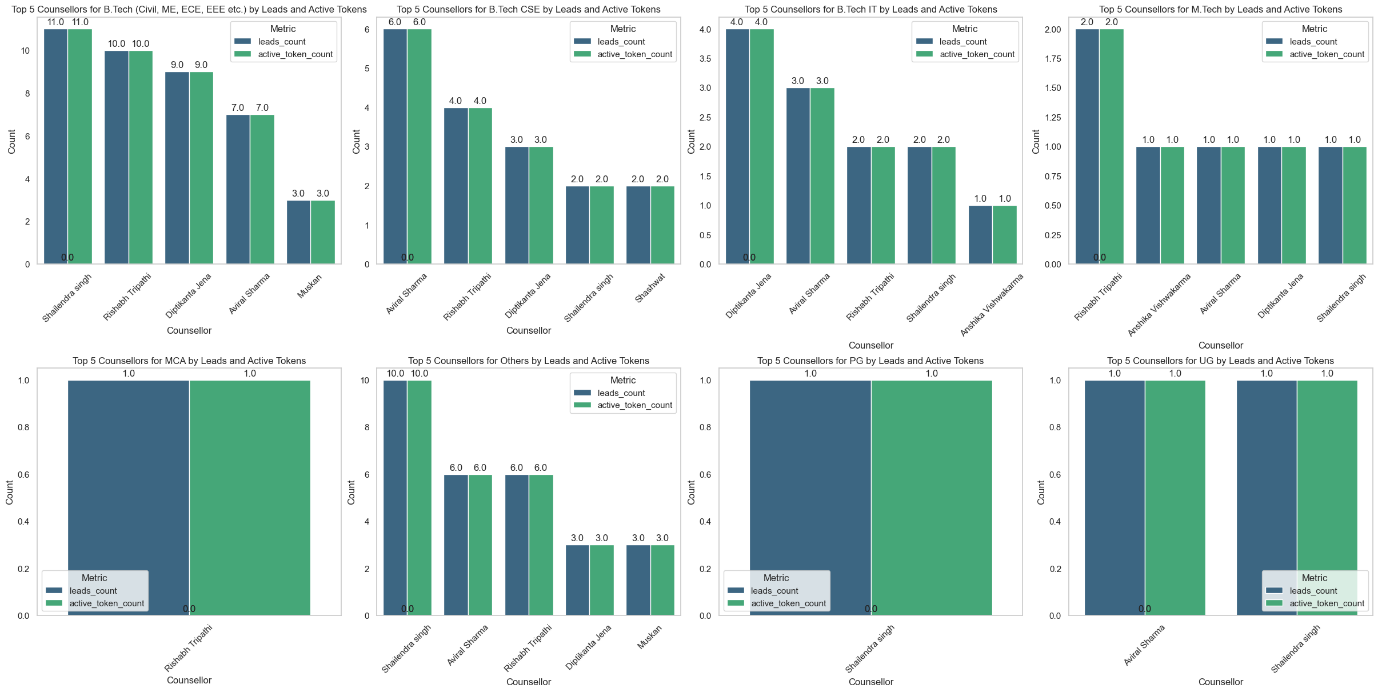
**2.The Peak is coming either at the starting or at the ending of the month.**

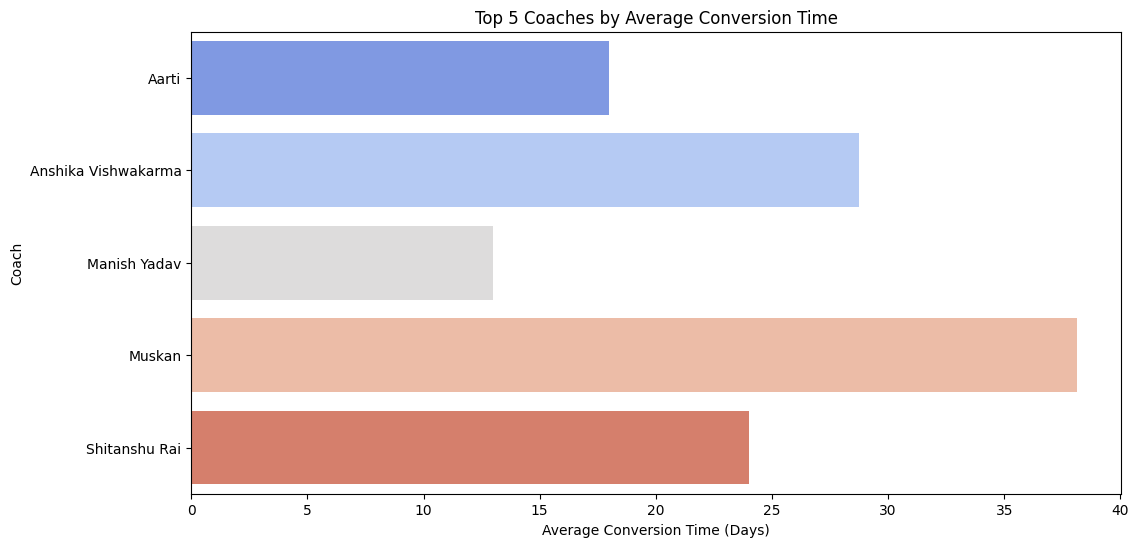
**Few Counsellors are taking more than one month time to make their converted leads to pay token amount.**

**Betterment is needed for :**

* **Shaswat**
* **Shailendra Singh**
* **Diptikanta Jna**
* **Rishabh Tripathi**
* **Muskan**
* **Aviral Sharma**
* **Anshikha Vishwakarma**

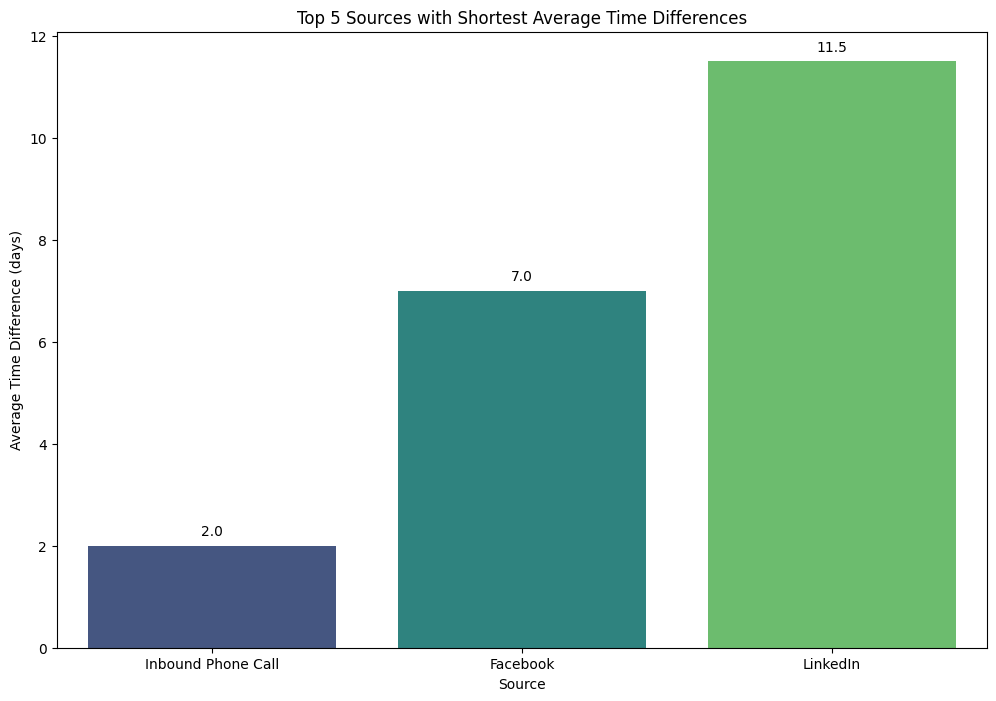
**Shaiendra singh,Diptikanta Jena,Aviral Sharma are the top 3 Counsellors with Most Active Tokens**

* **MCA,PG,UG students are being handled by relatively Less Number of counsellors,indicating betterment in the handling the students with these Academic background**
* **Shailendra Singh,Rishabh Tripathi are one of the best performing counslelords across Several Academic Backgrounds available**

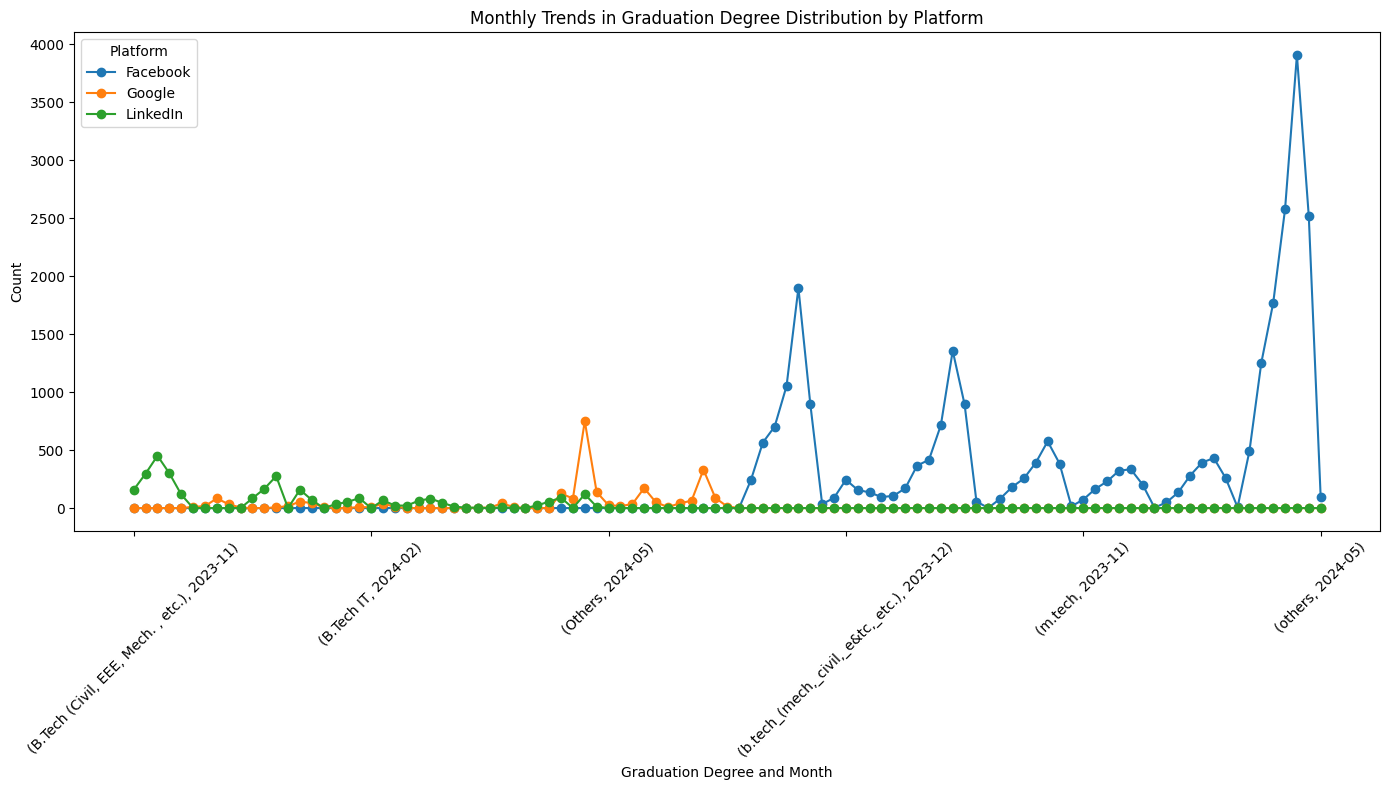
Based on above plot we clearly see that Manish Yadav take least time for lead conversion.

