The CRO claimed win rate has dropped over the last two quarters but pipeline volume looks healthy. In other words, the company is still generating opportunities, but fewer of those opportunities are converting into wins.

We start by loading the data just to confirm the dataset shape (rows/columns) and inspect a few example rows to understand what each field represents, also checking for missing values and inconsistent category labels.

In [124…

```python
import numpy as np
import pandas as pd

df = pd.read_csv("skygeni_sales_data.csv")

print(df.shape)
print(df.head())

#check for missing values
df.columns
df.isna().sum().sort_values(ascending=False)
```

```
(5000, 12)
  deal_id created_date closed_date sales_rep_id    industry         region  \
0  D00001   2023-11-24  2023-12-15       rep_22        SaaS  North America
1  D00002   2023-01-17  2023-01-27        rep_7        SaaS          India
2  D00003   2023-10-29  2023-12-10        rep_5  HealthTech           APAC
3  D00004   2023-07-14  2023-08-02       rep_18     FinTech          India
4  D00005   2024-02-29  2024-05-26        rep_2  HealthTech           APAC

  product_type lead_source   deal_stage  deal_amount  sales_cycle_days outcome
0   Enterprise    Referral    Qualified         4253                21     Won
1         Core    Referral       Closed         3905                10     Won
2         Core     Inbound     Proposal        10615                42    Lost
3         Core     Partner  Negotiation         4817                19     Won
4         Core    Outbound    Qualified        45203                87    Lost
```

Out[124…

```
deal_id            0
created_date       0
closed_date        0
sales_rep_id       0
industry           0
region             0
product_type       0
lead_source        0
deal_stage         0
deal_amount        0
sales_cycle_days   0
outcome            0
dtype: int64
```

In [125…

```
#covert dates to standard format == datetime objects
df["created_date"] = pd.to_datetime(df["created_date"], errors="coerce")
df["closed_date"] = pd.to_datetime(df["closed_date"], errors="coerce")

#df[["created_date", "closed_date"]].head()
```

In [126…

```
#Quantifying/checking the totals
# outcome values
df["outcome"].value_counts(dropna=False)

# deal stages
#df["deal_stage"].value_counts(dropna=False).head()

# deal_amount
#df["deal_amount"].describe()
```

Out[126…

```
outcome
Lost    2737
Won     2263
Name: count, dtype: int64
```

In [127…

```
#key columns to analyse sales cycle, win rate/pipeline vol per quarter etc,.

#deal duration is basically the sales cycle length
df["deal_duration_days"] = (df["closed_date"] - df["created_date"]).dt.days
df["created_quarter"] = df["created_date"].dt.to_period("Q").astype(str)
```

```
df["closed_quarter"] = df["closed_date"].dt.to_period("Q").astype(str)
df[["deal_id", "created_date", "closed_date", "deal_duration_days", "created_quarter", "closed_quarter", "outcome"]].head(10)
```

Out[127…

	deal_id	created_date	closed_date	deal_duration_days	created_quarter	closed_quarter	outcome
0	D00001	2023-11-24	2023-12-15	21	2023Q4	2023Q4	Won
1	D00002	2023-01-17	2023-01-27	10	2023Q1	2023Q1	Won
2	D00003	2023-10-29	2023-12-10	42	2023Q4	2023Q4	Lost
3	D00004	2023-07-14	2023-08-02	19	2023Q3	2023Q3	Won
4	D00005	2024-02-29	2024-05-26	87	2024Q1	2024Q2	Lost
5	D00006	2024-03-19	2024-04-07	19	2024Q1	2024Q2	Won
6	D00007	2023-11-08	2024-02-04	88	2023Q4	2024Q1	Won
7	D00008	2024-03-07	2024-06-20	105	2024Q1	2024Q2	Lost
8	D00009	2023-07-22	2023-11-19	120	2023Q3	2023Q4	Lost
9	D00010	2023-10-26	2023-12-23	58	2023Q4	2023Q4	Won

Win rate only makes sense for deals that have reached an outcome. Therefore, when computing win rate we filter the dataset to deals where outcome is either Won or Lost (and closed_date is present) i.e, open deals are excluded

In [128…

```
#Subset of closed deals
closed_df = df[df["outcome"].isin(["Won", "Lost"])].copy()

print("Closed deals:", closed_df.shape[0])
closed_df["outcome"].value_counts()
```

```
Closed deals: 5000
```

Out[128…

```
outcome
Lost    2737
Won     2263
Name: count, dtype: int64
```

Win rate is the fraction of closed deals that were won. It is calculated as:

$$\text{Win Rate} = \frac{\#\text{Won}}{\#\text{Won} + \#\text{Lost}}$$

It summarizes how efficiently the sales team converts pipeline into revenue. However, win rate can change because of various factors like the sales team performance, changes in industried/lead sources/regions, or because the market environment changes.

Additonally, win rate is computed by closed_quarter (rather than created_quarter) because the CRO's complaint is about conversion outcomes. A deal created in Q1 might close in Q2, so grouping by closed_quarter captures when wins/losses actually happened.

In [129…

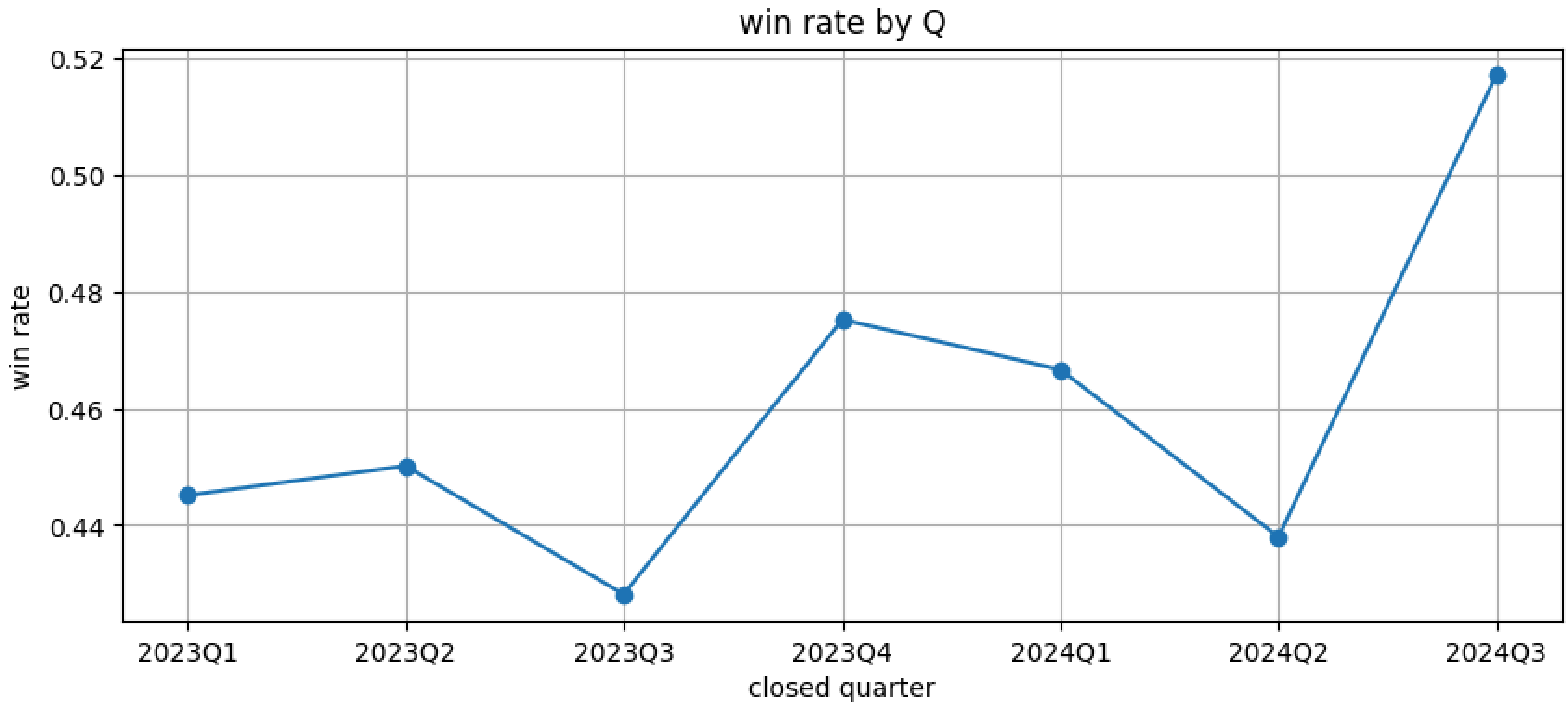
```python
#win rate per Q == wins/wins + loses
win_rate_by_q = (
    closed_df
    .groupby("closed_quarter")["outcome"]
    .apply(lambda x: (x == "Won").mean())
    .sort_index()
)

win_rate_by_q
```

