Wise Assets Conversion & Growth Analysis

Walid Bayoud – Analytics Intern Candidate

Funnel Steps

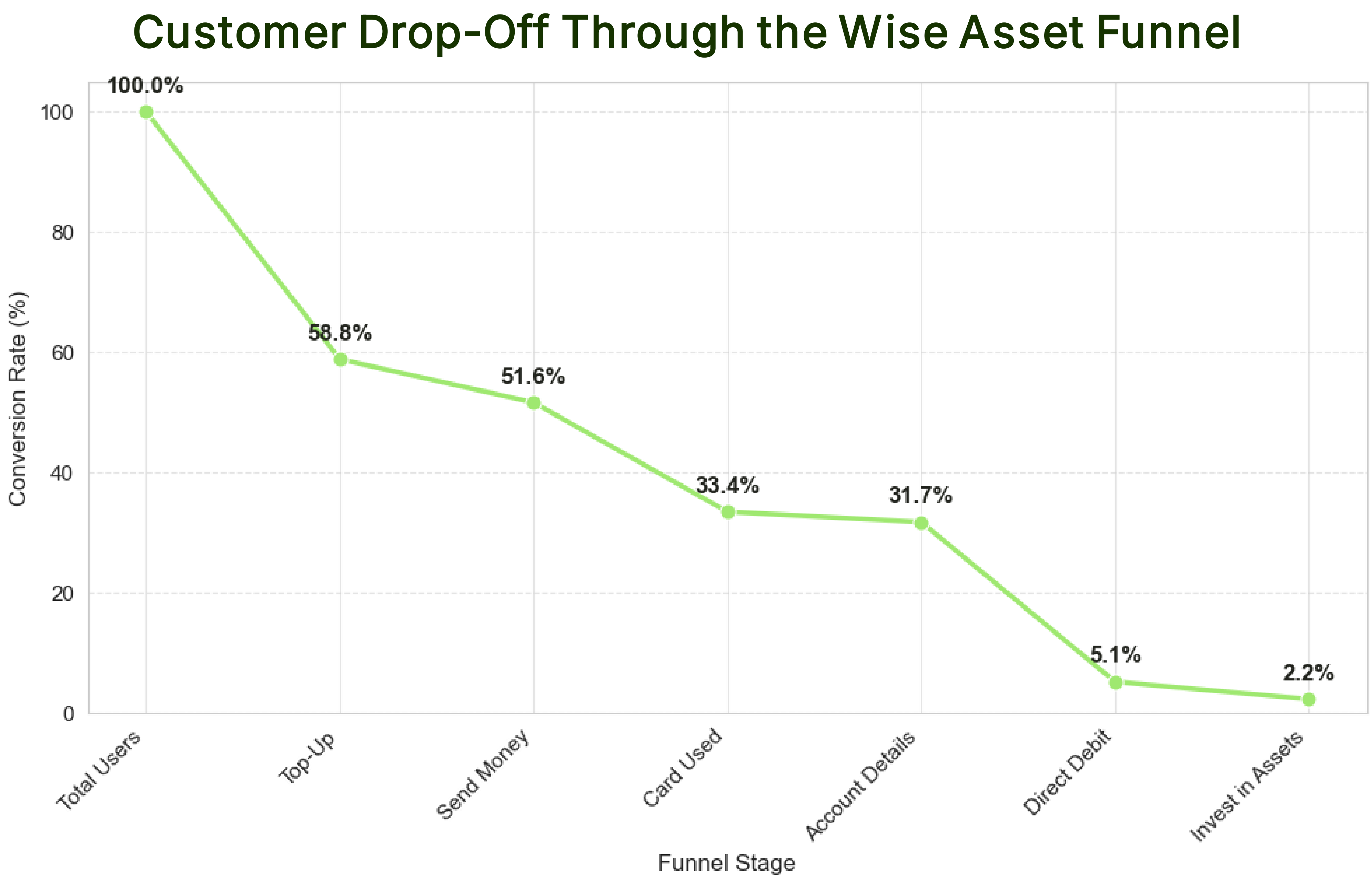
1. Profile Created
2. First Top-Up/ Balance
3. First Send
4. First Card Transaction
5. First Account Details Request
6. First Direct Debit
7. Invest In Assets

2.25%

conversion rate to Assets

Conversion Funnel Overview

- 41% of users sign up but never Top-Up
- Top-Up incentives could reduce this major drop-off



Seaborn line plot visualizing conversion funnel stages.

Factors driving conversion rates to Assets

Personal vs. Business Users

1.91%

Personal

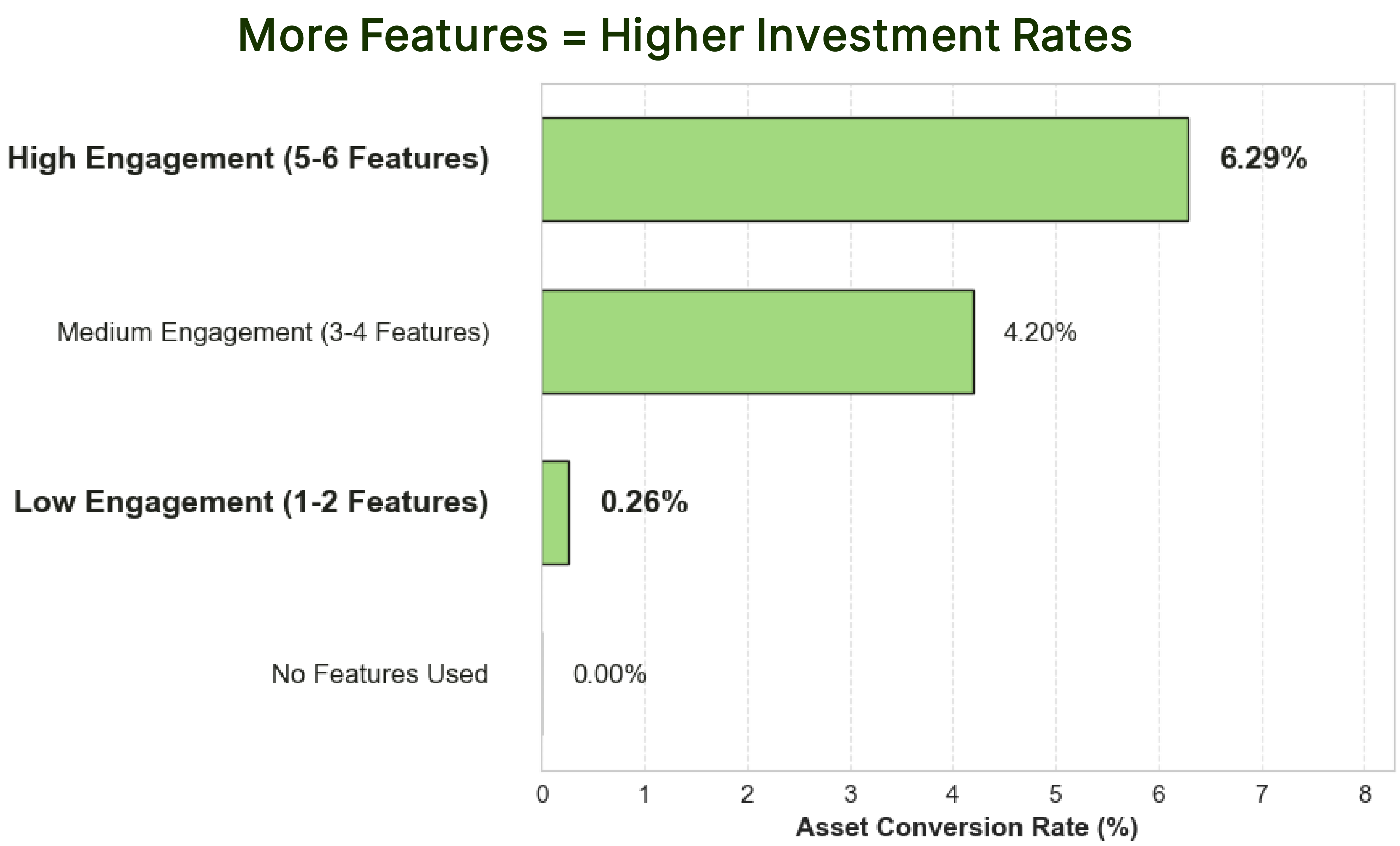
4.16%

Business

Early vs. Late Users

1.99%
Q1'23

2.51%
Q2'23



Seaborn bar plot of asset conversion rates by engagement level.