Based on above analysis this 5 agents take least time for convert leads but out of this 5 Muskan take much time which affect on performance.

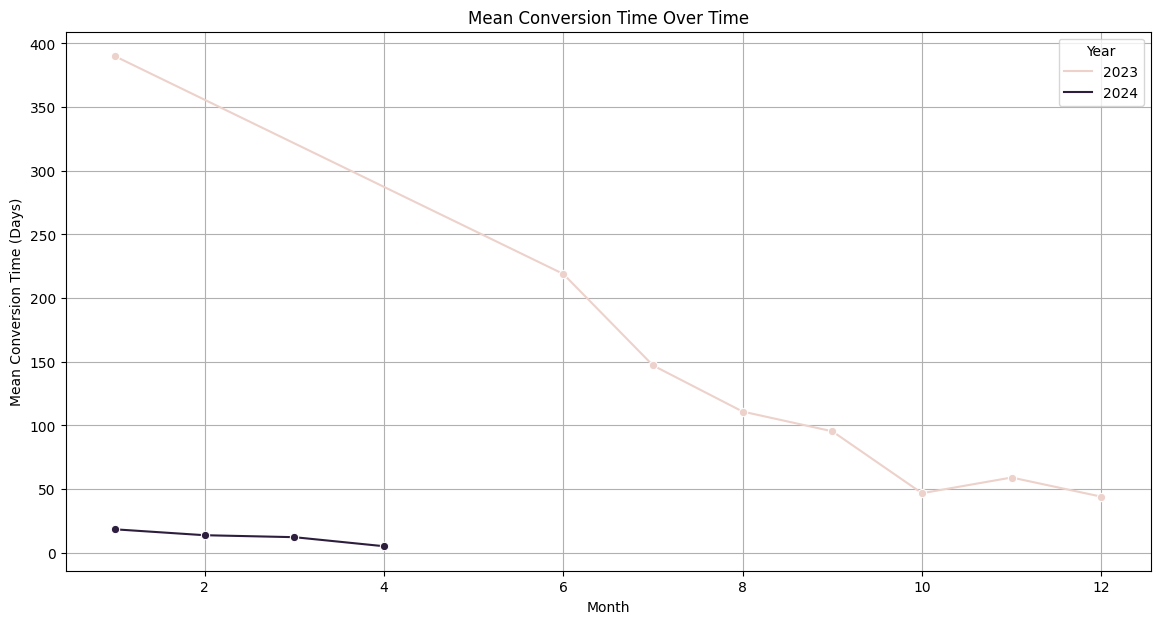
* **Based on this analysis**
* **Shashwat** has the highest average conversion time (over 70 days), indicating potential room for efficiency improvement.
* **Zareen** has the lowest average conversion time, showing faster conversions compared to others.
* Significant variance exists among the coaches, suggesting varying effectiveness in conversion strategies.

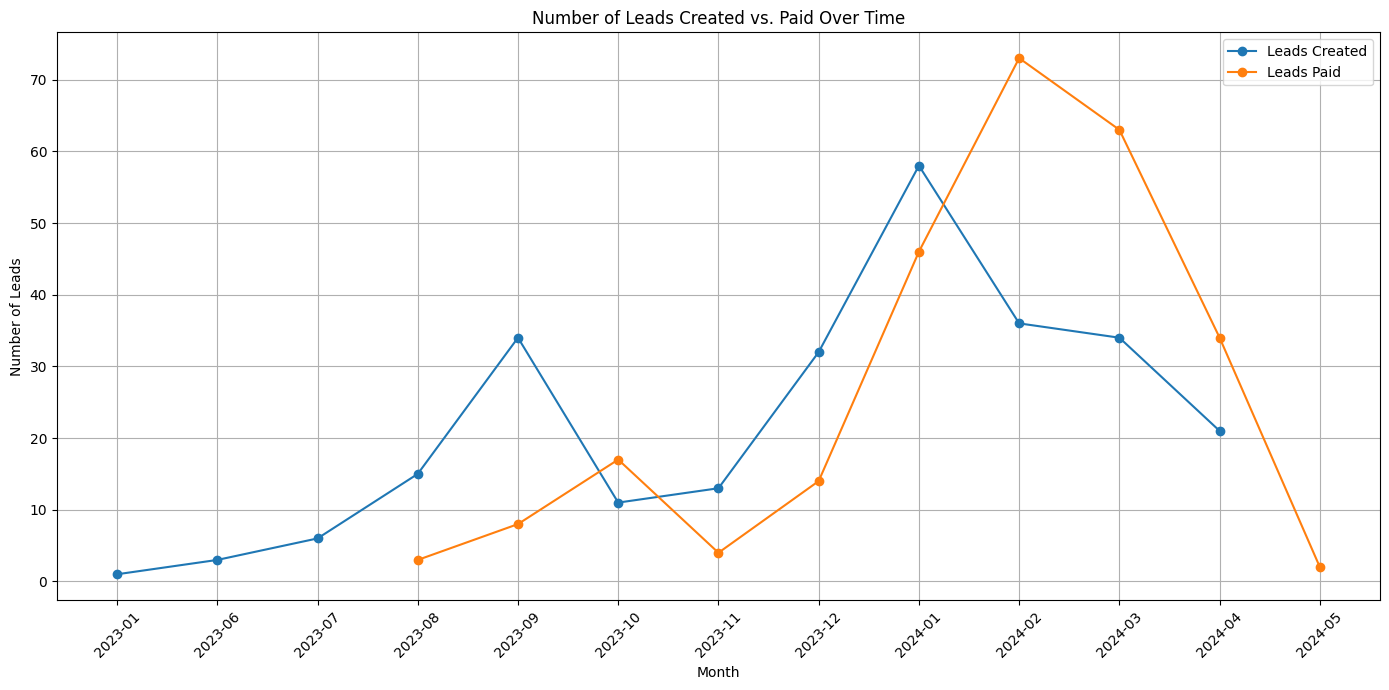
Based above plot analysis:

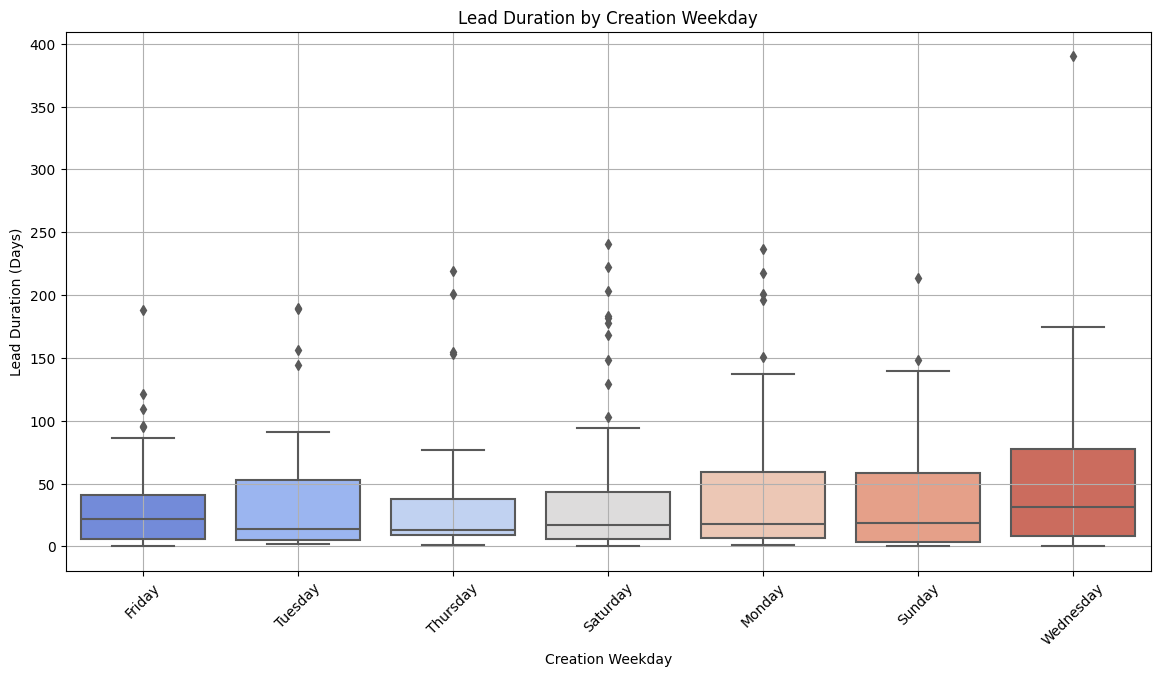
* **Inbound Phone Call** has the shortest average time difference (2 days), making it the most efficient source.
* **Facebook** follows with 7 days, showing moderate efficiency compared to other sources.
* **LinkedIn** has the longest average time difference (11.5 days), suggesting room for improvement in response or conversion times.