Out[129…

```
closed_quarter
2023Q1    0.445122
2023Q2    0.450154
2023Q3    0.428150
2023Q4    0.475170
2024Q1    0.466667
2024Q2    0.437991
2024Q3    0.517241
Name: outcome, dtype: float64
```

In [130…

```python
import matplotlib.pyplot as plt

plt.figure(figsize=(10,4))
win_rate_by_q.plot(marker="o")
plt.title("win rate by Q")
plt.ylabel("win rate")
plt.xlabel("closed quarter")
plt.grid(True)
plt.show()
```



Pipeline volume is approximated using deals created per quarter and total deal amount created per quarter. This measures pipeline inflow so how many new opportunities are entering the funnel. If this volume is stable but win rate drops, it would mean the problem is downstream (conversion quality, execution, or market conditions) rather than top-of-funnel volume.

In [131…

```
#pipeline volume per created Q

deals_created_by_q = df.groupby("created_quarter")["deal_id"].count().sort_index()
deals_created_by_q
```

Out[131…

```
created_quarter
2023Q1    1006
2023Q2    1014
2023Q3    1006
2023Q4    1013
2024Q1     961
Name: deal_id, dtype: int64
```

In [132…

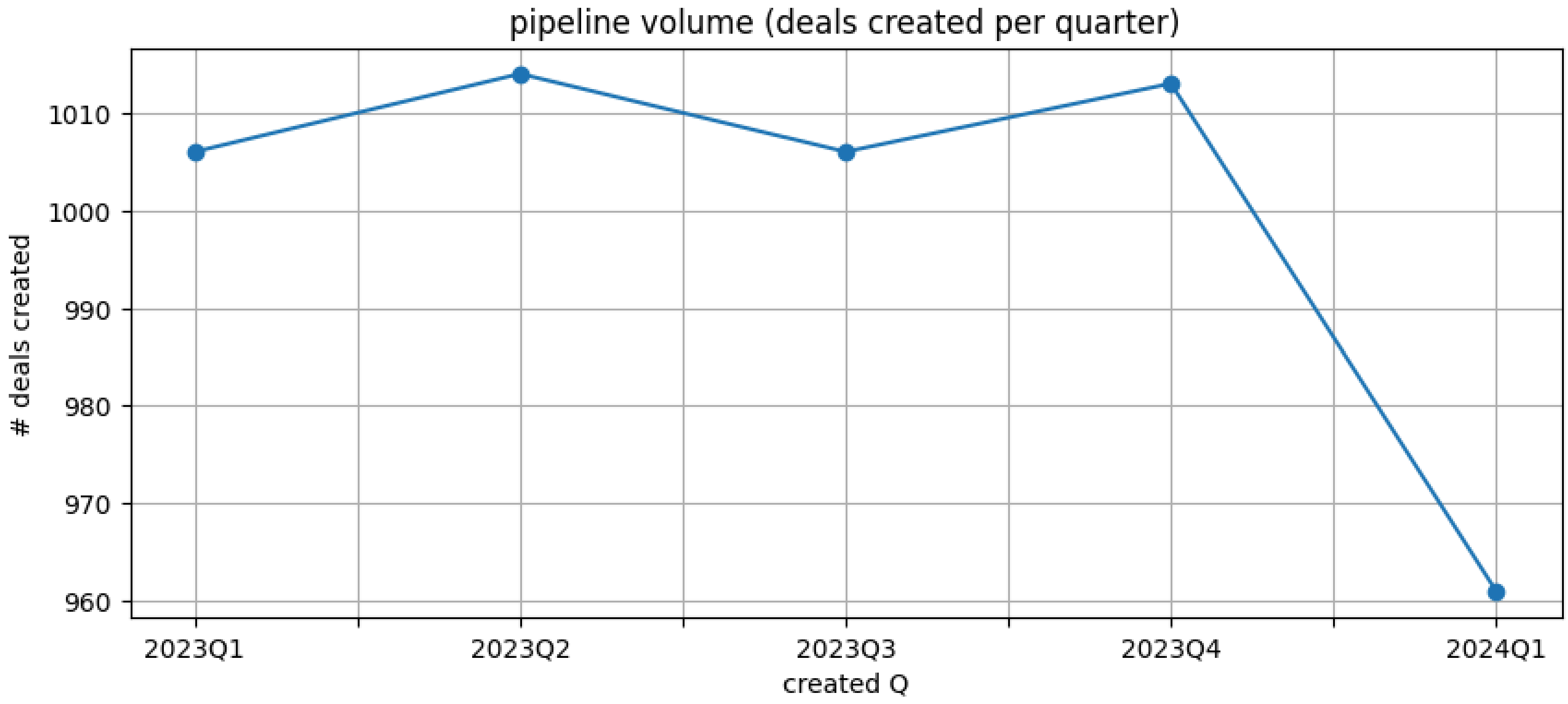
```
amount_created_by_q = df.groupby("created_quarter")["deal_amount"].sum().sort_index()
amount_created_by_q
```

Out[132…

```
created_quarter
2023Q1    25286077
2023Q2    27115555
2023Q3    26375100
2023Q4    26977557
2024Q1    25678175
Name: deal_amount, dtype: int64
```

In [133…

```
plt.figure(figsize=(10,4))
deals_created_by_q.plot(marker="o")
plt.title("pipeline volume (deals created per quarter)")
plt.ylabel("# deals created")
plt.xlabel("created Q")
plt.grid(True)
plt.show()
```



The first step is to check whether the CRO’s statement is supported by the data. When computed by closed quarter, win rate dips in 2024Q2 compared to 2024Q1. At the same time, the number of deals created per quarter remains relatively stable, which supports the CRO’s belief that pipeline inflow is healthy. This suggests the problem is not “not enough opportunities,” but rather reduced conversion and/or slower deal execution.

