# Marketing KPI Analysis and Model Interpretation with SHAP

A data analytics learning project for evaluating campaign success

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**Tools used:** Python (pandas, matplotlib, shap), Excel, Jupyter Notebook

## 1. Objective

The goal of this analysis is to develop an artificially constructed, data-driven composite metric – the Performance Score. This score combines multiple key marketing KPIs into a single, objective, comparable, and actionable value for evaluating campaigns. It eliminates the need for relying on isolated metrics or subjective judgment.  
  
At the same time, the score forms the foundation for an executive dashboard tailored to those managing campaigns and client relationships within the company (“Executives”).  
  
This dashboard enables users to:  
- quickly gain an overview of campaign performance,  
- explore KPI and score details in depth,  
- and reach out to clients directly.  
  
Thus, the project pursues two main goals:  
1. Construction of a data-driven, synthetic Performance Score   
2. Development of a user-friendly dashboard for supporting campaign management decisions

## 2. Data Basis and Context

The dataset contains information on 1,000 simulated marketing campaigns. It combines:  
  
- Metadata (e.g., campaign name, duration, channel)   
- Client data (e.g., contact person, contact details)   
- Performance metrics (e.g., views, clicks, conversions, expenses)  
  
A selection of key columns includes:

|  |  |
| --- | --- |
| **Column** | **Description** |
| Campaign Number | Unique campaign ID |
| Name | Campaign name |
| Start Date | Campaign Start Date |
| End Date | Campaign End Date |
| Channel | Marketing channel used |
| Client | Client name |
| Address | Client address |
| Email | Client e-mail |
| Phone | Client phone number |
| Contact | Client representative |
| Audience | Campaign target audience |
| Location | Target country |
| Views | Impressions |
| Likes | Engagement |
| Clicks | User responses |
| Conversions | Goal achievement |
| Expense | Campaign cost in USD |
| Executive | Internal contact responsible |
| CR | Conversion Rate (Conversions / Clicks) |

## 3. Data Cleaning

Before analysis, the dataset was systematically cleaned using Google Sheets to ensure consistent processing. The following steps were taken:

|  |  |
| --- | --- |
| **Cleaning Step** | **Purpose / Effect** |
| |  | | --- | | Removed timestamp from dates |  |  | | --- | |  | | Date fields always included “00:00:00” – removed for clarity |
| Standardized client names | Ensures consistent grouping and assignment Split address into parts |
| Split address i   |  | | --- | | Standardized phone numbers |  |  | | --- | |  |   nto parts | Extracted street, city, ZIP, and country separately |
| Vereinheitlichung von Telefonnummern | |  | | --- | |  |  |  | | --- | | Improved readability and data handling | |
| Split audience info | Separated audience into “Age” and “Gender” |

This cleaned dataset served as the foundation for KPI construction and for filter and contact features within the executive dashboard.

## 4. Feature Engineering

To prepare for analysis, five core marketing KPIs were calculated using Python (pandas). These KPIs formed the basis for the data-driven Performance Score.

|  |  |  |
| --- | --- | --- |
| **KPI** | **Formel** | **Description** |
| ER (Engagement Rate) | (Likes + Conversions) / Views | |  | | --- | | Share of views that led to engagement |  |  | | --- | |  | |
| CTR (Click-Through Rate) | Clicks / Views | |  | | --- | | Share of views that led to clicks |  |  | | --- | |  | |
| CPC (Cost per Click) | Expense / Clicks | |  | | --- | | Average cost per click |  |  | | --- | |  | |
| CPA (Cost per Acquisition) | Expense / Conversions | |  | | --- | | Average cost per acquisition |  |  | | --- | |  | |
| CR (Conversion Rate) | Conversions / Clicks | Share of clicks that resulted in conversions (preexisting column) |

These KPIs were calculated entirely in Python and added as new columns to the dataset. They serve as input features for the weighting analysis and Performance Score construction in the next steps.

## 5.1 Artificial Weighting Using Random Forest

Since this analysis doesn't rely on a real-world target metric like revenue or ROAS, a synthetic target variable was used: the number of conversions. This serves solely as a functional proxy to enable a data-driven weighting of the KPIs using modeling techniques.

