Final project:

Analytical report on data from an educational company. Key findings and recommendations

Project goal

Analysis and cleaning of data from the CRM system in order to improve the efficiency of the online programming school.

Description of data

CRM contains information about customers, calls, advertising costs and sales. Key indicators include dates, call durations, lead sources and payment data. This information helps to evaluate marketing and sales effectiveness.

The data for analysis is contained in four Excel tables:

- **Contacts** : information about customers, including the date the record was created and modified.
- **Calls** : Call details such as type, duration, status and source.
- **Spend** : Data about your advertising campaigns, including costs, impressions, clicks, and sources.
- **Deals** : sales information such as deal stages, rejection reasons, payment amounts and customer cities.

Tasks of the analysis

1. Data preparation and cleaning.
2. Conducting descriptive statistics .
3. Time series analysis.
4. Evaluation of marketing campaigns.
5. Analysis of the sales department work.
6. Study of payments and products.
7. Geographic analysis.

1. Data preparation and cleaning.

General transformations

- Dates are converted to `datetime64[ns] format` for time series analysis.
- Categorical fields (e.g. "Contact Owner Name", "Call Type", "Quality") have been converted to type `category` to optimize memory.
- Numeric values (e.g. "Call Duration (in seconds)", "Impressions", "Clicks") are cast to `int` or `float types` .

Deals

- **Filling in blanks in 'Deal Owner Name':** All empty values have been replaced with `Unknown` .
- **Transformation 'Closing Date':** Data converted to `datetime64[ns] format` .
- **'Quality' handling:** Empty values are replaced with `Unknown` , column is converted to categorical type.
- **'Lost Reason' handling:** For trades with the status **Lost** where the reason for the loss is not specified, the value has been replaced with `Unknown` .
- **Processing 'Campaign', 'Source' and 'Product':** Missing values replaced with `Unknown` , columns converted to categorical type.
- **Processing 'Education Type':** Removed rows with incorrect `#REF! value` . Other blanks replaced with `Unknown` , column converted to categorical type.
- **Processing 'Created Time':** Converted to date and time format.
- **Processing 'Course duration':** Missing values replaced with 0, column converted to `Int8 type` .
- **Processing 'Initial Amount Paid' and 'Offer Total Amount':**
    - Incorrect data has been replaced.

```
deals['Initial Amount Paid'] = deals['Initial Amount Paid'].replace(' € 3.500.00', '3500 ')
deals['Offer Total Amount'] = deals['Offer Total Amount'].replace(' € 2.900.00', '2900 ')
deals['Offer Total Amount'] = deals['Offer Total Amount'].replace(' € 11398.00', '11398 ')
```

    - Missing values are filled with zeros.
    - Columns are converted to `float64 type` .

Data analysis and normalization

Analysis and normalization of the field **'Months of study'**

Initially, I planned to fill in the empty values in the 'Months of study' field with data from 'Course duration' if the deal had positive financial parameters:

- `Initial Amount Paid > 0` (prepayment was made).
- `Offer Total Amount > 0` (the total offer amount is positive).

However, I later changed the decision, since a student could pay for a course but not start studying. As a result, the remaining empty values were filled with zeros and converted to the `Int8 type`.

Analysis of the **'Payment Type' field**

During my analysis I found that some transactions do not have a 'Payment Type' specified, even though they are at stages where this information should be available.

To solve the problem, I applied the following steps:

1. Created a mask for deals at the 'Waiting For Payment' or 'Payment Done' stages where 'Payment Type' is missing and filled the field with the value `Unknown`.
2. For the remaining gaps, I used the `Non applicable value`.

However, I later reconsidered this decision. A student could pay for a course but never start studying. To avoid data distortion, I decided not to change the original values. 'Payment Type' .

Analysis fields **'Closing Date'** And **'Created Time'**

I decided to remove the time and leave only the date. For this, the following transformations were applied:

- `deals['Closing Date'] = pd.to_datetime(deals['Closing Date']).dt.date`
- `deals['Created Time'] = pd.to_datetime(deals['Created Time']).dt.date`

After that I did a comparison and found 44 records where 'Closing Date' was less than 'Created Time'. I assumed that the data was filled in incorrectly and swapped them to present it correctly.

Analysis data in the **'City' field**

During data processing, incorrect entries in the 'City' field were identified, which contained either full addresses or erroneous values. Such entries were converted into city names.

```
deals['City'] = deals['City'].replace('Karl-Liebknecht str. 24,
Hildburghausen, Thüringen', 'Thüringen')
deals['City'] = deals['City'].replace('Halle (Saale)', 'Halle')
deals['City'] = deals['City'].replace('Vor Ebersbach 1, 77761 Schiltach',
'Schiltach')
deals['City'] = deals['City'].replace('Poland , Gdansk , Al. Grunwaldzka
7, ap. 1a', 'Gdansk')
deals['City'] = deals['City'].replace('-', 'Unknown')
```

Analysis of normalization of the field **'SLA** '

The 'SLA' (service level agreement duration) field has been normalized to bring the data to a common format:

1. Empty values are replaced with 0 seconds.
2. The data is converted to `timedelta format` and normalized in hours.
3. After processing, the values are converted back to `timedelta format` .

This ensured that the data was standardized and ready for analysis.

Analysis of cleaning and normalization of the field ' **Level of Deutsch'**

The 'Level of Deutsch' field has been cleaned and normalized to remove errors and bring the data into a consistent format:

```
# deleted all symbols except A1|A2|A1|A2|B1|Б1|Б2|B2|C1|C2|C1|C2,
replaced Cyrillic with Latin.
deals['Level of Deutsch'] = deals['Level of Deutsch'].str.upper()\
.str.extract(r"^(A1|A2| A 1| A 2|B1| B 1| B 2|B2|C1|C2| C 1| C 2)$",
expand=False).replace({' A 1': 'A1', ' A 2': 'A2',' B 1': 'B1', ' B
2': 'B2', ' C 1': 'C1','C2'}).fillna('Unknown')
```

As a result, the data was standardized, which allows it to be used for further analysis.

Summary data

Calls

```
RangeIndex: 95874 entries, 0 to 95873
Data columns (total 9 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Id                         95874 non-null  object
 1   Call Start Time            95874 non-null  datetime64[ns]
 2   Call Owner Name            95874 non-null  category
 3   CONTACTID                  91941 non-null  object
 4   Call Type                  95874 non-null  category
 5   Call Duration (in seconds) 95874 non-null  float64
 6   Call Status                95874 non-null  category
 7   Outgoing Call Status       86875 non-null  object
 8   Scheduled in CRM           86875 non-null  category
```

- Number of lines: **95,874**
- Number of columns: **9**
- Transformations:
  - "Call Start Time" → `datetime64[ns]`
  - "Call Owner Name", "Call Type", "Call Status", "Outgoing Call Status", "Scheduled in CRM" → `category`
  - "Call Duration (in seconds)" → `int64`

Expenses (Spend)

```
RangeIndex: 19862 entries, 0 to 19861
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Date         19862 non-null  datetime64[ns]
 1   Source       19862 non-null  category
 2   Campaign     19862 non-null  category
 3   Impressions  19862 non-null  int32
 4   Spend        19862 non-null  float64
 5   Clicks       19862 non-null  int32
```

- Number of lines: **19,862 (** `917 duplicates` removed)
- Number of columns: **6**
- Transformations:
  - "Date" → `datetime64[ns]`
  - "Campaign", "Source" → `category`
  - "Impressions", "Clicks" → `int32`

Deals

```
Index: 21593 entries, 0 to 21592
Data columns (total 20 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Id                   21593 non-null  object
 1   Deal Owner Name      21564 non-null  object
 2   Closing Date         21593 non-null  datetime64[ns]
 3   Quality              21593 non-null  category
 4   Stage                21593 non-null  object
 5   Lost Reason          16171 non-null  object
 6   Campaign             21593 non-null  object
 7   SLA                  21593 non-null  timedelta64[ns]
 8   Source               21593 non-null  category
 9   Payment Type         496 non-null    object
 10  Product              21593 non-null  category
 11  Education Type       21593 non-null  category
 12  Created Time         21593 non-null  datetime64[ns]
 13  Course duration      21593 non-null  Int8
 14  Months of study      21593 non-null  Int8
 15  Initial Amount Paid  21593 non-null  float64
 16  Offer Total Amount   21593 non-null  float64
 17  Contact Name         21532 non-null  object
 18  City                 21593 non-null  object
 19  Level of Deutsch     21593 non-null  object
```

- Number of lines: **21,593**
- Number of columns: **20**
- Transformations:
  - "Closing Date", "Created Time" → `datetime64[ns]`
  - "Course duration", "Months of study" → `Int8`
  - "Initial Amount Paid", "Offer Total Amount" → `float`

Contacts

```
RangeIndex: 18548 entries, 0 to 18547
Data columns (total 4 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Id                  18548 non-null  object
 1   Contact Owner Name  18548 non-null  category
 2   Created Time        18548 non-null  datetime64[ns]
 3   Modified Time       18548 non-null  datetime64[ns]
```

- Number of lines: **18,548**
- Number of columns: **4**
- Transformations:
  - "Created Time", "Modified Time" → `datetime64[ns]`
  - "Contact Owner Name" → `category`
  - Fixed a bug in "Contact Owner Name" (the `False value` was replaced with `Unknown`).

2. Conducting descriptive statistics

- For numeric fields, summary statistics (mean, median, range) are calculated.
- Categorical fields such as quality, stage, source and product were analyzed.
- Visualization techniques such as histograms and correlation heat maps are discussed to reveal relationships between variables.

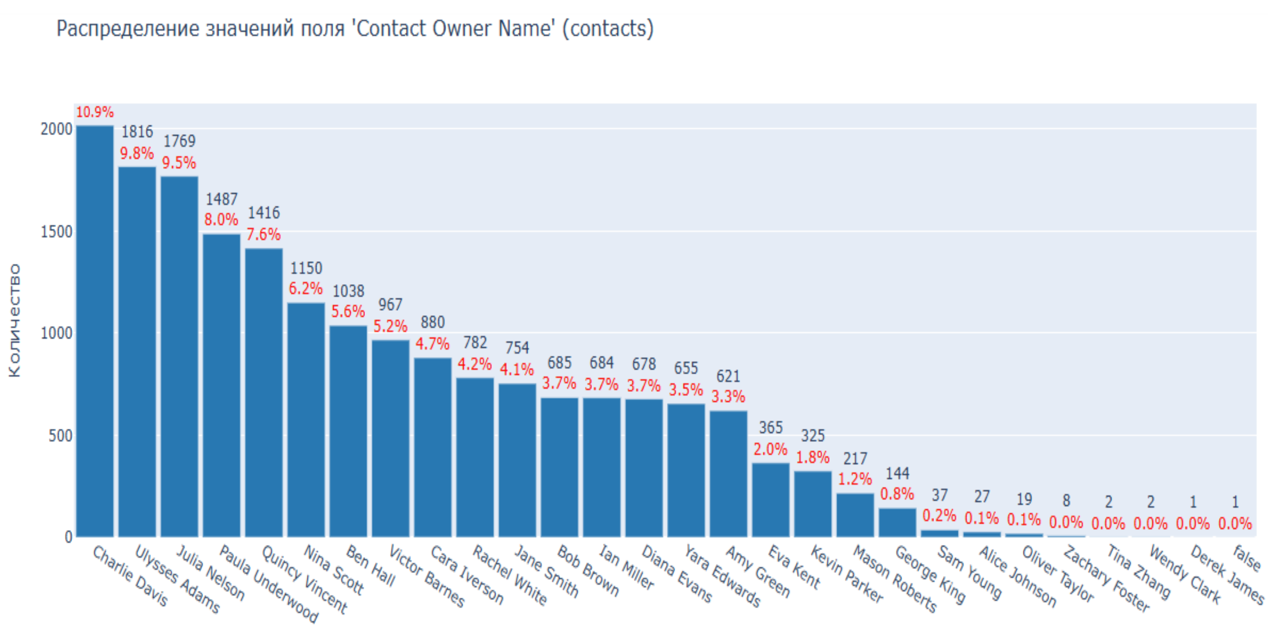
Key points

Number of successful transactions `3,307`

Total number of transactions `21,593`

Analysis of the **'Contacts' dataframe**

- The distribution of the number of contacts among the persons responsible for contact management (CM) is uneven. There are a few CMs with very large numbers of contacts (e.g. Charlie Davis, Ulysses Adams, Julia Nelson), while most CMs have much smaller numbers of contacts.
- This may indicate that the bulk of the customer service burden falls on a small group of the most active OLs. The remaining OLs are either less involved in the process or have other responsibilities.
- Such concentration of contacts among several Responsible Persons may create risks of overload and reduction of service quality. It is necessary to analyze the reasons and, if necessary, redistribute the load more evenly.



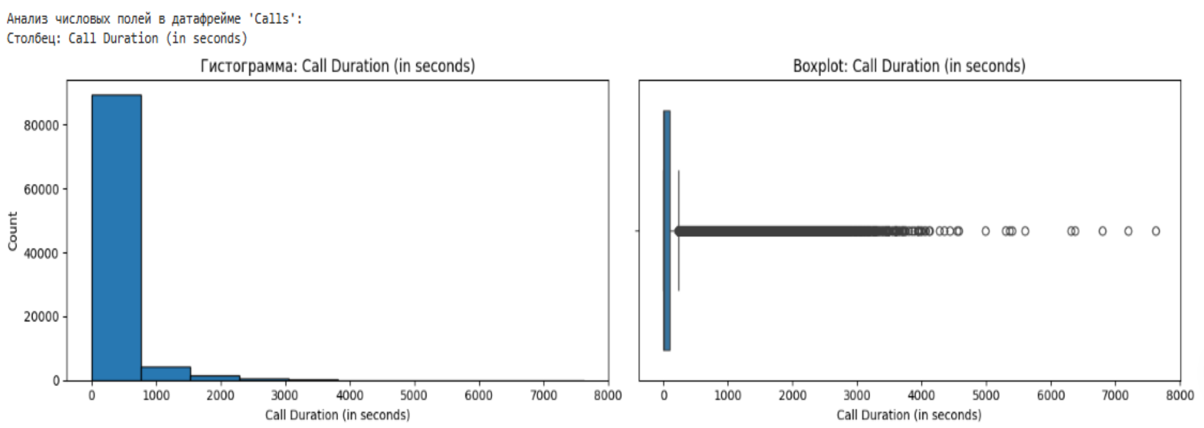
Analysis of the **'Calls ' dataframe**

General information
Number of records: 95874.0

Data Period : Call Start Time ranges from June 30, 2023 to June 21, 2024, which covers approximately 12 months (about a year). This indicates a full annual cycle of data and allows for the analysis of seasonality or trends over time.

- **Id** , **CONTACTID** : these are identifiers, probably generated automatically. The distribution appears uniform, without anomalies.
- **Call Duration (in seconds)** :
- **Average** : 164.83 seconds (about 2 minutes 45 seconds) - most calls are relatively short, but there are some that are longer.
- **Minimum (min)** : 0.0 seconds - may indicate missed, cancelled or failed calls.
- **Maximum (max)** : 7625.0 seconds (about 2 hours 7 minutes).
- **Quantiles** :
    - 25% of calls lasted less than 4.0 seconds,
    - 50% (median) - 8.0 seconds, which may indicate a high number of missed, cancelled, or quickly terminated calls,
    - 75% of calls lasted less than 97.0 seconds (1 minute 37 seconds).
- **Standard Deviation (std)** : 401.27 seconds - significant, indicating that there are long calls that are very different from the majority.