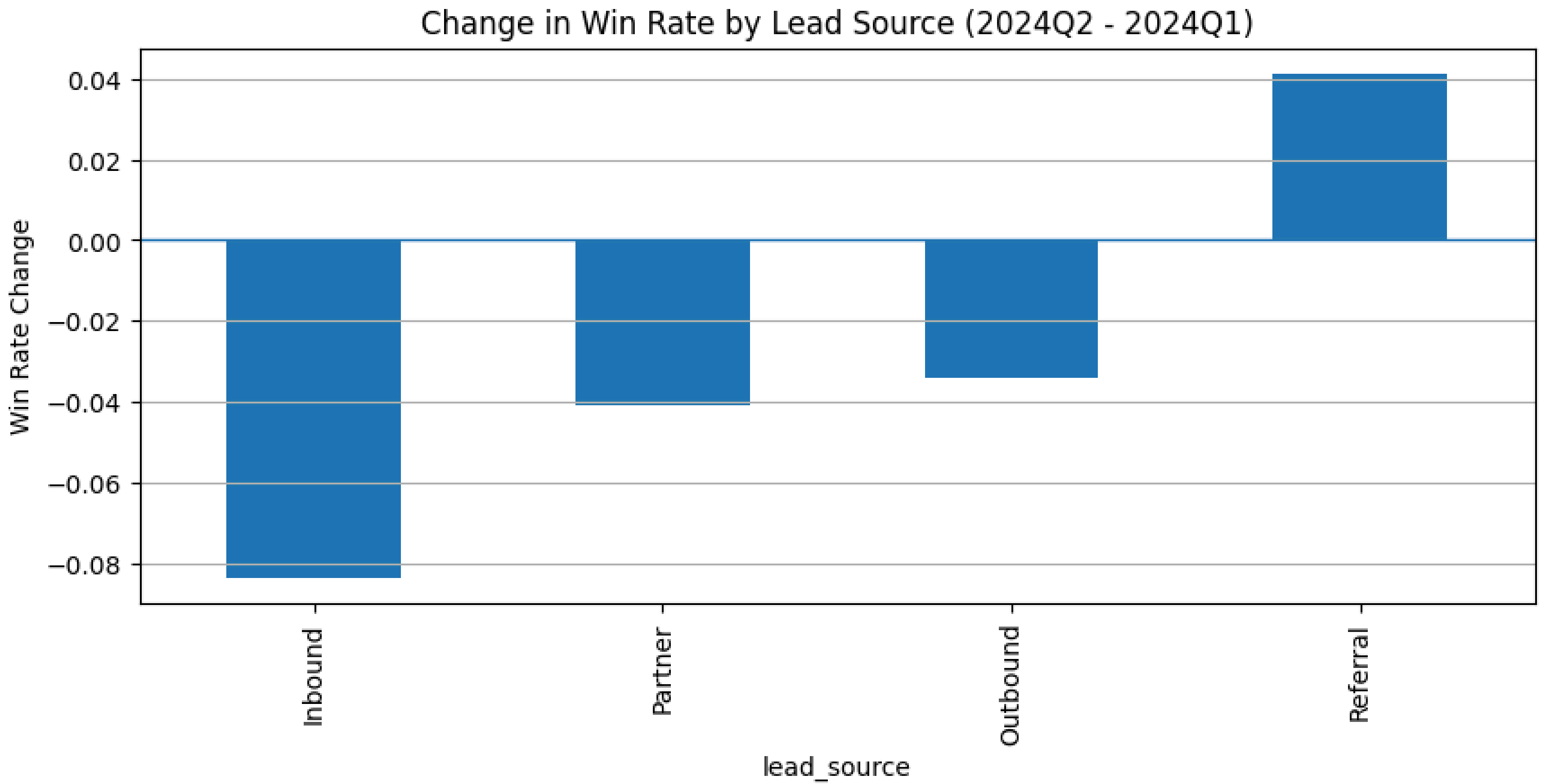
Now that we have an idea of the original problem statement and the data confirming that problem, we can compute win rate per Q according to category so we know what actually is the issue (if anything). To speed up analysis and keep the notebook consistent, \a helper function (win_rate_table) is created that computes deal count, wins, losses, win rate, average deal amount, and median deal duration for any grouping.

In [134…

```
#create a function to compute win rate wrt category

def win_rate_table(df, group_cols):
    """
    returns a table with:
    - deals
    - wins
    - losses
    - win_rate
    """
    output = (
        df
        .groupby(group_cols)
        .agg(
            deals=("deal_id", "count"),
            wins=("outcome", lambda x: (x == "Won").sum()),
            losses=("outcome", lambda x: (x == "Lost").sum()),
            win_rate=("outcome", lambda x: (x == "Won").mean()),
            avg_amount=("deal_amount", "mean"),
            median_duration=("deal_duration_days", "median"),
        )
        .reset_index()
    )
    return output
```

In [135…

```
#weaker leads
#win rate by lead source

lead_source_wr = win_rate_table(closed_df, ["closed_quarter", "lead_source"])
lead_source_wr.sort_values(["closed_quarter", "win_rate"]).head(20)

qtrs = ["2024Q1", "2024Q2"]
tmp_source = lead_source_wr[lead_source_wr["closed_quarter"].isin(qtrs)].copy()

pivot_source = tmp_source.pivot(index="lead_source", columns="closed_quarter", values="win_rate")
pivot_source = pivot_source.sort_values("2024Q2")

delta_source = (pivot_source["2024Q2"] - pivot_source["2024Q1"]).sort_values()

plt.figure(figsize=(10,4))
delta_source.plot(kind="bar")
plt.axhline(0, linewidth=1)
plt.title("Change in Win Rate by Lead Source (2024Q2 - 2024Q1)")
plt.ylabel("Win Rate Change")
plt.grid(True, axis="y")
plt.show()
```



In [136…

```
'''
We look at how the deals in the inbound lead source pipeline fared over the last 3 quarters
-- win rate
-- revenue
-- cycle duration

'''


focus_inbound = closed_df[
    (closed_df["lead_source"] == "Inbound") &
    (closed_df["closed_quarter"].isin(["2024Q1", "2024Q2", "2024Q3"]))
].copy()

focus_inbound.groupby("closed_quarter").agg(
    deals=("deal_id", "count"),
    win_rate=("outcome", lambda x: (x == "Won").mean()),
    avg_amount=("deal_amount", "mean"),
    median_duration=("deal_duration_days", "median"),
)
```

Out[136…

	deals	win_rate	avg_amount	median_duration
closed_quarter				
2024Q1	254	0.488189	26499.913386	63.5
2024Q2	168	0.404762	26748.678571	87.5
2024Q3	8	0.375000	25866.750000	109.0

In [137…

```
'''
look at the share of deals + win rate in each category of the lead sourcing
'''

tmp_source["share"] = tmp_source.groupby("closed_quarter")["deals"].transform(lambda x: x / x.sum())

tmp_source[["closed_quarter", "lead_source", "deals", "share", "win_rate"]].sort_values(
    ["closed_quarter", "share"], ascending=[True, False]
)
```

Out[137…

	closed_quarter	lead_source	deals	share	win_rate
17	2024Q1	Outbound	260	0.262626	0.453846
16	2024Q1	Inbound	254	0.256566	0.488189
19	2024Q1	Referral	241	0.243434	0.464730
18	2024Q1	Partner	235	0.237374	0.459574
21	2024Q2	Outbound	174	0.273155	0.419540
20	2024Q2	Inbound	168	0.263736	0.404762
23	2024Q2	Referral	166	0.260597	0.506024
22	2024Q2	Partner	129	0.202512	0.418605

In [138…

```
duration_tbl = (
    closed_df[closed_df["closed_quarter"].isin(["2024Q1", "2024Q2"])]
    .groupby(["closed_quarter", "lead_source"])["deal_duration_days"]
    .median()
    .reset_index()
)

duration_pivot = duration_tbl.pivot(index="lead_source", columns="closed_quarter", values="deal_duration_days")
duration_pivot
```