It’s important to note that two of the independent variables – CPA (Cost per Acquisition) and CR (Conversion Rate) – are mathematically linked to the target variable “Conversions”:

* CPA = Expense / Conversions
* CR = Conversions / Clicks

This relationship represents a known issue in modeling called “target leakage” – using features that directly contain or influence the target. In this analysis, this is done intentionally, since there is no true target variable available, and the goal is to explore relative KPI importance.

The objective here is not to build a predictive model, but to identify which method is most suitable for constructing an objective, weighted KPI score.

Therefore, a Random Forest ensemble method was used to derive a weighted, data-driven performance score from the five core KPIs.

## 5.2 Random Forest Regressor – Feature Importance

To determine how much each KPI contributes to the synthetic target “Conversions,” a Random Forest Regressor was trained. This algorithm is part of the nonlinear ensemble family and is particularly effective at modeling complex, nonlinear relationships between variables.

The implementation was done in Python using the scikit-learn library. The model was trained on 80 % of the data and tested on the remaining 20 %. Model performance reached:

R² = 0.86

This shows that the Random Forest captures the “Conversions” variable quite well – even though it's artificially constructed.

The estimated feature importances were calculated in Python and visualized using a bar chart. The table below (originally shown in the document) summarizes the results:

A screen shot of a computer

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Conversion Rate (CR) clearly had the strongest impact on the model predictions – which is expected due to its direct link to the target.

Nonetheless, other KPIs like CPA, ER, CTR, and CPC also made measurable contributions.

The following figure shows the feature importance as a bar chart, created using matplotlib and seaborn in Python.

A graph with blue squares

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## 6.1 Introduction to SHAP

To better understand the feature weights identified by the Random Forest, the SHAP method (Shapley Additive Explanations) was used in addition. SHAP enables a model-agnostic analysis based on game theory and explains how much each individual feature contributes to a specific model prediction.

Even though this project does not aim to build a production-ready prediction model, the trained Random Forest can still be used to explore the relative importance of the KPIs in a data-driven way. SHAP is well suited for this purpose because it quantifies the contribution of each feature to the model output — regardless of whether the model is used in practice or just for interpretation.

At the core is the question:  
*Which features influence the model decision — and by how much?*

The SHAP analysis confirms the dominance of Conversion Rate (CR) and Cost per Acquisition (CPA) already observed in the Random Forest. Together, these two features explain most of the model's output.

## 6.2 Model Interpretation with SHAP

To deepen the interpretation of the KPI weights identified by the Random Forest, the SHAP method (SHapley Additive Explanations) was applied.

SHAP is based on game theory and analyzes how much each individual feature contributes to the model’s prediction — not just globally, but also locally for each observation. This makes SHAP a transparent tool for interpreting model behavior, even if the model is used solely for explanatory purposes rather than for real-world prediction.

**SHAP-Based Feature Importance & Model Performance:**

A screenshot of a computer

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The Output shows the mean SHAP values (Mean Absolute SHAP) for each feature and their relative importance in percentage terms.

As with the Random Forest results, Conversion Rate (CR) and Cost per Acquisition (CPA) dominate the model. SHAP confirms the previous importance ranking with high precision.

**SHAP Summary Plot (Scatter):**

A graph of blue and red dots

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This summary plot visualizes the impact of each feature on the model's prediction.

Each dot represents a campaign. Blue stands for low feature values, Pink stands for high feature values. The horizontal position shows whether a feature increased or decreased the prediction

**Example:**

* High CR values (pink on the right) significantly increase predicted conversions
* High CPA values (pink on the left) lower the predicted value

**🌊 SHAP Waterfall Plot (Campaign #100)**

A graph with numbers and a number

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This plot shows how each individual feature value contributes to the model prediction for a specific campaign. The baseline value (expected output across all data) is around 504. The final prediction for this campaign is 920. The Conversion Rate (+163), CPA (+163), ER (+92), and CTR (+54) have a positive effect on the prediction, while only CPC (−0.08) has a slightly negative effect.

## 7. Decision: Using SHAP for Weighting

This analysis used two methods to determine which KPIs had the greatest influence on conversions:

1. Feature importance from the Random Forest model
2. SHAP values (SHapley Additive Explanations)

Both methods produced a similar ranking of the most important features. However, SHAP has major advantages because it shows exactly how much each KPI contributes, both to the model overall and to each individual campaign.