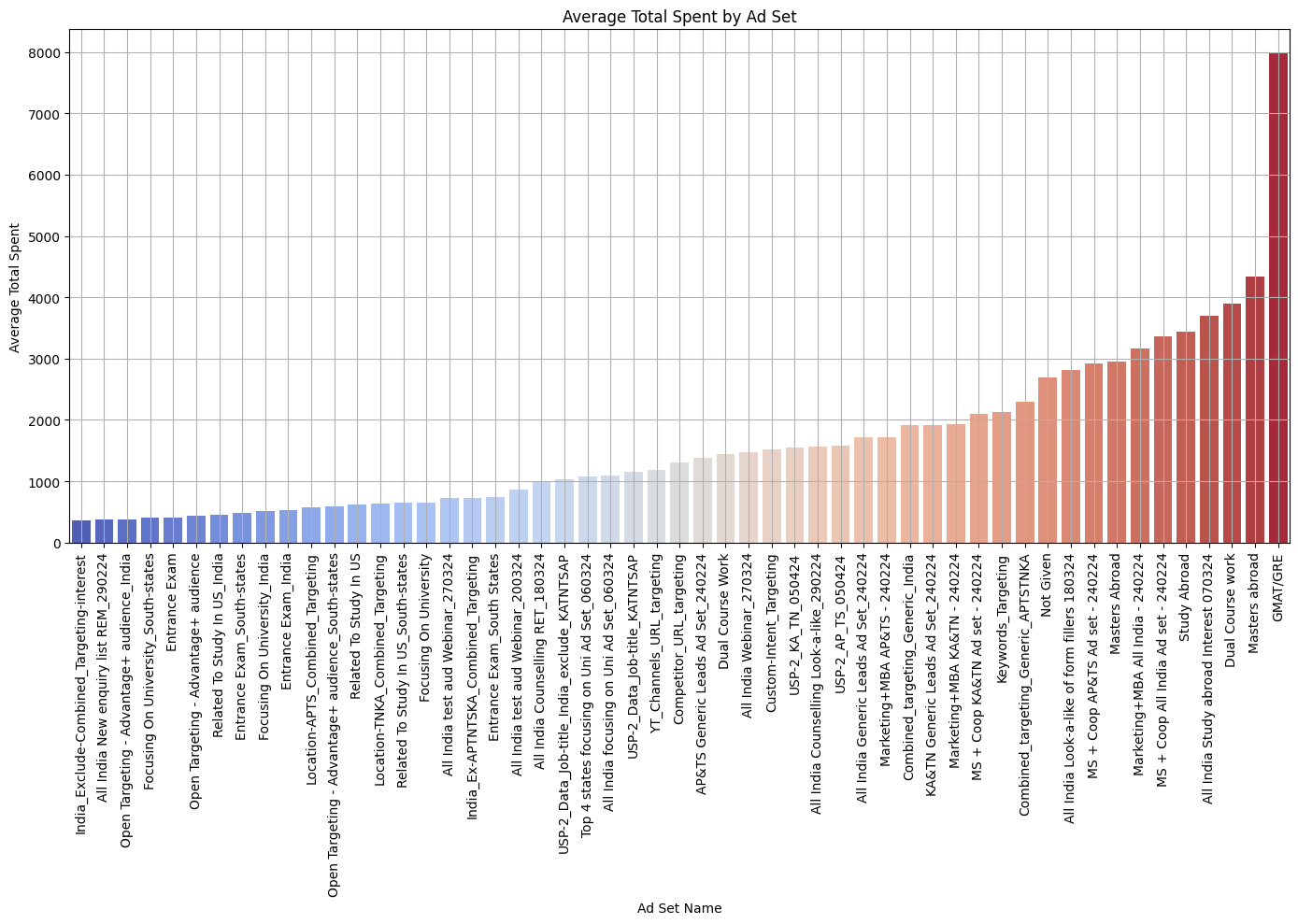
* **LinkedIn** shows a significant surge in activity towards the end of 2023, indicating its growing influence in engagement.
* Other platforms, such as **Google** and **Facebook**, show relatively minimal and stable activity, suggesting limited or niche use.



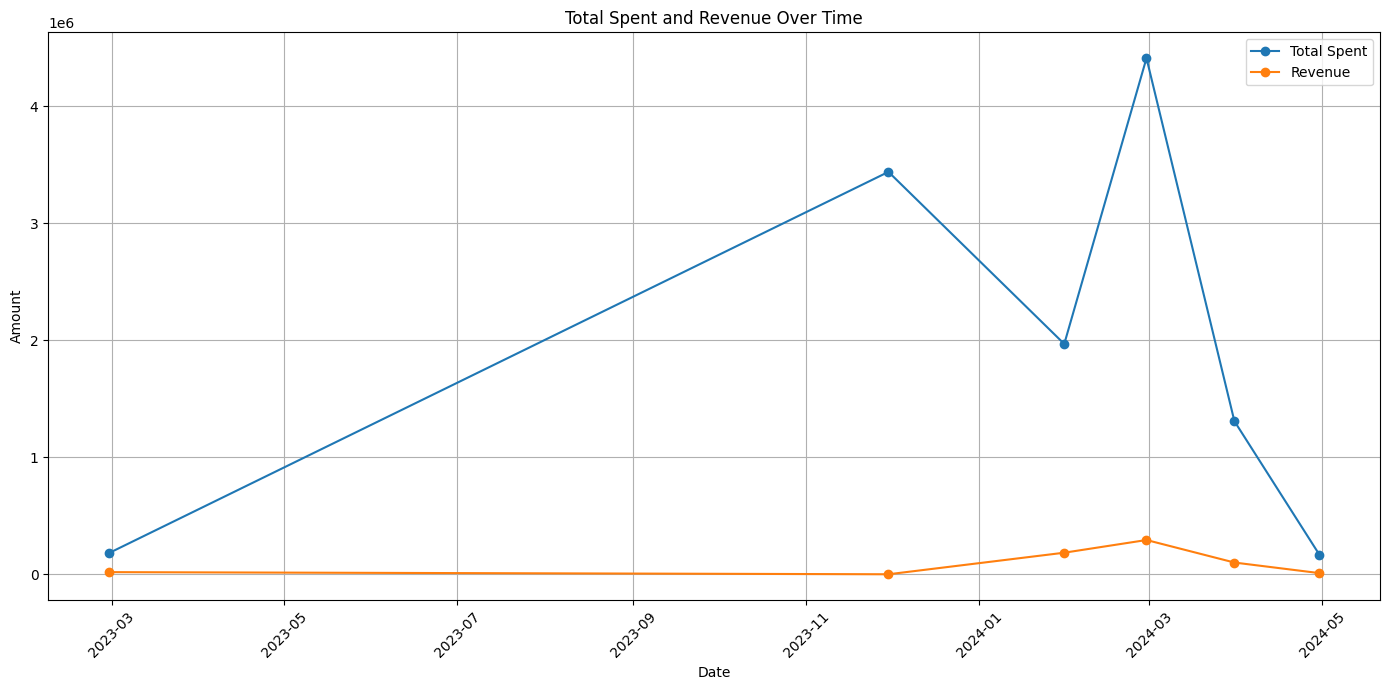
* The mean conversion time steadily declines in 2023, reflecting improved efficiency in conversion processes over the year.
* In 2024, conversion times remain consistently low and stable, highlighting sustained improvements in operational performance.
* This plot analysis shows:
* a general upward trend in both lead creation and lead payment over time. However, there are peaks and troughs in both lines, suggesting fluctuations in lead generation and conversion rates.

The plot say that the significant differences in lead duration across weekdays. Leads created on Friday and Wednesday tend to have the longest durations compared to other days.

There are some outliers with exceptionally long lead durations, especially on Wednesday and Friday. These might be due to specific lead characteristics or unusual circumstances.

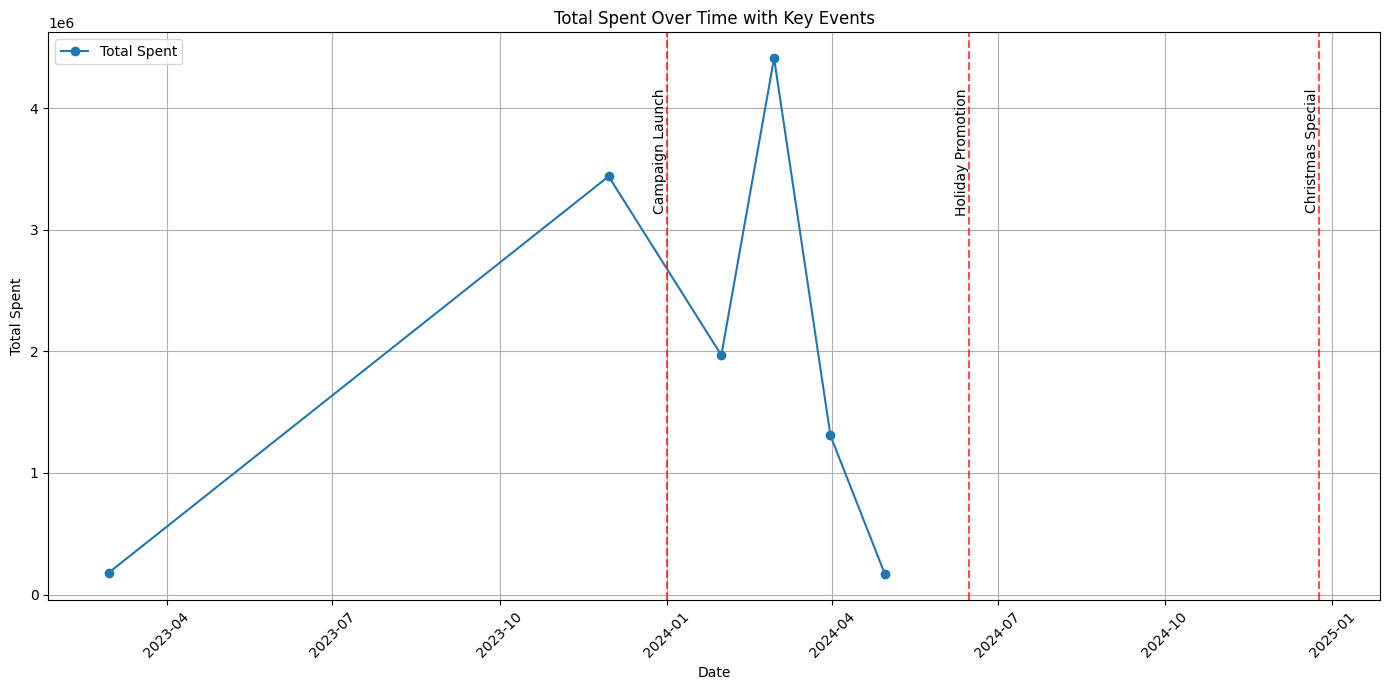
A few ad sets stand out with significantly higher average spending compared to others. These might be targeting high-potential audiences or running high-budget campaigns.

The wide range of spending across ad sets suggests varying levels of performance. It's worth analyzing which ad sets are delivering the best return on investment (ROI).