Calls longer than 3000 seconds should be considered abnormal. The following analysis methods can be used to understand the nature of abnormally long calls: Plotting a histogram of call duration distribution and Identifying outliers using box plot methods

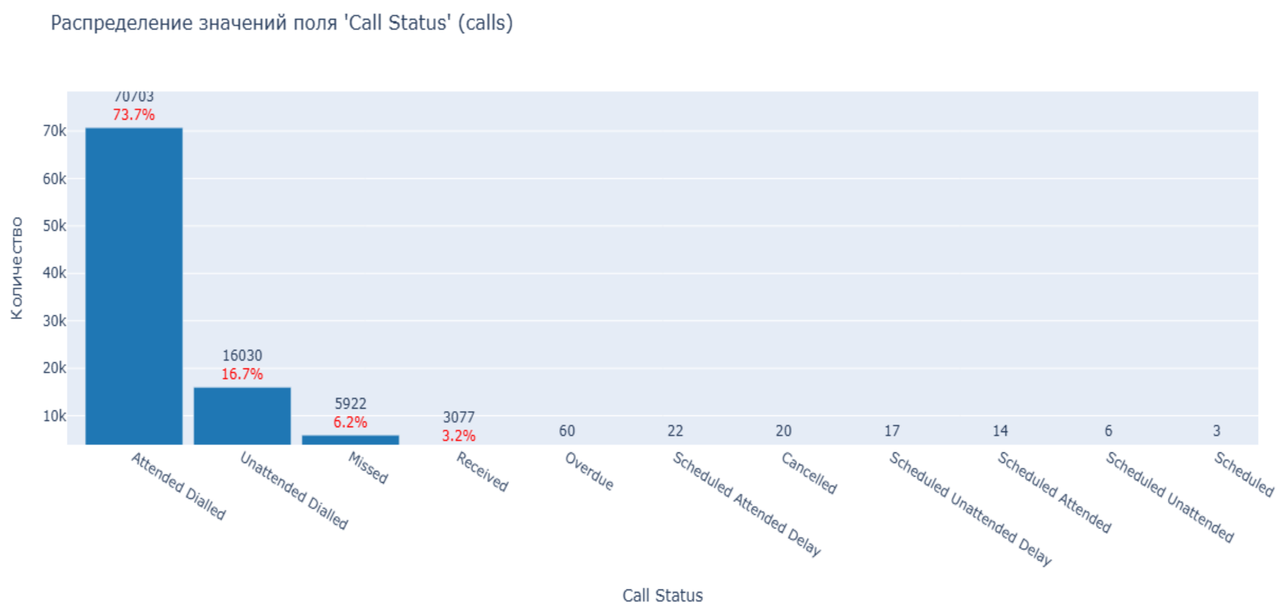


There are 7 calls that are very long (more than 1.5 hours each). These are unusually long calls and may indicate complex cases that require detailed discussion or possible problems with ending the call.

- **Call types:** 6 out of 7 calls are outgoing, one is incoming. This may indicate that the company is actively initiating long conversations with customers. Outgoing calls have the status "Completed", which indicates a successful completion. The incoming call has the status "Unknown", which was assigned to the gaps during data cleanup.

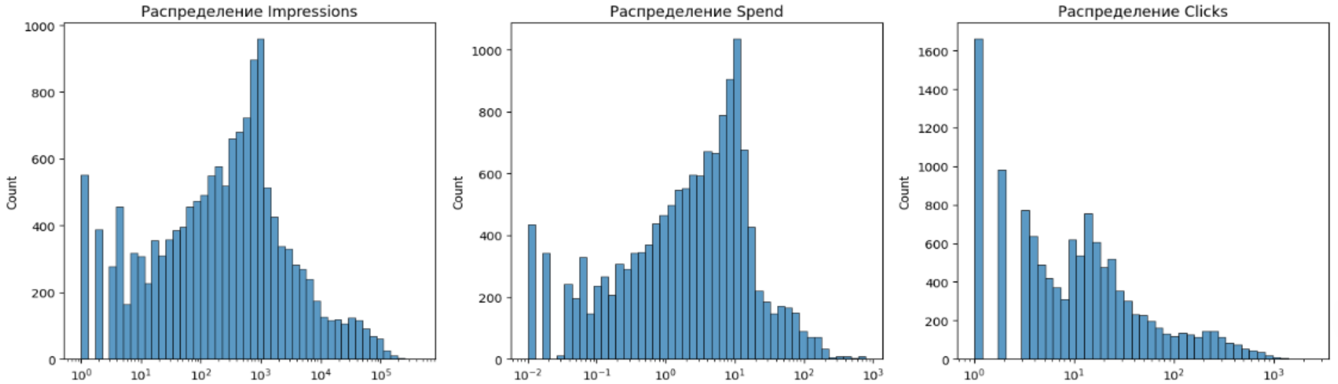
- **Call Owners:** The calls belong to different employees: Sam Young, Eva Kent, John Doe, Charlie Davis and Victor Barnes. This may indicate that these long calls were made by different people within the organization.

Conclusion: Conduct an analysis of the reasons for such long calls. Investigate whether long calls are related to specific products or services that may require improvement or additional documentation.



- An analysis of the distribution of the values of the "Call Status" and "Call Type" fields shows that most calls were successfully completed. Thus, **73.7%** of calls have the "Attended Dialled" status, which means that they were successfully established and completed. In addition, **91.4%** of calls are categorized as "Outbound", i.e. they were **outgoing** .
- The distribution of the "Call Owner Name" field shows that the majority of calls (about 39%) are handled by only **the 5 most active** operators, while the remaining operators are significantly less involved.
- Overall, it can be concluded that the call processing system is generally functioning effectively, but requires some improvements to reduce the percentage of unanswered and missed calls (about 39%).

Analysis of the **'Spend' dataframe**



Number of records - 19862

Data period - From July 3, 2023 to June 21, 2024 (about 12 months), which covers a full annual cycle. **Average date** - January 10, 2024, 18:21:56 is the central data point, indicating a uniform distribution of records over time with a possible bias towards late 2023 and early 2024.

Impressions field (Number of ad impressions)

- **Average** : 2571.70 - The average value shows a moderate number of impressions.
- **Median** : 82.00 - significantly below the mean, indicating a skewed distribution with outliers.
- **Minimum** : 0 - records without impressions are possible (for example, inactive campaigns).
- **Maximum** : 431445.00 - very high, indicating the presence of large campaigns or outliers.
- **Quantiles** : 25% - 1, 50% - 82, 75% - 760.75 - 75% of the data have values less than 760.75, confirming the presence of outliers.
- **Standard** Deviation: 11691.23 - a high value, which highlights significant deviations from the mean and the presence of anomalies.
- **Range** : 431445.00 - 0 = 431445.00.

Conclusion : The distribution is heavily skewed to the right due to large campaigns (outliers around 431,445 impressions). Most campaigns have low or average values (up to 760.75), requiring outlier filtering to analyze typical values.

Spend field (Advertising costs)

- **Average** : 7.53 - the average cost is relatively low.
- **Median** : 0.74 - even lower than average, indicating a predominance of low-cost campaigns.
- **Minimum** : 0.00 - no-cost entries possible (inactive or testing campaigns).
- **Maximum** : 774.00 - a significant amount, indicating a large investment.
- **Quantiles** : 25% - 0.00, 50% - 0.74, 75% - 6.16 - 75% of records have costs less than 6.16, confirming the low typical costs.
- **Standard** Deviation: 27.33 - high relative to the mean, indicating the presence of outliers.
- **Range** : 774.00 - 0.00 = 774.00.

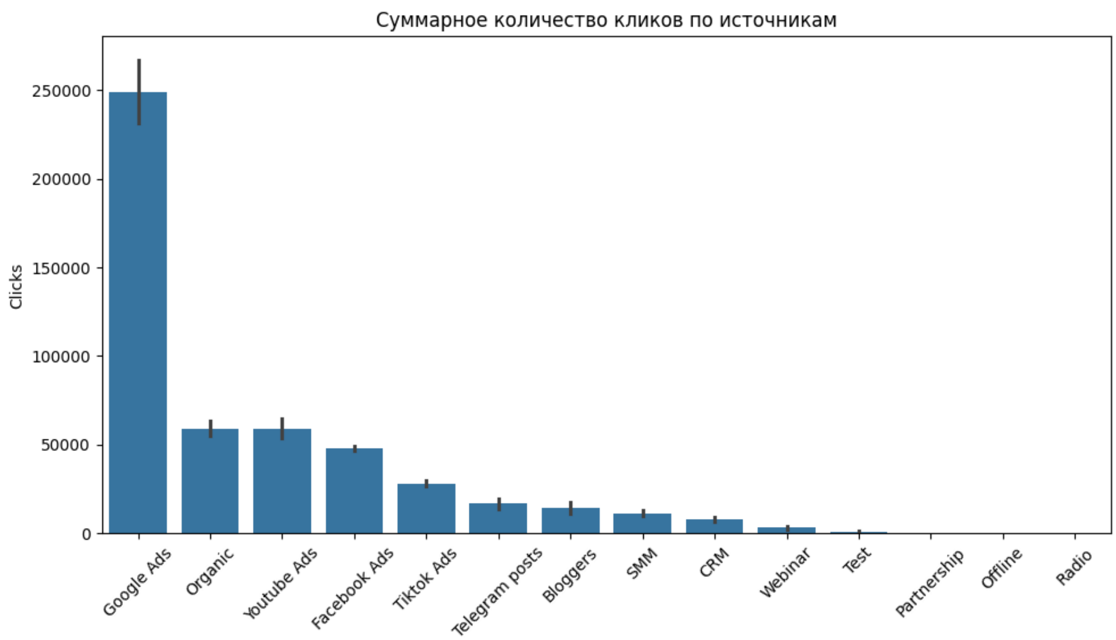
Conclusion : Spends have a skewed distribution with a predominance of low values (median 0.74) and occasional large spends (up to 774). This may indicate a testing strategy or a focus on small campaigns with occasional large spends .

Clicks field (Number of clicks)

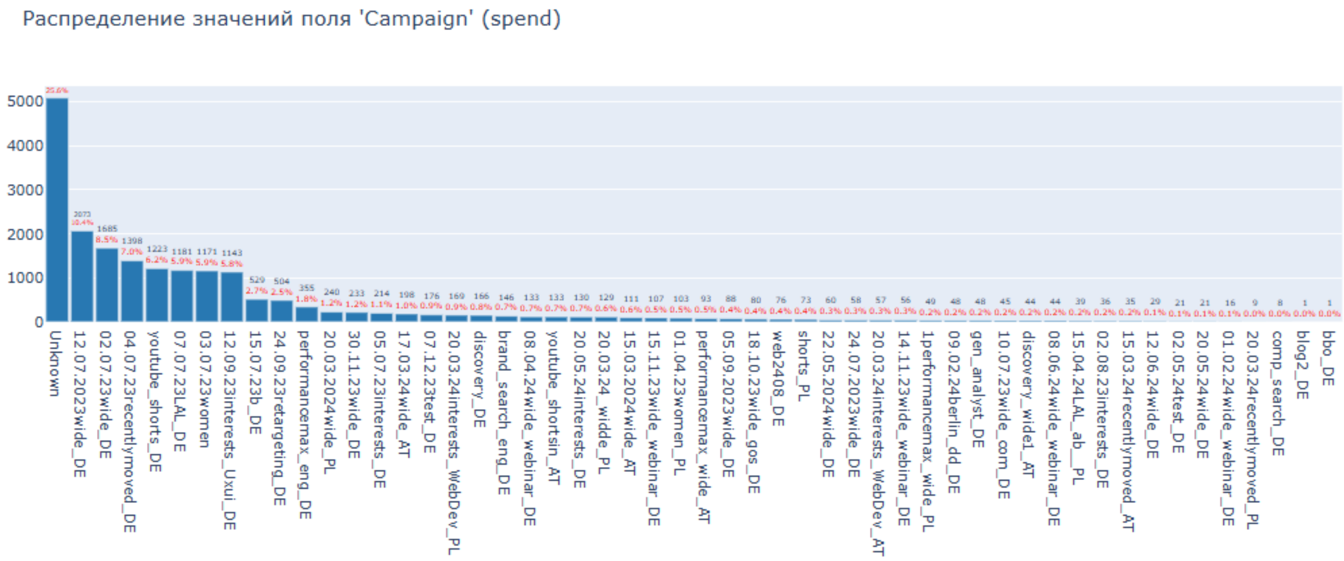
- **Average** : 25.10 - average clicks are moderate.
- **Median** : 2.00 - significantly below the mean, indicating a skewed distribution.
- **Minimum** : 0.00 - records without clicks are possible (for example, impressions without interaction).
- **Maximum** : 2415.00 - very high, indicating abnormally successful campaigns.
- **Quantiles** : 25% - 0.00, 50% - 2.00, 75% - 13.00 - 75% of records have less than 13 clicks.
- **Standard** Deviation: 87.03 - a high value, which confirms the presence of outliers.
- **Range** : 2415.00 - 0.00 = 2415.00.

Conclusion: The distribution of clicks is heavily skewed to the right due to rare campaigns with high click counts (up to 2415). Most campaigns have low activity (median 2), which requires performance analysis.

Relationship between fields



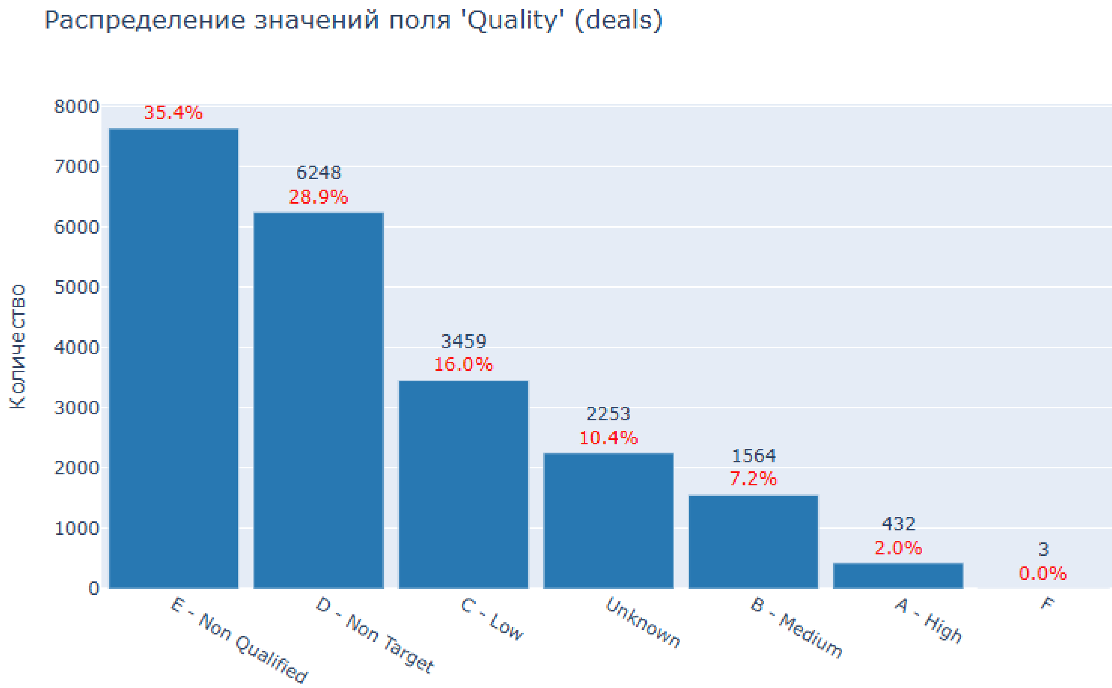
- CTR (Click-Through Rate): Average CTR = (25.10 / 2571.70) * 100 ≈ 0.98%, which is lower than typical values (1-2%). This may indicate low user engagement.
- Cost per click (CPC): Average cost = 7.53 / 25.10 ≈ 0.30, which is relatively low for advertising campaigns, but requires checking for outliers. **Conclusion** : Low CTR and low CPC may be due to the dominance of campaigns with zero or minimal clicks and costs, which requires data segmentation. **Summary** : The data shows an uneven distribution of advertising activity, with a predominance of low rates and rare large campaigns. Low CTR and CPC require further analysis of the effectiveness, and outliers and zero values need to be checked.