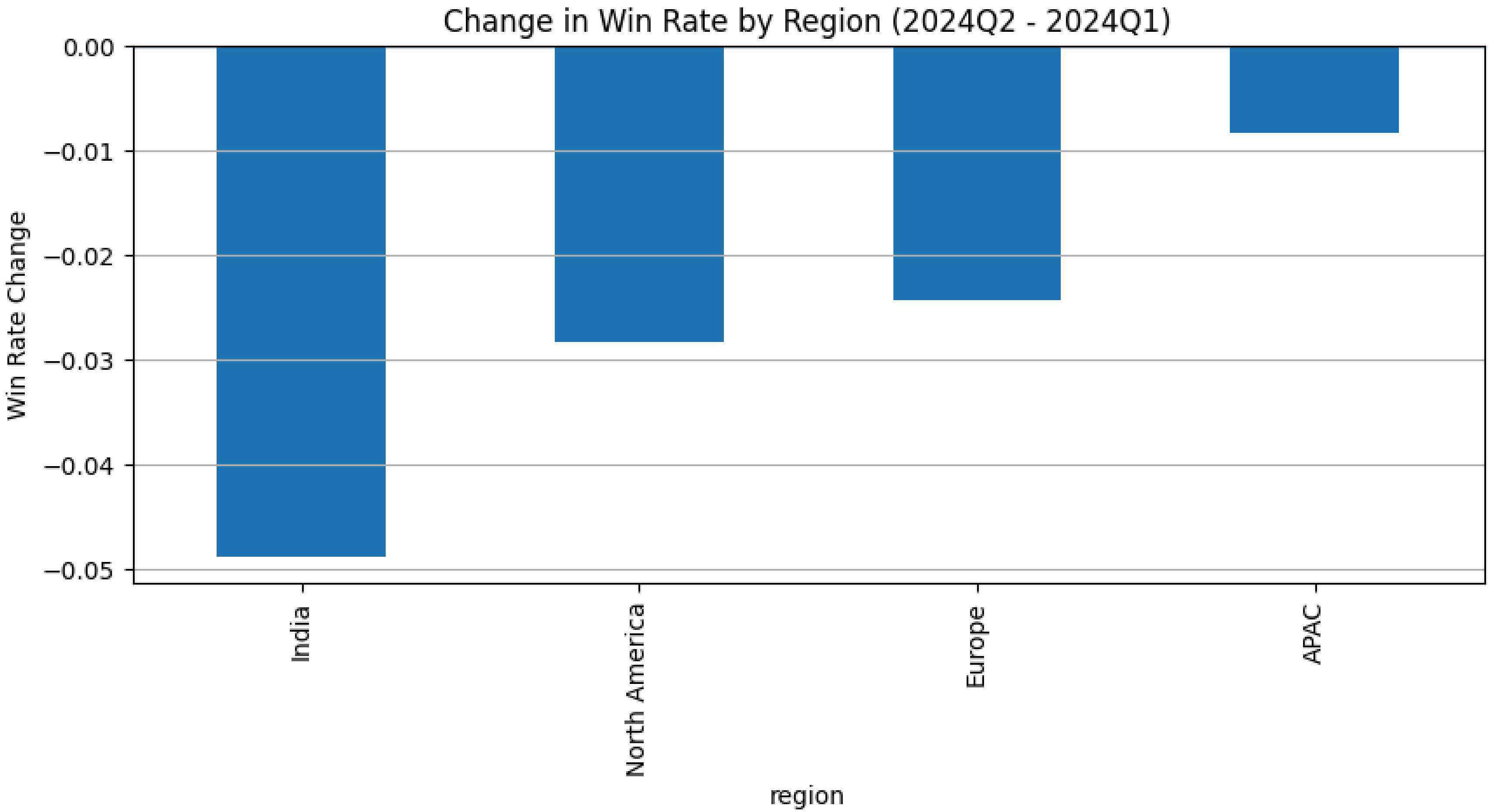
Out[138…

closed_quarter	2024Q1	2024Q2
lead_source		
Inbound	63.5	87.5
Outbound	67.0	82.5
Partner	61.0	86.0
Referral	62.0	88.5

Inbound deals show the largest win-rate decline from 2024Q1 to 2024Q2, and inbound deal durations increase substantially. Inbound win rate drops from roughly 48.8% to 40.5%, and median deal duration increases from about 63.5 days to 87.5 days. Because inbound deal volume is large in both quarters, this change is unlikely to be explained by small sample randomness. This might suggest that inbound opportunities in Q2 are both slower and less likely to convert, which is consistent with less leads qualifying, lower intent inbound traffic, or a slowdown in customer decision-making.

In [139…

```
region_wr = win_rate_table(closed_df, ["closed_quarter", "region"])
region_wr.sort_values(["closed_quarter", "win_rate"]).head(20)

qtrs = ["2024Q1", "2024Q2"]
tmp_region = region_wr[region_wr["closed_quarter"].isin(qtrs)].copy()

pivot_region = tmp_region.pivot(index="region", columns="closed_quarter", values="win_rate")
pivot_region = pivot_region.sort_values("2024Q2")

delta_region = (pivot_region["2024Q2"] - pivot_region["2024Q1"]).sort_values()

plt.figure(figsize=(10,4))
delta_region.plot(kind="bar")
plt.axhline(0, linewidth=1)
plt.title("Change in Win Rate by Region (2024Q2 - 2024Q1)")
plt.ylabel("Win Rate Change")
plt.grid(True, axis="y")
plt.show()
```