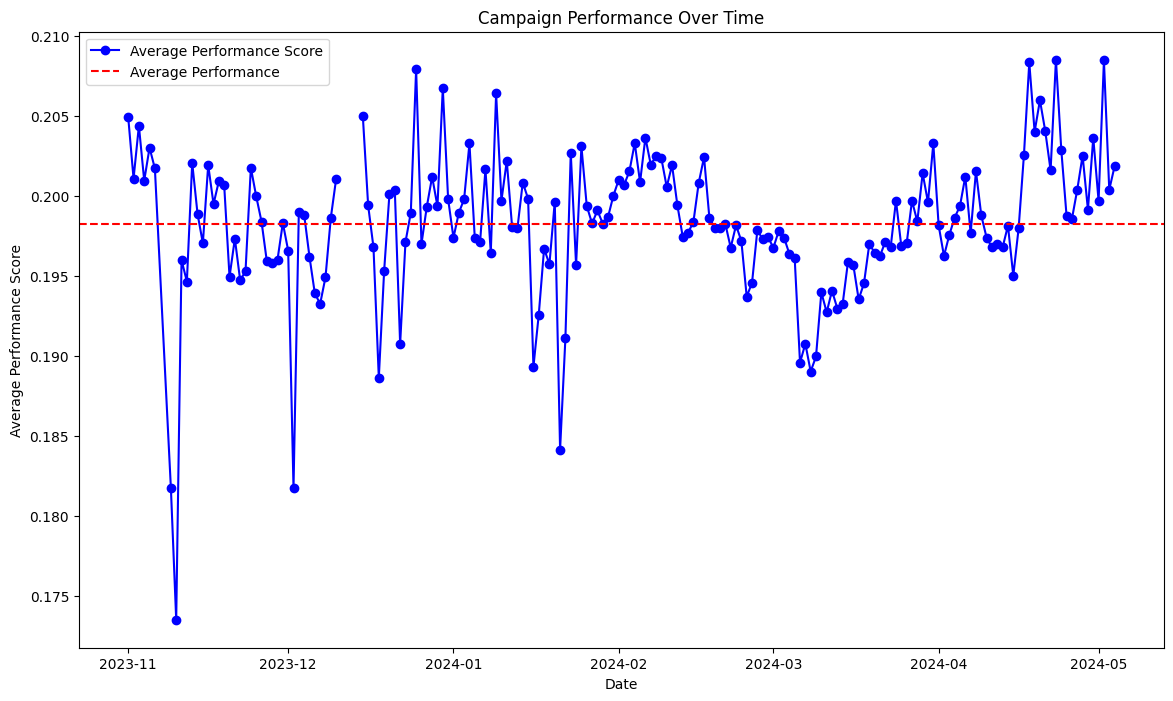
Revenue consistently lags behind total spending, indicating a delay between investment and return. This might be due to factors like sales cycles, marketing campaign effectiveness, or customer decision-making processes.

There are significant fluctuations in total spending over time. This could be due to changes in marketing strategies, seasonal variations, or economic factors.

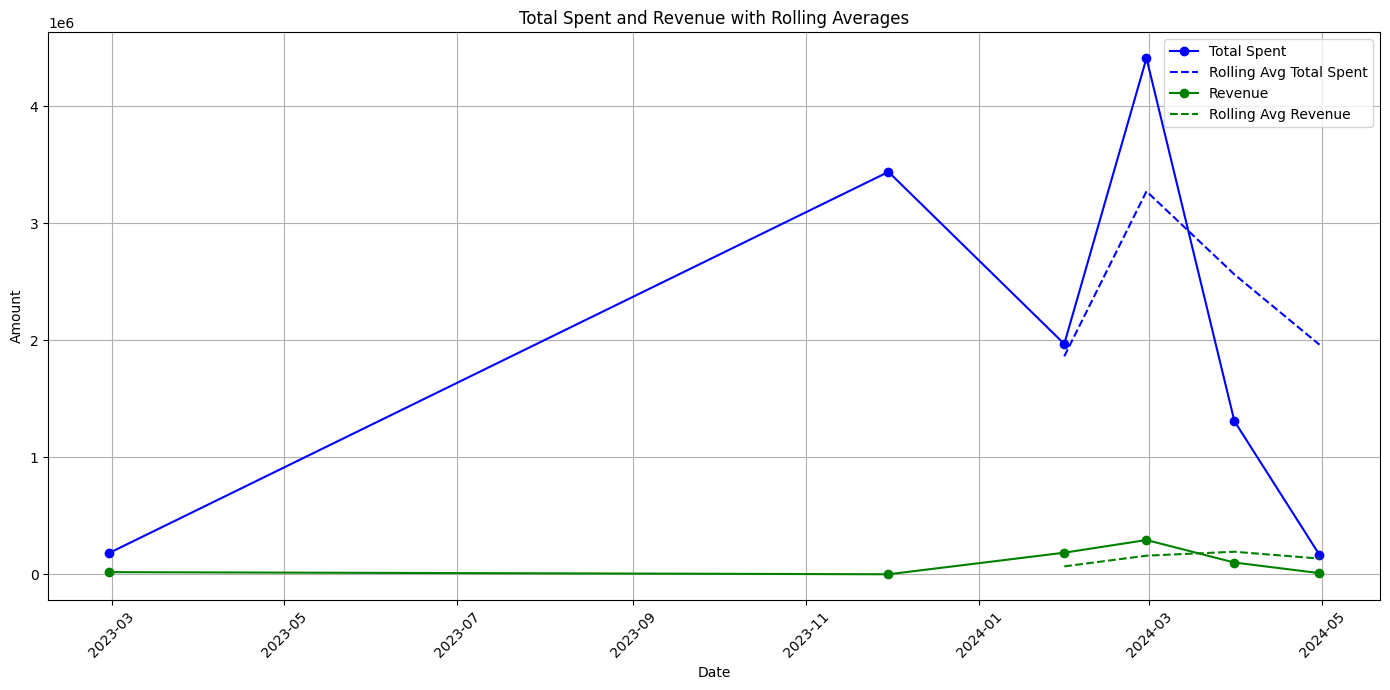
While revenue is generally increasing over time, the growth rate is not consistent. There are periods of rapid growth followed by slower periods. Understanding the reasons behind these fluctuations is crucial for optimizing spending and revenue.

The campaign launch in 2024-04 coincides with a significant spike in spending, indicating a successful campaign in driving spending.

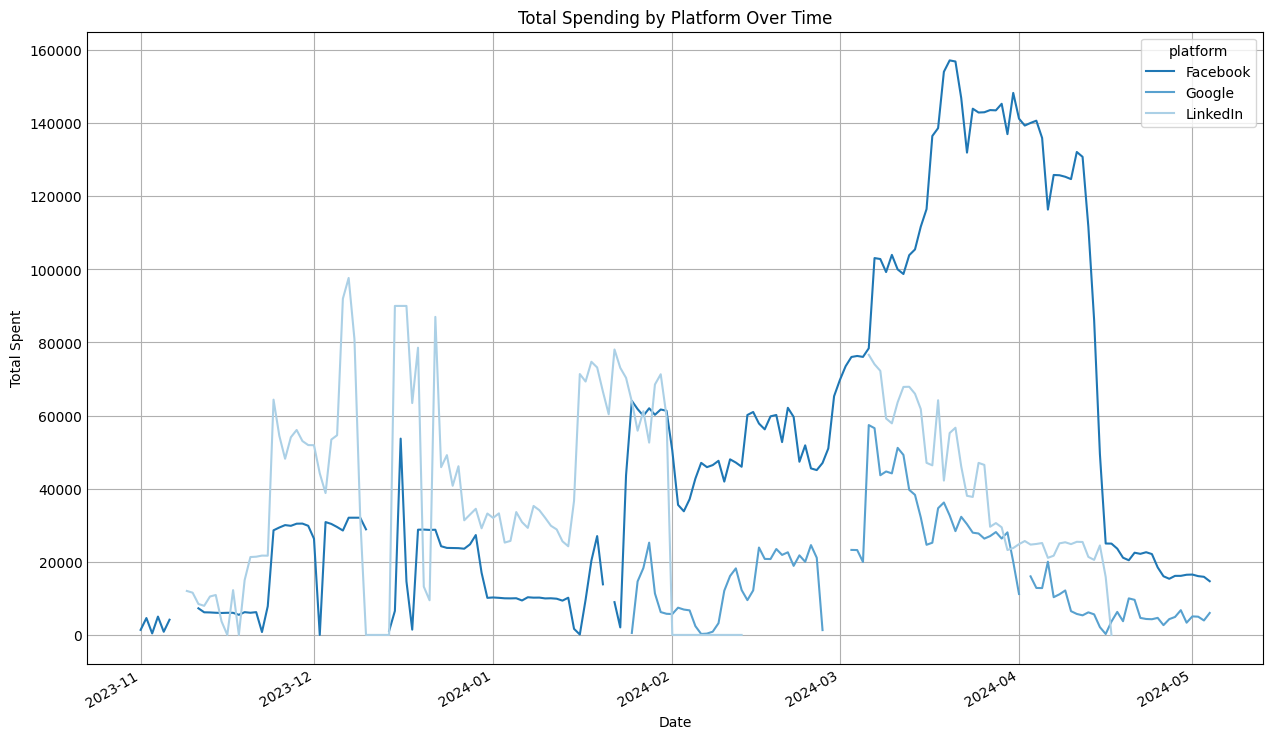
The overall trend shows fluctuations in spending, with periods of higher and lower investment. Understanding the reasons behind these fluctuations can help optimize spending strategies.

The campaign performance score exhibits significant fluctuations over time, suggesting variability in campaign effectiveness.