High vs. Low Engagement Users

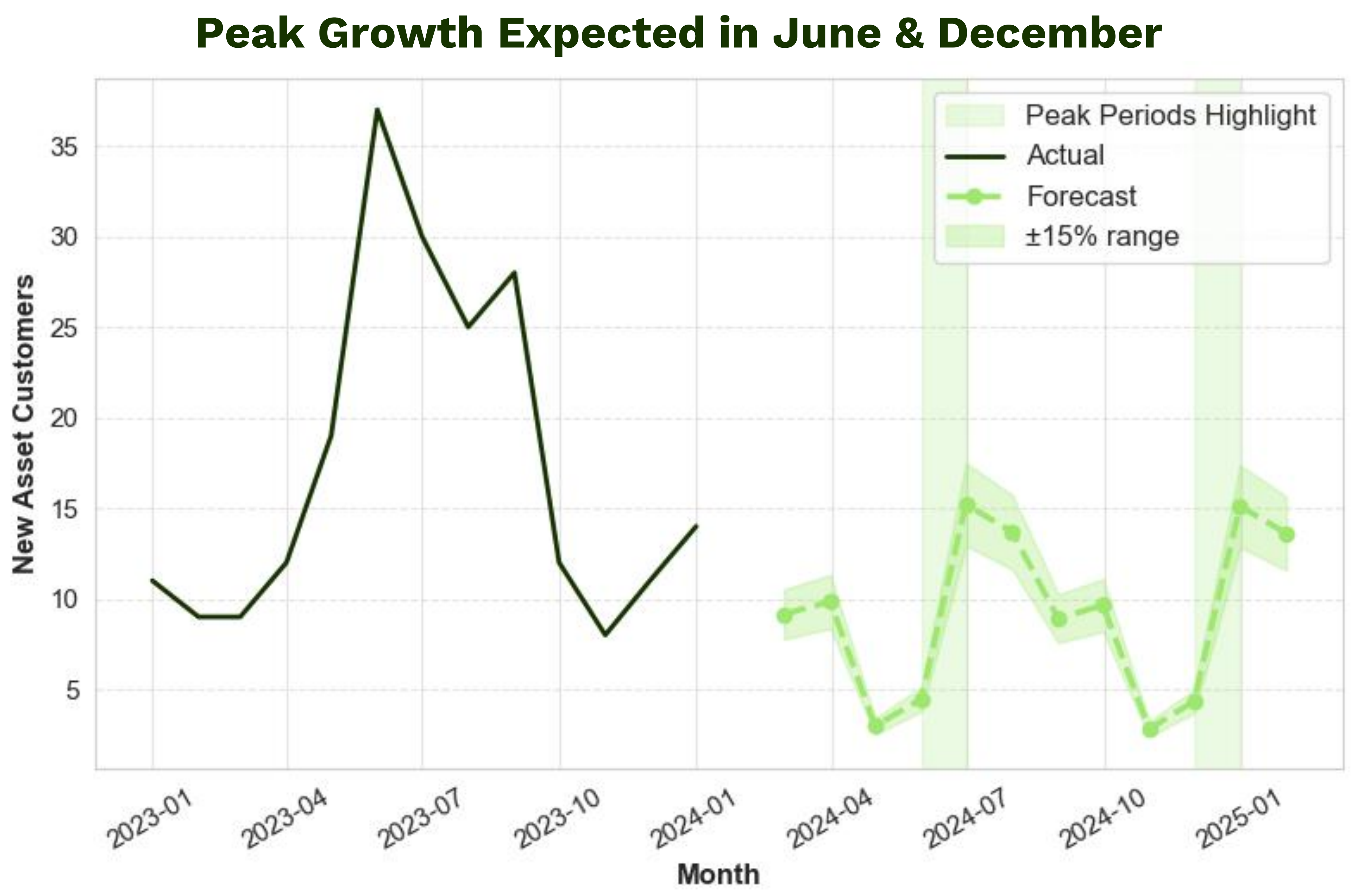
24x

more likely to invest

Forecasting Asset Adoption & Total Holdings

Forecasting Asset Adoption

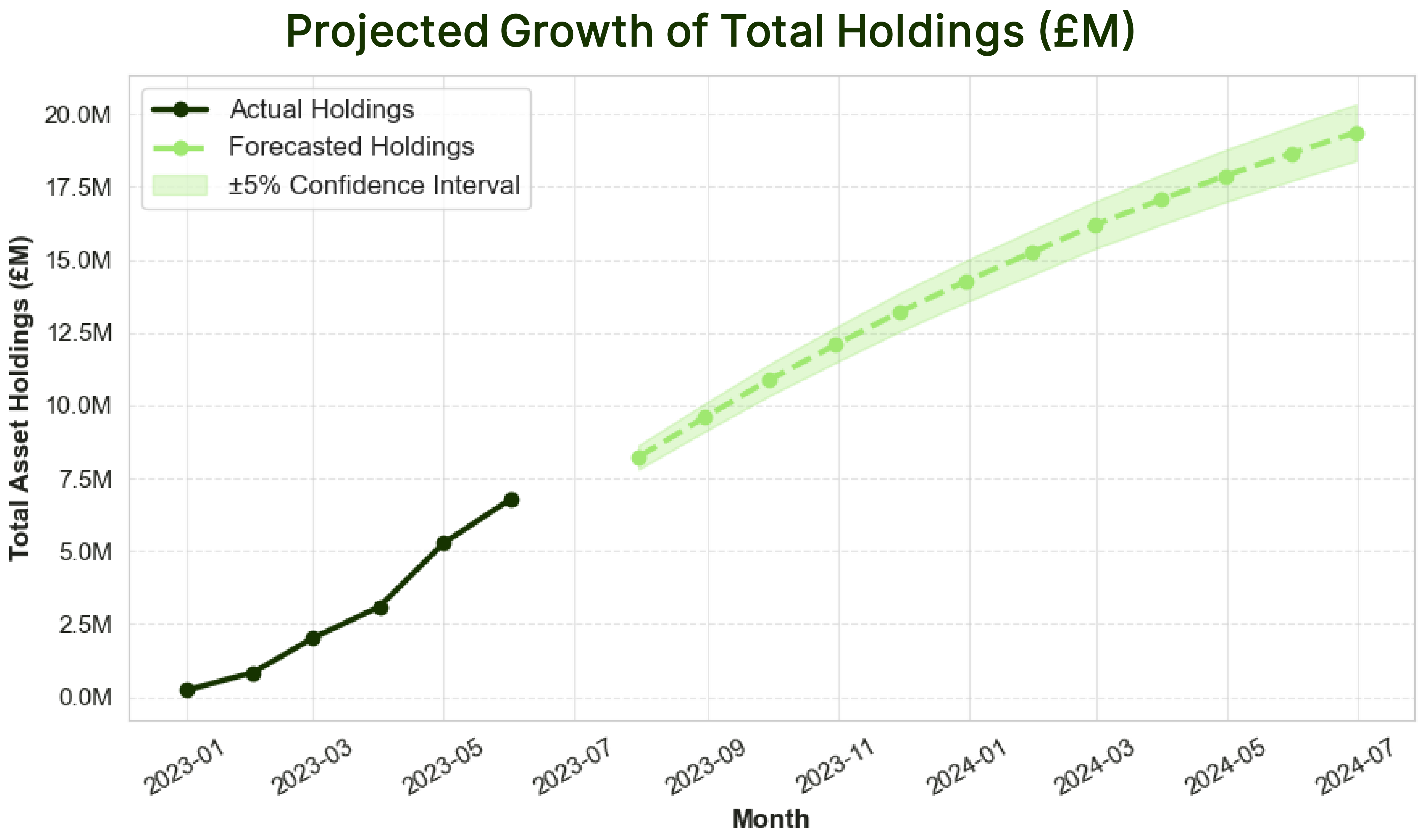
- 5 to 18 new asset customers per month, with surges every 3 months
- Maximize acquisition efforts ahead of June and December peaks