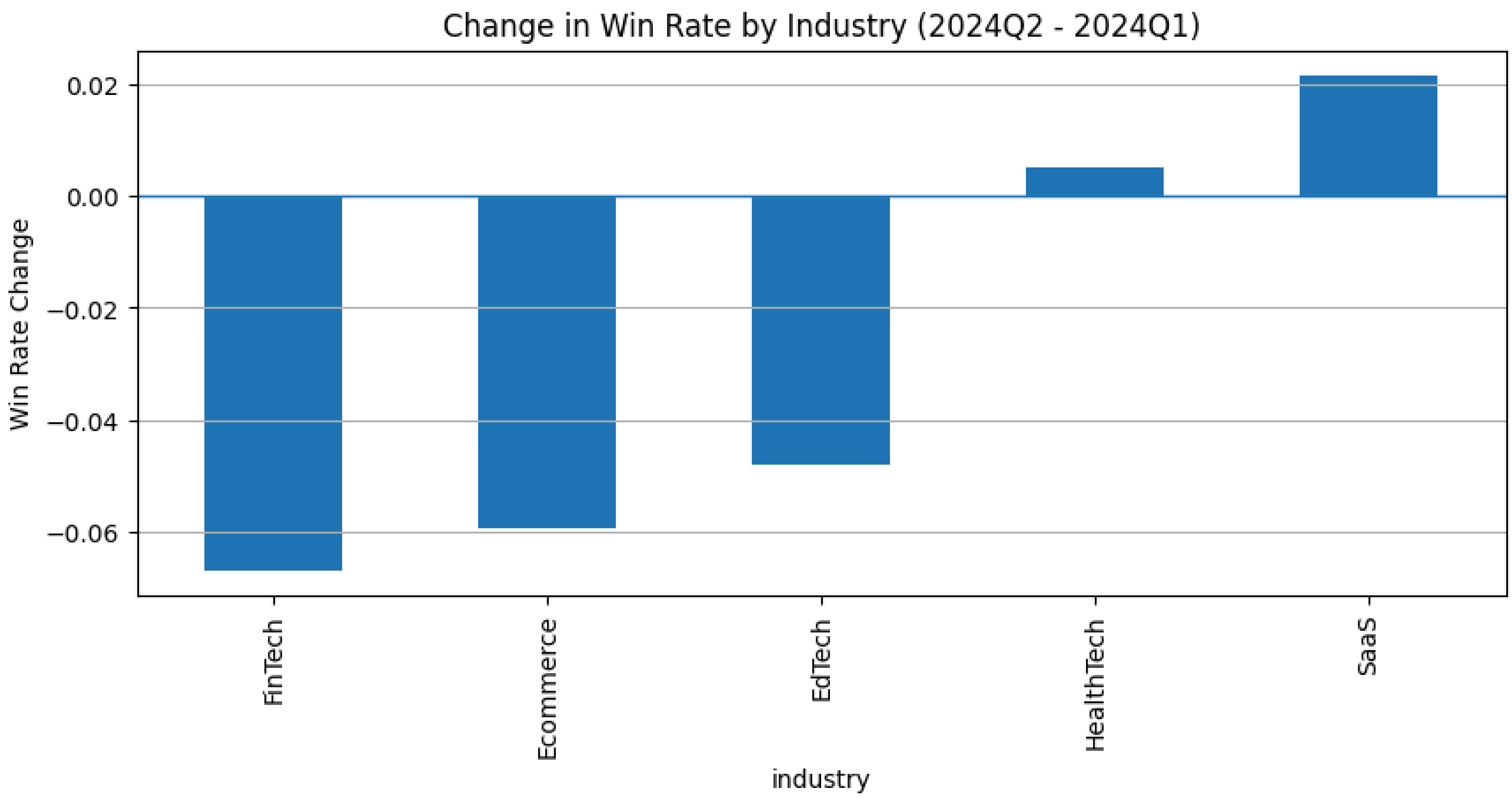


Region is a super common driver in B2B sales because different regions behave differently due to economic conditions, local competition etc,. Region specific winrates were checked. While they did change, I focused more on lead source, industry, and deal velocity which showed stronger signals.

In [140…

```
industry_wr = win_rate_table(closed_df, ["closed_quarter", "industry"])
industry_wr.sort_values(["closed_quarter", "win_rate"]).head(20)

qtrs = ["2024Q1", "2024Q2", "2024Q3"]
tmp_industry = industry_wr[industry_wr["closed_quarter"].isin(qtrs)].copy()
```

```
pivot_industry = tmp_industry.pivot(index="industry", columns="closed_quarter", values="win_rate")
pivot_industry = pivot_industry.sort_values("2024Q2")

delta_industry = (pivot_industry["2024Q2"] - pivot_industry["2024Q1"]).sort_values()
#delta_industry_2 = (pivot_industry["2024Q3"] - pivot_industry["2024Q2"]).sort_values()

plt.figure(figsize=(10,4))
delta_industry.plot(kind="bar")
plt.axhline(0, linewidth=1)
plt.title("Change in Win Rate by Industry (2024Q2 - 2024Q1)")
plt.ylabel("Win Rate Change")
plt.grid(True, axis="y")
plt.show()
```



In [141…

```
industry_wr = win_rate_table(closed_df, ["closed_quarter", "industry"])

qtrs = ["2024Q1", "2024Q2"]
tmp_industry = industry_wr[industry_wr["closed_quarter"].isin(qtrs)].copy()

tmp_industry["share"] = tmp_industry.groupby("closed_quarter")["deals"].transform(lambda x: x / x.sum())

tmp_industry.sort_values(["closed_quarter", "share"], ascending=[True, False])[
    ["closed_quarter", "industry", "deals", "share", "win_rate", "median_duration"]
]
```

Out[141…

	closed_quarter	industry	deals	share	win_rate	median_duration
20	2024Q1	Ecommerce	207	0.209091	0.478261	63.0
21	2024Q1	EdTech	203	0.205051	0.443350	65.0
23	2024Q1	HealthTech	195	0.196970	0.456410	64.0
24	2024Q1	SaaS	194	0.195960	0.448454	60.5
22	2024Q1	FinTech	191	0.192929	0.507853	61.0
29	2024Q2	SaaS	134	0.210361	0.470149	83.5
28	2024Q2	HealthTech	130	0.204082	0.461538	88.0
26	2024Q2	EdTech	129	0.202512	0.395349	90.0
27	2024Q2	FinTech	127	0.199372	0.440945	85.0
25	2024Q2	Ecommerce	117	0.183673	0.418803	82.0

In [142…

```
focus = closed_df[
    (closed_df["industry"] == "FinTech") &
    (closed_df["closed_quarter"].isin(["2024Q1", "2024Q2", "2024Q3"]))
].copy()

focus.groupby("closed_quarter").agg(
    deals=("deal_id", "count"),
    win_rate=("outcome", lambda x: (x == "Won").mean()),
    avg_amount=("deal_amount", "mean"),
    median_duration=("deal_duration_days", "median"),
)
```

Out[142…

	deals	win_rate	avg_amount	median_duration
closed_quarter				
2024Q1	191	0.507853	28282.664921	61.0
2024Q2	127	0.440945	26060.330709	85.0
2024Q3	4	0.250000	29503.000000	111.0

Industry-level breakdown shows that the win-rate decline is not evenly distributed across all industries. FinTech in particular shows a meaningful drop with large deal volume: win rate declines from approximately 50.8% (191 deals) in 2024Q1 to approximately 44.1% (127 deals) in 2024Q2, and median deal duration increases from 61 to 85 days. The sample size is pretty large for both Q's so unlikely to be noise.

We also checked whether the Q2 win-rate decline could be explained by the company doing “more of the wrong kinds of deals”. Looking at industry share of closed deals, the mix is actually pretty stable between 2024Q1 and 2024Q2 -- each industry stays around 18–21% of the quarter. FinTech’s share increases slightly (19.3% to 19.9%), but the bigger story is that FinTech’s win rate drops significantly (50.8% to 44.1%) while the median deal duration jumps (61 to 85 days). So this isn’t mainly a "kind of deals" issue; it’s more that performance inside FinTech (and also EdTech/Ecommerce) got worse in Q2.

In [143…

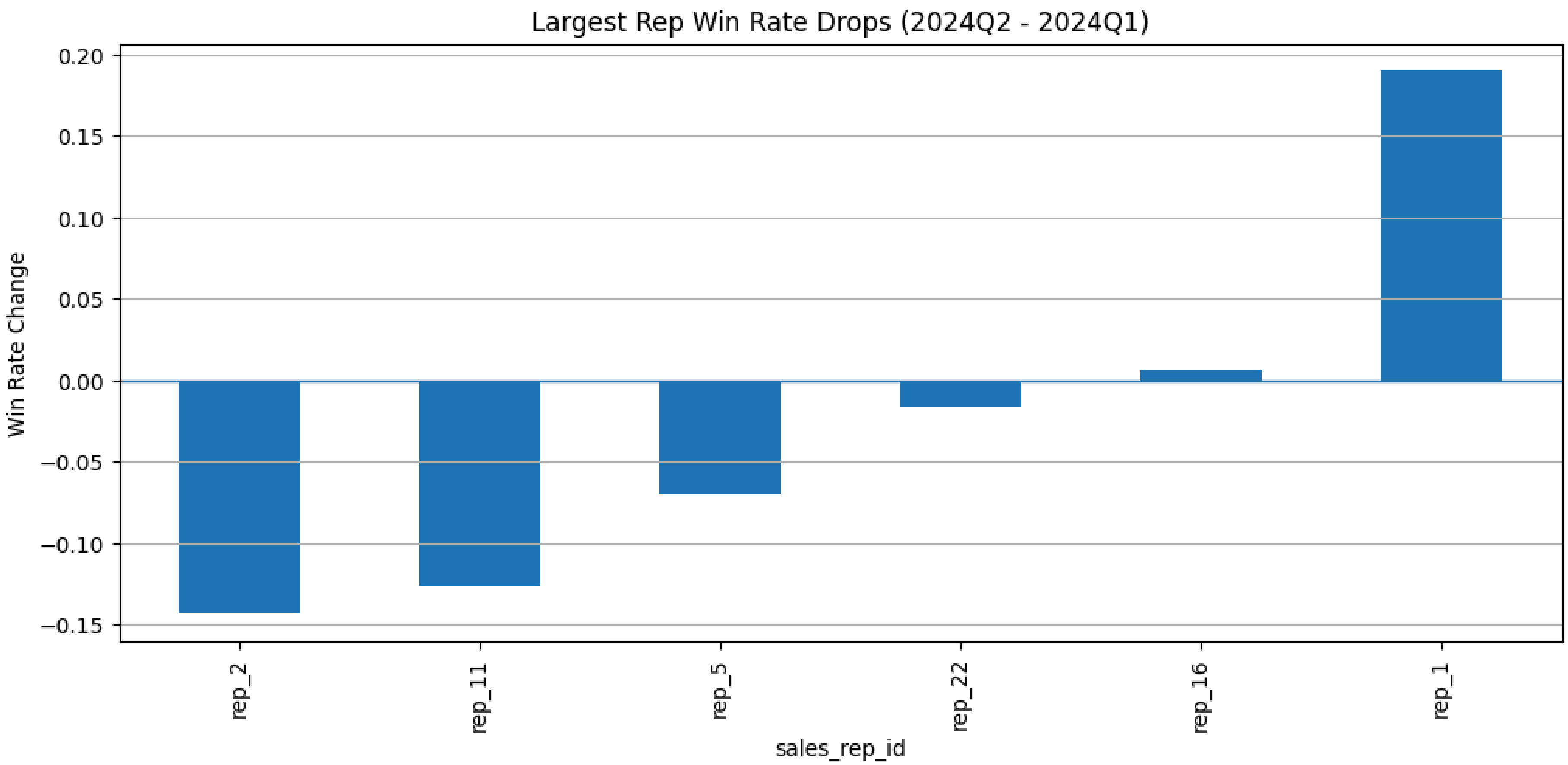
```
#sales rep quality
#win rate by rep/Q

rep_wr = win_rate_table(closed_df, ["closed_quarter", "sales_rep_id"])
rep_q2 = rep_wr[rep_wr["closed_quarter"].isin(["2024Q1", "2024Q2"])].copy()
rep_q2 = rep_q2[rep_q2["deals"] >= 30]  # filter small sample reps

#rep_q2.sort_values("win_rate").head(15)

pivot_rep = rep_q2.pivot(index="sales_rep_id", columns="closed_quarter", values="win_rate")
pivot_rep = pivot_rep.dropna()

pivot_rep["delta"] = pivot_rep["2024Q2"] - pivot_rep["2024Q1"]
pivot_rep = pivot_rep.sort_values("delta")

pivot_rep.head(15)
```