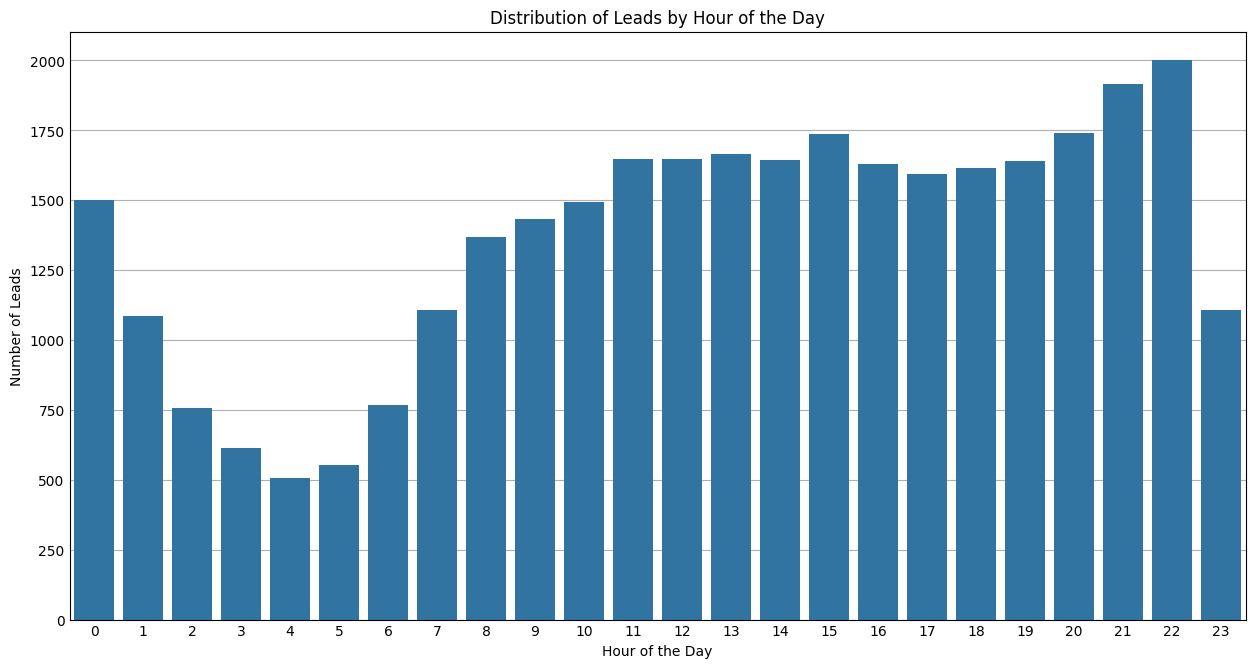
There might be seasonal patterns in performance, with certain periods showing higher or lower scores. Understanding these patterns can help identify opportunities for improvement.

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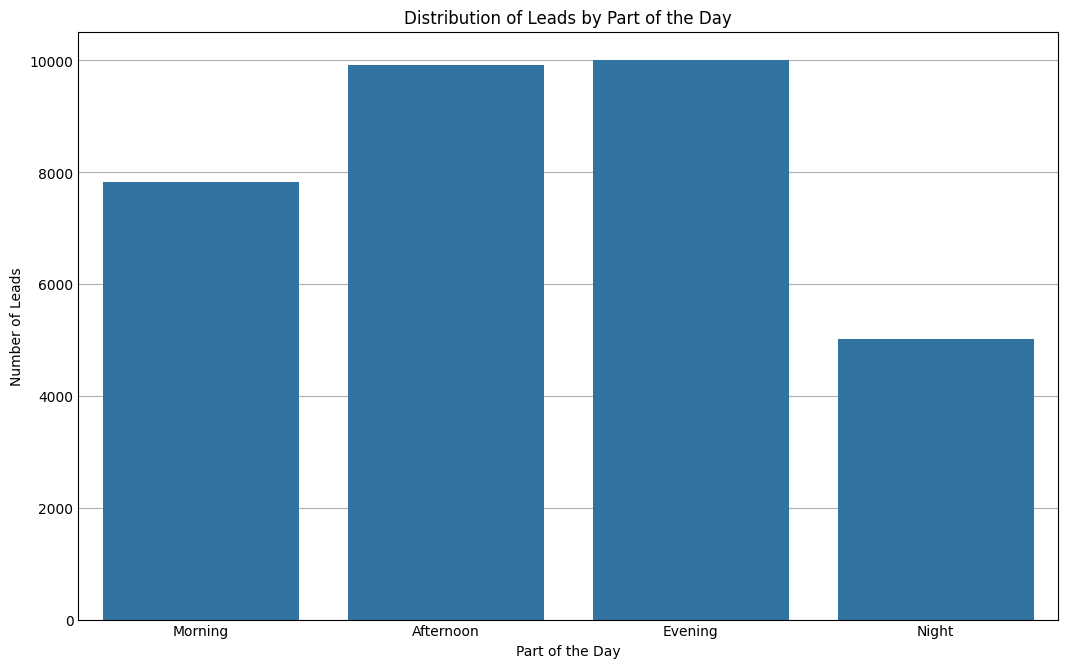
While revenue is generally increasing over time, the growth rate is not consistent. There are periods of rapid growth followed by slower periods. Understanding the reasons behind these fluctuations is crucial for optimizing spending and revenue.



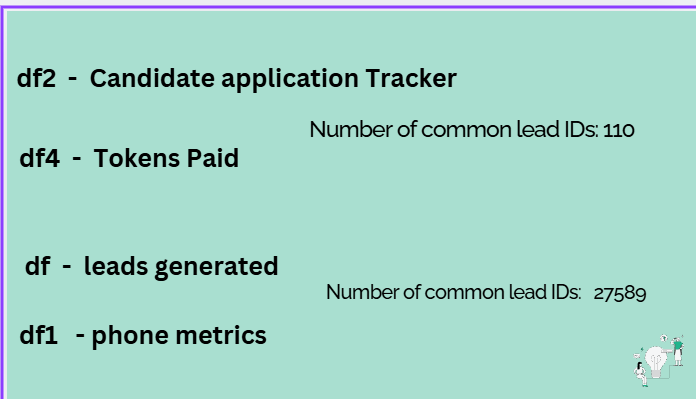
* The total spent in facebook platform on april 2024 reached nearly 160000 as it being after the result of exams like GATE.
* The total spent in Linkedin platform on December 2023 reached nearly 100000 as it being the highest.

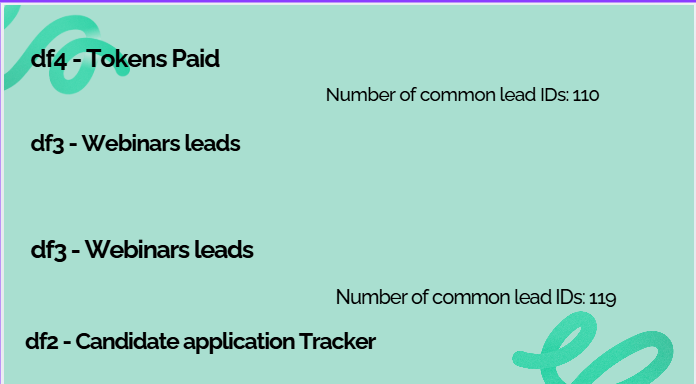


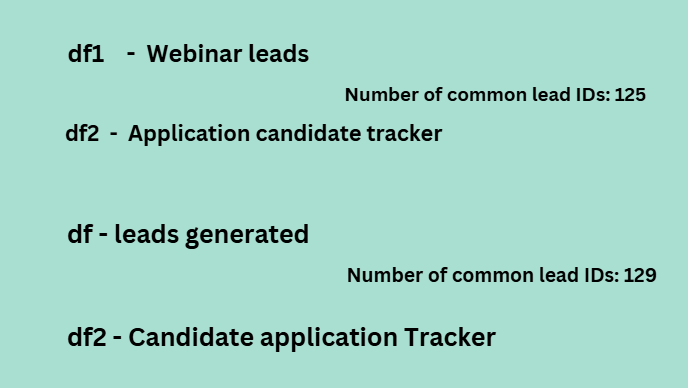
* This Generates at which time the most no of leads were active and the students who are interested for the us pathway and sign as lead.

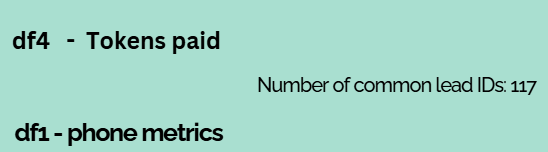


* This represents the leads generated or active leads where interested to the pathway in part of the day.
* **MERGED DATA SHEETS ANALYSIS**
* As the data sheets were allotted as a process of analysing from the lead collection ,Phone Confirmation, Token Paid to selecting favourable University.
* For better process analysing the data sheets were merged and checked for the common lead ids present for every two datasheets.

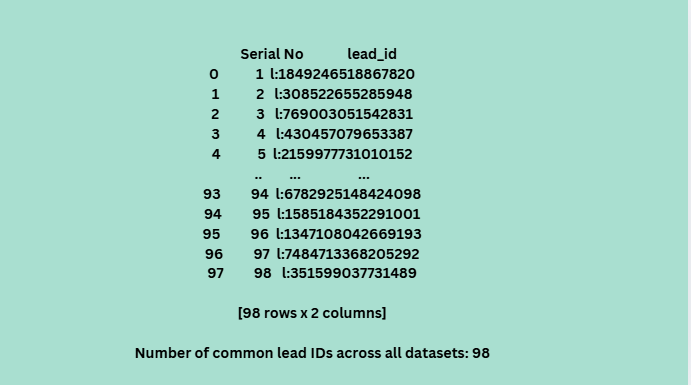




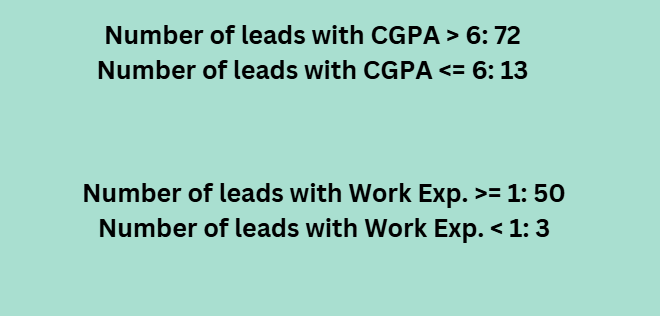




* When the whole 6 datasheets were merged and analysed as the total number of students who were selected from the very first campaign performance to the token paid i.e., Total selected students were 98.