12-month forecast using Holt-Winters with 6-month seasonality

Forecasting Total Holdings

- Total holdings projected to reach £19.37M by June 2024.
- £1M MoM growth reinforces a stable upward trend.



12-month forecast using ARIMA (1,1,1) model

Wise Assets: Conversion & Forecast

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Objective

Analyze **Assets adoption**, key **conversion trends**, and growth opportunities.

Focus Areas

- **Customer Funnel:** Track user progression to Assets.
- **Conversion Drop-offs:** Identify friction points.
- **Growth Forecasting:** Predict future investors.
- **Business Strategy:** Optimize engagement and adoption.

Business Context

Wise is expanding beyond **money transfers** into **investments**. Understanding user behavior helps refine **onboarding, marketing, and product strategy** to drive **Assets adoption**.

Executive Summary: Wise Assets Conversion & Forecast

Key Insights

- **2.25%** of users progress from sign-up to investing in Wise Assets.
- **59%** drop-off at the **Top-Up** stage — the most significant loss point.
- Business users convert better (**4.16%**) than personal users (**1.91%**).
- Newer users have higher conversion rates (Q2: **2.52%** vs. Q1: **1.99%**).

Key Findings

1. **Conversion Bottlenecks:**
    - Major drop-off from sign-up to top-up.

- Users engaged with **5-6 features** convert **24x** more than low-engagement users.

2. **High-Impact Features:**
   - **Direct Debit** users have the highest conversion rate (**8.09%**).
   - **Send Money-first** users are least likely to invest (**0.70%**).
3. **Forecasted Growth:**
   - Predicted fluctuation in Q2 2024 (~**3 users in April**).
   - Peaks in **June** and **December** signal strategic marketing opportunities.
4. **Total Holdings Forecast:**
   - Expected growth from **£6.77M** (June 2023) to **£19.37M** (June 2024).

Strategic Recommendations

1. **Address Top-Up Drop-offs:** Improve onboarding, offer incentives.
2. **Boost Personal User Conversion:** Target them with cashback or APY bonuses.
3. **Leverage Feature Adoption:** Encourage early feature use to drive engagement.
4. **Capitalize on Peaks:** Align marketing campaigns with **June** and **December** spikes.
5. **Re-engage Older Users:** Email campaigns, targeted incentives, and app notifications.

Data Preparation

We use an SQLite database containing three key tables:

- `profile_lifetime_activity` – Each user's lifecycle events (e.g., date of first transaction, first card use, first asset investment).
- `profile_historical_holdings_monthly` – Monthly snapshots of customers' asset holdings (total value, equity portion, interest earned).
- `profiles_onboarded_monthly` – Aggregated count of new customer profiles created each month.

Importing Libraries

In [233…

```
import sqlite3
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.patches as patches
import matplotlib.ticker as mtick
import seaborn as sns
from statsmodels.tsa.holtwinters import ExponentialSmoothing
import warnings
```

Connecting to SQLite

In [234…

```
# Connect to SQLite database
conn = sqlite3.connect("wise_data.sqlite")

# Load tables into DataFrames
profile_lifetime_activity = pd.read_sql("SELECT * FROM profile_lifetime_acti
profile_historical_holdings_monthly = pd.read_sql("SELECT * FROM profile_his
profiles_onboarded_monthly = pd.read_sql("SELECT * FROM profiles_onboarded_m

print(profile_lifetime_activity.shape, profile_historical_holdings_monthly.s
```

```
(10000, 11) (18010, 8) (10, 3)
```

Set Wise Brand Colors

In [235…

```
# Set Wise brand style for visualizations
WISE_BRIGHT_GREEN = "#9FE870"   # Wise primary green
WISE_FOREST_GREEN = "#163300"   # Darker green for contrast
WISE_DARK_CHARCOAL = "#21231D"  # Neutral dark for text and grid

sns.set_style("whitegrid")
plt.rcParams.update({
    "axes.titlesize": 14,
    "axes.labelsize": 12,
    "xtick.labelsize": 11,
    "ytick.labelsize": 11,
    "grid.alpha": 0.5
})
warnings.filterwarnings("ignore")
```

1. Conversion Rate Analysis

🟩**a.** Customer Funnel

Funnel Definition:

We define key stages in the Wise customer funnel leading up to Assets:

1. **Profile Created** – user signs up for a Wise account.
2. **First Top-Up/Balance** – first time the user adds money to their Wise account (or receives a balance).
3. **First Send** – first money transfer sent via Wise.
4. **First Card Transaction** – first purchase or ATM withdrawal using the Wise card.
5. **First Account Details Request** – first time the user requests local account details.
6. **First Direct Debit** – first direct debit set up by the user.

7. **Invests in Assets** – user makes their first investment in Wise Assets.

By analyzing conversion at each step, we can identify where users drop off before reaching the **Assets** stage.

In [236…

```
# SQL Query to calculate conversion rates at each funnel step
query = """
WITH conversion_counts AS (
    SELECT
        COUNT(DISTINCT profile_id) AS total_users,
        COUNT(DISTINCT CASE WHEN first_top_up IS NOT NULL THEN profile_id EN
        COUNT(DISTINCT CASE WHEN first_send IS NOT NULL THEN profile_id END)
        COUNT(DISTINCT CASE WHEN first_card IS NOT NULL THEN profile_id END)
        COUNT(DISTINCT CASE WHEN first_account_details IS NOT NULL THEN prof
        COUNT(DISTINCT CASE WHEN first_direct_debit IS NOT NULL THEN profile
        COUNT(DISTINCT CASE WHEN first_assets IS NOT NULL THEN profile_id EN
    FROM profile_lifetime_activity
)
SELECT
    total_users AS "Total Users",
    ROUND(100.0 * top_up_users / total_users, 2) AS "Sign-up to Top-up (%)",
    ROUND(100.0 * send_users / total_users, 2) AS "Sign-up to Send (%)",
    ROUND(100.0 * card_users / total_users, 2) AS "Sign-up to Card (%)",
    ROUND(100.0 * account_details_users / total_users, 2) AS "Sign-up to Acc
    ROUND(100.0 * direct_debit_users / total_users, 2) AS "Sign-up to Direct
    ROUND(100.0 * assets_users / total_users, 2) AS "Sign-up to Assets (%)"
FROM conversion_counts;
"""

conversion_rates = pd.read_sql(query, conn)
conversion_rates
```