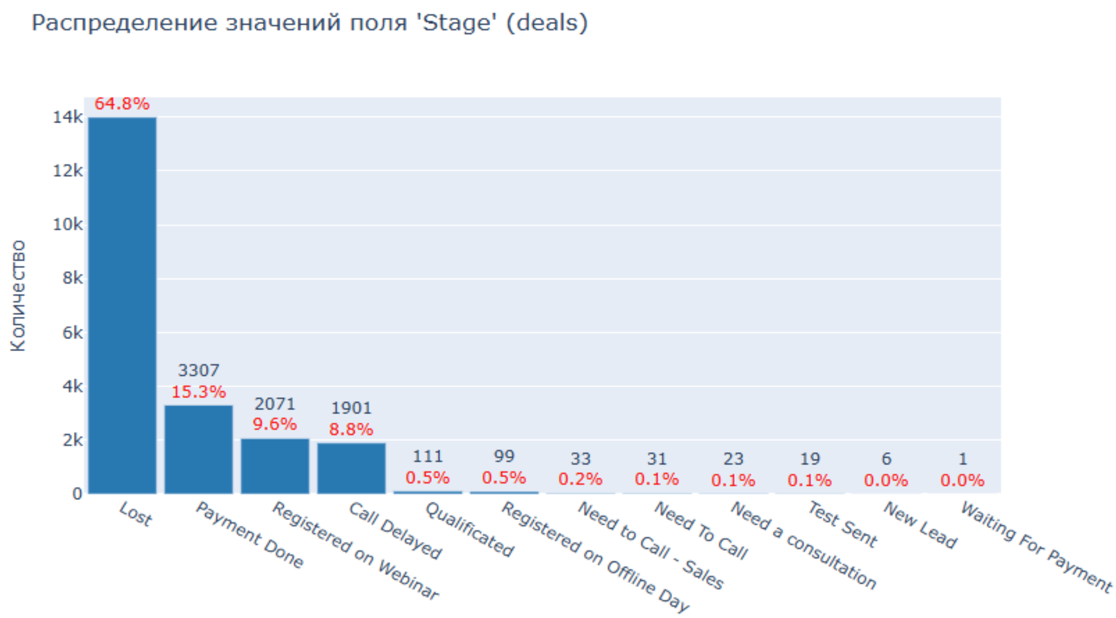
- **Google Ads** accounted for the largest total number of clicks , followed by **YouTube Ads and Facebook Ads** . This speaks to the effectiveness of these advertising channels.
- Facebook Ads is the primary channel, accounting for the vast majority (58.1%) of all spending.
- Among **the campaigns** , several large ones stand out (for example, " **performancemax_eng_DE** ", "b_DE"_). However, most of the campaigns are marked as Unknown, which indicates the need to improve tracking and analytics systems.
- Among the segmented campaigns, there is a noticeable emphasis on video formats, webinars and targeting specific audiences (for example, **recently moved or female audiences** -
- recentlymoved, LAL1, and women).
- Overall, the cost structure shows a strong reliance on a few large channels (Facebook, Tiktok, Youtube) and the need to optimize for smaller sources to improve their performance **.**

Analysis of the **'Deals' dataframe**

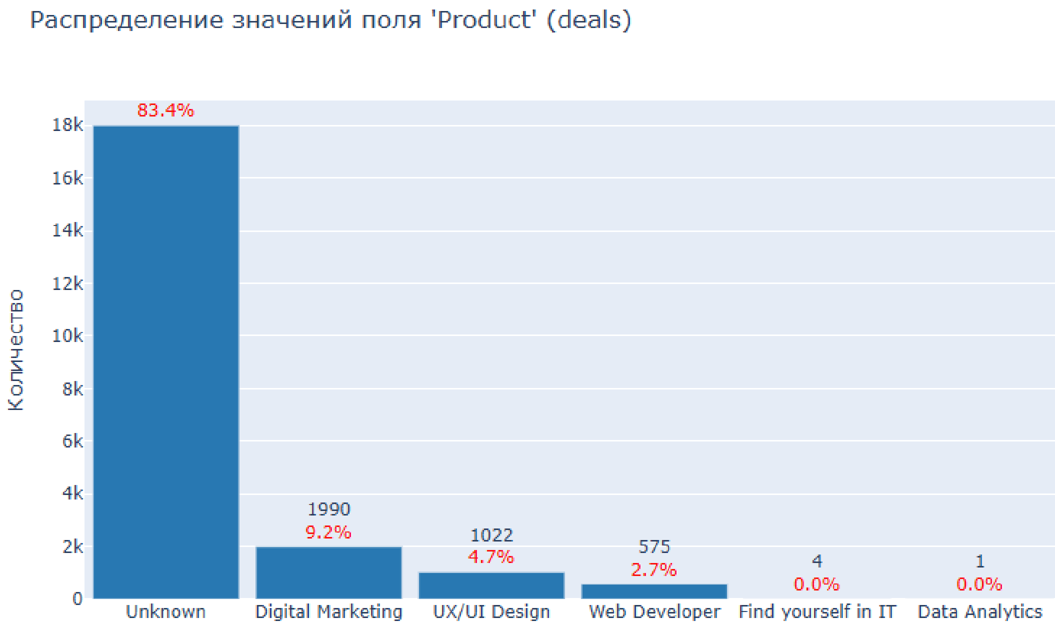
- Distribution of "Quality" field values: The prevalence of "Non Qualified" (35.4%) and "Non Target" (29.0%) categories indicates the ineffectiveness of current customer acquisition methods. It is necessary to audit marketing channels and qualification criteria to increase the share of high-quality leads (only 9.2%).



- Distribution of the "Stage" field values: A high percentage of lost deals (64.9% at the "Lost" stage) indicates serious problems in the process of converting leads into customers. A detailed analysis of each stage of the sales funnel is required, especially the transitions between the "Call Delayed", "Registered on Webinar" and final payment stages (only 15.3% of deals are completed).

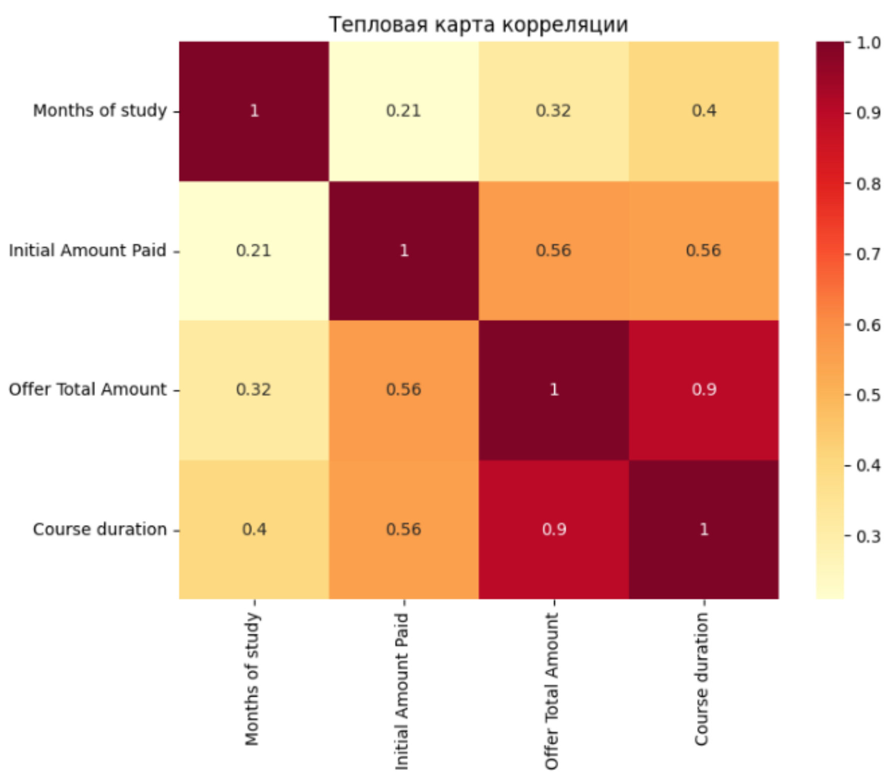


- Distribution of the "Product" field values: The high share of the "Unknown" category (83.4%) indicates the need to improve the product accounting system. The popularity of the "Digital Marketing" (9.2%) and "UX/UI Design" (4.7%) products can be used to strengthen marketing campaigns.



Multivariate analysis

- **High positive correlation** between *course duration* and *total offer* amount
- **A moderate positive correlation** is observed between *the initial payment amount* ("Initial Amount Paid") and *the total offer amount* ("Offer Total Amount")
- **A weak positive correlation** was found between *the number of months* of study and *the initial amount of payment* .



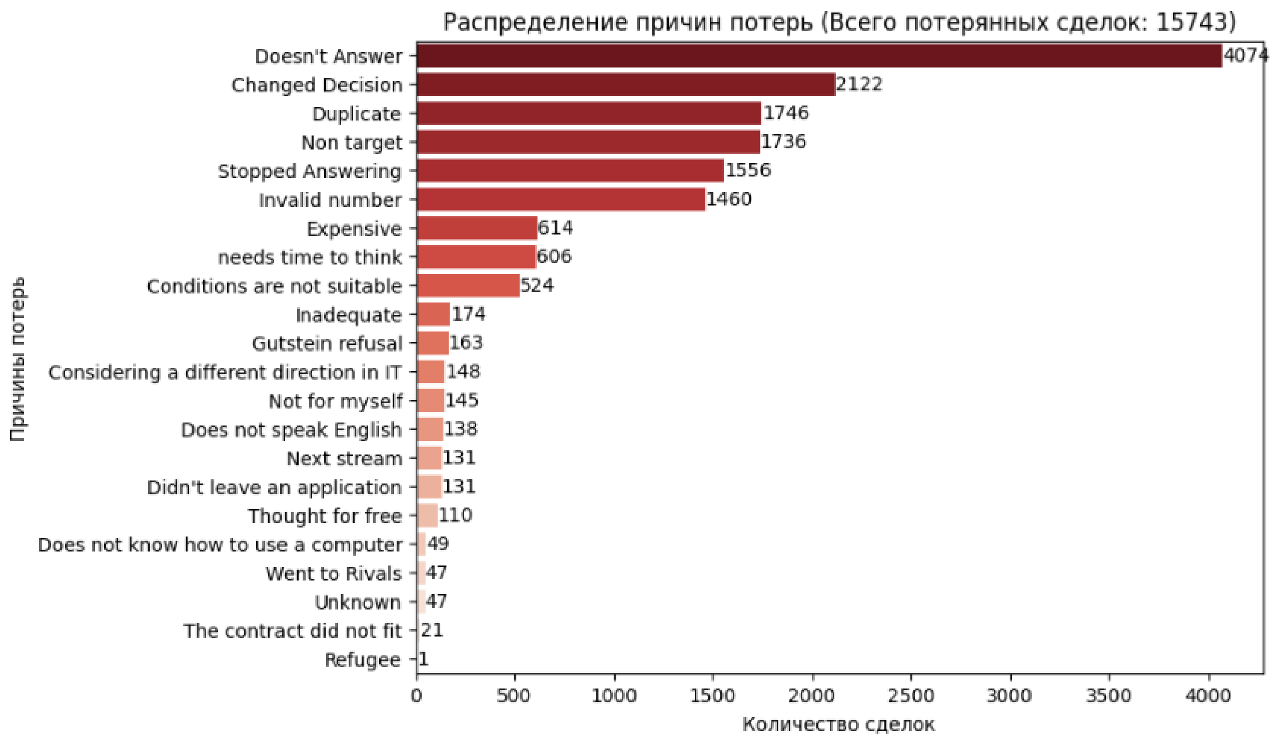
Supplement analysis

Reasons for losses

Objective: To visualize the distribution of reasons for lost deals to identify the main issues leading to customer loss and identify areas for improvement.

Reason: Understanding the root causes of deal loss will allow you to focus your efforts on the most significant areas and develop effective strategies to reduce losses and increase conversion.

What to look for: Pay attention to the most common reasons for losing trades, displayed as a bar chart. Pay special attention to the reasons with the highest number of lost trades, as these represent the greatest opportunity for improvement.



Conclusions on the graph "Distribution of causes of losses":

The main reason for losses

- **"Does** n't Answer" remains the most common reason with over 4,000 occurrences. This confirms a communication problem at the follow-up stage or after the first contact, which requires immediate attention.

Significant reasons

- **"** Changed Decision" - about 2000 cases. This may indicate customer uncertainty or lack of confidence in the product/service.
- **"Stopped** Answering" - about 1500 cases. Loss of customer interest or weak engagement from the company remains relevant.

- **"Invalid** Number" - about 1200 cases. This highlights the problem with the quality of lead contact data.

Problems with product perception

- **"Expensive"** (too expensive) and **"Conditions are not suitable"** (conditions are not suitable) - about 1000 and 800 cases respectively. This indicates a discrepancy between the expectations of customers and the company's offer, especially in terms of price and conditions.

Language barrier and qualifications

- **"Does not** speak English" - about 700 cases. The language barrier remains a significant problem.
- **"Does** not know how to use a computer" - about 400 cases. Some leads do not meet technical requirements, which indicates insufficient qualifications.

Rare causes

- Reasons like **"Refugee"** , **"Thought for free"** , **"The contract did not fit"** (less than 200 cases) do not have a significant impact, but can be taken into account for narrow segments.

Recommendations

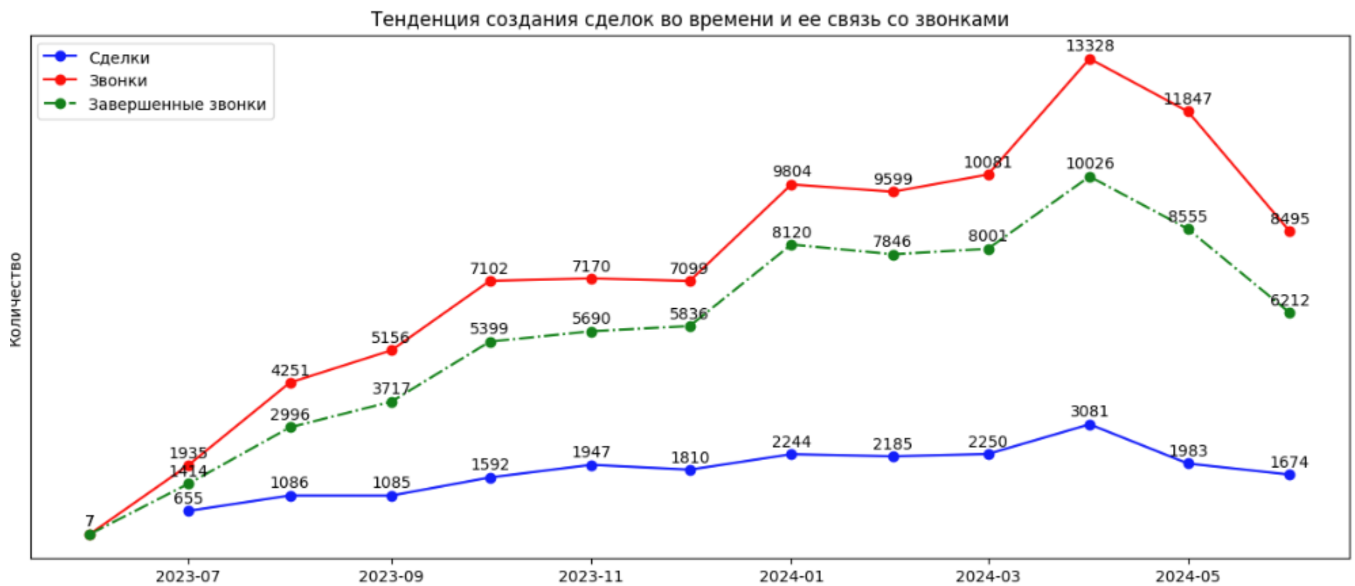
- **Critical Communication Issue** : Over 4,000 "Doesn't Answer" and 1,500 "Stopped Answering" cases show that current customer engagement processes are ineffective. This is a key growth point - improving communication can significantly reduce waste. Research is needed to understand why customers are not responding and develop a strategy to improve engagement.
- **Optimize lead qualification process** : High "Invalid Number" (1200) and "Does not know how to use a computer" (400) indicate the need for more stringent lead qualification at the lead acquisition stage. I recommend checking customer contact information and its relevance to the target audience at an early stage.
- **Consider multilingual support** : If a significant portion of your customers face a language barrier, this can significantly improve your conversion rates.
- **Working with the price offer:** The reason for "Expensive" may be related to the perception of the value of the product. The pricing policy should be revised or the emphasis should be placed on the benefits .