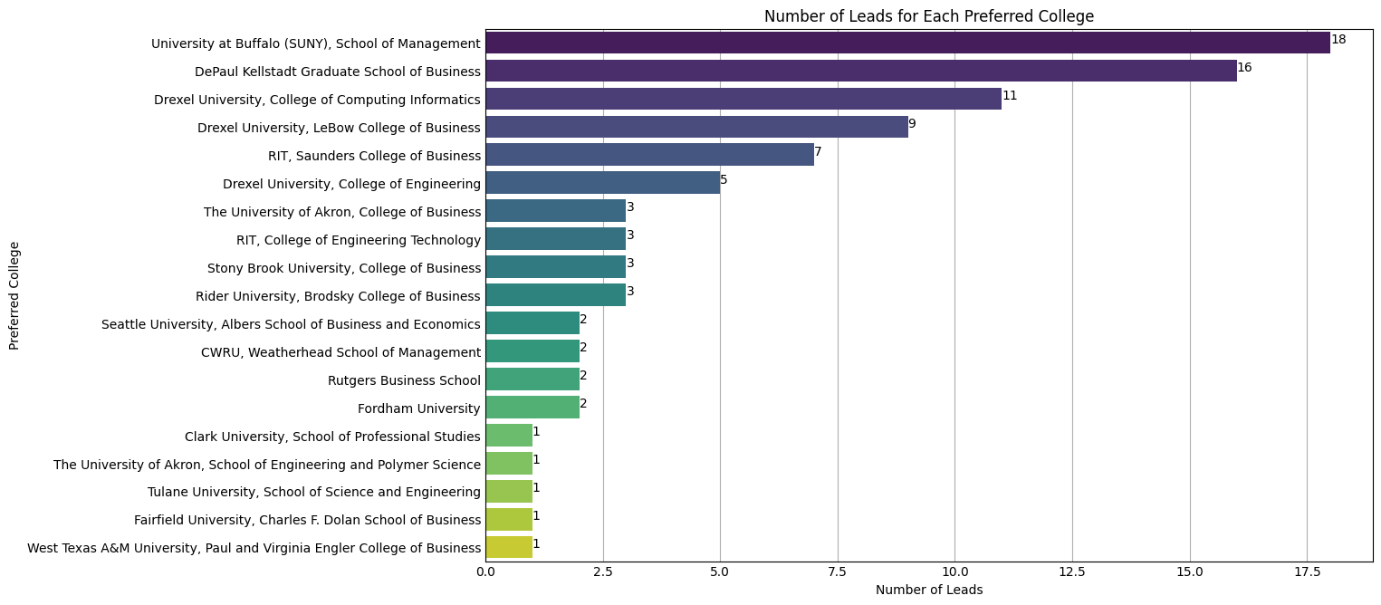
* As the futurense company is having minimum criteria as CGPA should be more than 6, 1 year of experience and graduate but some unique selections happened with distinct rules.
* Comparison between the Futurense Company Basic requirements and



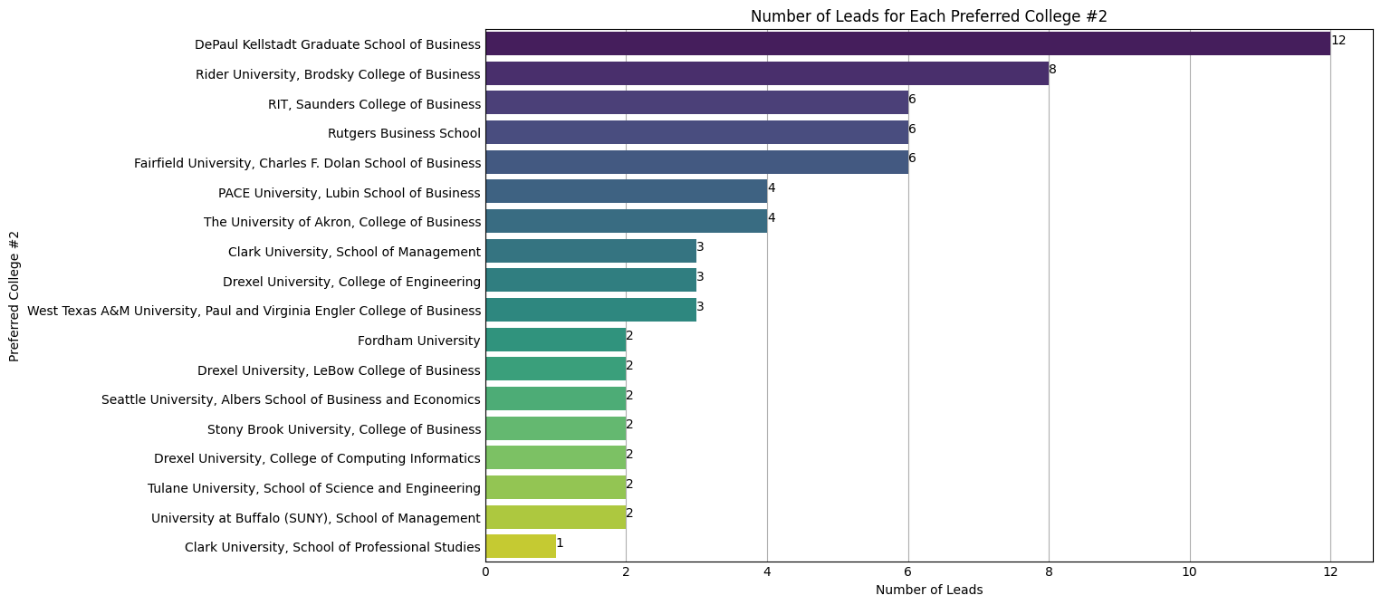
* From Here Every Analysis will be based on the successful candidates who had given the opportunity to select their favourable universities and the successful counsellors who were part of their journey.



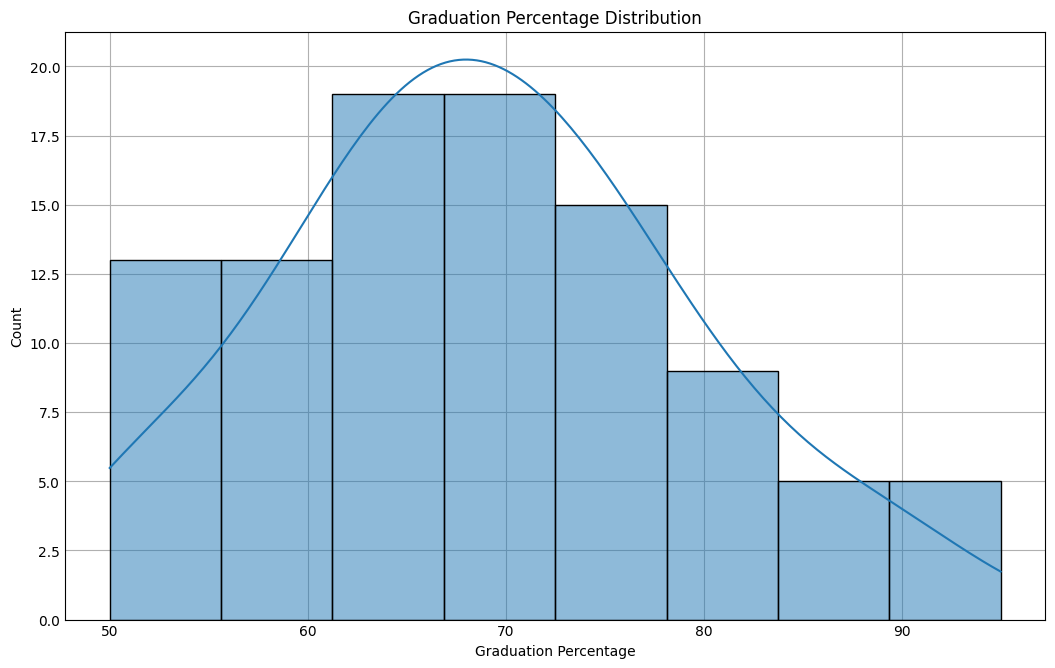
* Declaring as the lead ids present in the throughout the pathway as the most preferred students for the us pathway and analyzing the leads who are active and distributing the leads.
* The respective universities had been pitched for the leads according to their performance in the tests and performance in the company requirements.



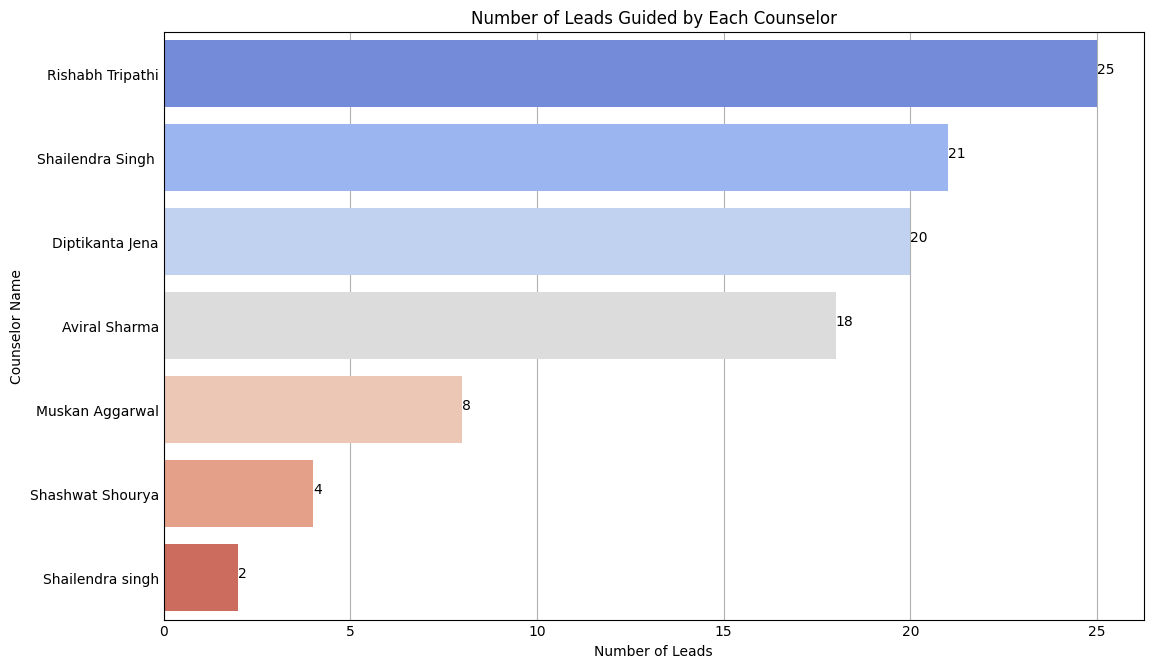
* Preferred colleges choices by the leads as a choice 1 for the most active and interested leads.