**Comparison of Methods:**

|  |  |  |
| --- | --- | --- |
| **Criterion** | **Random Forest** | **SHAP** |
| |  | | --- | | Explains individual campaigns |  |  | | --- | |  | | No | Yes |
| |  | | --- | | Explains individual campaigns |  |  | | --- | |  | | globaony | global + local |
| |  | | --- | | Transparent and additive |  |  | | --- | |  | | Limied | yes |
| |  | | --- | | Reconstructs model predictions |  |  | | --- | |  | | No | yes (R² = 1.00) |

**Conclusion**:  
Because SHAP delivers a more objective and interpretable basis, its values were chosen to define the final KPI weights.

|  |  |
| --- | --- |
| **KPI** | **SHAP Weight** |
| CR | 43.06 % |
| CPA | 32.06 % |
| ER | 11.7 % |
| CTR | 8.11 % |
| CPC | 5.07 % |

These weights are used in the next step to calculate the Performance Score.

## 8. Calculating the Performance Score

After determining the relative importance of the five core KPIs using SHAP, the next step was to calculate a unified Performance Score for each campaign.

The goal was to combine different KPIs – each with their own units and scales – into a single score between 0 and 100, enabling comparison across campaigns.

All steps were implemented in Python using pandas and matplotlib.

**1. Normalization of KPIs**

All five KPIs were normalized to a 0–1 scale using Min-Max scaling:

**Normalized Value = (Value − Minimum) / (Maximum − Minimum)**

KPIs normalized:

* CTR (Click-Through Rate)
* CR (Conversion Rate)
* ER (Engagement Rate)
* CPC (Cost per Click)
* CPA (Cost per Acquisition)

**2. Weighting the Normalized KPIs**

The normalized values were then multiplied by **the SHAP-based weights and summed to** create a weighted index.

Formula (simplified):

**Performance Index = 100 × (w₁ × CTR\_norm + w₂ × CR\_norm + …)**

**3. Median Shift & Clipping**

The resulting score was shifted so that the median of all campaigns equals exactly 50.  
In addition, the score was clipped to the range [0, 100] to limit outliers and ensure a standardized scale.

Formula (simplified):

**Performance Score = 100 × (weighted Performance index − campaign median + 50), clipped to the range [0, 100]**

**4.** **Percentile Rank**

To enhance interpretability and provide a clear benchmark, each campaign was also assigned a percentile rank based on its adjusted performance score.  
This relative score shows **how a campaign performs compared to others** (e.g., top 10%, bottom 25%).

* Percentiles were calculated across all campaign scores.
* Results were rounded to integer values from **0 to 100**, where 100 represents the highest-performing campaign.
* This method helps identify performance tiers (e.g., quartiles) and is especially useful in executive dashboards and communication.

**5. Visual Analysis of Score Distributions and Percentile Transformation**

To better understand the effectiveness and interpretability of the Performance Score, we visualized the distribution of the original score and the newly introduced percentile-based score. This transformation was introduced to make the results more actionable and intuitive for non-technical stakeholders.

**Plot 1: Histogram of Performance Score (0–100)**

A graph of performance scores

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* Interpretation: The score distribution is tightly clustered around 50. This narrow range results from clipping and median-centering and makes it hard to distinguish between campaigns with similar values.

**Plot 2: Boxplot of Performance Score (0–100)**

A graph of performance score

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* Interpretation: The interquartile range is small, and many values appear as statistical outliers, although these are often still relevant business cases.

**Plot 3: Histogram of Score Percentile (0–100)**

A graph of performance score

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* Interpretation: The percentile distribution is nearly uniform. Each percentile contains a similar number of campaigns, which allows executives to easily interpret and rank performance.

**Plot 4: Boxplot of Score Percentile (0–100)**

A graph with a bar and a line

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* Interpretation: This plot confirms a well-balanced and evenly spread score distribution, with no artificial outliers and a median at 50.

**Output: Summary Statistics (Median & Mean)**

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Interpretation: Although Campaigns 2 and 4 have nearly identical scores (~50.10), they fall into the 55th and 54th percentiles – placing them exactly in the middle.  
In contrast, Campaign 1 has a slightly lower score (~47.83) but ranks only in the 8th percentile, meaning it performs worse than 92% of all campaigns.