3. Time series analysis

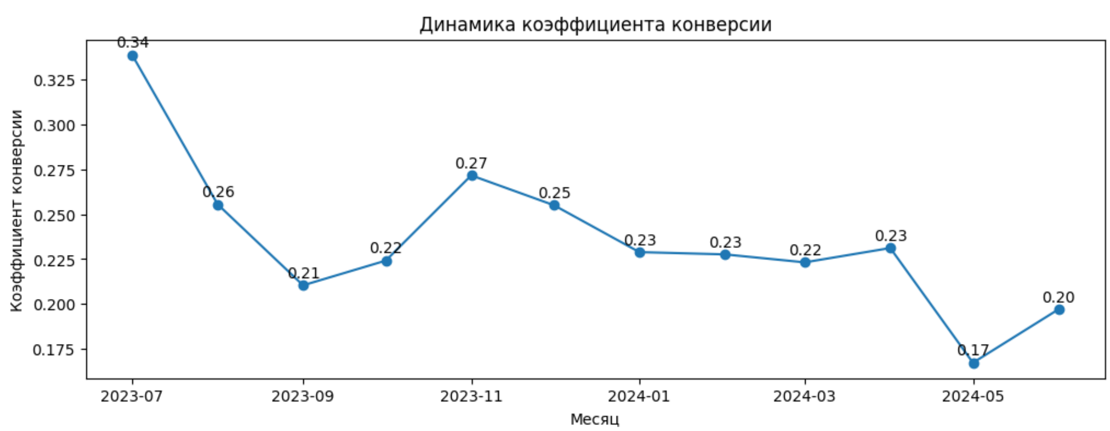
3.1. Analysis of deal creation trends over time and their relationship to calls.

Key points

- The growth of transactions is observed in March and April, and a decline in May and June.
- Average duration of successful trades: 38.43 days
- Average duration of transactions: 13.56 days
- Pearson correlation between the number of trades and the average closing duration is 0.75



Trade creation trend over time and its relationship with calls:



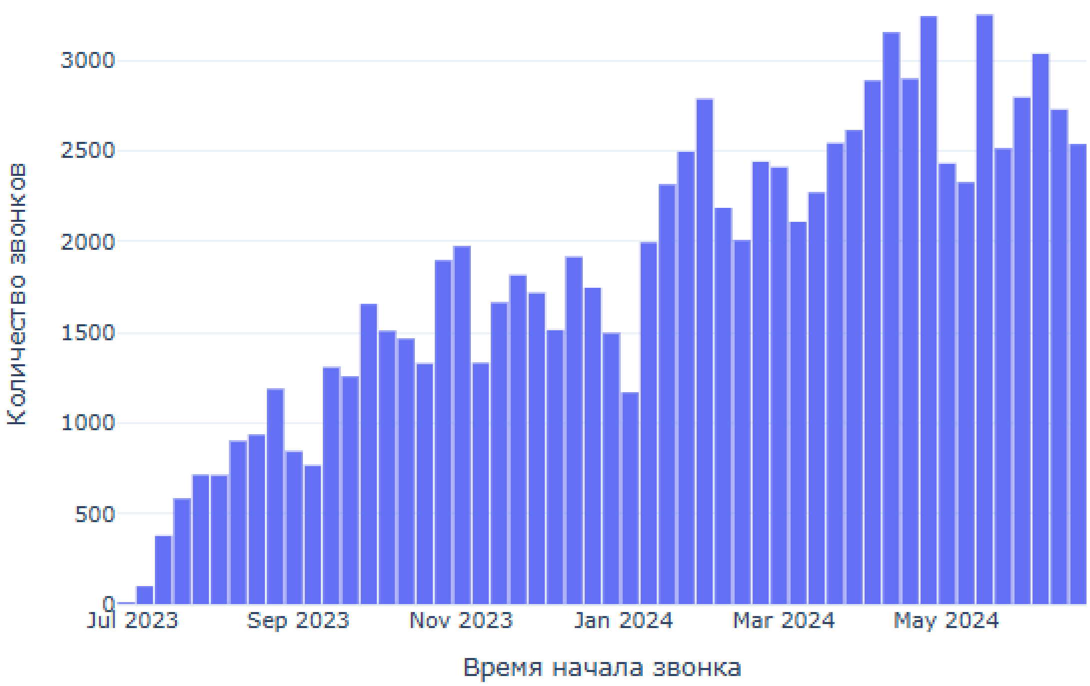
- The number of calls increases from 1,935 in July 2023 to a peak of 13,328 in April 2024, after which there is a decline to 8,495 in June 2024.
- The number of deals also increases from 655 in July 2023 to a peak of 3,081 in March 2024, then declines to 1,674 in June 2024.

- The number of completed calls shows a similar trend, increasing from 4 in July 2023 to 10,026 in March 2024 and decreasing to 6,212 in June 2024.
- It is clear that there is a close relationship between the number of calls and deals - an increase in calls leads to an increase in the number of deals, and a decrease in calls leads to a decrease in deals.

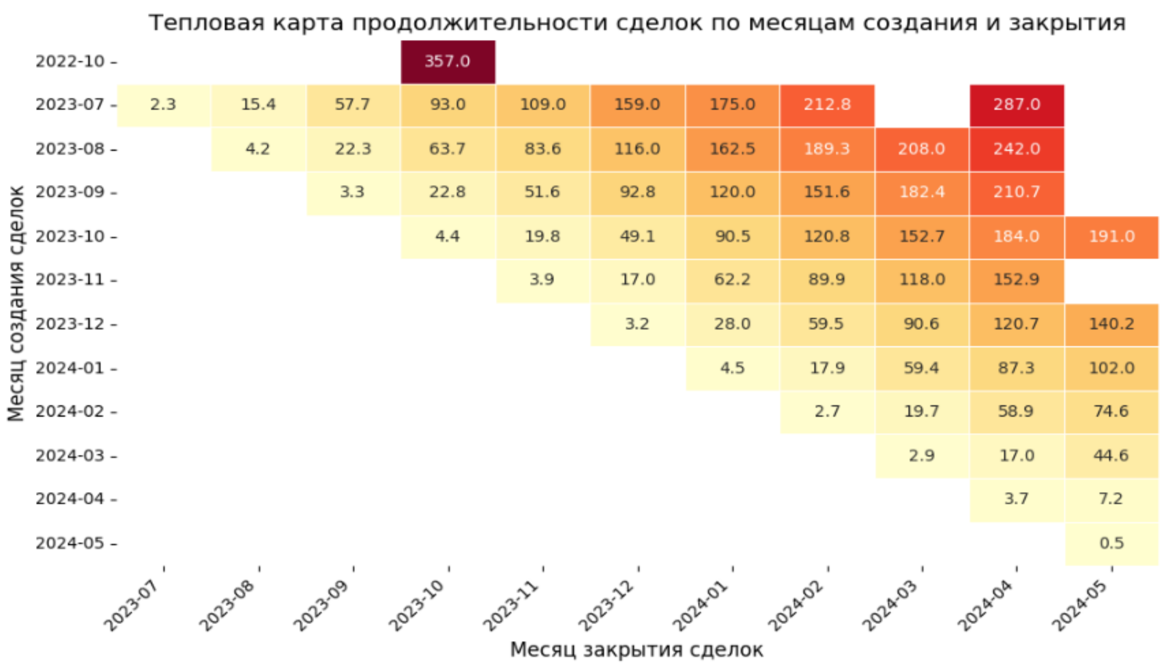
Conversion rate dynamics:

- At the beginning (July 2023) the conversion rate was quite high - 0.34. This means that out of 100 calls during this period, about 34 deals were obtained.
- But then the ratio began to decline. By May 2024, it had fallen to 0.21.
- Then the situation stabilized a little - the coefficient remained at the level of 0.22-0.23 in the period from March to April 2024 x

Analysis Supplement: Number of Calls Over Time.



3.2. Distribution of trade closing times and duration of the period from creation to closing



Key findings:

- **Work with a small number of transactions** : When there are few transactions (17-98), they are closed quickly - in 1.2-3.2 days (July-August 2023). This shows that with a small volume everything works well.
- **Problems with a large number of transactions** When the number of transactions increases to 400-575 (for example, 489 in November 2023 or 575 in April 2024), the duration increases to 14-23.7 days. Perhaps there are not enough people or the process becomes more complex.

- **Progress in 2024** : In 2024, the number of deals peaked (575 in April), but the average duration remained moderate - around 15-23 days (for example, 15.9 days in May with 314 deals). This means that the work has become better organized despite the high workload.

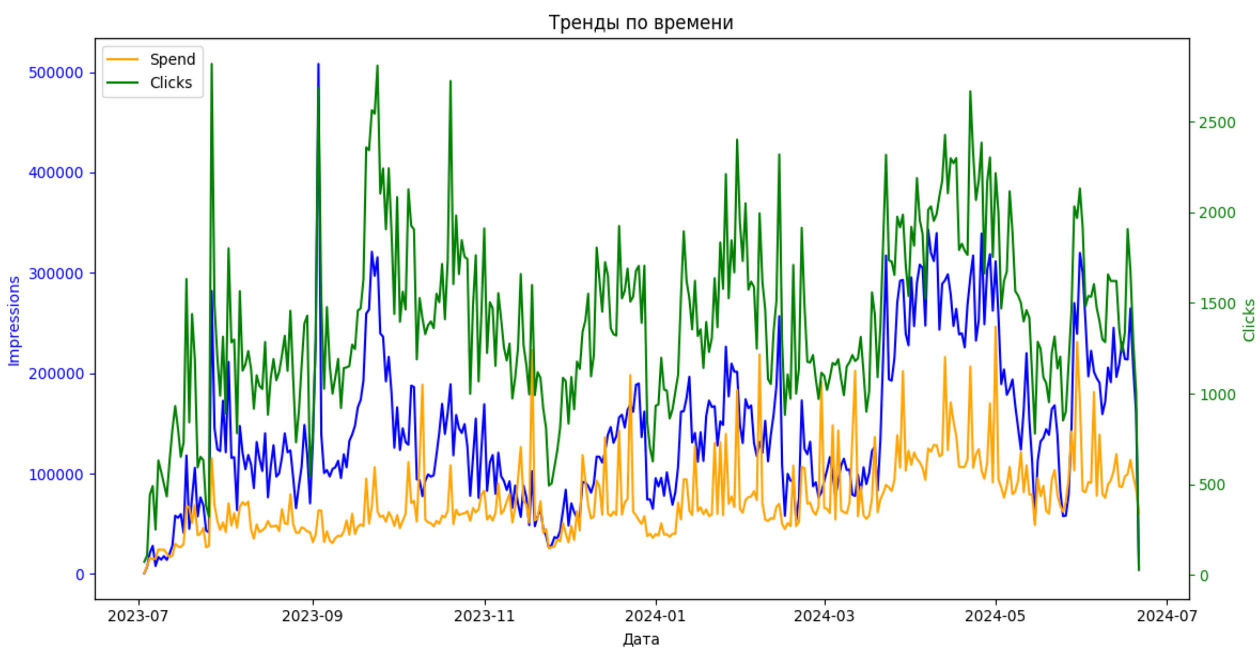
Recommendations

Review the distribution of tasks and possibly increase the number of staff during periods of high workload.

Analysis supplement. Seasonal activity.

Objective: To study trends and seasonality by the `Date` field for `Impressions`, `Spend` and `Clicks` **.**

What to look for: Seasonal peaks (e.g. end of year), correlation between `Spend` and `Clicks`, abnormal spikes **.**



The data covers the time period from July 2023 to July 2024.

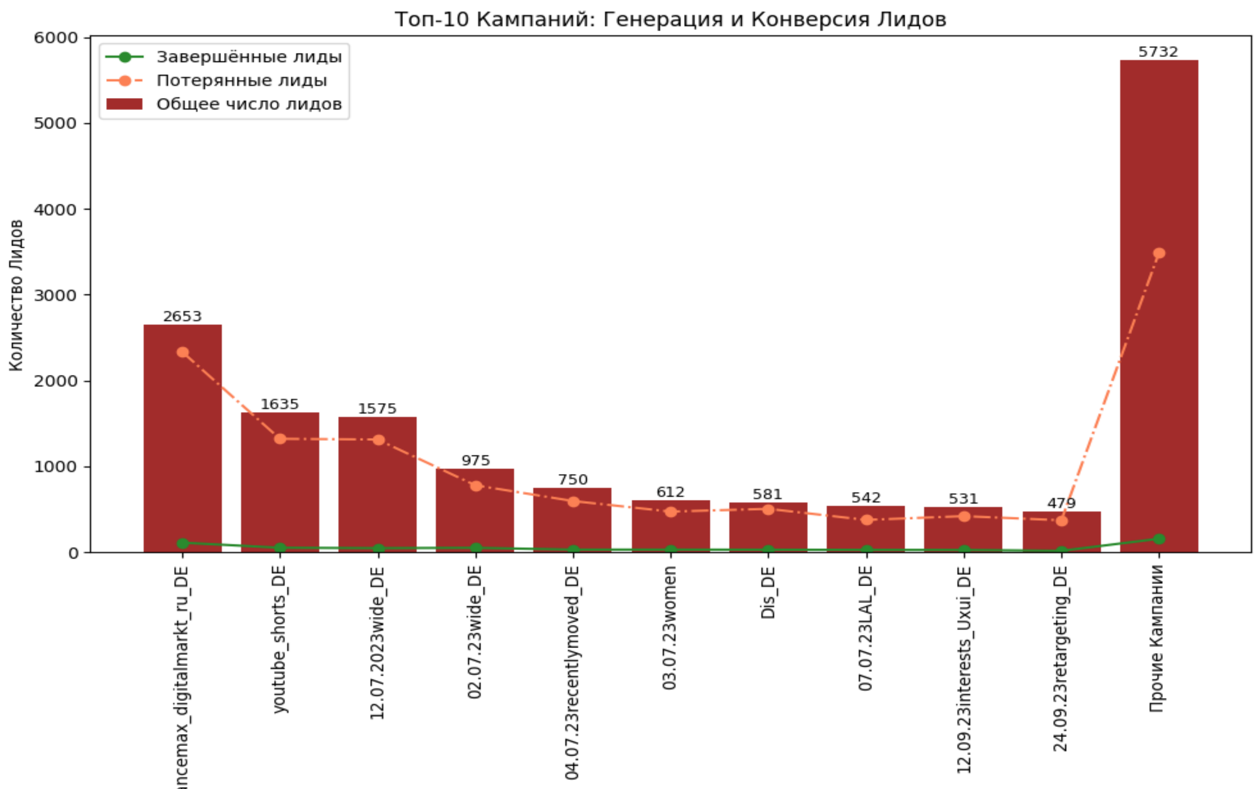
- **Activity peaks** in certain months, such as 2023-07 and 2023-11, where click-through and impression rates are highest.