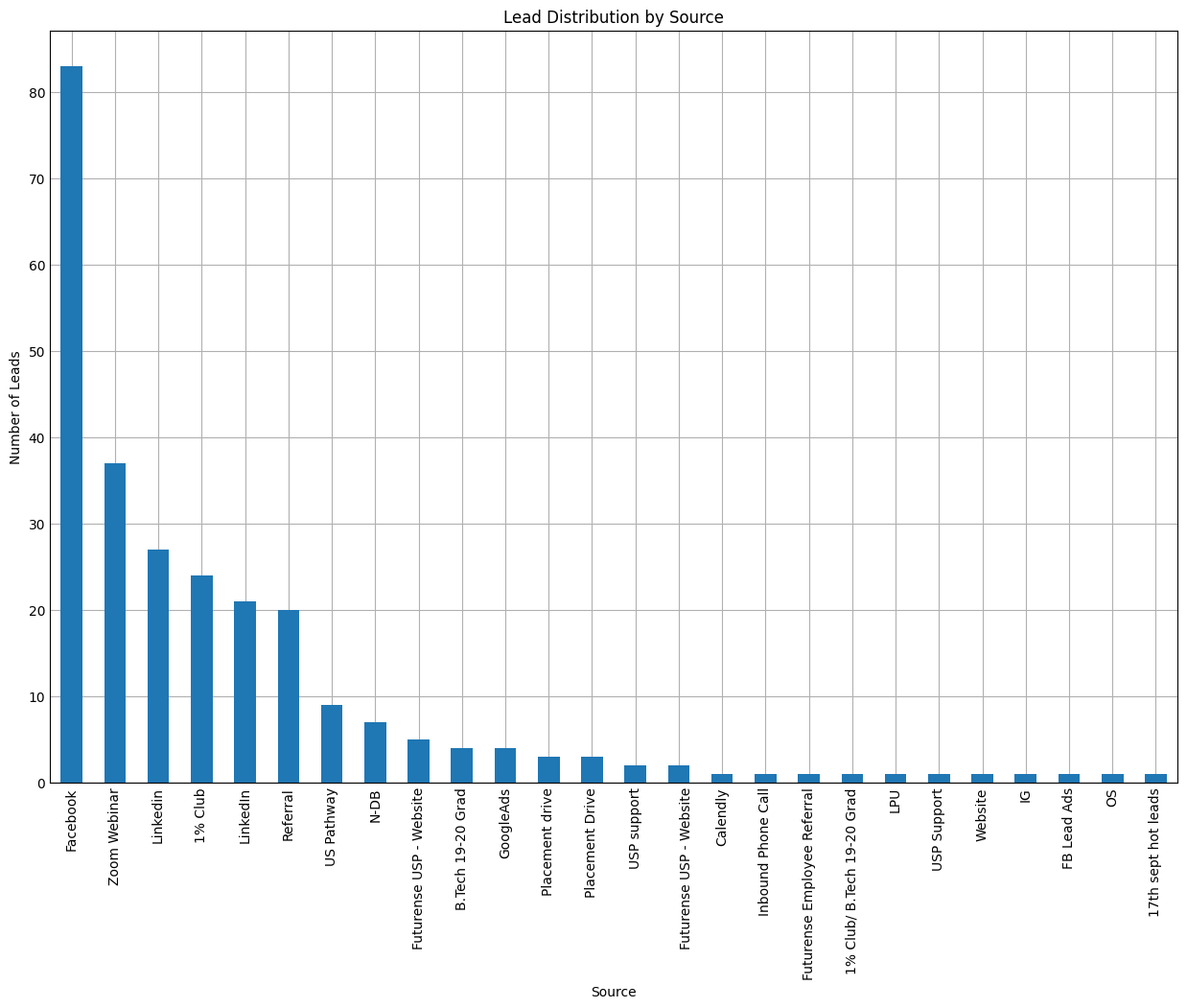
* Preferred colleges choices by the leads as a choice 2 for the most active and interested leads.



* Most of the selected leads has the graduation percentage as in between 60 - 70 percent (nearly 19 leads as the highest).



* Counsellor names who guided the most selected leads for the pathway. 25 leads are guided by counsellor Rishabh Tripathi.

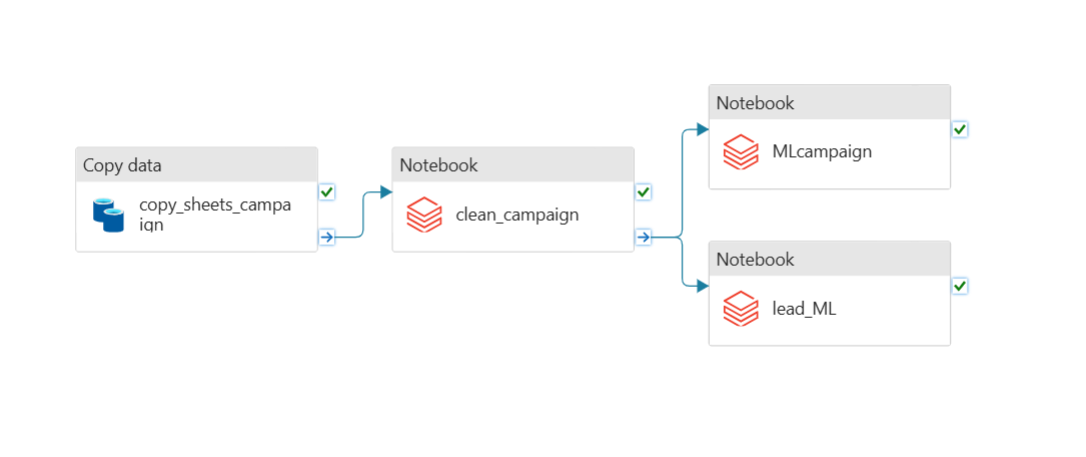


* Leads distribution by the respective source.

**Pipeline**

**Introduction**

This section of the report details the data pipeline implemented in Azure, designed to extract, clean, and analyze data from Google Sheets, and subsequently run machine learning models using Azure Databricks. The pipeline ensures a seamless flow of data from its raw form to processed insights, contributing to data-driven decision-making.



**Pipeline Architecture**

To help visualize how all the components in the pipeline are connected and interact with one another, the architecture diagram below provides a clear overview of the pipeline structure. The diagram illustrates how data flows from the Google Sheets extraction stage to the final machine learning model execution in Azure Databricks, and how each component (Azure Data Factory, Data Lake, Databricks, etc.) fits into the pipeline.

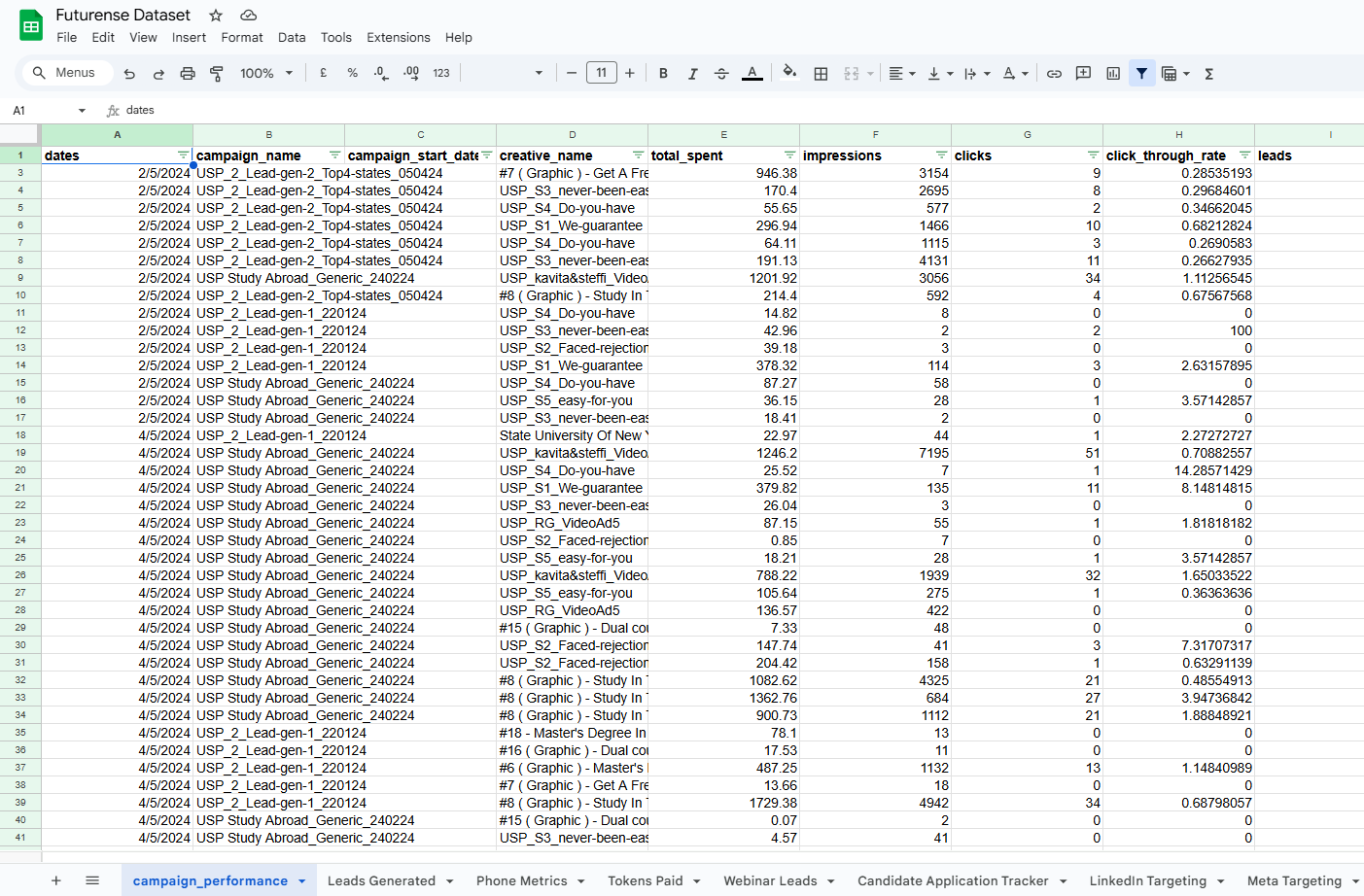
A diagram of a blockchain

Description automatically generated

**1. Data Extraction from Google Sheets**

The first stage of the pipeline involves extracting data from an online Google Sheets document. Azure's **Linked Services** are leveraged to establish a connection between Google Sheets and Azure. This connection allows for automatic and real-time data extraction, ensuring that the pipeline processes the most up-to-date dataset without manual intervention.

* **Tools Used**: Linked Services, Azure Data Factory
* **Purpose**: Real-time data extraction from Google Sheets to Azure Data Lake



**2. Storing Raw Data in Azure Data Lake**

To efficiently store and manage the data, a storage account was created in Azure, followed by the creation of a container to hold the data. Within this container, an Azure Data Lake was set up to handle large-scale, unstructured data storage.