Out[143...

closed_quarter	2024Q1	2024Q2	delta
sales_rep_id			
rep_2	0.543478	0.400000	-0.143478
rep_11	0.459459	0.333333	-0.126126
rep_5	0.538462	0.468750	-0.069712
rep_22	0.405405	0.388889	-0.016517
rep_16	0.509434	0.516129	0.006695
rep_1	0.294118	0.483871	0.189753

In [144...

```
plt.figure(figsize=(12,5))
pivot_rep["delta"].head(15).plot(kind="bar")
plt.axhline(0, linewidth=1)
plt.title("Largest Rep Win Rate Drops (2024Q2 - 2024Q1)")
plt.ylabel("Win Rate Change")
plt.grid(True, axis="y")
plt.show()
```



In [145…

```
rep_detail = (
    closed_df[closed_df["closed_quarter"].isin(["2024Q1", "2024Q2"])]
    .groupby(["closed_quarter", "sales_rep_id"])
    .agg(
        deals=("deal_id", "count"),
        win_rate=("outcome", lambda x: (x == "Won").mean()),
        avg_amount=("deal_amount", "mean"),
        median_duration=("deal_duration_days", "median"),
    )
    .reset_index()
)
```

```
rep_detail[rep_detail["sales_rep_id"].isin(pivot_rep.head(5).index)]
```

Out[145…

	closed_quarter	sales_rep_id	deals	win_rate	avg_amount	median_duration
2	2024Q1	rep_11	37	0.459459	37283.405405	61.0
7	2024Q1	rep_16	53	0.509434	24479.264151	57.0
11	2024Q1	rep_2	46	0.543478	34997.000000	52.0
14	2024Q1	rep_22	37	0.405405	19677.135135	64.0
20	2024Q1	rep_5	39	0.538462	25913.743590	67.0
27	2024Q2	rep_11	39	0.333333	30677.179487	95.0
32	2024Q2	rep_16	31	0.516129	25662.387097	95.0
36	2024Q2	rep_2	30	0.400000	24958.700000	88.5
39	2024Q2	rep_22	36	0.388889	21451.666667	76.5
45	2024Q2	rep_5	32	0.468750	31411.875000	86.5

In addition to segment-level drivers, rep-level breakdown shows that some reps experienced significant declines in win rate between 2024Q1 and 2024Q2. For example, rep_11 declines from approximately 46% to 33% win rate, and rep_2 declines from approximately 54% to 40%. These declines coincide with sharp increases in median deal duration for those reps. However, since the overall company median deal duration also increased substantially in Q2, rep-level declines should be interpreted as part of a broader slowdown rather than an individual problem.

We also compute the median deal duration (closed_date − created_date). Between 2024Q1 and 2024Q2, median duration increases sharply (63 to 86 days). This might suggest a company-wide slowdown in deal velocity -- in B2B SaaS, longer deal cycles often correlate with lower win rates because deals lose momentum, customers delay decisions, and more deals stall before closing.

In [146…

```
overall_duration = (
    closed_df[closed_df["closed_quarter"].isin(["2024Q1", "2024Q2"])]
    .groupby("closed_quarter")["deal_duration_days"]
    .median()
)

overall_duration
```

Out[146…

```
closed_quarter
2024Q1    63.0
2024Q2    86.0
Name: deal_duration_days, dtype: float64
```

CUSTOM METRICS

% of deals taking > 90 days?

One of the most common early warning signs in B2B SaaS sales is deal stalling: when deals remain in the pipeline for an unusually long time before closing. Even if pipeline volume looks healthy, a rising number of stalled deals often indicate weaker momentum which might be seen as a reduction in win rate. To quantify the stalling, we look at the fraction of closed deals whose duration exceeds a fixed threshold (here, 90 days is chosen as most deals are expected to close within one quarter).

DEAL STALL RATE

As mentioned above, when deals start taking longer and losing momentum, the pipeline can still look “healthy” because deals are still being created, but fewer deals actually close successfully. Deal Stall Rate is meant to capture this, so instead of only looking at whether deals were won or lost, it measures whether the business is accumulating an unusually large number of long-running deals. As mentioned above, threshold is not meant to be a perfect universal cutoff.

$$\text{Deal Stall Rate} = P(\text{deal duration} > 90\text{days})$$

In a stable sales system, Deal Stall Rate should be relatively consistent quarter to quarter. If the business is healthy, it might fluctuate slightly but should not jump dramatically. If the sales process slows down, the rate typically increases, because more deals get stuck and take longer to resolve.

Please note, the analysis does not assume that every deal over 90 days is guaranteed to lose. The purpose is to measure whether the business is experiencing a shift toward longer-running deals.

In this dataset, the stall rate increases from approximately 25% in 2024Q1 to 43% in 2024Q2, indicating a sharp rise in long-running deals.

In [147…

```
temp = closed_df[closed_df["closed_quarter"].isin(["2024Q1","2024Q2"])].copy()
temp["over_90"] = temp["deal_duration_days"] > 90

over_ninety = (
    temp.groupby("closed_quarter")["over_90"]
    .mean()
)

over_ninety
```

Out[147…

```
closed_quarter
2024Q1    0.254545
2024Q2    0.430141
Name: over_90, dtype: float64
```

REVENUE WEIGHTED WIN RATE

standard win rate treats every deal as equally important. A 5K deal and a 50K deal both contribute equally to the win-rate calculation. In reality, losing one high-value deal can matter more than losing several low-value deals. For this reason, a second custom metric is introduced: Revenue Weighted win rate. This metric measures conversion in terms of total revenue value rather than deal count. It's computed by summing deal_amount separately for Won and Lost deals in each quarter.

$$\text{Revenue weighed WR} = \frac{\text{Revenue of Won deals}}{\sum \text{Revenue of Won deals} + \sum \text{Revenue of Lost deals}}$$

If this metric declines sharply, it suggests the company is losing a larger fraction of high-value revenue opportunities. This is a more severe business outcome than simply losing more deals. If standard win rate declines but ACV-weighted win rate remains stable, it suggests the company may be losing more low-value deals while still successfully converting higher-value deals. It is highly useful for prioritization.