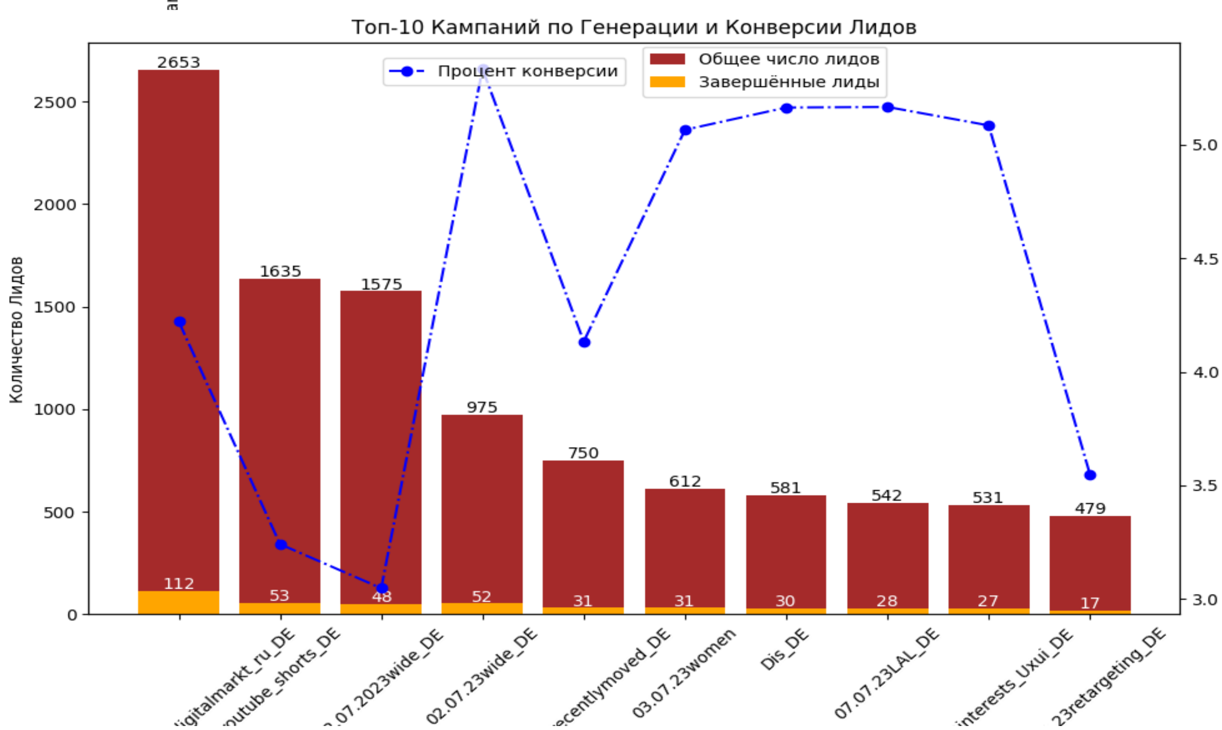
- In some periods (e.g. 2024-01) there is a decrease in activity, which may be due to seasonal fluctuations or a decrease in advertising activity **.**

4. Analysis of campaign effectiveness

4.1. Performance of different campaigns in terms of lead generation and conversion rate:

Since there are 152 advertising campaigns, I will keep the top 10 for analysis. All the rest will be grouped into "Other". Based on the results, **the Top 10** includes advertising campaigns that attracted more than 500 customers.





Top 3 companies by number of successful leads:

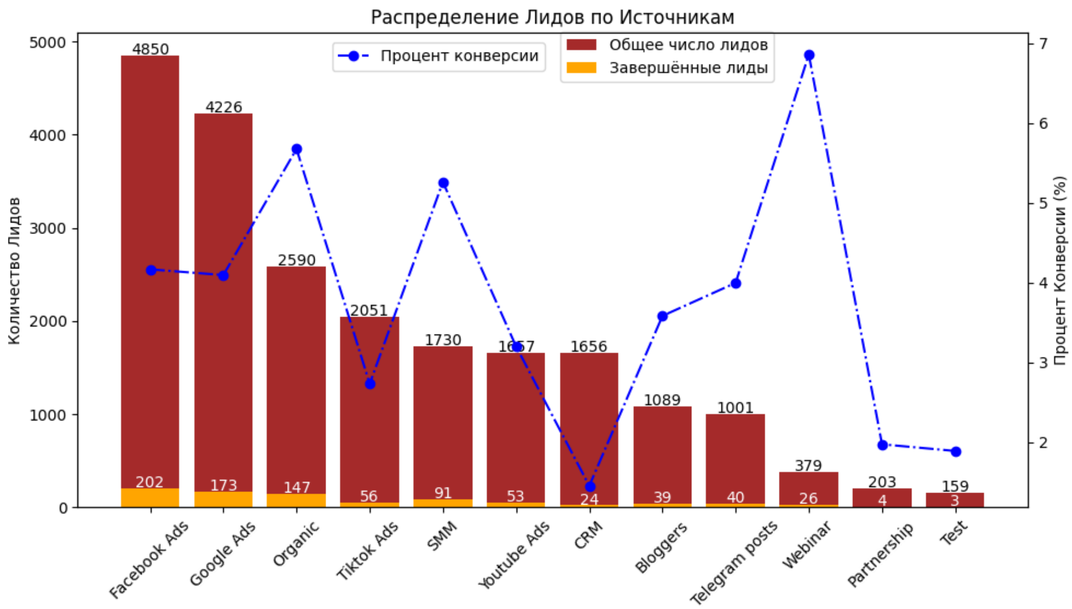
Campaign	total leads	completed leads	Completed leads(%)
performancemax_digitalmarkt_en_DE	2653	112	4.22%
youtube_shorts_DE	1635	53	3.24%
02.07.23wide_DE	975	52	5.33%

Top 3 companies by conversion rate:

Campaign	total leads	completed leads	Completed leads(%)
02.07.23wide_DE	975	52	5.33%
07.07.23LAL_DE	542	28	5.16%
Dis_DE	581	30	5.16%

Leader in **maximum** A/C ratio: **03.07.23women** (0.18), where A-High: 22, C-Low: 119
Leader in **minimum** A/C ratio: **07.07.23LAL_DE** (0.09) , where A-High: 13, C-Low: 145

4.2. Effectiveness of different marketing sources (Source) in generating quality leads.



Top 3 sources by number of successful leads:

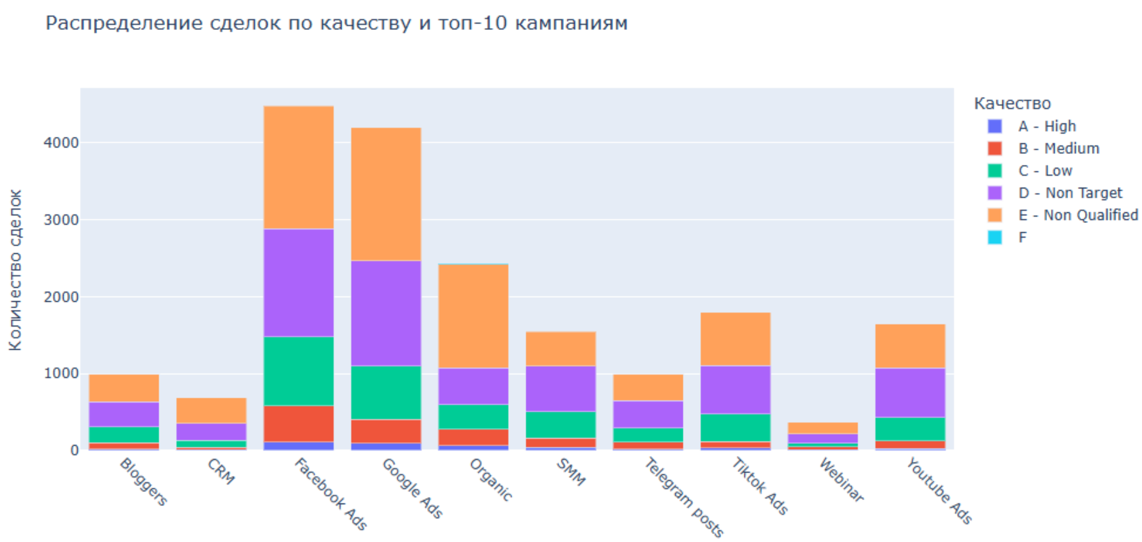
Source	total leads	completed leads	Completed leads(%)
Facebook Ads	4850	202	4.16%
Google Ads	4226	173	4.09%
Organic	2590	147	5.68%

Top 3 sources by conversion rate :

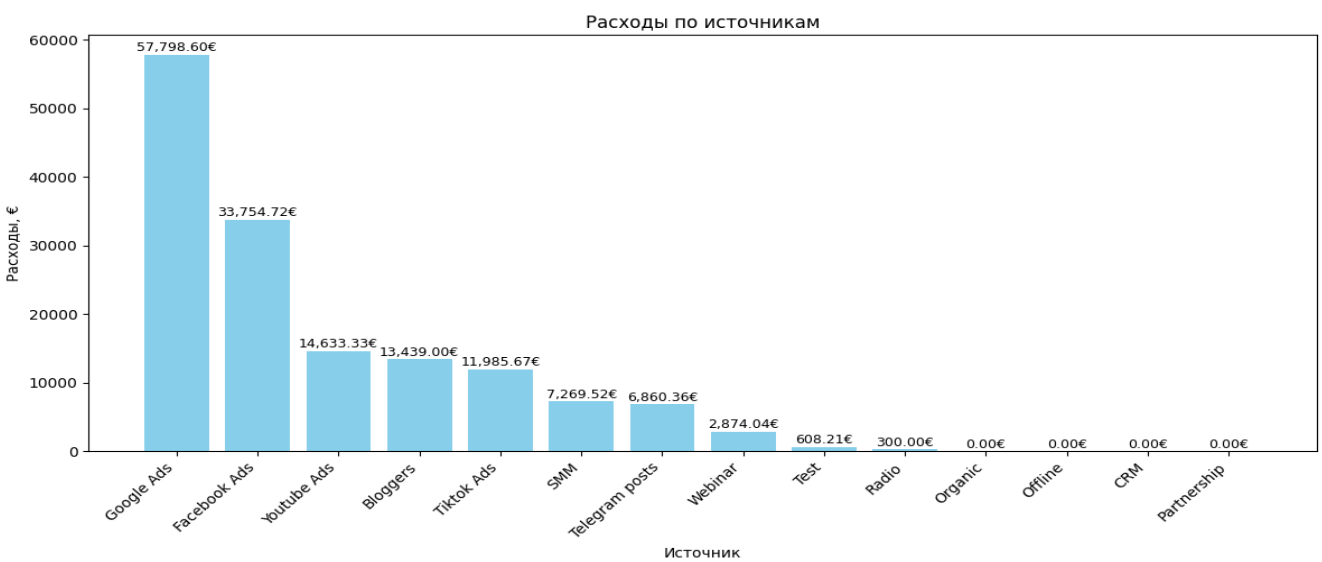
Source	total leads	completed leads	Completed leads(%)
Webinar	379	81	6.86%
Organic	2590	147	5.68%
SMM	2590	147	5.67%

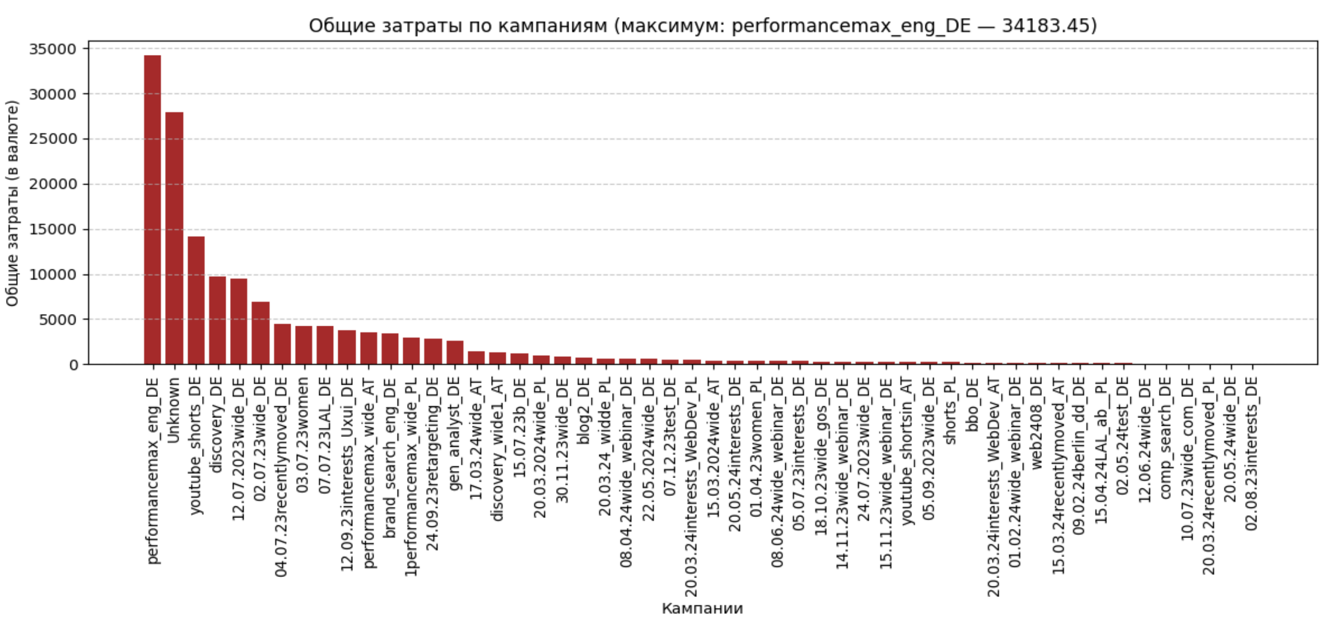
Leader in **maximum** A/C ratio: **Webinar** (0.30),
where A-High: 15, C-Low: 50

Leader in **minimum** A/C ratio: **Telegram posts** (0.09) ,
where A-High: 16, C-Low: 186

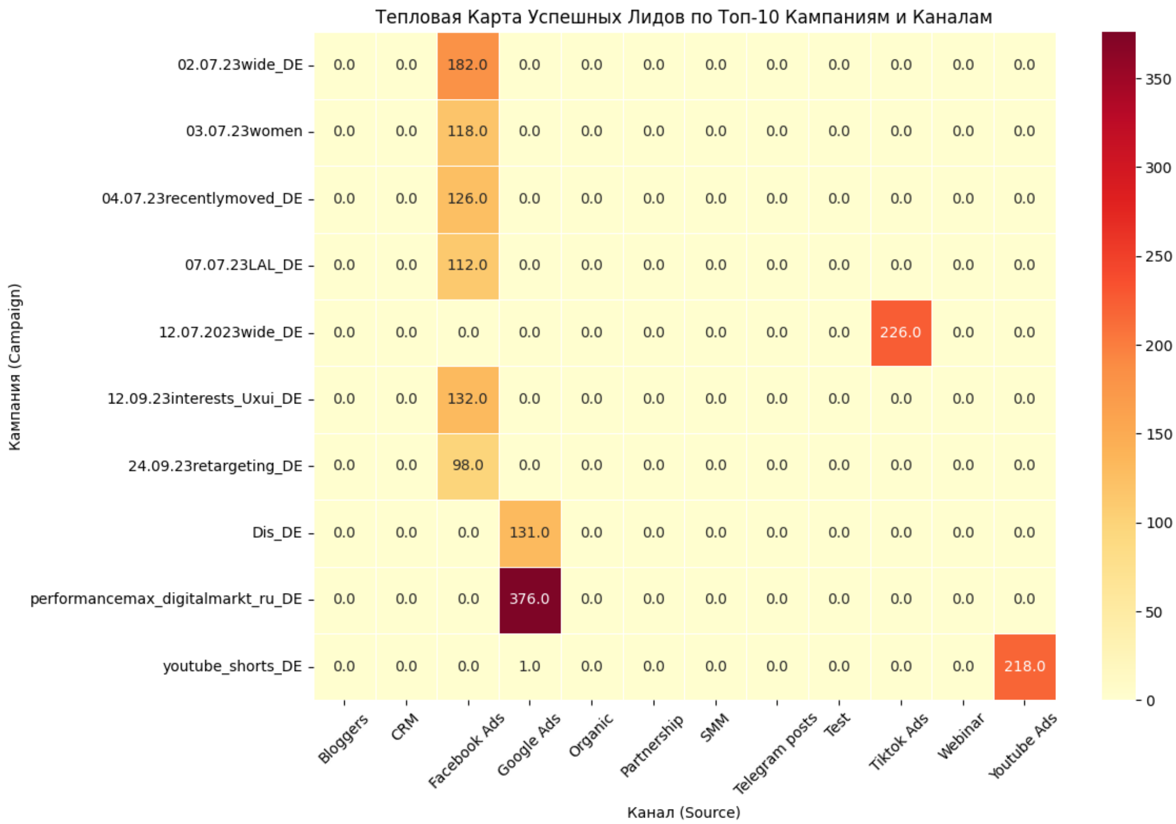


Supplement Analysis (Marketing Costs)





Comparison and Supplementation of Analysis - Linking Sources and Campaigns



Interpretation in the context of a heat map

- **In-source campaigns:**

The heat map shows that not all companies within a channel are equally effective. For example:

- **Google Ads** shows high results for the company **performancemax_digitalmarkt_ru_DE** (376 successful leads), but other companies have less efficiency.
- **Tiktok Ads** are showing success for the company **07/12/2023wide_DE** (226 leads), which indicates the potential for campaign optimization in this channel.