**6. Conclusion**

Percentile ranking provides a clearer and more intuitive positioning, without distorting the original distribution. The ranking is immediately understandable – especially for non-technical decision-makers.

## 9. Campaign Analysis in the Interactive Dashboard

The interactive Tableau dashboard provides a comprehensive overview of campaign performance for individual clients. In the example shown, the filter in the top-right corner is set to the client *Edwards LLC*, which automatically limits the displayed data to their campaigns. This setup allows executives to focus their analysis on a single client without being distracted by others.

**Dashboard 1 – Funnel Performance Overview (Edwards LLC):**

A screenshot of a graph

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The main dashboard aggregates performance metrics from all campaigns associated with the selected client and visualizes the full funnel from page views to final conversions. Each KPI panel (e.g., Conversion Rate, CPA, CTR) is accompanied by a color-coded dot, indicating how the respective campaign performs compared to all others in the dataset. These indicators follow a standardized color legend — from 🟢 *Top 25% (excellent)* to 🔴 *Bottom 25% (needs improvement)* — allowing for instant visual assessment.

The performance score, displayed in the upper left, is always calculated at the campaign level. The shown value reflects the aggregated score based on the current filter selection — either for one specific campaign or for all campaigns of a given client.

Executives can flexibly filter the dashboard not only by client or campaign, but also by responsible executive. This enables personalized analysis tailored to specific roles and reporting needs.

The funnel visualization at the center illustrates the customer journey in stages: from *views* to *likes*, *clicks*, and ultimately *conversions*. This makes it easy to track how users engage with each campaign along the funnel.

To dive deeper, users can click the icon with the list and magnifying glass to the left of the dashboard title ('Campaign Conversion Funnel'). This opens a detailed view listing all campaigns associated with the selected client, including demographic information (such as gender and age), campaign durations, all relevant KPIs, and the assigned performance category ('Score Cat.') — consistently visualized using the same color scheme as in the overview

**Dashboard 2 – Campaign Details and Client Contact** (including tooltip example):

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**Campaign Score Visibility in Detail View**:  
In the detailed view, each campaign is now clearly color-coded according to its performance score. This visual coding enables executives to instantly assess the quality of individual campaigns at a glance, without having to interpret each KPI manually.

**Tooltip Functionality**:  
Hovering over a campaign opens a tooltip window on the right side of the dashboard, which provides a concise summary of key performance metrics. These include views, likes, clicks, conversions, total expenses, and the overall performance score. This immediate overview supports quick, data-driven decisions without the need for further exploration.

**Client Contact Details**:  
At the bottom of the page, the "Client Details" section displays key contact information for the respective customer, including name, phone number, email, and address. A dedicated email button enables users to initiate direct communication, allowing for fast and efficient follow-up.

## 10. Reflection

In the course of this project, a simulated marketing dataset was used to explore the role of key KPIs such as CTR, CPC, CPA, CR, and ER. The focus was not on predicting actual campaign outcomes but on understanding the relationships between metrics and explaining them using data analytics methods—particularly SHAP (SHapley Additive Explanations).

However, in real-world marketing, many other factors influence campaign success:  
revenue figures, ROAS (Return on Ad Spend), Customer Lifetime Value, and soft interactions like likes, comments, and shares—especially in branding campaigns. Additionally, the actual impact of clicks and engagement on conversions is more complex than a purely numerical dataset can reflect.

Despite these limitations, the project provided a practical introduction to applying statistical and analytical methods:

• **Statistical techniques**  
 – Min-max normalization to ensure comparability of KPIs  
 – Median adjustment for robust centering  
 – Score scaling to avoid distortions in model interpretation

• **Technical tools**  
 – Python (especially pandas, matplotlib, shap) for data processing, visualization, and model interpretation  
 – Excel for transparent KPI calculations  
 – Jupyter Notebook as the central platform for structured analysis and documentation, integrating code, comments, and outputs in one interactive format

• **Skills acquired**  
 – Data cleaning and preparation  
 – Development and application of marketing KPIs  
 – Interpretation and visualization of key figures  
 – Critical evaluation of artificial data structures  
 – Use of SHAP for interpretable model analysis

Overall, this project not only strengthened my technical skills but also deepened my understanding of how data-driven decisions are prepared in marketing—and how essential it is to always interpret results within the context in which they were generated.