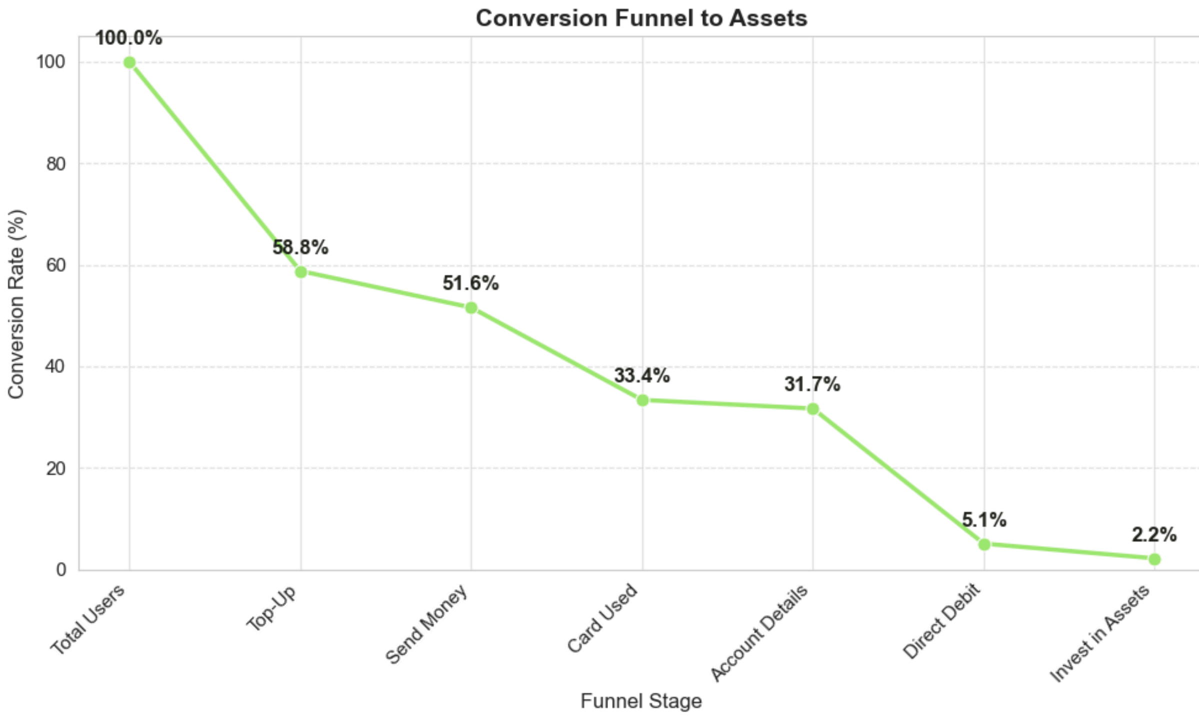
Out[236…

	Total Users	Sign-up to Top-up (%)	Sign-up to Send (%)	Sign-up to Card (%)	Sign-up to Account Details (%)	Sign-up to Direct Debit (%)	Sign-up to Assets (%)
0	10000	58.79	51.65	33.36	31.72	5.07	2.25

In [251…

```
#Seaborn line plot visualizing conversion funnel stages

plt.figure(figsize=(10, 6))

# Add markers
sns.lineplot(x=steps, y=conversion_rates_list, marker="o", linestyle="-", ma

# Add percentages
for i, rate in enumerate(conversion_rates_list):
    plt.annotate(f"{rate:.1f}%", (steps[i], rate), textcoords="offset points
                 fontsize=12, fontweight="bold", color=WISE_DARK_CHARCOAL)

plt.title("Conversion Funnel to Assets", fontweight="bold")
plt.xlabel("Funnel Stage")
plt.ylabel("Conversion Rate (%)")
plt.xticks(rotation=45, ha='right')
```

```
plt.ylim(0, 105)
plt.grid(axis="y", linestyle="--", alpha=0.5)
plt.tight_layout()


plt.show()
```



Conversion Funnel Analysis

Major Drop-Off Points

Stage	Conversion Rate (%)	Fix & Impact
Sign-up → First Top-up	59% (-41%)	**Better onboarding + incentives** to recover up to **15% losses**.
Top-up → Send Money	93% (-7%)	**Highlight Wise's low fees & speed** at top-up confirmation.
Send → Card Usage	75% (-18%)	**Push Wise card benefits** in post-transfer UI.
Direct Debit → Assets	**2.25%** (-3%)	**Auto-invest options + higher APY incentives**.

💡 **Takeaway:** Fixing **top-ups** is the **fastest way** to increase Asset adoption.

🟩**b.** Factors driving conversion rates to Assets

Personal vs. Business Users

Why It Matters

- Business and personal users engage differently.
- Businesses may invest more due to multi-currency needs.
- If businesses convert higher, Wise should refine marketing to boost personal user adoption.

In [238…

```
# Conversion rates by user segment (Personal vs Business)
query = """
SELECT
    class AS user_type,  -- Consumer vs. Business
    COUNT(profile_id) AS total_users,
    COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_id END) AS asset_u
    ROUND(100.0 * COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_id E
FROM profile_lifetime_activity
GROUP BY class;
"""

segment_analysis = pd.read_sql(query, conn)
segment_analysis
```

Out[238…

	user_type	total_users	asset_users	asset_conversion_rate
0	Business	1513	63	4.16
1	Personal	8487	162	1.91

Key Findings

- **Business Users Convert More: 4.16%** vs. **1.91%** for personal users.
- **Personal Users Are the Majority:** They dominate Wise's user base.
- **Why?** Businesses hold larger balances and seek yield, making them more likely to invest.

Business Implications

- **Target Personal Users:** Largest untapped opportunity.
- **Incentives Needed:** Offer interest boosts or cashback to drive adoption.

Early vs. Late Users

Why It Matters

- **Higher conversion in newer users** suggests onboarding improvements are working.
- **Lower adoption in older users** signals a need for re-engagement.
- **Cohort insights** help refine marketing and product strategy.

In [239…

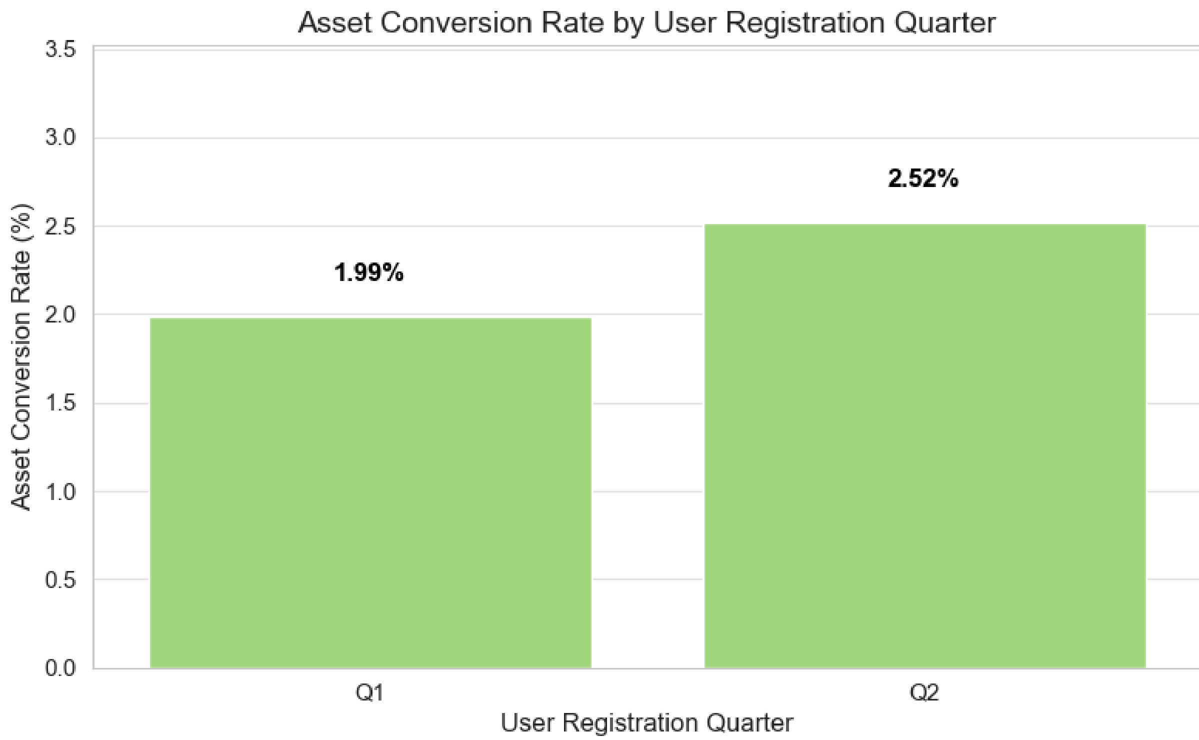
```
# Analyze asset conversion by user registration period
query = """
SELECT
    CASE
        WHEN strftime('%m', profile_created) IN ('01', '02', '03') THEN 'Q1'
        WHEN strftime('%m', profile_created) IN ('04', '05', '06') THEN 'Q2'
    END AS user_registration_quarter,
    COUNT(DISTINCT profile_id) AS total_users,
    COUNT(DISTINCT CASE WHEN first_assets IS NOT NULL THEN profile_id END) A
    ROUND(100.0 * COUNT(DISTINCT CASE WHEN first_assets IS NOT NULL THEN pro
FROM profile_lifetime_activity
GROUP BY user_registration_quarter
ORDER BY asset_conversion_rate DESC;


"""

registration_analysis = pd.read_sql(query, conn)
registration_analysis
```