In [148…

```
temp_rev = closed_df[closed_df["closed_quarter"].isin(["2024Q1","2024Q2"])].copy()

Rev_wr = (
    temp_rev.groupby(["closed_quarter", "outcome"])["deal_amount"]
    .sum()
    .reset_index()
)

Rev_pivot = (
    Rev_wr.pivot(index="closed_quarter", columns="outcome", values="deal_amount")
    .fillna(0)
)

Rev_pivot["Rev_weighted_win_rate"] = Rev_pivot["Won"] / (Rev_pivot["Won"] + Rev_pivot["Lost"])

Rev_pivot
```

Out[148…

outcome	Lost	Won	Rev_weighted_win_rate
closed_quarter			
2024Q1	13711434	12702445	0.480900
2024Q2	9490480	7518918	0.442045

This metric dropped from around 48.1% in 2024Q1 to 44.2% in 2024Q2. This suggests that the Q2 decline is not only a deal-count issue, it also reflects a shift toward losing a larger fraction of revenue value, meaning the drop likely mattered materially to the business.

P.S. the weighted win rate should be interpreted as a proportion, not as a total revenue comparison.

CATEGORY-ADJUSTED EXPECTED WIN RATE

Win rate can decrease for 2 general reasons: first, because the company's performance worsened within the same types of deals (for example, inbound deals used to convert at 49% but now convert at 41%). Second, even if performance did not change, simply because the mix of deals shifted toward segments that historically win less. This distinction is important because the action taken is either strategic or operational i.e, change targeting or improve execution.

This is a one-dimensional mix adjustment based on lead source; in production this could be extended to a multivariate expected win-rate model and is highly actionable. It estimates what win rate would be expected in Q2 if lead-source performance had stayed the same as Q1, given the lead sources we are closing deals from.

The metric is computed in two steps. First, baseline win rates are computed for each lead source using a baseline quarter (in this case, 2024Q1). This produces a reference win rate for inbound, outbound, partner, and referral. Second, the lead-source mix in the target quarter (2024Q2) is computed as the share of closed deals coming from each lead source. The expected win rate is then computed as a weighted average:

$$\text{Expected}WR_{Q2} = \sum share_{Q2} + winrate_{Q1}$$

In [149…

```
# baseline win rate per lead_source from Q1
base = lead_source_wr[lead_source_wr["closed_quarter"]=="2024Q1"].set_index("lead_source")["win_rate"]

# Q2 lead_source shares
q2 = lead_source_wr[lead_source_wr["closed_quarter"]=="2024Q2"].copy()
q2["share"] = q2["deals"] / q2["deals"].sum()

# expected Q2 win rate if lead_source performance stayed like Q1
expected_q2_wr = (q2["share"] * q2["lead_source"].map(base)).sum()

# actual Q2 win rate
actual_q2_wr = (q2["share"] * q2["win_rate"]).sum()

expected_q2_wr, actual_q2_wr, actual_q2_wr - expected_q2_wr
```

Out[149…

```
(0.4669000210352798, 0.4379905808477237, -0.028909440187556 09)
```

Even if Q2 had the exact same lead-source performance as Q1, the mix of lead sources would predict a Q2 win rate of ~46.7%. But the real Q2 win rate is only ~43.8%.

So about 2.9 percentage points of the drop can explained by lead sources performing worse.

DECISION ENGINE

WIN RATE DRIVER ANALYSIS

This decision engine is made to convert the exploratory analysis we did prior into a repeatable system that can answer the question: “What should the sales team focus on right now to improve outcomes?” The engine decomposes the win-rate change into segment-level drivers (lead source, industry, and sales rep).

The engine ranks segments not only by how much their win rate changed, but by how important they are to the business. This is necessary because a segment with a large win-rate drop might still have little impact if it represents only a small number of deals.

The engine computes an impact score for each segment defined as the segment’s win-rate change multiplied by its share of closed deals in Q2. This produces a prioritized list of drivers that are both -- performing worse -- large enough to materially influence overall performance.

For each segment (lead source, industry, sales rep), the engine computes:

- win rate in 2024Q1
- win rate in 2024Q2
- change in win rate (Q2 – Q1)
- share of closed deals in 2024Q2
- impact score, defined as:

$$\text{Impact} = (\text{win rate Q2 - win rate Q1}) \times (\text{Q2 share})$$

The engine also reports changes in median deal duration for each segment to identify whether declining performance coincides with slower deal velocity, which was a major pattern observed in Q2.

In [150…

```
#Lead source drivers

q1 = lead_source_wr[lead_source_wr["closed_quarter"]=="2024Q1"][["lead_source","deals","win_rate"]]
q2 = lead_source_wr[lead_source_wr["closed_quarter"]=="2024Q2"][["lead_source","deals","win_rate"]]

lead_drivers = q1.merge(q2, on="lead_source", suffixes=("_q1","_q2"))
lead_drivers["q2_share"] = lead_drivers["deals_q2"] / lead_drivers["deals_q2"].sum()
lead_drivers["delta_win_rate"] = lead_drivers["win_rate_q2"] - lead_drivers["win_rate_q1"]
lead_drivers["impact"] = lead_drivers["delta_win_rate"] * lead_drivers["q2_share"]

lead_drivers.sort_values("impact")
```

Out[150…

	lead_source	deals_q1	win_rate_q1	deals_q2	win_rate_q2	q2_share	delta_win_rate	impact
0	Inbound	254	0.488189	168	0.404762	0.263736	-0.083427	-0.022003
1	Outbound	260	0.453846	174	0.419540	0.273155	-0.034306	-0.009371
2	Partner	235	0.459574	129	0.418605	0.202512	-0.040970	-0.008297
3	Referral	241	0.464730	166	0.506024	0.260597	0.041294	0.010761

Inbound is a huge portion of deals, and it got substantially worse. Outbound and partner also decline, but with smaller impact. Referral improves significantly, meaning not all channels degraded in Q2.

In [151…

```
#Industry drivers

industry_wr = win_rate_table(closed_df, ["closed_quarter","industry"])

q1 = industry_wr[industry_wr["closed_quarter"]=="2024Q1"][["industry","deals","win_rate"]]
q2 = industry_wr[industry_wr["closed_quarter"]=="2024Q2"][["industry","deals","win_rate"]]

industry_drivers = q1.merge(q2, on="industry", suffixes=("_q1","_q2"))
industry_drivers["q2_share"] = industry_drivers["deals_q2"] / industry_drivers["deals_q2"].sum()
industry_drivers["delta_win_rate"] = industry_drivers["win_rate_q2"] - industry_drivers["win_rate_q1"]
industry_drivers["impact"] = industry_drivers["delta_win_rate"] * industry_drivers["q2_share"]

industry_drivers.sort_values("impact")
```

Out[151…

	industry	deals_q1	win_rate_q1	deals_q2	win_rate_q2	q2_share	delta_win_rate	impact
2	FinTech	191	0.507853	127	0.440945	0.199372	-0.066909	-0.013340
0	Ecommerce	207	0.478261	117	0.418803	0.183673	-0.059457	-0.010921
1	EdTech	203	0.443350	129	0.395349	0.202512	-0.048001	-0.009721
3	HealthTech	195	0.456410	130	0.461538	0.204082	0.005128	0.001047
4	SaaS	194	0.448454	134	0.470149	0.210361	0.021696	0.004564

Industry analysis shows that the Q2 decline is concentrated in specific industries. FinTech has the largest negative impact, driven by a meaningful win-rate drop and high deal share (~20%). Ecommerce and EdTech also show significant negative impact. Meanwhile, SaaS and HealthTech are stable or improving.