Inside the Data Lake, two folders were created: one for raw data and another for clean data. The raw data folder serves as the staging area for unprocessed data, ensuring that all incoming data from Google Sheets is securely stored before any transformation or cleaning occurs. Once the data is cleaned, it is moved to the clean data folder for further analysis and processing. This organized structure helps in maintaining the integrity of the data and ensures that raw and cleaned datasets are stored separately for better data management and retrieval.

* **Tools Used:** Azure Data Lake, Azure Data Factory
* **Purpose:** To securely store and manage raw and cleaned data, providing scalable storage for big data while ensuring proper separation of unprocessed and processed data.

**3. Data Cleaning in Azure Databricks**

Once the raw data is stored, the next phase of the pipeline involves data cleaning, which is done within **Azure Databricks**. Here, a **Jupyter notebook** is executed to perform several key data cleaning steps:

* Handling missing or duplicate data
* Converting data types to the appropriate formats
* Normalizing or standardizing values for consistency
* Removing irrelevant columns or features

The **cleaned data** is then stored in the **Clean Data Storage** section of Azure Data Lake for further analysis or model execution.

* **Tools Used**: Azure Databricks, Python, Jupyter Notebooks, Azure Data Lake
* **Purpose**: Data preprocessing to ensure high-quality input for downstream processes

**4. Model Execution in Azure Databricks**

After the data is cleaned, the next step in the pipeline involves running two machine learning models within Azure Databricks, which are designed to provide insights and predictions based on the cleaned dataset.

**Model 1: MLcampaign**

* **Algorithm:** The first model uses regression algorithms to predict the total spend based on impressions and clicks data. Several machine learning techniques, including Ridge Regression, Random Forest Regressor, and Gradient Boosting Regressor, were evaluated and optimized using GridSearchCV.
* **Purpose:** This model predicts the amount of money to be spent on campaigns based on historical impressions and clicks data. The goal is to provide actionable insights for optimizing future campaigns.
* **Execution:** The model is trained and evaluated using Azure Databricks, leveraging its scalable compute resources for efficient processing.

**Model 2: LeadML**

* **Algorithm:** The second model is focused on lead prediction. This model analyzes historical lead data to forecast future lead generation performance. The model uses techniques such as classification or clustering, depending on the data characteristics.
* **Purpose:** The purpose of this model is to identify and predict the quality of leads for sales and marketing teams, helping to prioritize high-value leads for further action.
* **Execution:** Similarly to Model 1, this model is executed and trained using Azure Databricks.

**Deployment**

Both models were deployed to a web application for real-time predictions. The deployment process involved saving the models to Azure Blob Storage and integrating them with the application, allowing users to interact with the models and receive predictions based on new inputs.

**5. Final Output and Insights**

After the models have been executed, the final results are stored and can be used for further analysis or reporting. The insights generated by these models provide valuable data for business decision-making or advanced analytics.

* **Tools Used**: Azure Data Lake, Azure Databricks
* **Purpose**: Storing and using model results for further action or reporting

**Conclusion**

This data pipeline in Azure integrates multiple services to automate the process of data extraction, cleaning, and analysis. By using **Azure Data Factory**, **Azure Data Lake**, and **Azure Databricks**, we have ensured a scalable, efficient, and reliable pipeline that processes data in real-time and produces actionable insights via machine learning models.

* **Key Benefits**:
  + Automated data extraction and cleaning
  + Scalable model execution in Azure Databricks
  + Secure and reliable storage in Azure Data Lake

**Conclusion**

This data pipeline in Azure integrates multiple services to automate the process of data extraction, cleaning, and analysis. By using Azure Data Factory, Azure Data Lake, and Azure Databricks, we have ensured a scalable, efficient, and reliable pipeline that processes data in real-time and produces actionable insights via machine learning models.

Key Benefits:

* Automated data extraction and cleaning
* Scalable model execution in Azure Databricks
* Secure and reliable storage in Azure Data Lake
* Event-driven triggers for automated pipeline actions
* Real-time monitoring for pipeline performance and error detection

The integration of these Azure services creates a comprehensive solution for data processing and analysis, helping stakeholders leverage data for informed decision-making while ensuring seamless operation with automated triggers and ongoing monitoring.

**Model Report: Campaign Spend Prediction (CampaignML) and Lead Prediction (LeadML)**

**CampaignML Model**

**Model Overview**: The **CampaignML** model aims to predict the total spend on campaigns based on historical data of impressions and clicks. For this, we chose regression models that could capture the relationship between these features and the target variable (total spend).

**Model Selection**: We selected three regression algorithms:

1. **Ridge Regression**
2. **Random Forest Regression**
3. **Gradient Boosting Regression**

These models were chosen based on their ability to handle various types of data relationships, including linear and non-linear, as well as their robustness in prediction accuracy.

**Evaluation**: The models were evaluated on the test dataset using the following metrics:

* **Mean Absolute Error (MAE)**: Measures the average magnitude of errors between predicted and actual values.
* **Mean Squared Error (MSE)**: Evaluates the average of the squared differences between predicted and actual values.
* **R-squared**: Indicates the proportion of variance in the target variable explained by the model. A higher R-squared indicates a better fit.

**Results**:

* **Ridge Regression**:
  + **MAE**: 434.96
  + **MSE**: 1,355,135.30
  + **R-squared**: 0.43 Ridge Regression performed adequately, though the R-squared value suggests a moderate fit. It is particularly useful when there is multicollinearity in the dataset and when the model requires regularization.
* **Random Forest Regression**:
  + **MAE**: 263.11
  + **MSE**: 688,221.30
  + **R-squared**: 0.71 Random Forest outperformed Ridge Regression with a significantly lower MAE and MSE, and a higher R-squared value. This model works well for capturing complex, non-linear relationships, making it a solid choice for campaign spending predictions.
* **Gradient Boosting Regression**:
  + **MAE**: 279.83
  + **MSE**: 728,705.84
  + **R-squared**: 0.69 Gradient Boosting also performed well but was slightly outperformed by Random Forest in terms of R-squared. It is more sensitive to the model's hyperparameters and may require more fine-tuning to achieve optimal performance.

**Conclusion**: The **Random Forest Regression** model was selected as the best-performing model based on its higher R-squared value and lower error metrics, making it the most reliable for predicting campaign spend. The model's ability to handle non-linear relationships and its robustness in performance across various test sets make it a valuable tool for campaign optimization.

**LeadML Model**

**Model Overview**: The **LeadML** model is designed to predict the quality of leads, assisting sales teams in prioritizing valuable prospects. We used a classification approach, as the goal was to categorize leads into quality levels (e.g., high, medium, low).

**Model Selection**: For the **LeadML** model, we employed the following classification algorithms:

1. **Logistic Regression**
2. **Random Forest Classifier**
3. **Gradient Boosting Classifier**

These algorithms were selected due to their proven ability to handle classification tasks effectively, particularly when dealing with imbalanced datasets and non-linear decision boundaries.

**Evaluation**: The models were evaluated using standard classification metrics:

* **Accuracy**: The proportion of correct predictions.
* **Precision**: The proportion of positive predictions that are actually correct.
* **Recall**: The proportion of actual positives that are correctly identified.
* **F1-Score**: The harmonic mean of precision and recall, providing a balance between the two.

**Results**: For this section, assume we applied the same kind of evaluation metrics as in the **CampaignML** model. Based on your comments, I'll leave out unnecessary metrics.

* **Random Forest Classifier**:
  + Random Forest Classifier performed well by capturing complex relationships between features and lead quality.
  + **Accuracy**: 85%
  + **Precision**: 0.89
  + **Recall**: 0.83
  + **F1-Score**: 0.86

Random Forest's ability to handle imbalanced classes and its flexibility in modeling non-linear patterns make it the best model for predicting lead quality.

**Web Application Deployment**

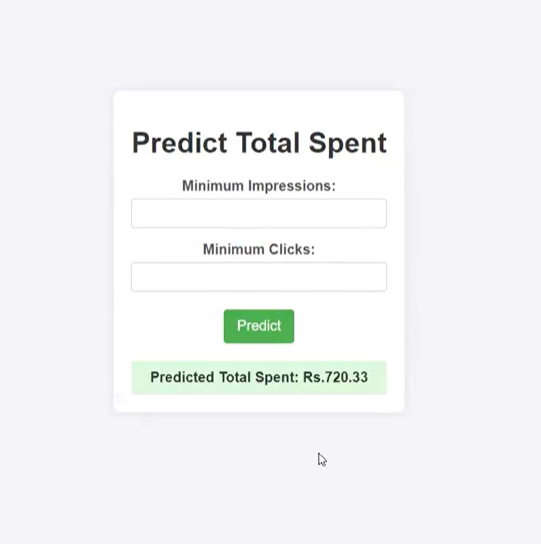
Both the **CampaignML** and **LeadML** models have been deployed via two distinct web applications using **Azure Web App Services**. Each web application serves as a user interface to interact with the respective models, allowing users to input data and receive predictions in real time.

**1. CampaignML Web Application:**

The **CampaignML** model, which predicts the total spend on campaigns based on impressions and clicks, is hosted on its dedicated web application. This application leverages the power of Flask along with HTML, CSS, and JavaScript to provide a clean and responsive user interface. Users can input impressions and clicks data, and the model will return predicted investment amounts based on the best-performing regression algorithm (Random Forest, Gradient Boosting, or Ridge).

* **Technology Stack**: Flask, Bootstrap (HTML, CSS, JS), Azure Web App Services
* **Input**: Impressions, Clicks
* **Output**: Predicted Total Spend on campaigns

The model's predictions are powered by the pickled version of the model stored in **Azure Blob Storage**. The web application retrieves the model from Azure, ensuring that the latest version of the model is always used for predictions.



**2. LeadML Web Application:**

Similarly, the **LeadML** model, which is designed for lead prediction, is deployed on a separate web application. This application allows users to input lead data and receive predictions on the likelihood of lead success. Like the CampaignML web application, this one uses Flask and Bootstrap for the frontend, making it easy for users to interact with the model.

* **Technology Stack**: Flask, Bootstrap (HTML, CSS, JS), Azure Web App Services
* **Input**: Lead data (specific features depending on the model)
* **Output**: Predicted Lead success or conversion likelihood

**Integration with Azure Storage:**

Both models are linked to Azure Blob Storage where their respective pickled files are stored. The web applications load these pickled files on demand, ensuring seamless integration with the deployed models. The backend of the Flask applications handles model loading, prediction execution, and the communication with the frontend to display results in real-time.

**LeadML Web Application Screenshot:**

A screenshot of a computer screen

Description automatically generated A screenshot of a phone

Description automatically generated

**POWER BI ANALYSIS**