Out[239…

	user_registration_quarter	total_users	asset_users	asset_conversion_rate
0	Q2	4926	124	2.52
1	Q1	5074	101	1.99

In [240…

```
registration_analysis = pd.read_sql(query, conn)

# Convert query output to DataFrame
df = registration_analysis.sort_values("user_registration_quarter")

plt.figure(figsize=(8, 5))
ax = sns.barplot(x="user_registration_quarter", y="asset_conversion_rate", c

# Add percentages
for i, val in enumerate(df["asset_conversion_rate"]):
    ax.text(i, val + 0.2, f"{val:.2f}%", ha='center', fontsize=12, fontweigh

plt.xlabel("User Registration Quarter")
plt.ylabel("Asset Conversion Rate (%)")
plt.title("Asset Conversion Rate by User Registration Quarter")
plt.ylim(0, max(df["asset_conversion_rate"]) + 1)  # add space above bars
plt.tight_layout()
plt.show()
```



Key Findings

- **Newer users convert at higher rates:**
  - **Q1: 1.99%**
  - **Q2: 2.52%**
- **Why?**
  - **Improved onboarding** drives early engagement.
  - **Recent marketing** better promotes Assets.
  - New users are **more financially engaged** from the start.

Business Implications

- **Re-engage older users** via email and app notifications.
- **Test time-limited incentives**: *“Invest in your first 90 days and get a bonus return!”*

Feature Usage (count) vs. Asset Conversion

Why It Matters

- **More engaged users invest more** → Wise should drive early feature adoption.
- **Low-engagement users rarely invest** → Targeted nudges may increase activity.
- **Identifying key features** can refine Wise’s marketing strategy.

In [241…

```
# Analyze conversion based on the number of Wise features used
query = """
WITH user_feature_counts AS (
    SELECT
        profile_id,
        -- Count the number of Wise features a user has engaged with
        (
          CASE WHEN first_send IS NOT NULL THEN 1 ELSE 0 END +
          CASE WHEN first_balance IS NOT NULL THEN 1 ELSE 0 END +
          CASE WHEN first_top_up IS NOT NULL THEN 1 ELSE 0 END +
          CASE WHEN first_account_details IS NOT NULL THEN 1 ELSE 0 END +
          CASE WHEN first_direct_debit IS NOT NULL THEN 1 ELSE 0 END +
          CASE WHEN first_card IS NOT NULL THEN 1 ELSE 0 END
        ) AS feature_count,
        first_assets  -- Track users who invested in assets
    FROM profile_lifetime_activity
)

SELECT
    CASE
      WHEN feature_count = 0 THEN 'No Features Used'
      WHEN feature_count BETWEEN 1 AND 2 THEN 'Low Engagement (1-2 Features)
      WHEN feature_count BETWEEN 3 AND 4 THEN 'Medium Engagement (3-4 Featur
      ELSE 'High Engagement (5-6 Features)'
    END AS engagement_level,
    COUNT(profile_id) AS total_users,
    COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_id END) AS asset_u
    ROUND(100.0 * COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_id E
FROM user_feature_counts
GROUP BY engagement_level
ORDER BY asset_conversion_rate DESC;


"""

engagement_level_analysis = pd.read_sql(query, conn)
engagement_level_analysis
```

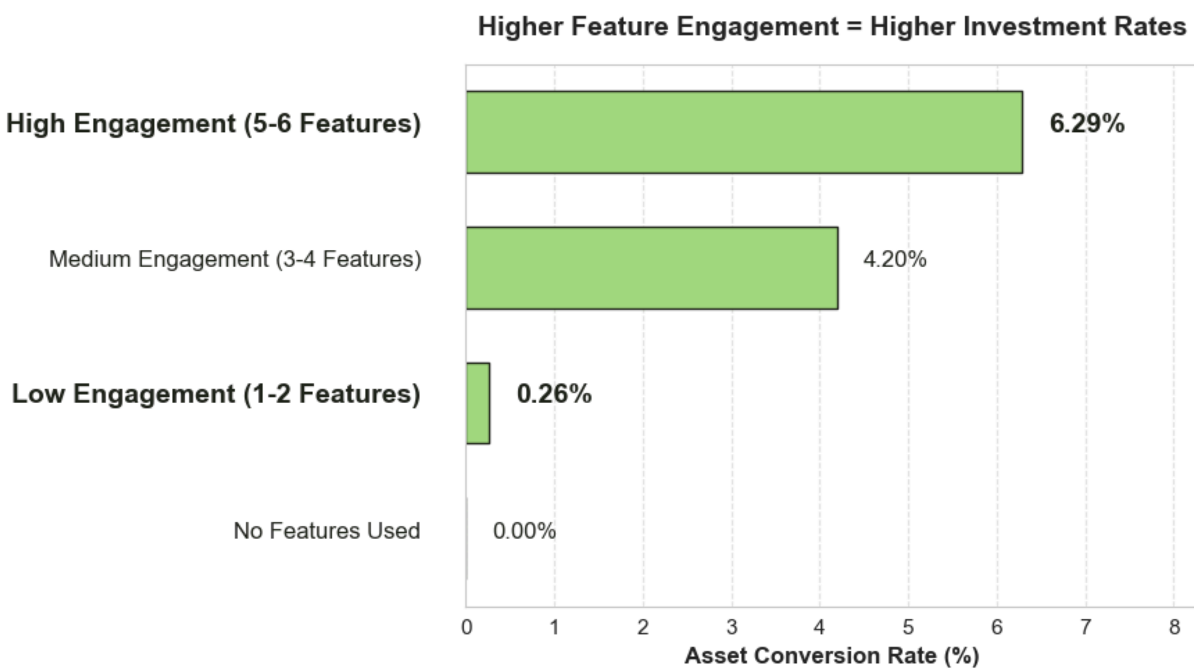
Out[241…

	engagement_level	total_users	asset_users	asset_conversion_rate
0	High Engagement (5-6 Features)	700	44	6.29
1	Medium Engagement (3-4 Features)	3974	167	4.20
2	Low Engagement (1-2 Features)	5314	14	0.26
3	No Features Used	12	0	0.00

In [253…

```
plt.figure(figsize=(9, 5))


ax = sns.barplot(
```

```
    y="engagement_level",
    x="asset_conversion_rate",
    data=engagement_level_analysis,
    color=WISE_BRIGHT_GREEN,
    edgecolor=WISE_DARK_CHARCOAL,
    width=0.6
)

# Make "High Engagement" and "Low Engagement" Bold
for i, val in enumerate(engagement_level_analysis["asset_conversion_rate"]):
    label = engagement_level_analysis["engagement_level"].iloc[i]
    font_size = 14 if label in ["High Engagement (5-6 Features)", "Low Engag
    font_weight = "bold" if label in ["High Engagement (5-6 Features)", "Low

    ax.text(val + 0.3, i, f"{val:.2f}%", ha='left', fontsize=font_size, font
    ax.text(-0.5, i, label, ha="right", fontsize=font_size, fontweight=font_

plt.xlabel("Asset Conversion Rate (%)", fontsize=12, fontweight="bold")

plt.ylabel("")
plt.title("Higher Feature Engagement = Higher Investment Rates", fontsize=14

plt.xlim(0, max(engagement_level_analysis["asset_conversion_rate"]) + 2)
plt.xticks(fontsize=11)
plt.yticks([])
plt.grid(axis='x', linestyle="--", alpha=0.5)
plt.tight_layout()

plt.show()
```



Feature Engagement & Asset Conversion

Key Findings

Feature Engagement Level	Asset Conversion Rate (%)
5-6 features	**6.29%**
3-4 features	**4.20%**
1-2 features	**0.26%**
0 features	**0.00%**

Impact of Feature Adoption

- Moving from **1-2 to 3-4 features** increases conversion **from 0.26% to 4.20%**.
- Users with **5-6 features convert 24x more than users with 1-2 features**.

Business Implications

- Encourage feature adoption early to drive investment.
- Nurture medium-engagement users with investment nudges.
- Offer exclusive benefits to high-engagement users.
- Incentivize low-engagement users with fee discounts or first-time bonuses.

Feature Usage (type) vs. Asset Conversion

This section examines how specific Wise features influence investment behavior.

Why It Matters

- Certain features may drive **higher investment conversion**.
- Identifying these features helps Wise **prioritize promotion**.
- Users engaging with key features may be **better investment targets**.

In [243…

```
# SQL query to analyze asset conversion rates by specific feature usage
query = """
WITH feature_analysis AS (
    SELECT
        'First Direct Debit Usage' AS feature,
        COUNT(profile_id) AS total_users,
        COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_id END) AS ass
        ROUND(100.0 * COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_
    FROM profile_lifetime_activity
    WHERE first_direct_debit IS NOT NULL

    UNION ALL

    SELECT
        'First Account Details Requested',
        COUNT(profile_id),
        COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_id END),
```

```
        ROUND(100.0 * COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_
    FROM profile_lifetime_activity
    WHERE first_account_details IS NOT NULL

    UNION ALL

    SELECT
        'First Card Usage',
        COUNT(profile_id),
        COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_id END),
        ROUND(100.0 * COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_
    FROM profile_lifetime_activity
    WHERE first_card IS NOT NULL

    UNION ALL

    SELECT
        'First Top-Up & Balance',
        COUNT(profile_id),
        COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_id END),
        ROUND(100.0 * COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_
    FROM profile_lifetime_activity
    WHERE first_top_up IS NOT NULL AND first_balance IS NOT NULL

    UNION ALL

    SELECT
        'First Send Money',
        COUNT(profile_id),
        COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_id END),
        ROUND(100.0 * COUNT(CASE WHEN first_assets IS NOT NULL THEN profile_
    FROM profile_lifetime_activity
    WHERE first_send IS NOT NULL
)

SELECT * FROM feature_analysis ORDER BY asset_conversion_rate DESC;

"""
feature_conversion = pd.read_sql(query, conn)
feature_conversion
```

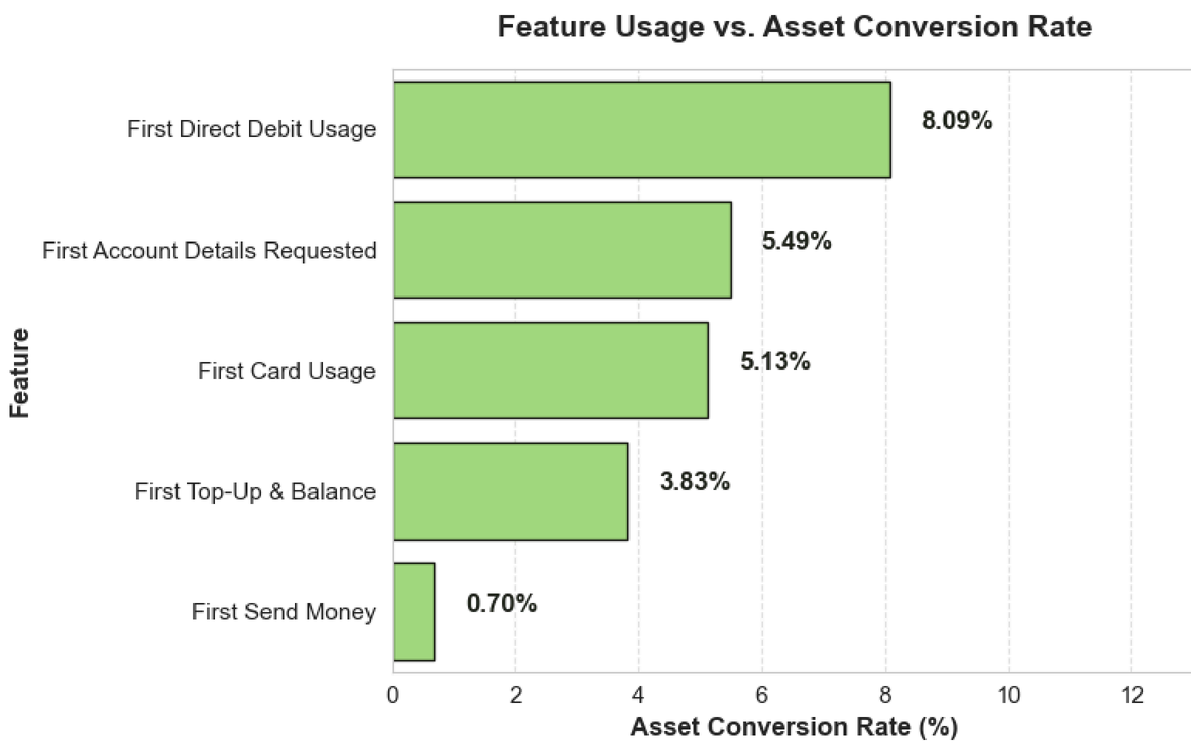
Out[243…

	feature	total_users	asset_users	asset_conversion_rate
0	First Direct Debit Usage	507	41	8.09
1	First Account Details Requested	3172	174	5.49
2	First Card Usage	3336	171	5.13
3	First Top-Up & Balance	5879	225	3.83
4	First Send Money	5165	36	0.70

In [244…

```
feature_conversion = feature_conversion.sort_values(by="asset_conversion_rat

plt.figure(figsize=(8, 5))
```

```
ax = sns.barplot(
    x="asset_conversion_rate",
    y="feature",
    data=feature_conversion,
    color=WISE_BRIGHT_GREEN,
    edgecolor=WISE_DARK_CHARCOAL
)

# Add percentages
for i, val in enumerate(feature_conversion["asset_conversion_rate"]):
    ax.text(val + 0.5, i, f"{val:.2f}%", ha='left', fontsize=12, fontweight=

plt.xlabel("Asset Conversion Rate (%)", fontsize=12, fontweight="bold")
plt.ylabel("Feature", fontsize=12, fontweight="bold")
plt.title("Feature Usage vs. Asset Conversion Rate", fontsize=14, fontweight

plt.xlim(0, max(feature_conversion["asset_conversion_rate"]) + 5)  # Extra s
plt.xticks(fontsize=11)
plt.yticks(fontsize=11)
plt.grid(axis='x', linestyle="--", alpha=0.5)
plt.tight_layout()

plt.show()
```



Key Findings

- **Direct Debit users convert the most (8.09%)** → Strongest investment link.
- **Account Details users (5.49%)** → Setup engagement correlates with investing.

- **Card Users (5.13%)** → Financially engaged but need more incentives.
- **Top-Up & Balance users (3.83%)** → View Wise as a spending tool.
- **Send Money-first users (0.70%)** → Least likely to invest.

Takeaway

- **Direct Debit and Account Details usage** signal higher investment potential.
- **Send Money-first users are unlikely to invest.**

🟩 Forecasting Asset Adoption

Why It Matters

- Anticipates **future demand** for Assets.
- Identifies **growth trends** and slowdowns.
- Informs **marketing and acquisition strategies**.

In [245…

```
# SQL query to extract the number of customers who invested in assets per mo
query = """
SELECT
    strftime('%Y-%m', FIRST_ASSETS) AS month,
    COUNT(PROFILE_ID) AS new_asset_customers
FROM profile_lifetime_activity
WHERE FIRST_ASSETS IS NOT NULL
GROUP BY month
ORDER BY month;
"""

new_asset_customers = pd.read_sql(query, conn)

# Convert to datetime format
new_asset_customers["month"] = pd.to_datetime(new_asset_customers["month"])
new_asset_customers.set_index("month", inplace=True)
new_asset_customers
```

Out[245…

month	new_asset_customers
2023-01-01	11
2023-02-01	9
2023-03-01	9
2023-04-01	12
2023-05-01	19
2023-06-01	37
2023-07-01	30
2023-08-01	25
2023-09-01	28
2023-10-01	12
2023-11-01	8
2023-12-01	11
2024-01-01	14

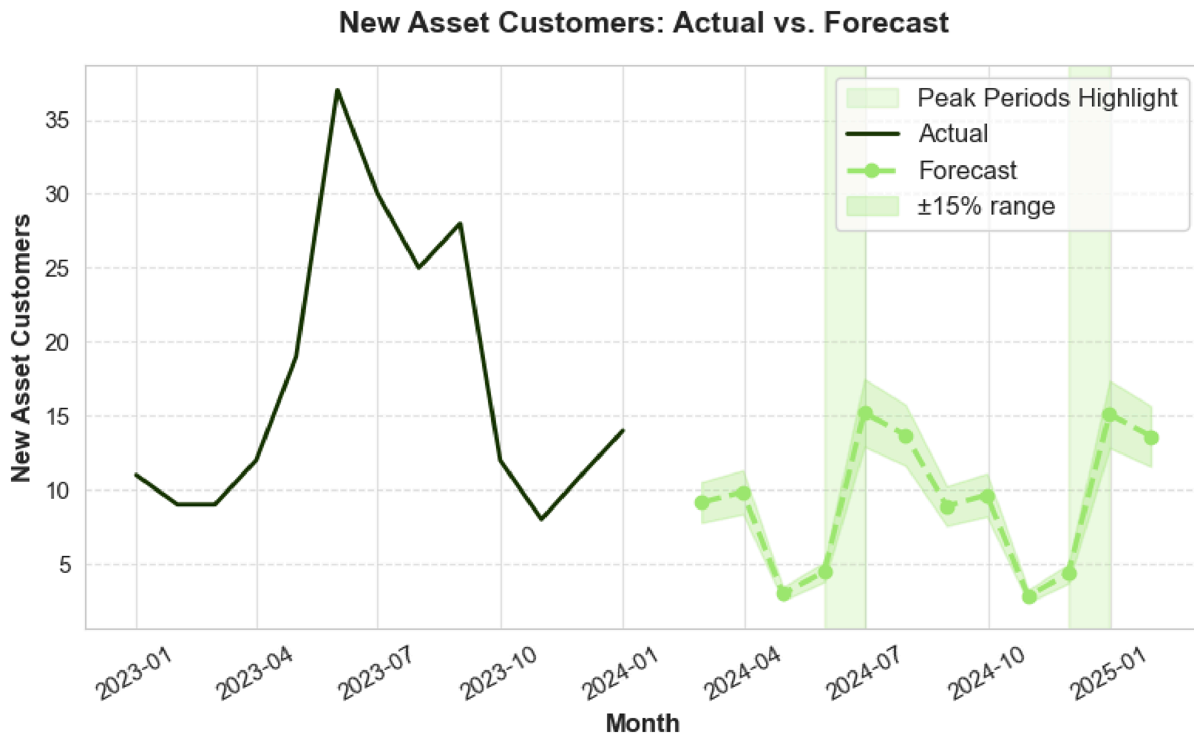
In [255…

```
# Applying Holt-Winters model
model = ExponentialSmoothing(
    new_asset_customers["new_asset_customers"],
    trend="add",
    seasonal="add",  # Additive seasonality
    seasonal_periods=6,  # semi-annual seasonality
    damped_trend=True  # Prevents unrealistic exponential growth
)

fit = model.fit(optimized=True)

forecast_index = pd.date_range(start=new_asset_customers.index[-1] + pd.Date
forecast_values = fit.forecast(steps=12)

forecast_df = pd.DataFrame({"month": forecast_index, "forecasted_customers":

print(forecast_df.to_string(index=False))
```

```
        month  forecasted_customers
   2024-02-29                  9.15
   2024-03-31                  9.84
   2024-04-30                  2.98
   2024-05-31                  4.46
   2024-06-30                 15.21
   2024-07-31                 13.70
   2024-08-31                  8.91
   2024-09-30                  9.65
   2024-10-31                  2.82
   2024-11-30                  4.33
   2024-12-31                 15.11
   2025-01-31                 13.62
```

In [256…

```
plt.figure(figsize=(8, 5))
ax = plt.gca()

# Highlight Peak Periods (June & December)
ax.axvspan(pd.Timestamp("2024-06-01"), pd.Timestamp("2024-06-30"),
           color=WISE_BRIGHT_GREEN, alpha=0.2)
ax.axvspan(pd.Timestamp("2024-12-01"), pd.Timestamp("2024-12-31"),
           color=WISE_BRIGHT_GREEN, alpha=0.2, label="Peak Periods Highlight

# Plot historical trend
plt.plot(new_asset_customers.index, new_asset_customers["new_asset_customers
         label="Actual", color=WISE_FOREST_GREEN, linewidth=2)

# Plot forecasted values
plt.plot(forecast_df["month"], forecast_df["forecasted_customers"],
         label="Forecast", color=WISE_BRIGHT_GREEN, linestyle="--", marker="

# Confidence interval shading (±15%)
plt.fill_between(forecast_df["month"],
                 forecast_df["forecasted_customers"] * 0.85,
                 forecast_df["forecasted_customers"] * 1.15,
                 color=WISE_BRIGHT_GREEN, alpha=0.3, label="±15% range")

# Labels & Title
plt.xlabel("Month", fontsize=12, fontweight="bold")
plt.ylabel("New Asset Customers", fontsize=12, fontweight="bold")
plt.title("New Asset Customers: Actual vs. Forecast", fontsize=14, fontweigh

# Style Adjustments
plt.legend(loc="upper right")
plt.xticks(fontsize=11, rotation=30)
plt.yticks(fontsize=11)
plt.grid(axis='y', linestyle="--", alpha=0.5)
plt.tight_layout()

plt.show()
```



Key Observations

- **Peak: June 2023 (37 users)**, sharp drop in **Q4 2023 (8 users in November)**.
- **Recovery: January 2024 (14 users)**, but volatility remains.
- **Forecast: Q2 2024 dip (~3 users in April), rebound in June (15 users)**.
- **Pattern: Peaks in June & December, dips in Q2/Q4**.

Takeaways

- **June & December peaks** → Align marketing efforts.
- **Q2 2024 dip** → Needs intervention.
- **Growth fluctuates** → External factors (marketing, economy) impact adoption.

Limitations

- **Market shifts affect trends.**
- **Patterns may change.**
- **Limited data.**

🟩 Forecasting Total Holdings

Why It Matters

- Tracks **asset investment trends**.
- Identifies **revenue growth potential**.
- Supports **product and liquidity planning**.

In [248…

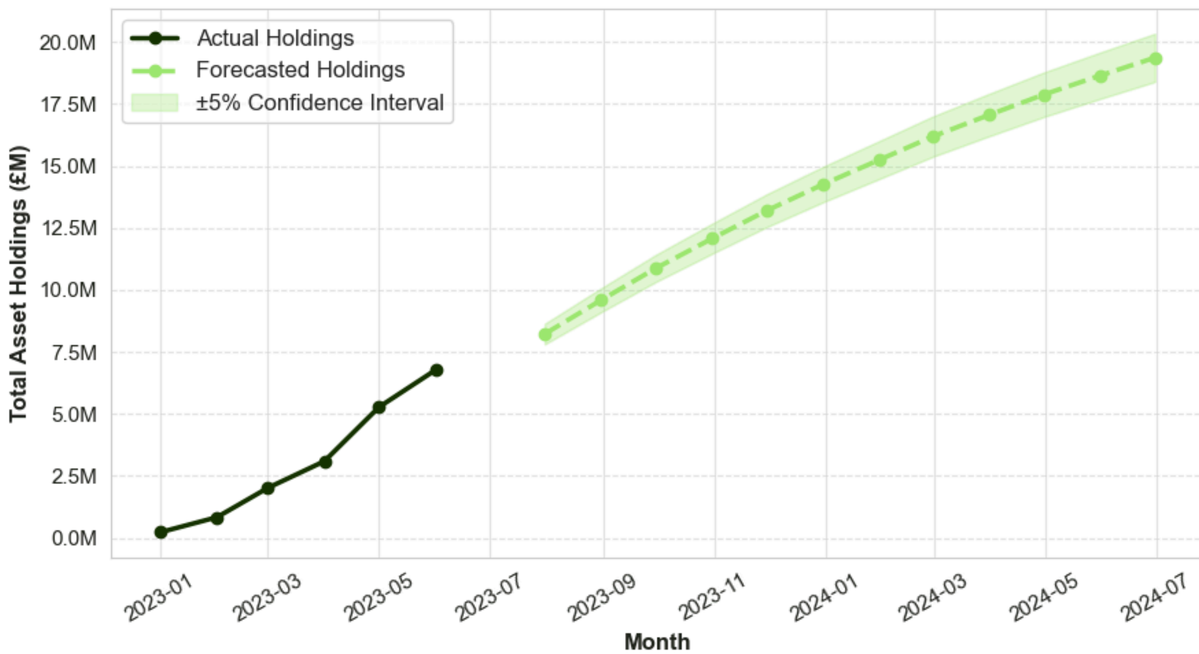
```
# extract total asset holdings per month
query = """
SELECT
    strftime('%Y-%m', month_balance) AS month,
    SUM(end_total_holdings_gbp) AS total_holdings
FROM profile_historical_holdings_monthly
GROUP BY month
ORDER BY month;
"""

total_holdings = pd.read_sql(query, conn)

total_holdings["month"] = pd.to_datetime(total_holdings["month"])

total_holdings.set_index("month", inplace=True)

#Convert and display in M£ format
total_holdings["total_holdings"] = total_holdings["total_holdings"] / 1e6
print(total_holdings.to_string(formatters={"total_holdings": lambda x: f"{x:
```

```
           total_holdings
month
2023-01-01          0.23M
2023-02-01          0.84M
2023-03-01          2.02M
2023-04-01          3.10M
2023-05-01          5.28M
2023-06-01          6.77M
```

In [257…

```
# Extract total asset holdings per month
query = """
SELECT
    strftime('%Y-%m', month_balance) AS month,
    SUM(end_total_holdings_gbp) AS total_holdings
FROM profile_historical_holdings_monthly
GROUP BY month
ORDER BY month;
"""

total_holdings = pd.read_sql(query, conn)
total_holdings["month"] = pd.to_datetime(total_holdings["month"])
total_holdings.set_index("month", inplace=True)
total_holdings["total_holdings"] = total_holdings["total_holdings"] / 1e6

# Fit ARIMA(1,1,1) model
model = ARIMA(total_holdings["total_holdings"], order=(1, 1, 1))
fit = model.fit()

# Generate 12-month forecast
```

```python
forecast_index = pd.date_range(start=total_holdings.index[-1] + pd.DateOffse
forecast_values = fit.forecast(steps=12)

forecast_df = pd.DataFrame({"month": forecast_index, "forecasted_holdings":

# --- PLOTTING ---
plt.figure(figsize=(9, 5))
plt.plot(total_holdings.index, total_holdings["total_holdings"],
         marker="o", linestyle="-", label="Actual Holdings",
         color=WISE_FOREST_GREEN, linewidth=2.5)

plt.plot(forecast_df["month"], forecast_df["forecasted_holdings"],
         marker="o", linestyle="--", label="Forecasted Holdings",
         color=WISE_BRIGHT_GREEN, linewidth=2.5)

plt.fill_between(
    forecast_df["month"],
    forecast_df["forecasted_holdings"] * 0.95,
    forecast_df["forecasted_holdings"] * 1.05,
    color=WISE_BRIGHT_GREEN, alpha=0.3, label="±5% Confidence Interval"
)


plt.xlabel("Month", fontsize=12, fontweight="bold", color=WISE_DARK_CHARCOAL
plt.ylabel("Total Asset Holdings (£M)", fontsize=12, fontweight="bold", colo
#plt.title("Historical vs. Forecasted Wise Asset Holdings (ARIMA)", fontsize

plt.gca().yaxis.set_major_formatter(mtick.FuncFormatter(lambda x, _: f"{x:.1

plt.legend(loc="upper left")
plt.xticks(fontsize=11, rotation=30, color=WISE_DARK_CHARCOAL)
plt.yticks(fontsize=11, color=WISE_DARK_CHARCOAL)
plt.grid(axis='y', linestyle="--", alpha=0.5)
plt.tight_layout()

plt.show()

forecast_df["forecasted_holdings"] = forecast_df["forecasted_holdings"]
print(forecast_df.to_string(index=False, formatters={"forecasted_holdings":
```




```
     month forecasted_holdings
2023-07-31               8.23M
2023-08-31               9.60M
2023-09-30              10.88M
2023-10-31              12.08M
2023-11-30              13.21M
2023-12-31              14.27M
2024-01-31              15.26M
2024-02-29              16.19M
2024-03-31              17.06M
2024-04-30              17.88M
2024-05-31              18.65M
2024-06-30              19.37M
```

Forecasting Wise Total Holdings – Insights

Growth Trends

- **Total holdings grew from £0.23M (Jan 2023) to £6.77M (Jun 2023)**.
- **Forecast: £19.37M by June 2024**, with consistent month-over-month increases.
- **£1M MoM growth**.

Takeaways

- **Sustained, predictable growth** supports long-term asset adoption.
- **No sharp spikes or declines**, indicating stable investor confidence.
- **Liquidity planning is key** as holdings approach **£20M**.

Limitations

- **Market conditions may shift growth patterns**.

- **Does not account for segmentation (business vs. personal users)**.
- **Future adoption may vary based on economic factors**.