Recommendations

Focus on successful campaigns: Conduct an analysis of performancemax_digitalmarkt_ru_DE" and "12.07.2023wide_DE", which demonstrate significantly higher number of successful leads, to identify the key factors and practices that ensure their effectiveness. Then develop a strategy to replicate these successful approaches to other channels and campaigns.

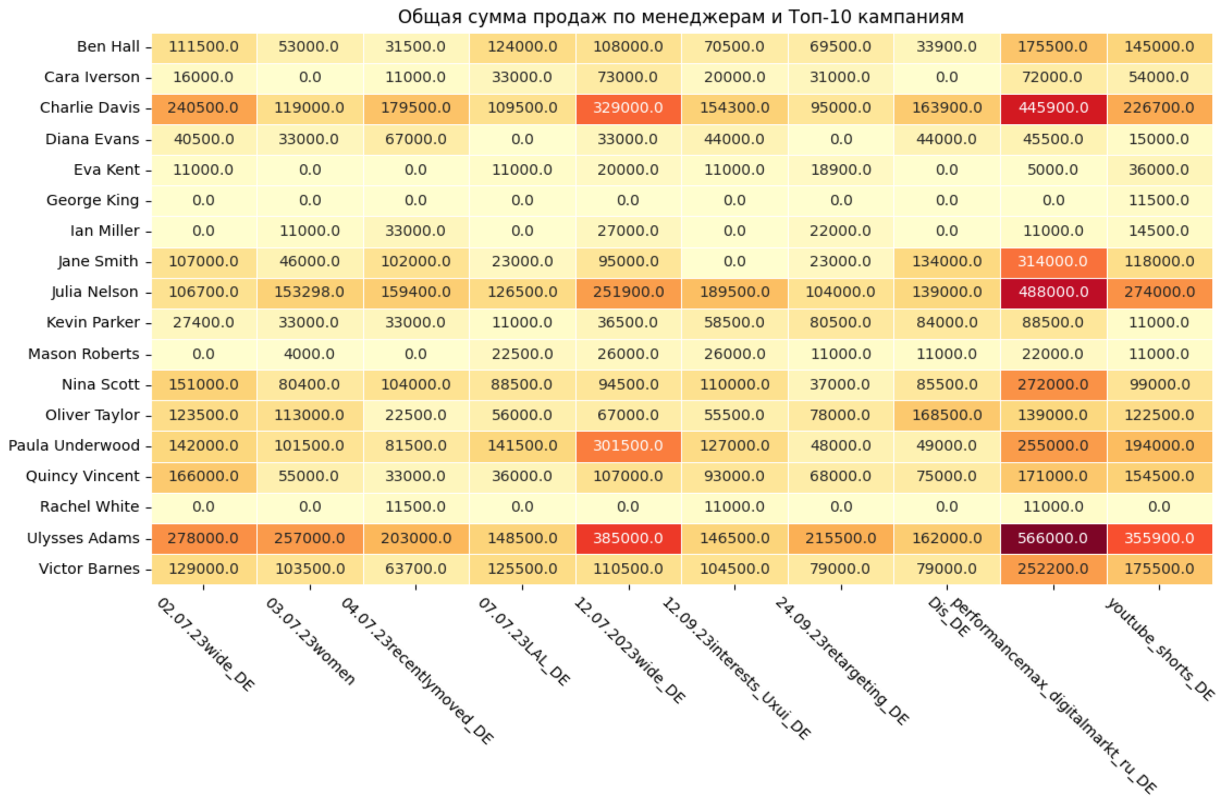
5. Analysis of the sales department performance

5.1 Evaluate the performance of individual deal owners and campaigns in terms of number of deals processed, conversion rate, and total sales.

Deal Owner Name	total_leads	completed_leads	total_sales	total_offer_amount	Completed_leads(%)
Oliver Taylor	163	50	$152,650.00	$1,660,500.00	30.7%
Kevin Parker	574	40	$86,850.00	$895,400.00	7.0%
Ulysses Adams	2,165	141	$541,050.00	$5,117,800.00	6.5%
John Doe	20	1	$4,600.00	$18,500.00	5.0%
Charlie Davis	2,963	148	$445,600.00	$3,822,500.00	5.0%
Paula Underwood	1,862	93	$326,750.00	$2,842,000.00	5.0%
Julia Nelson	2,241	93	$382,961.00	$3,575,311.00	4.1%
Eva Kent	459	18	$65,200.00	$554,300.00	3.9%
Nina Scott	1,283	46	$207,150.00	$1,962,400.00	3.6%
Victor Barnes	1,232	44	$348,900.00	$2,196,800.00	3.6%
Quincy Vincent	1,884	65	$221,601.00	$1,788,900.00	3.5%
Ben Hall	1,345	46	$241,700.00	$2,030,800.00	3.4%
Jane Smith	988	31	$140,050.00	$1,468,500.00	3.1%
Cara Iverson	1,056	27	$688,400.00	$912,000.00	2.6%
George King	94	2	$2,900.00	$33,500.00	2.1%
Ian Miller	497	8	$33,050.00	$299,000.00	1.6%
Mason Roberts	268	3	$19,300.00	$222,000.00	1.1%
Diana Evans	1,013	1	$50,450.00	$562,500.00	0.1%
Alice Johnson	25	0	$0.00	$0.00	0.0%
Bob Brown	337	0	$950.00	$13,500.00	0.0%
Amy Green	66	0	$0.00	$0.00	0.0%
Sam Young	67	0	$0.00	$0.00	0.0%
Rachel White	871	0	$14,000.00	$44,500.00	0.0%
Wendy Clark	2	0	$0.00	$0.00	0.0%
Xander Dean	3	0	$0.00	$0.00	0.0%
Yara Edwards	85	0	$0.00	$0.00	0.0%
Zachary Foster	1	0	$0.00	$0.00	0.0%

[Interactive Sales Funnel Analysis Chart]

tableau



Deal Owner Performance

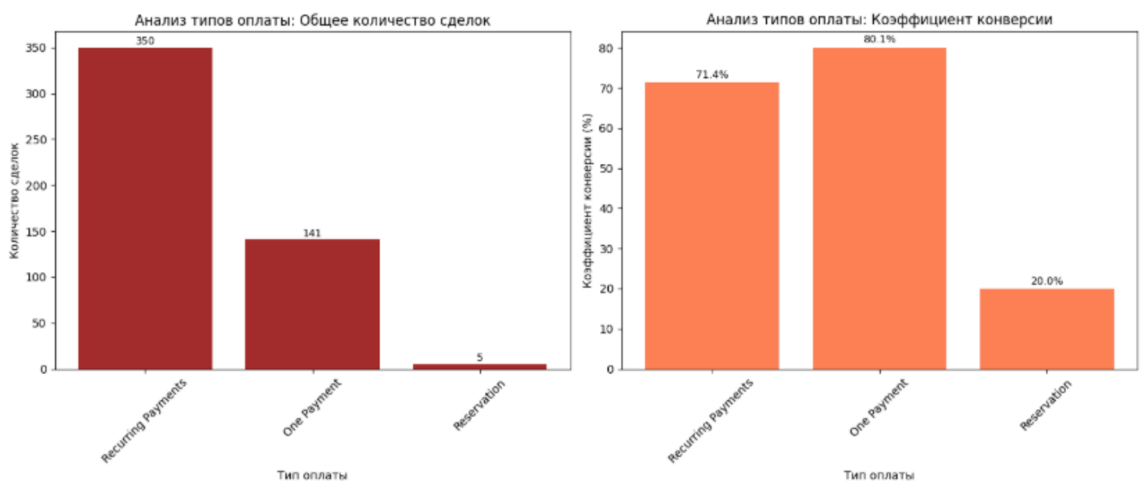
An analysis of the performance of Deal Owner Names and campaigns based on the provided data reveals key differences in performance. Deal Owners processed between 2 and 2,950 leads, with conversion rates ranging from 0% to 96.8% and total sales ranging from 0 to 3.77 million. The most effective in terms of conversion was **Oliver Taylor** with 96.8% (153 successful deals out of 158 leads) and sales amount of $1,660,500.00, which highlights its exceptional ability to close deals with minimal volume. However, in terms of the number of leads processed, **Charlie Davis** (2,950 leads) and **Ulysses Adams** (2,164 leads) lead, although their conversion rates are 14.6% and 26.1% respectively, and the sales amounts are $440,400.00 and $540,050.00, which makes them the leaders in overall contribution. Among less active agents, such as John Doe (16 leads, 12.5% conversion) or George King (94 leads, 4.3% conversion), low sales amounts are noticeable ($3,600.00 and $2,900.00 respectively), which indicates limited efficiency. Operators with zero conversion (Amy Green, Alice Johnson, etc.) require a strategy review, as they have not closed a single deal while processing leads.

Recommendations

The analysis showed that the most effective deal owners are **Oliver Taylor, Ulysses Adams and Charlie Davis** , who demonstrate high results in both sales volume and conversion rate. However, there is potential for improvement for owners with low efficiency. It is recommended to implement measures to train and optimize the lead strategy.

6. Analysis of payments and products

6.1 Study the distribution of payment types and their impact on transaction success.



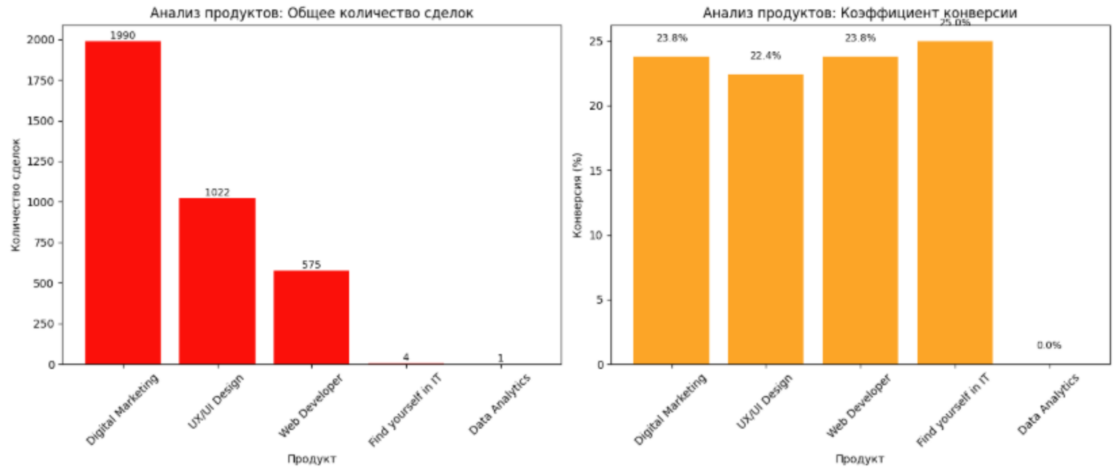
Payment Type	Total Deals	Successful Deals	Unsuccessful Deals	Conversion Rate
Recurring Payments	350	250	100	71.4%
One Payment	141	113	28	80.1%
Reservation	5	1	4	20.0%

The most frequently used payment type is **Recurring Payments** , with a total of 350 transactions, of which 250 were successful, which corresponds to a conversion of 71.4%. In turn, **One Payment** also shows good results, although it is inferior to Recurring Payments in the number of transactions: the total number of paid transactions was 141, of which 113 were successful, with a conversion of 80.1%. The lowest indicators are observed for **Reservation** - only 5 transactions, but at the same time 20% conversion. Although this type of payment has a low conversion rate, its small number of transactions indicates the need to revise the strategy of promotion and customer acquisition in this direction.

Recommendations

Overall, the data shows that One Payment is the most successful payment type with a conversion rate of 80.1%.

6.2 Analyze the popularity and success of different products and types of training.



Product	Total Deals	Successful Deals	Conversion Rate
Digital Marketing	1,990	474	23.8%
UX/UI Design	1,022	229	22.4%
Web Developer	575	137	23.8%
Find yourself in IT	4	1	25.0%
Data Analytics	1	0	0.0%

Popular products : Digital Marketing, Web Developer, UX/UI Design.

Analysis by types of training

Education Type	Product	Total Deals	Successful Deals	Total Sales	Unsuccessful Deals	Conversion Rate
Morning	Digital Marketing	1,533	354	€3,432,000	1,179	23.1%
Morning	UX/UI Design	808	171	€1,616,900	637	21.2%
Morning	Web Developer	545	137	€583,100	408	25.1%
Evening	Digital Marketing	250	113	€408,800	137	45.2%
Evening	UX/UI Design	153	58	€217,500	95	37.9%
Evening	Web Developer	1	0	€0	1	0.0%

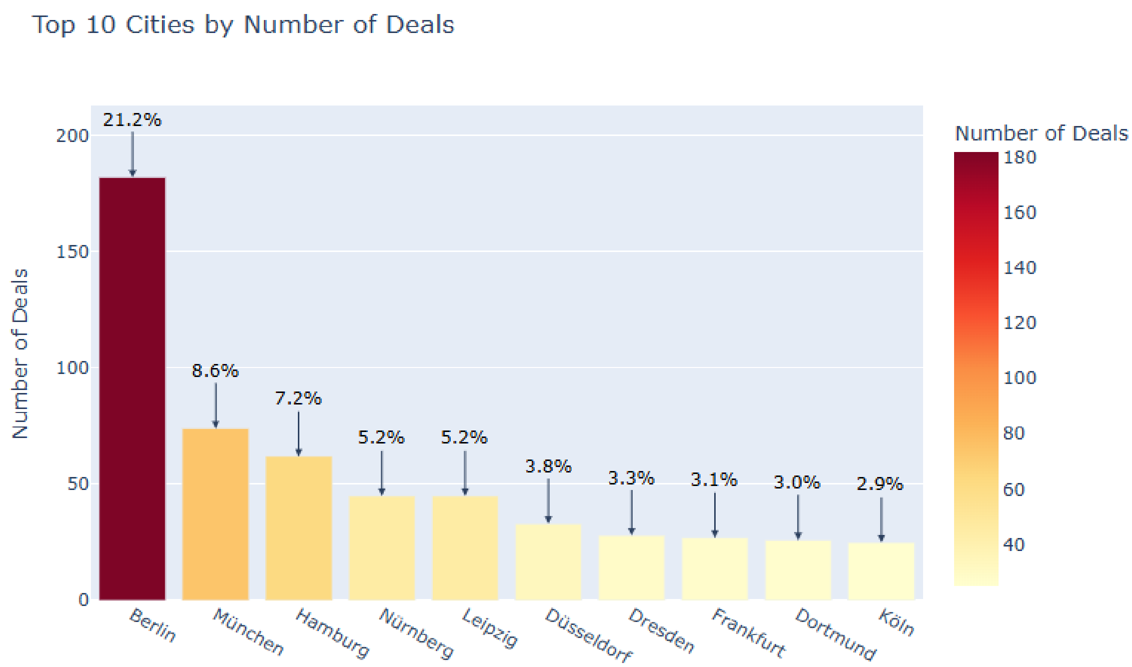
Analysis of the table data shows that the "Morning" training type attracted the largest number of deals in the "Digital Marketing" category (1,533 deals) with a total sales amount of €3,432,000. Also, the morning courses on "UX/UI Design" and "Web Developer" demonstrated 808 and 545 deals respectively, with sales amounts of €1,616,900 and €583,100.

At the same time, the "Evening" training type showed less activity: 250 deals in "Digital Marketing" with a sales amount of €408,800, 153 deals in "UX/UI Design" with €217,500 and only one deal in "Web Developer" that was not successful.

Recommendations

The low number of deals on evening courses, especially in the "Web Developer" category (only one deal), indicates the need to review the strategy. In general, morning courses are the main source of income and success, while evening courses require some work. It may be worthwhile to increase the marketing of evening programs, improve their content, or review the schedule to make them more attractive to clients.

7. Geographical analysis



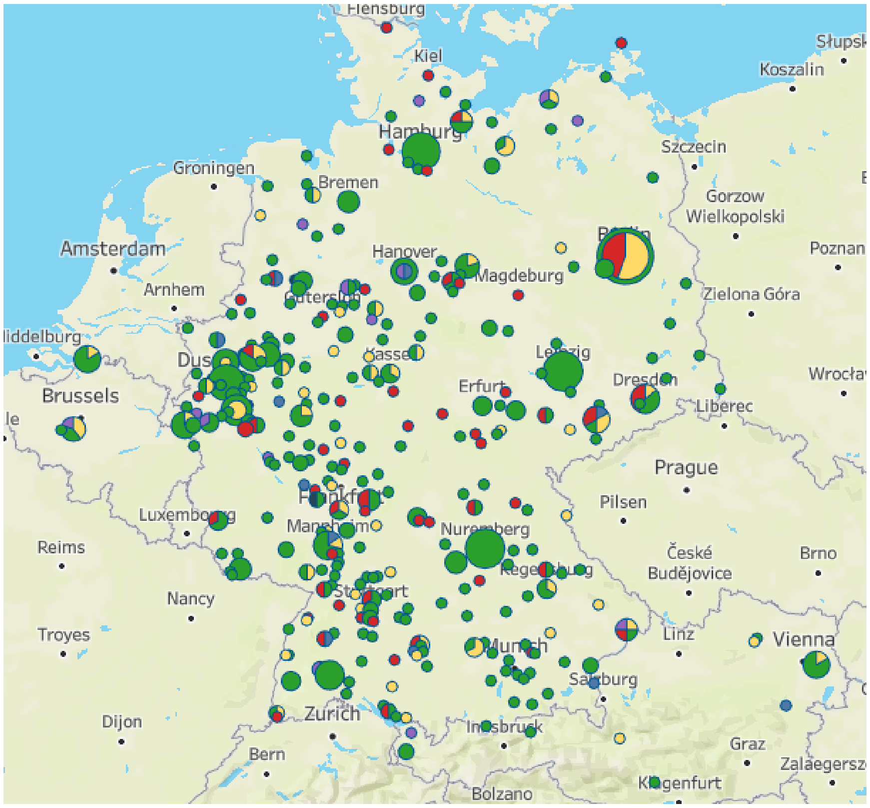
Distribution of transactions by territory

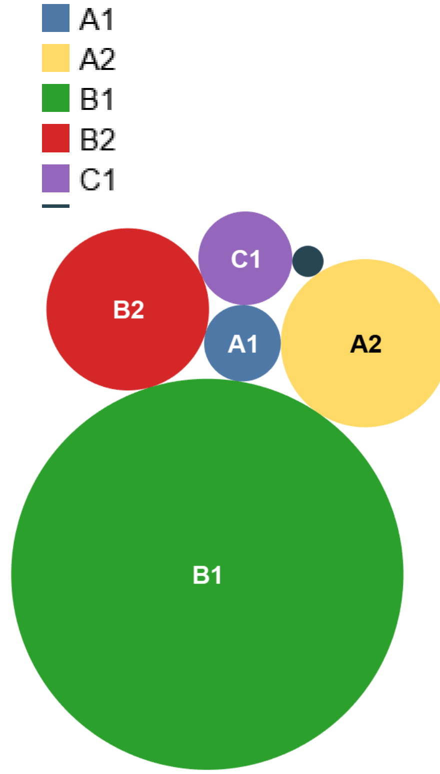
The data we examined shows that the bulk of the deals are in Central Europe, with a clear preponderance in Germany. The map shows the leadership of Berlin, followed by Munich and Hamburg at a noticeable distance. There are also deals in Eastern Europe, the Middle East, and North America, but their numbers are modest. North America and some Asian regions appear as rare hotspots of activity.

Top Cities for Deals

1. Berlin is the clear leader in terms of the number of transactions.
2. Munich and Hamburg are in second place, but with much smaller volumes.
3. Cities such as Nuremberg, Leipzig, Düsseldorf, Frankfurt, Dresden, Dortmund and Cologne lag noticeably behind, highlighting the concentration of business in a few key hubs.

Assessing the Impact of Language Level on Transaction Success





[Interactive Dashboard](#)
[(or screenshot in this document)](#)

- Berlin: Predominantly B 1, B2 And A 2 . A large number of transactions (large dots) can correlate with a high level of success, as language knowledge is at B2 level
- Munich and Hamburg: Mix of B1 , B2 and C1, with a notable presence of A2 (yellow). Success is likely to be higher where B2 and C1 predominate, while A2 may indicate deals with potentially lower conversion.
- Nuremberg, Leipzig: More A1 and A2, which may indicate less successful transactions.

Eastern Europe and the Middle East show moderate interest but fall short of the leaders. The US and other international territories remain on the periphery, which may be due to low demand or insufficient expansion.

Recommendations

Look to neighboring European countries and the Middle East as promising growth areas. Strengthen positions in other German cities to reduce dependence on Berlin.

Unit economics and business growth points

Product Analysis:

	UA	C1	B	AOV	COGS	Revenue	T	APC	CLTV	LTV	AC	CPA	CM
Web Developer	18,548	0.74%	137	829.34	0	418,816	505.00	3.69	3,057.05	22.58	149,523.45	8.06	269,292.34
Digital Marketing	18,548	2.56%	474	850.20	0	2,463,037	2897.00	6.11	5,196.28	132.79	149,523.45	8.06	2,313,513.26
UX/UI Design	18,548	1.23%	229	960.76	0	1,124,084	1170.00	5.11	4,908.66	60.60	149,523.45	8.06	974,560.37
Find yourself in IT	18,548	0.01%	1	0.00	0	0	0.00	0.00	0.00	0.00	149,523.45	8.06	-149,523.45
Data Analytics	18,548	0.00%	0	0.00	0	0	0.00	0.00	0.00	0.00	149,523.45	8.06	-149,523.45
Total	**18,548**	**4.63%**	**858**	**876.84**	**0**	**4,008,906**	**4572.00**	**5.33**	**4,672.38**	**216.14**	**149,523.45**	**8.06**	**3,859,382.50**

➢ **High** Potential Products :

- **Digital Marketing** : High CLTV **(5,196.28**), positive marginality (CM = **2,313,513.26**) and high conversion (C1 = **2.56%**). **Growth point:** Launching courses related to popular trends such as AI or project management can attract more unique users (UA).
- **UX/UI Design** : High CLTV (**4,908.66**), positive marginality (CM = **974,560.37**) and good conversion (C1 = **1.23%**). **Growth point** : Implementing automatic sending of test results can increase trust in the product and improve user experience, which will lead to an increase in conversion (C1).
- **Web Developer:** Average CLTV **(3,057.05),** positive marginality (CM = **269,292.34)** and stable conversion (C1 = **0.74%**). **Growth point:** Launching a loyalty program can encourage students to return for new knowledge, increasing APC.

➢ **Low efficiency** products :

- **Find yourself in IT and Data Analytics** : Zero revenue and negative margins (**-149,523.45**). The product may not be relevant to the target audience. The strategy needs to be revised or the product needs to be eliminated.

Business Metrics Tree

5.00%	UA	C1	B	AOV	COGS	Revenue	T	APC	CLTV	LTV	AC	CPA	CM
UA	19,475	4.41%	901	876.84	0	4,008,906	4,572	5.33	4,672.38	205.84	149,523.45	7.68	**3,859,382.50**
C1	18,548	**4.86%**	901	876.84	0	4,008,906	4,572	5.33	4,672.38	226.94	149,523.45	8.06	**4,059,827.80**
AOV	18,548	4.63%	858	**920.68**	0	4,209,351	4,572	5.33	4,906.00	226.94	149,523.45	8.06	**4,059,827.80**
APC	18,548	4.63%	858	876.84	0	4,209,351	4,572	**5.60**	4,906.00	226.94	149,523.45	8.06	**4,059,827.80**
CPA	18,548	4.63%	858	876.84	0	4,008,906	4,572	5.33	4,672.38	216.14	149,523.45	**€8.46**	**3,851,906.33**

Target metric

- Marginal Profit (CM)

Decision making metrics

Customer acquisition:

- Number of unique users (UA).
- Conversion to buyer (C1).
- Cost per acquisition (CPA).

Profitability:

- Average order value (AOV).
- Revenue.
- Customer Lifetime Value (CLTV).

Profitability:

- Average Purchase Frequency (APC)

Tree of metrics

Unit Economics Metrics	
UA (User Acquisition)	Number of attracted users.
C1 (Conversion Rate)	Conversion to purchase.
AOV (Average Order Value)	Average bill.
COGS (Cost of Goods Sold)	Cost price (not in the current dataset)
APC (Average Purchase Count)	Average frequency of purchases.
CPA (Cost Per Action)	Cost of customer acquisition.
CLTV (Customer Lifetime Value)	Customer Lifetime Value

Product metrics	
T (Total Transactions)	Total number of transactions.
Revenue	Revenue.
AC (Acquisition Cost)	User acquisition cost.
UA (User Acquisition)	Number of attracted users.
C1 (Conversion Rate)	Conversion to purchase.
B (Users Bought)	Number of users who made a purchase.
Course Duration	Duration of the course.
Months of Study	Client training time.
Initial Amount Paid	Amount of the first payment.
Offer Total Amount	Total amount of the offer.

Atomic metrics	
Created Time	Time of trade creation.
Contact Name (ID)	Client ID.
Product Name	Product name.
Campaign	Marketing campaign title.
Source	Lead source
Payment Type	Payment method.
City	Geographical location of the client.
SLA	Transaction processing time.
Course Duration	Duration of the course.
Months of Study	Client training time.
Initial Amount Paid	Amount of the first payment.
Offer Total Amount	Total amount of the offer.

Improvement Hypotheses

Hypothesis 1 : Sending test results to users

- Description: Automatically send test results after completion on site to reduce customer doubts and increase conversion.
- Metric: C1 Growth.
- Mechanics: Implement automatic sending for experimental group, measure C1 growth.

Hypothesis 2 : Increase in repeat purchases (APC)

- Description: Launch of loyalty program and advanced courses, email campaign with offers for past students.
- Metric: APC Growth.
- Mechanics: Divide customers into groups, launch a loyalty program for the experimental group, measure APC growth.

Hypothesis 3 : Increase in average order value (AOV)

- Description: Development of premium courses with additional services.
- Metric: AOV increase.
- Mechanics: Launch premium courses for some clients, evaluate the change in the average check.

Hypothesis 4 : Introduction of a new course

- Description: Explore audiences interested in non-standard courses (e.g. project management or AI) to increase engagement by 20%.
- Metric: Growth in Unique Users (UA).
- Mechanics: Conduct an audience survey, launch a pilot course, evaluate UA growth through A/B testing.

Impact of hypotheses:

- Hypothesis 1: Growth of C1 and Revenue.
- Hypothesis 2: APC and CLTV growth.
- Hypothesis 3: Increase in AOV and Revenue.
- Hypothesis 4: Increase in UA and Revenue.

Example of hypothesis testing mechanics

Hypothesis : Sending test results and personalized recommendations to users

1. **Purpose of the test**

Test whether automatically sending test results to users will increase the conversion rate (C1).

2. **Testing Methodology**

A/B testing with control and test groups is used.

3. **Test conditions**

- **Testing period:** 2 weeks.
- **Sample:** all users who have passed testing on the site.

- Control group (A): users without automatic results submission.
- Test Group (B): Clients who receive test results with course recommendations.

4. **Metrics for measurement**

- **Main metric: C1 (Conversion Rate):** the share of users who paid for the course after receiving the test results.
- **Secondary metrics:**

- The percentage of users who opened the email with results.
- The percentage of users who clicked through to the course page from the email.

5. **Segmentation and control of variables**

Groups A and B are formed randomly from users who have passed the test.

First, we find out, based on current CRM data, that approximately **277 users visit the site per week.** A planned advertising campaign could increase traffic to **577 transactions per week (see chart)**

The test will use this potential growth to achieve the required sample size within **2 weeks** . For this purpose, the minimum detectable effect (MDE) is taken to be **0.0 5**

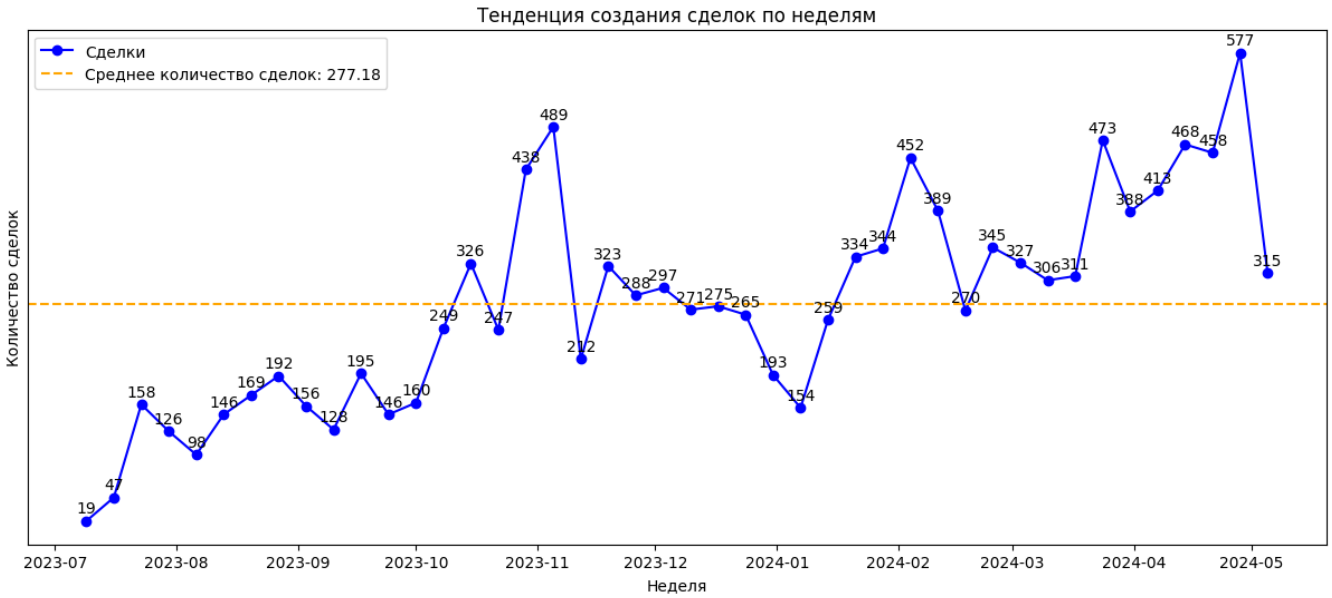
$n = (15.68 * p * (1 - p)) / x^2$ Where:

- (p = 0.0463) (baseline conversion),
- (x = 0.0 5) (minimum detectable effect),

$n = (15.68 * 0.0463 * (1 - 0.0463)) / (0.05)^2 = 0.692 / 0.0025 \approx 276.94$

n ≈ 2 77 (people for each group)

Thus, for each variation (groups A and B) it is required **2 77 people** , and the total sample size will be **5 5 4 people** , which corresponds to the capabilities of the school's CRM system .



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6. Testing procedure

- Set up automatic sending of test results and personalized recommendations for the test group.
- **Data Collection** : Conversion data is collected through CRM and web analytics tools.
- **Analysis** : After the test is completed, data is analyzed to evaluate the effectiveness of the changes.

7. Criteria for the success of a hypothesis

- Base Conversion (C1) = 4.63%
- The hypothesis is confirmed if the conversion in the test group increases by 5%:
  CR(B) = CR(A) + 5% · CR(A)
  CR(B) = 4.63%+ 0.05 · 4.63%=4.86%
- Thus, the expected conversion (C1) in the test group must be at least **4.86%** for the hypothesis to be **confirmed .**

Key findings:

- The most effective acquisition channels are Facebook Ads and webinars.
- There is a high workload on individual employees.
- Evening courses require optimization to increase their effectiveness.
- There is significant potential for growth through expansion of geographic coverage.
- Low customer engagement requires further analysis of the causes

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Recommendations:

- Optimize task distribution.
- Strengthen marketing of successful products and campaigns.
- Expand coverage to new regions.
- Conduct research into the reasons for low customer engagement and develop measures to increase their activity and interest.

Conclusions (details) :

1. Analysis of the client base

- Groups of clients with high activity and contribution to profits have been identified, but there is no segmentation by key characteristics (age, region, preferences). This makes it difficult to develop targeted marketing strategies.
- There is a significant concentration of contacts among a small number of responsible persons, which creates risks of overload and a possible reduction in the quality of service.

*2. **Effectiveness of marketing campaigns***

- Most advertising campaigns have low click-through rates (CTR), which indicates that advertising is not effective enough. Outliers in costs and impressions indicate the need to review the budget allocation strategy.
- There is no analysis of the relationship between advertising campaigns and conversion into sales. This limits the ability to assess the real impact of marketing on revenue.

*3. **Work of the sales department***

- A high percentage of lost deals (Lost) requires a detailed analysis of the reasons for refusals at different stages of the sales funnel.
- Abnormally long calls may indicate complex cases that require additional resources or improved customer engagement processes.

*4. **Data quality***

- Errors were found in the "Closing Date" and "Created Time" fields, as well as incorrect entries in the "City" field. This indicates a need to improve the data entry and validation processes in CRM.
- Missing Payment Type data for late funnel deals may skew your analysis results.

5. ***Geographical analysis***

- Customer geographic information is unevenly distributed, making it difficult to identify regional patterns of demand and customer behavior.

Recommended actions :

1. ***Optimization of marketing strategies***

- Conduct A/B testing of advertising campaigns to evaluate the effectiveness of different creatives and channels.
- Reallocate budget to more successful channels based on ROI and CTR analysis.
- Develop targeted marketing strategies for key customer segments, including regional characteristics and preferences.

2. ***Improving the performance of the sales department***

- Implement regular analysis of the reasons for deal failures at each stage of the sales funnel and develop measures to eliminate them.
- Provide training to employees on managing complex customer cases to reduce call duration and improve their efficiency.
- Redistribute the workload between responsible persons to more evenly process contacts and improve the quality of service.

3. ***Improving data quality***

- Develop a system for automatic data validation when entering into CRM to minimize errors.
- Implement regular data auditing, including checking the City, Payment Type and timestamp fields.
- Create standards for filling in fields to avoid gaps and incorrect values.

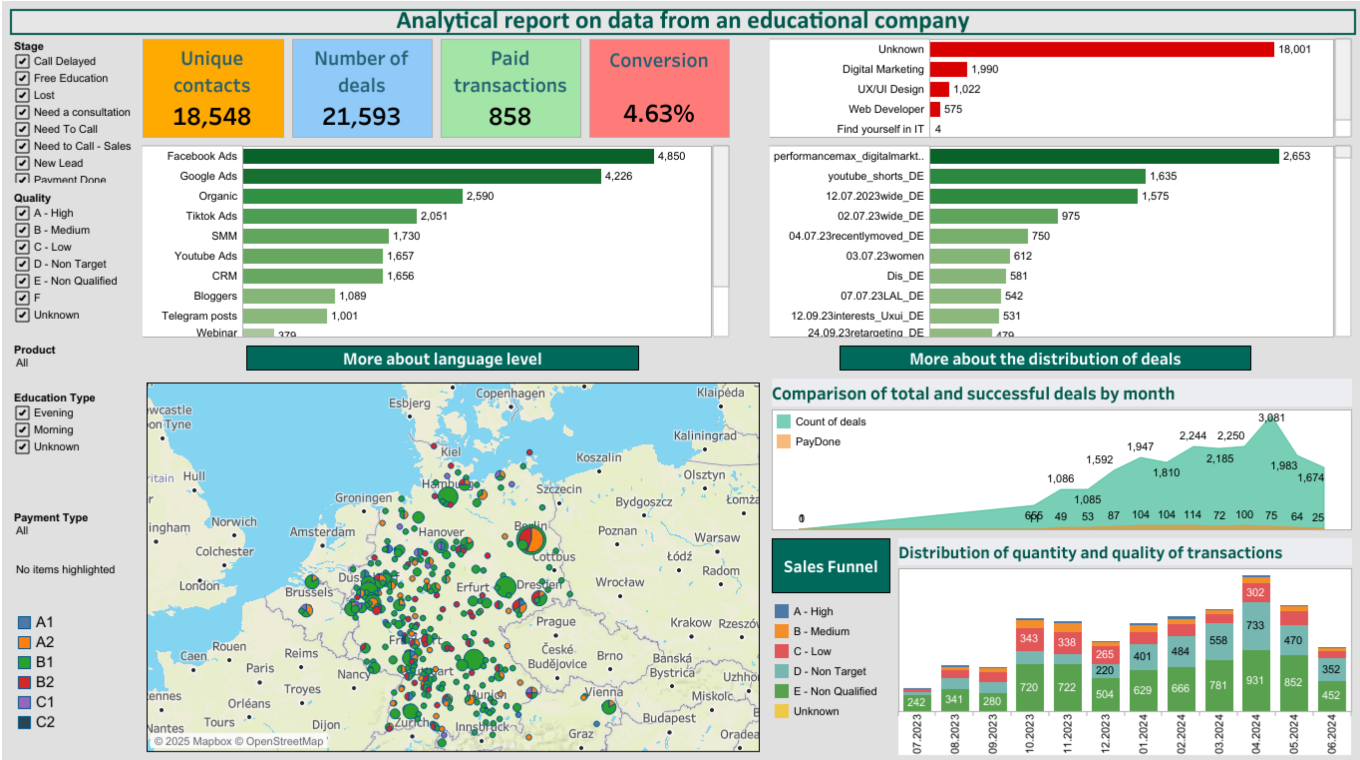
4. ***Geographical analysis***

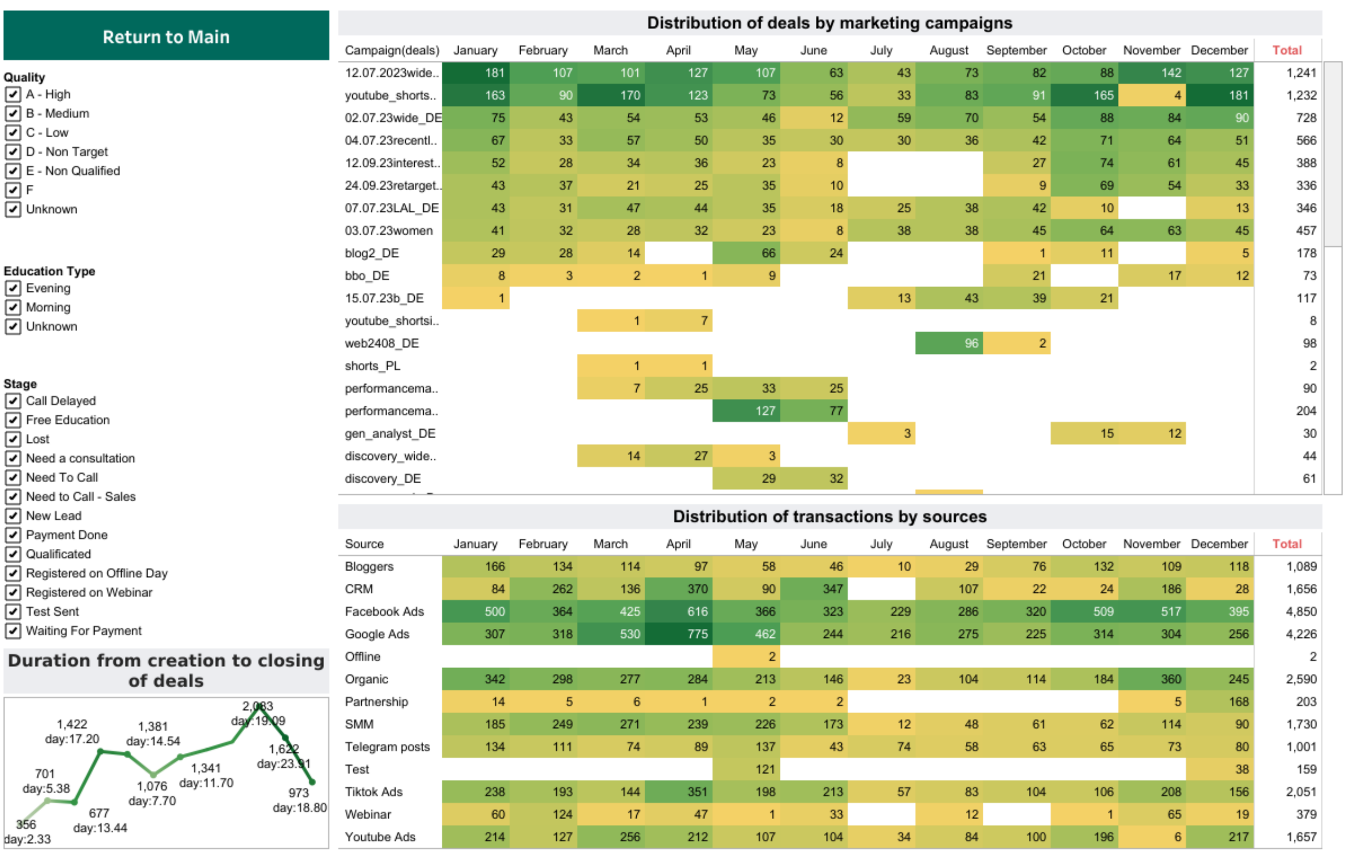
- Conduct a more detailed analysis of geographic data to identify regions with high growth potential.
- Develop regional sales and marketing strategies tailored to the specific needs of each region.

5. ***Automation of analytics***

- Invest in analytics automation tools (e.g. BI systems) to make it easier to analyze data and visualize key metrics.
- Implement dashboards to track marketing, sales, and customer activity performance in real time.

Dashboard for exploring data and insights .





Distribution of deals by marketing campaigns

Campaign(deals)	January	February	March	April	May	June	July	August	September	October	November	December	Total
12.07.2023wide..	181	107	101	127	107	63	43	73	82	88	142	127	1,241
youtube_shorts..	163	90	170	123	73	56	33	83	91	165	4	181	1,232
02.07.23wide_DE	75	43	54	53	46	12	59	70	54	88	84	90	728
04.07.23recentl..	67	33	57	50	35	30	30	36	42	71	64	51	566
12.09.23interest..	52	28	34	36	23	8			27	74	61	45	388
24.09.23retarget..	43	37	21	25	35	10			9	69	54	33	336
07.07.23LAL_DE	43	31	47	44	35	18	25	38	42	10		13	346
03.07.23women	41	32	28	32	23	8	38	38	45	64	63	45	457
blog2_DE	29	28	14		66	24			1	11		5	178
bbo_DE	8	3	2	1	9				21		17	12	73
15.07.23b_DE	1						13	43	39	21			117
youtube_shortsi..			1	7									8
web2408_DE								96	2				98
shorts_PL			1	1									2
performancema..			7	25	33	25							90
performancema..					127	77							204
gen_analyst_DE							3			15	12		30
discovery_wide..			14	27	3								44
discovery_DE					29	32							61

Distribution of transactions by sources

Source	January	February	March	April	May	June	July	August	September	October	November	December	Total
Bloggers	166	134	114	97	58	46	10	29	76	132	109	118	1,089
CRM	84	262	136	370	90	347		107	22	24	186	28	1,656
Facebook Ads	500	364	425	616	366	323	229	286	320	509	517	395	4,850
Google Ads	307	318	530	775	462	244	216	275	225	314	304	256	4,226
Offline					2								2
Organic	342	298	277	284	213	146	23	104	114	184	360	245	2,590
Partnership	14	5	6	1	2	2					5	168	203
SMM	185	249	271	239	226	173	12	48	61	62	114	90	1,730
Telegram posts	134	111	74	89	137	43	74	58	63	65	73	80	1,001
Test					121							38	159
Tiktok Ads	238	193	144	351	198	213	57	83	104	106	208	156	2,051
Webinar	60	124	17	47	1	33		12		1	65	19	379
Youtube Ads	214	127	256	212	107	104	34	84	100	196	6	217	1,657

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Sales Funnel Stage Data Analysis

Stage	10.2022	07.2023	08.2023	09.2023	10.2023	11.2023	12.2023	01.2024	02.2024	03.2024	04.2024	05.2024	06.2024
Call Delayed		18	28	48	59	62	140	316	291	335	368	388	195
Free Education									1				
Lost	1	611	976	974	1,434	1,326	1,367	1,740	1,433	1,754	2,014	1,425	688
Need a consultation													23
Need To Call													31
Need to Call - Sales					1						1	4	27
New Lead													6
Payment Done		11	49	53	87	104	104	114	72	100	75	64	25
Qualificated		13		9	1		2	1	3	6	6	21	66
Registered on Offline Day									75	25			
Registered on Webinar			32			447	178	56	289		576		494
Test Sent							1	1	2	1	2	5	13
Waiting For Payment		2	1	1	10	8	18	16	19	29	39	76	106

Month of Created Time

Deal Owner Name

- [x] Null
- [x] Alice Johnson
- [x] Amy Green
- [x] Ben Hall
- [x] Bob Brown
- [x] Cara Iverson
- [x] Charlie Davis
- [x] Diana Evans
- [x] Eva Kent
- [x] George King
- [x] Ian Miller
- [x] Jane Smith
- [x] John Doe
- [x] Julia Nelson
- [x] Kevin Parker
- [x] Mason Roberts
- [x] Nina Scott
- [x] Oliver Taylor
- [x] Paula Underwood
- [x] Quincy Vincent
- [x] Rachel White
- [x] Sam Young
- [x] Ulysses Adams
- [x] Victor Barnes
- [x] Wendy Clark
- [x] Xander Dean
- [x] Yara Edwards
- [x] Zachary Foster

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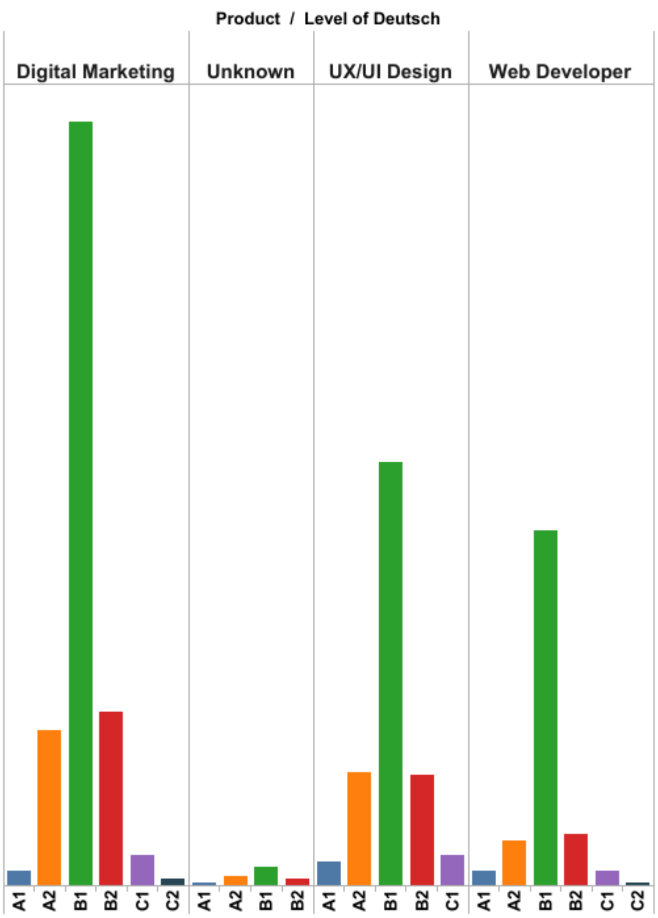

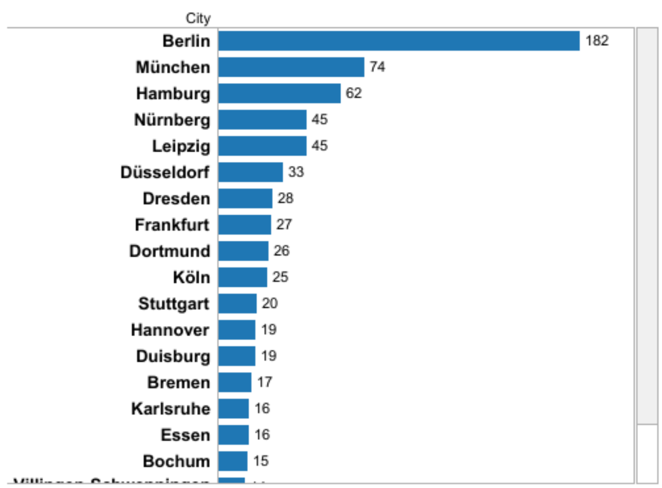

Level Deutch