In [157…

```
#Rep drivers

rep_wr = win_rate_table(closed_df, ["closed_quarter","sales_rep_id"])

q1 = rep_wr[rep_wr["closed_quarter"]=="2024Q1"][["sales_rep_id","deals","win_rate"]]
q2 = rep_wr[rep_wr["closed_quarter"]=="2024Q2"][["sales_rep_id","deals","win_rate"]]

rep_drivers = q1.merge(q2, on="sales_rep_id", suffixes=("_q1","_q2"))
rep_drivers = rep_drivers[rep_drivers["deals_q2"] >= 30]  # avoid noise
rep_drivers["q2_share"] = rep_drivers["deals_q2"] / rep_wr[rep_wr["closed_quarter"]=="2024Q2"]["deals"].sum()
rep_drivers["delta_win_rate"] = rep_drivers["win_rate_q2"] - rep_drivers["win_rate_q1"]
rep_drivers["impact"] = rep_drivers["delta_win_rate"] * rep_drivers["q2_share"]

rep_drivers.sort_values("impact").head(10)
```

Out[157…

	sales_rep_id	deals_q1	win_rate_q1	deals_q2	win_rate_q2	q2_share	delta_win_rate	impact
2	rep_11	37	0.459459	39	0.333333	0.061224	-0.126126	-0.007722
11	rep_2	46	0.543478	30	0.400000	0.047096	-0.143478	-0.006757
20	rep_5	39	0.538462	32	0.468750	0.050235	-0.069712	-0.003502
14	rep_22	37	0.405405	36	0.388889	0.056515	-0.016517	-0.000933
7	rep_16	53	0.509434	31	0.516129	0.048666	0.006695	0.000326
0	rep_1	34	0.294118	31	0.483871	0.048666	0.189753	0.009234

Rep-level analysis highlights which pipelines experienced the largest conversion declines from Q1 to Q2. Several reps show substantial drops in win rate with meaningful Q2 deal volume (for example rep_11 and rep_2). The most practical use of rep-level outputs is to identify which pipelines should be reviewed first for stalling, qualification issues, or segment-specific challenges.

In [158…

```
top_lead = lead_drivers.sort_values("impact").head(2).copy()
top_lead["dimension"] = "lead_source"
top_lead = top_lead.rename(columns={"lead_source":"segment"})

top_industry = industry_drivers.sort_values("impact").head(3).copy()
top_industry["dimension"] = "industry"
top_industry = top_industry.rename(columns={"industry":"segment"})

top_rep = rep_drivers.sort_values("impact").head(5).copy()
top_rep["dimension"] = "sales_rep_id"
top_rep = top_rep.rename(columns={"sales_rep_id":"segment"})

final_drivers = pd.concat([top_lead, top_industry, top_rep], ignore_index=True)

final_drivers = final_drivers[
    ["dimension","segment","deals_q2","q2_share","win_rate_q1","win_rate_q2","delta_win_rate","impact"]
].sort_values("impact")

final_drivers
```

Out[158…

	dimension	segment	deals_q2	q2_share	win_rate_q1	win_rate_q2	delta_win_rate	impact
0	lead_source	Inbound	168	0.263736	0.488189	0.404762	-0.083427	-0.022003
2	industry	FinTech	127	0.199372	0.507853	0.440945	-0.066909	-0.013340
3	industry	Ecommerce	117	0.183673	0.478261	0.418803	-0.059457	-0.010921
4	industry	EdTech	129	0.202512	0.443350	0.395349	-0.048001	-0.009721
1	lead_source	Outbound	174	0.273155	0.453846	0.419540	-0.034306	-0.009371
5	sales_rep_id	rep_11	39	0.061224	0.459459	0.333333	-0.126126	-0.007722
6	sales_rep_id	rep_2	30	0.047096	0.543478	0.400000	-0.143478	-0.006757
7	sales_rep_id	rep_5	32	0.050235	0.538462	0.468750	-0.069712	-0.003502
8	sales_rep_id	rep_22	36	0.056515	0.405405	0.388889	-0.016517	-0.000933
9	sales_rep_id	rep_16	31	0.048666	0.509434	0.516129	0.006695	0.000326

In [159…

```
print("=== SkyGeni Decision Engine Output ===\n")

print("Main story:")
print("- Win rate dropped in 2024Q2 vs 2024Q1")
print("- Deal duration increased sharply (more stalled deals)")
print()

print("Top drivers by impact (largest contributors to decline):")
for _, row in final_drivers.iterrows():
    print(
        f"- [{row['dimension']}] {row['segment']}: "
        f"ΔWR={row['delta_win_rate']:.3f}, "
        f"share={row['q2_share']:.2f}, "
        f"impact={row['impact']:.4f}"
    )
```

```
=== SkyGeni Decision Engine Output ===

Main story:
- Win rate dropped in 2024Q2 vs 2024Q1
- Deal duration increased sharply (more stalled deals)

Top drivers by impact (largest contributors to decline):
- [lead_source] Inbound: ΔWR=-0.083, share=0.26, impact=-0.0220
- [industry] FinTech: ΔWR=-0.067, share=0.20, impact=-0.0133
- [industry] Ecommerce: ΔWR=-0.059, share=0.18, impact=-0.0109
- [industry] EdTech: ΔWR=-0.048, share=0.20, impact=-0.0097
- [lead_source] Outbound: ΔWR=-0.034, share=0.27, impact=-0.0094
- [sales_rep_id] rep_11: ΔWR=-0.126, share=0.06, impact=-0.0077
- [sales_rep_id] rep_2: ΔWR=-0.143, share=0.05, impact=-0.0068
- [sales_rep_id] rep_5: ΔWR=-0.070, share=0.05, impact=-0.0035
- [sales_rep_id] rep_22: ΔWR=-0.017, share=0.06, impact=-0.0009
- [sales_rep_id] rep_16: ΔWR=0.007, share=0.05, impact=0.0003
```

Each line in the output represents a segment (such as a lead source, industry, or sales rep) and includes three key pieces of information. The first is the win-rate change for that segment (ΔWR), which measures how much the segment's win rate increased or decreased from Q1 to Q2. The second is the segment's share of Q2 closed deals, which measures how large the segment is in the business. The third is an impact score.

This impact score is not meant to be a causal estimate, only a heuristic factor: segments with large declines and large deal share will appear at the top of the list because they are more likely to materially influence overall company performance.

The output shows that the largest negative driver is Inbound lead source, which experienced a meaningful win-rate drop (ΔWR ≈ −8.3 percentage points) while also representing a large share of Q2 closed deals (~26%). FinTech, Ecommerce, and EdTech are the top negative industry drivers, each representing roughly ~18–20% of Q2 deals and showing meaningful win-rate declines. Rep-level drivers also appear in the list but have smaller impact scores than inbound or the top industries because each rep represents only ~5–6% of the Q2 closed deal volume.

ACTIONABLES

1. Investigate inbound quality and qualification
2. Prioritize FinTech / Ecommerce / EdTech enablement
3. Run a targeted stalled-deal review
4. Preserve what is working

A CRO could use this decision engine output as a weekly or monthly prioritization dashboard. The top drivers provide a ranked shortlist of where attention is likely to have the largest impact. For example, the output suggests the CRO should focus first on inbound conversion decline, FinTech performance decline, and the pipelines of reps. The CRO could then use the supporting EDA results to decide what interventions to try.

In [ ]: