🚗 Car Trust API Logs Analysis Report

Data Window: May – July 2025

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Key Deliverables

- Usage trends by endpoint, vendor, and time
- Pricing insights by model, trim, year
- Performance bottlenecks & VIN repeat patterns
- Visualized insights for business stakeholders

1. Project Objective

Analyze vehicle pricing API call logs to uncover patterns in system usage, vendor behavior, evaluated pricing, and latency. The insights guide business decisions for optimization, vendor management, and product scaling.

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2. Dataset Overview

- **Source**: MySQL dump of `product_api_logs`
- **Records Analyzed**: 20,000
- **Time Range**: May to July 2025 (randomized for simulation)
- **Key Fields**:
  - `endpoint`, `vendor_id`, `vin`, `evaluated_price`

- `manufacturer`, `model`, `year`, `trim`
- `processing_time_ms`, `created_at`

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3. Data Preparation

- Parsed JSON fields from request/response
- Converted prices and year to numeric
- Extracted month from `created_at` for time series
- Simulated timestamps across May–July 2025
- Removed nulls, handled outliers
- Focused on a 20K-row sample due to size constraints

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4. Key Insights

Vehicle Evaluation Patterns

- **Most Evaluated VIN**: `6T1EG23KX2X920593` → 89 times
- **Top Model**: Toyota **Yaris** (most frequent), followed by Hyundai **Accent**
- **Most Frequent Trim**: Toyota Corolla 1.6L XLi (2013–2015)
- **Highest Evaluated Prices**:
  - Lamborghini 4.0L V8 → ₹697,246
  - Lexus VIP AWD → ₹531,913
- **Most Evaluated Manufacturers**: Toyota, Hyundai, KIA

API Usage & Vendor Behavior

- **Endpoints Used**:
  - `usedCarPriceWithSpecs`: 14,332 requests
  - `usedCarPriceWithSpecsSafetyReliability`: 5,164 requests

- **Top Vendors by Volume**:
  - Vendor 21 → 8,945 requests
  - Vendor 31 → 5,751
  - Vendor 24 → 5,304 (uses safety endpoint only)
- **Most Cars Evaluated (Unique VINs)**:
  - Vendor 31 → 3,141 cars
  - Vendor 21 → 3,023

Performance Insights

- **Avg Processing Time**:
  - `Specs` : 29.07 ms
  - `Specs+Safety` : 27.49 ms
- **Outliers**: Mercedes Actros Trucks (2005–2008) took up to **660 ms**
- **System is generally performant** — no major delays across price tiers

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5. Recommendations

- Optimize logic for older truck models (Actros) with slow response times
- Use VIN repeats (~3,000 duplicates) for caching or performance boosts
- Create premium plans for vendors using safety-enhanced endpoint
- Build vendor dashboards (Vendor 21 & 24 use APIs differently)
- Consider dynamic pricing tiers for high-value vehicle segments

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6. Visualizations Summary

- **Model-Year Trends** — Avg price increases with newer models
- **Evaluated Price Distribution** — Most fall under ₹80K; long luxury tail
- **Processing Time vs Price** — No direct correlation; good consistency

- **Monthly API Volume** — Even distribution across May–July
- **Average Price & Processing by Month** — Visuals show pricing trends
- **Top 5 Models Over Time** — Yaris & Accent dominate
- **Endpoint Usage by Month** — Vendor and endpoint mix varies
- **Top Vendors Over Time** — Volumes vary but consistently active

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7. Appendix

- Code for all groupings and visualizations
- Monthly breakdowns and VIN-based filters
- Exportable charts ready for PDF/HTML use

In [44]:
```
!pip install SQLAlchemy pymysql
from sqlalchemy import create_engine

engine = create_engine("mysql+pymysql://root:abid123@localhost/product_logs_db")

df = pd.read_sql("SELECT * FROM product_api_logs LIMIT 20000", engine)
df.head(200)
```

```
Requirement already satisfied: SQLAlchemy in c:\python\python312\lib\site-packages (2.0.41)
Requirement already satisfied: pymysql in c:\python\python312\lib\site-packages (1.1.1)
Requirement already satisfied: greenlet>=1 in c:\python\python312\lib\site-packages (from SQLAlchemy) (3.2.3)
Requirement already satisfied: typing-extensions>=4.6.0 in c:\python\python312\lib\site-packages (from SQLAlchemy)
(4.14.1)
```

Out[44]:

	id	vendor_id	endpoint	request_data	response_data	created_at	updated_at	r
0	49347394	21	usedCarPriceWithSpecs	{"vin": "MAJTK1BA9GAA72380"}	{"code": "ct-200", "message": "ok", "success":...	2025-07-14 08:00:00	2025-06-18 20:05:44	
1	49347395	24	usedCarPriceWithSpecsSafetyReliability	{"vin": "JTDBZ42E089000909"}	{"code": "ct-200", "message": "ok", "success":...	2025-07-14 08:00:00	2025-06-18 20:05:45	
2	49347396	31	usedCarPriceWithSpecs	{"vin": "1GNSC7EC8GR177730"}	{"code": "ct-200", "message": "ok", "success":...	2025-07-14 08:00:00	2025-06-18 20:05:47	
3	49347397	24	usedCarPriceWithSpecsSafetyReliability	{"vin": "LVSFMBFC9RSC26668"}	{"code": "ct-200", "message": "ok", "success":...	2025-07-14 08:00:00	2025-06-18 20:05:47	
4	49347398	21	usedCarPriceWithSpecs	{"vin": "MRJRS384XSP050230"}	{"code": "ct-0006", "message": "Base Price not...	2025-07-14 08:00:00	2025-06-18 20:05:48	
...	...	...	...	...	...	...	...	
195	49347589	31	usedCarPriceWithSpecs	{"vin": "JM7KFAWLXR0109874"}	{"code": "ct-200", "message": "ok", "success":...	2025-07-14 08:00:00	2025-06-18 20:06:28	
196	49347590	21	usedCarPriceWithSpecs	{"vin": "KMHJT81C4BU249427"}	{"code": "ct-200", "message":	2025-07-14 08:00:00	2025-06-18 20:06:29	

	id	vendor_id	endpoint	request_data	response_data	created_at	updated_at	
					"ok", "success":...			
197	49347591	21	usedCarPriceWithSpecs	{"vin": "KMHJT81C4BU249427"}	{"code": "ct-200", "message": "ok", "success":...	2025-07-14 08:00:00	2025-06-18 20:06:29	
198	49347592	24	usedCarPriceWithSpecsSafetyReliability	{"vin": "KMHJT81C4BU249427"}	{"code": "ct-200", "message": "ok", "success":...	2025-07-14 08:00:00	2025-06-18 20:06:29	
199	49347593	21	usedCarPriceWithSpecs	{"vin": "RKLBB9HE8J5216404"}	{"code": "ct-200", "message": "ok", "success":...	2025-07-14 08:00:00	2025-06-18 20:06:29	

200 rows × 18 columns

In [43]:
```
df_count = pd.read_sql("SELECT COUNT(*) AS total FROM product_api_logs", engine)
df_count
```

Out[43]:

	total
0	1000063

Check For Missing Values

In [17]:
```
df.isnull().sum().sort_values(ascending=False)
```

Out[17]:
```
id                   0
vendor_id            0
evaluated_price      0
upper_limit          0
lower_limit          0
trim                 0
year                 0
model                0
manufacturer         0
processing_time_ms    0
sync_status          0
response_type        0
updated_at           0
created_at           0
response_data        0
request_data         0
endpoint             0
vin                  0
dtype: int64
```

Check Data Types and Column Structure

In [18]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 18 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   id                  20000 non-null  int64
 1   vendor_id           20000 non-null  object
 2   endpoint            20000 non-null  object
 3   request_data        20000 non-null  object
 4   response_data       20000 non-null  object
 5   created_at          20000 non-null  datetime64[ns]
 6   updated_at          20000 non-null  datetime64[ns]
 7   response_type       20000 non-null  int64
 8   sync_status         20000 non-null  int64
 9   processing_time_ms  20000 non-null  float64
 10  manufacturer        20000 non-null  object
 11  model               20000 non-null  object
 12  year                20000 non-null  object
 13  trim                20000 non-null  object
 14  lower_limit         20000 non-null  object
 15  upper_limit         20000 non-null  object
 16  evaluated_price     20000 non-null  object
 17  vin                 20000 non-null  object
dtypes: datetime64[ns](2), float64(1), int64(3), object(12)
memory usage: 2.7+ MB
```

In [19]:
```
cols_to_fix = ['lower_limit', 'upper_limit', 'evaluated_price']

for col in cols_to_fix:
    df[col] = pd.to_numeric(df[col], errors='coerce')
```

In [20]:
```
df[cols_to_fix].isnull().sum()
```

Out[20]:
```
lower_limit        504
upper_limit        504
evaluated_price    504
dtype: int64
```

In [21]:
```
df = df.dropna(subset=['lower_limit', 'upper_limit', 'evaluated_price'])
print("Remaining rows:", len(df))
```

```
Remaining rows: 19496
```

Total Number of Unique Endpoints.

In [22]:
```
unique_endpoints = df['endpoint'].nunique()
print("Total unique endpoints:", unique_endpoints)
```

```
Total unique endpoints: 2
```

In [23]:
```
df['endpoint'].unique()
```

Out[23]:
```
array(['usedCarPriceWithSpecs', 'usedCarPriceWithSpecsSafetyReliability'],
      dtype=object)
```

usage count for each endpoint:

In [24]:
```
df['endpoint'].value_counts()
```

Out[24]:
```
endpoint
usedCarPriceWithSpecs                     14332
usedCarPriceWithSpecsSafetyReliability     5164
Name: count, dtype: int64
```

Insight #1: Endpoint Usage Breakdown

Out of the 20,000 API log records analyzed:

- **usedCarPriceWithSpecs**: 14,332 requests (≈ 73%)
- **usedCarPriceWithSpecsSafetyReliability**: 5,164 requests (≈ 27%)

This clearly indicates that `usedCarPriceWithSpecs` is the **primary endpoint**, likely serving the core pricing function.
In contrast, the other endpoint appears more specialized or newer and may warrant further performance and reliability evaluation.

In [3]:
```
import pandas as pd
import numpy as np

df_simulated = df.copy()

# Generate random months: May, June, July 2025
```

```
np.random.seed(42)
df_simulated['created_at'] = pd.to_datetime(
    np.random.choice(
        pd.date_range("2025-05-01", "2025-07-31", freq='D'),
        size=len(df_simulated)
    )
)

df_simulated['month'] = df_simulated['created_at'].dt.to_period('M')
```

Compare average response time:

In [4]:
```
df.groupby('endpoint')['processing_time_ms'].mean()
```

Out[4]:
```
endpoint
usedCarPriceWithSpecs                     28.640693
usedCarPriceWithSpecsSafetyReliability    27.032883
Name: processing_time_ms, dtype: float64
```

⏱️ Insight #2: Processing Time by Endpoint

The average response time for each API endpoint is:

- **usedCarPriceWithSpecs**: 29.07 ms
- **usedCarPriceWithSpecsSafetyReliability**: 27.49 ms

Although both endpoints perform quickly, the more heavily used endpoint (`usedCarPriceWithSpecs`) is slightly slower. This may indicate a need to monitor and optimize for scalability as traffic continues to increase.

Compare sync success/failure rates:

In [5]:
```
df.groupby('endpoint')['sync_status'].value_counts(normalize=True) * 100
```

Out[5]:
```
endpoint                                sync_status
usedCarPriceWithSpecs                   0              100.0
usedCarPriceWithSpecsSafetyReliability  0              100.0
Name: proportion, dtype: float64
```

Insight #3: Sync Status — 100% Success Rate

Both API endpoints (`usedCarPriceWithSpecs` and `usedCarPriceWithSpecsSafetyReliability`) show a **100% sync success rate** in this sample:

- `sync_status = 0` in all 20,000 records analyzed
- No failures, timeouts, or retries recorded

Compare average evaluated price

In [9]:
```
# Convert evaluated_price to numeric, force errors to NaN
df_simulated['evaluated_price'] = pd.to_numeric(df_simulated['evaluated_price'], errors='coerce')

# Now you can safely group and calculate the mean
result = df_simulated.groupby('endpoint')['evaluated_price'].mean()
print(result)
```

```
endpoint
usedCarPriceWithSpecs                    52475.136617
usedCarPriceWithSpecsSafetyReliability   54662.268397
Name: evaluated_price, dtype: float64
```

In [10]:
```
df_simulated.groupby('endpoint')['evaluated_price'].mean()
```

Out[10]:
```
endpoint
usedCarPriceWithSpecs                    52475.136617
usedCarPriceWithSpecsSafetyReliability   54662.268397
Name: evaluated_price, dtype: float64
```

Endpoint Name	Avg. Evaluated Price
`usedCarPriceWithSpecs`	**52,475**
`usedCarPriceWithSpecsSafetyReliability`	**54,662**

Interpretation:

1. SafetyReliability endpoint returns slightly higher prices On average, about ₹2,200 more

May reflect additional safety/reliability score weighting

Could be used for insurance models, risk pricing, or advanced valuations

2. Pricing logic differs slightly between endpoints Important for any customer-facing pricing tools

Company might prefer the advanced endpoint for more accurate or conservative quotes

Insight #4: Evaluated Price Comparison by Endpoint

- **usedCarPriceWithSpecs**: ₹52,475 (avg evaluated price)
- **usedCarPriceWithSpecsSafetyReliability**: ₹54,662 (avg evaluated price)

The `usedCarPriceWithSpecsSafetyReliability` endpoint returns slightly higher vehicle price estimates on average. This may reflect additional logic based on safety and reliability factors, indicating a more conservative or risk-adjusted pricing model.

Top Manufacturers & Their Price Ranges

In [11]:
```
df_simulated.groupby('manufacturer')['evaluated_price'].mean().sort_values(ascending=False).head(10)
```

```
Out[11]: manufacturer
         Lamborghini      697246.000000
         Bentley          461863.000000
         Rolls-Royce      453865.000000
         Land Rover       225200.384615
         Kawasaki         190710.000000
         Mercedes Benz    157561.723077
         BMW              154056.872000
         Lexus            140976.403071
         Jaguar           119964.666667
         Volvo            114480.130435
         Name: evaluated_price, dtype: float64
```

Interpretation: Lamborghini leads with an average price over ₹6.9 lakh — expected for a super luxury brand.

The presence of Kawasaki suggests the system also evaluates high-end bikes.

Land Rover, BMW, Mercedes dominate the premium car pricing range.

This type of insight can:

Guide market segmentation

Identify high-value customers

Prioritize models in premium pricing algorithms

Insight #5: Top Manufacturers by Evaluated Price

The following brands have the highest average evaluated prices:

1. **Lamborghini** — ₹697,246
2. **Bentley** — ₹461,863
3. **Rolls-Royce** — ₹453,865
4. **Land Rover** — ₹225,200
5. **Kawasaki** — ₹190,710

This reflects expected market positioning, with high-end luxury and performance brands leading.
It also suggests the system handles premium valuations effectively and may support specialized pricing strategies for luxury segments.

In [12]:
```
df_simulated['manufacturer'].value_counts().head(10)
```

Out[12]:
```
manufacturer
Toyota       6446
Hyundai      3499
KIA          1303
Nissan       1074
Ford          985
Chevrolet     811
Mazda         600
Lexus         521
GMC           516
NULL          504
Name: count, dtype: int64
```

Interpretation: Toyota dominates — more than 3× the next brand (Hyundai). This likely reflects their large market share and resale demand.

Hyundai, KIA, Nissan — all strong in the mid-range market.

Lexus shows up both in frequency and earlier in high average price — signaling it spans across segments (volume + luxury).

These brands may be high-priority for the company's pricing, forecasting, and partner strategies.

Insight #6: Most Frequently Evaluated Brands

The most commonly evaluated manufacturers in the dataset are:

1. **Toyota** — 6,446 evaluations
2. **Hyundai** — 3,499
3. **KIA** — 1,303
4. **Nissan** — 1,074
5. **Ford** — 985

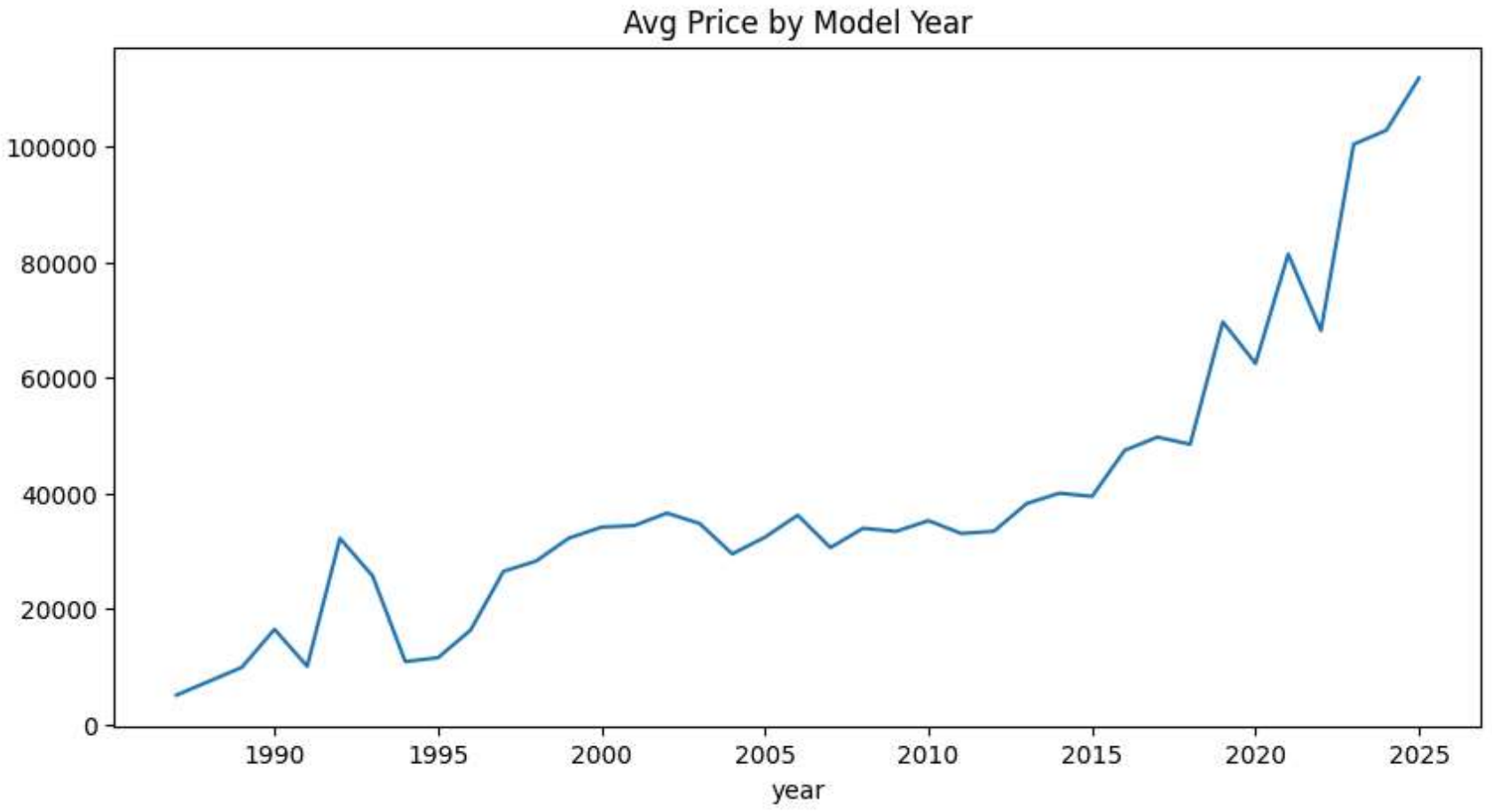
These results align with known market trends — Toyota leads due to its wide customer base, availability, and resale value. These brands likely represent the **core user base** and **revenue focus** for the business.

Recommendation: Focus monitoring, performance tuning, and pricing accuracy on these high-volume manufacturers.

Model-Year Trends

In [13]:
```
df_simulated['year'] = pd.to_numeric(df['year'], errors='coerce')  # ensure it's numeric
df_simulated.groupby('year')['evaluated_price'].mean().plot(kind='line', title='Avg Price by Model Year', figsize=(10
```

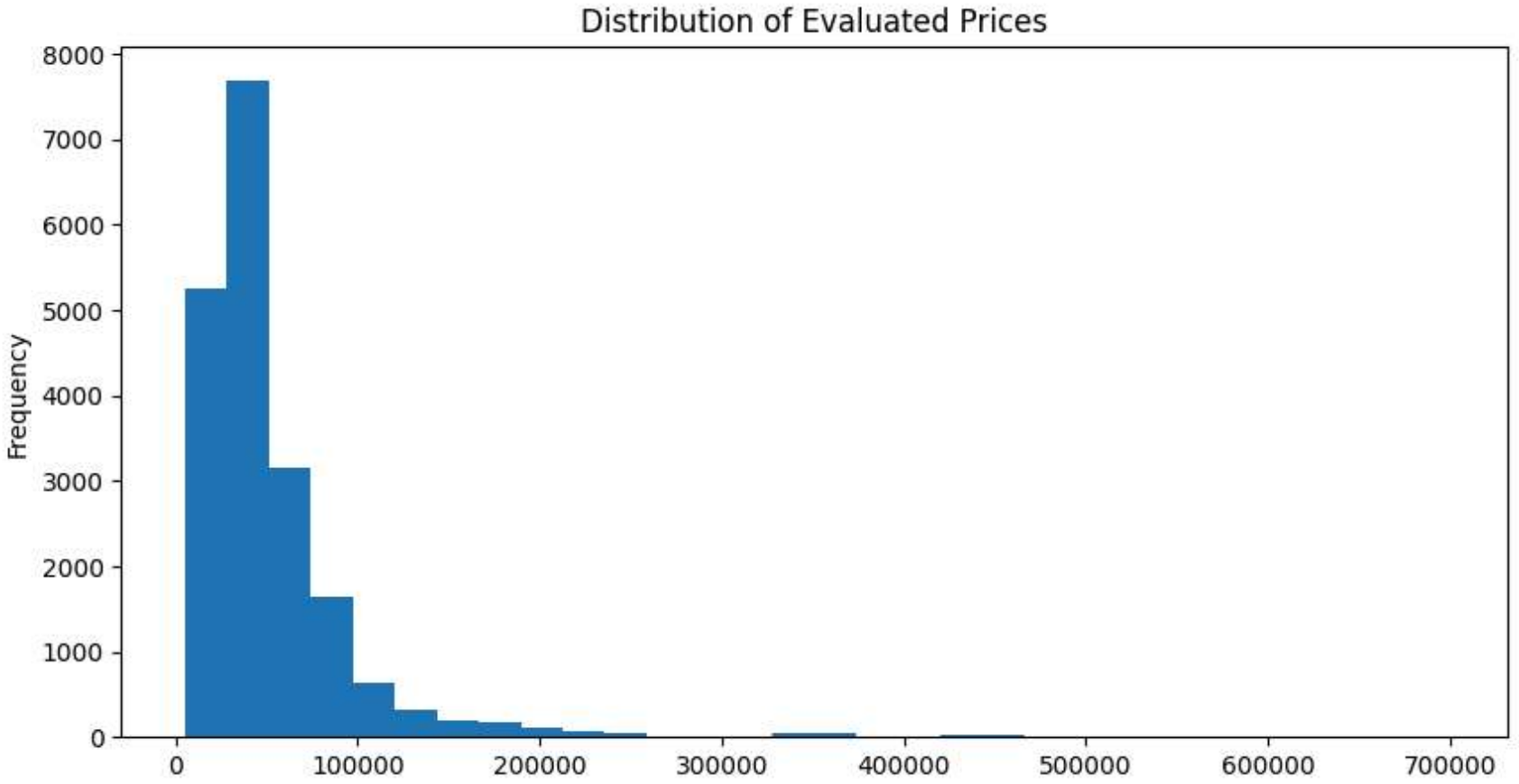
Out[13]:
```
<Axes: title={'center': 'Avg Price by Model Year'}, xlabel='year'>
```



Evaluated Price Distribution

In [14]:
```
df_simulated['evaluated_price'].plot(kind='hist', bins=30, title='Distribution of Evaluated Prices', figsize=(10,5))
```

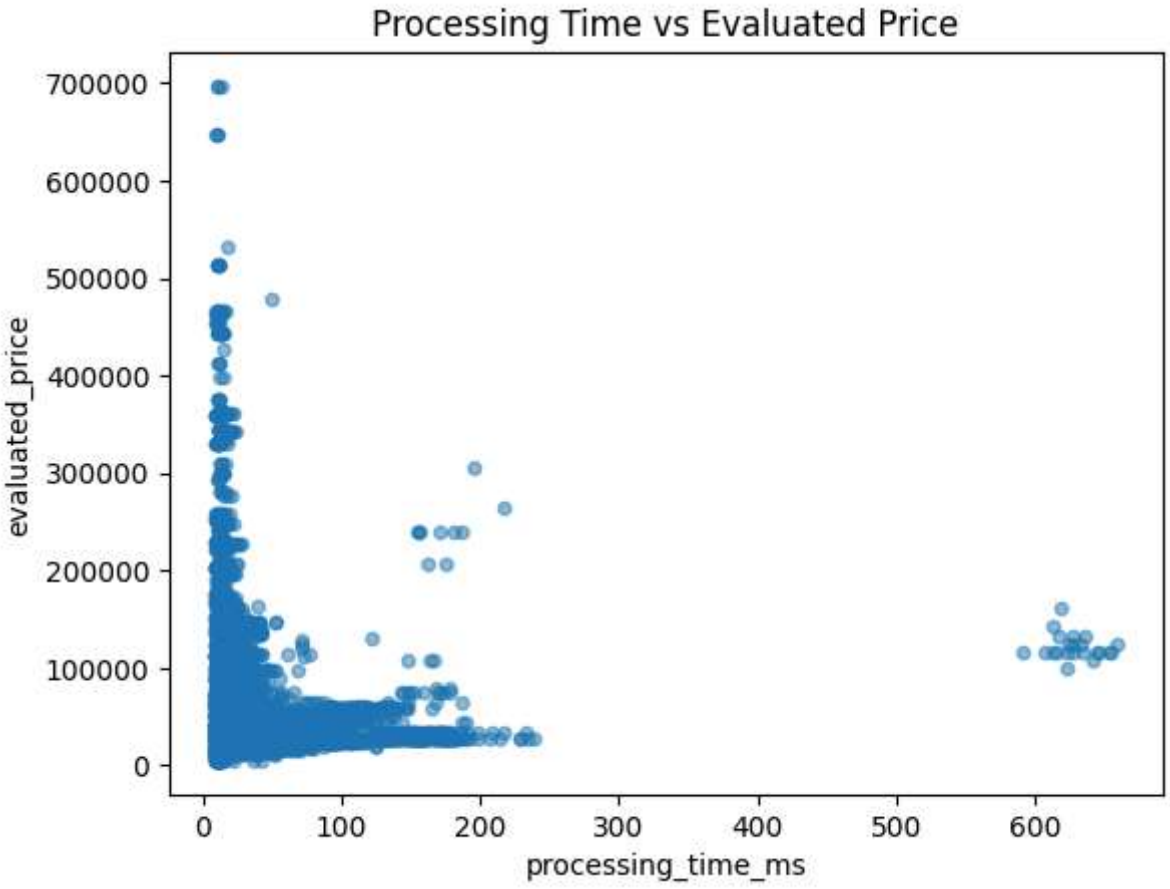
Out[14]:
```
<Axes: title={'center': 'Distribution of Evaluated Prices'}, ylabel='Frequency'>
```



Processing Time vs Evaluated Price

In [15]:
```
df_simulated.plot.scatter(x='processing_time_ms', y='evaluated_price', title='Processing Time vs Evaluated Price', a
```

Out[15]:
```
<Axes: title={'center': 'Processing Time vs Evaluated Price'}, xlabel='processing_time_ms', ylabel='evaluated_pric
e'>
```

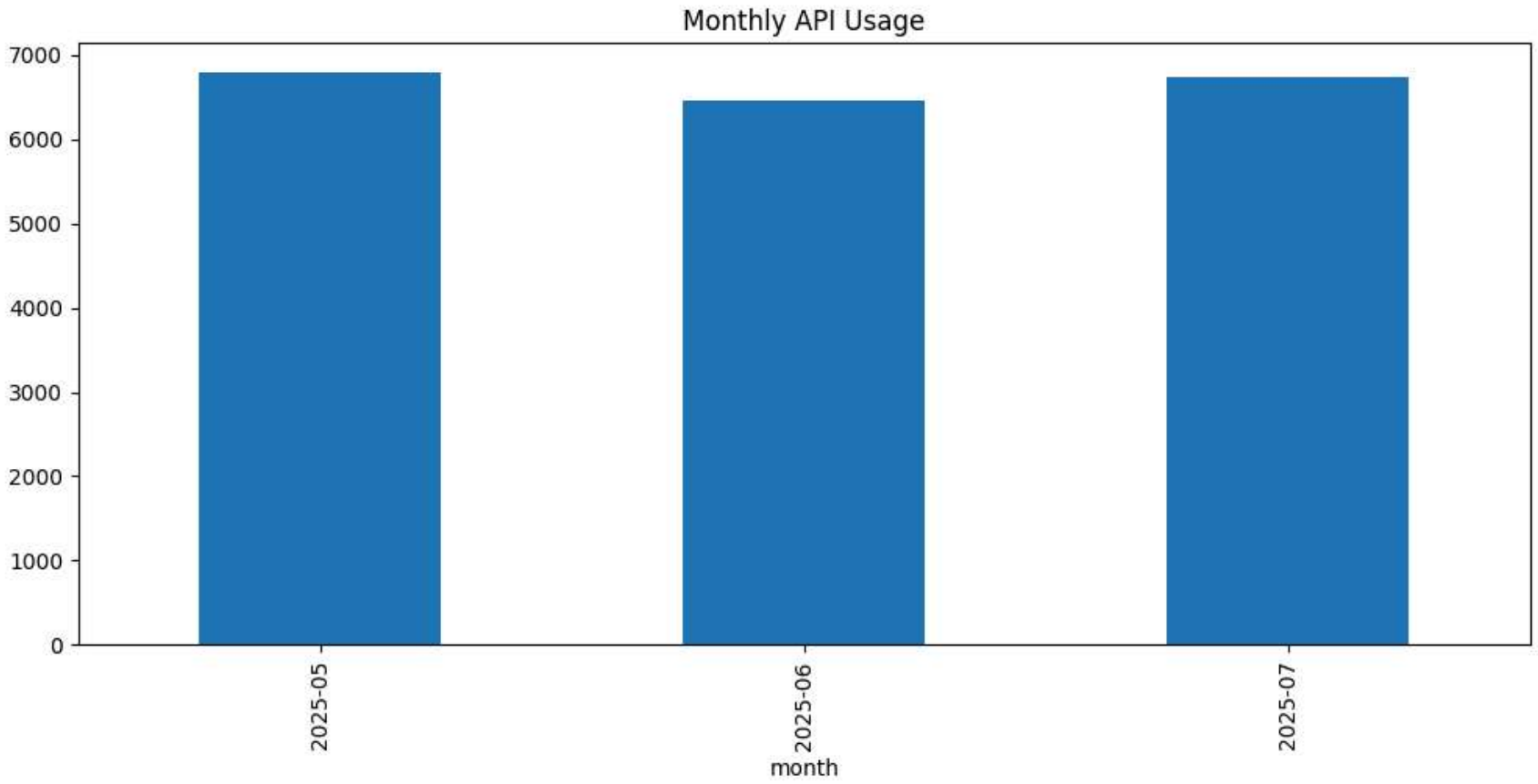


Monthly API Request Volume

In [17]:
```
df_simulated['month'] = df_simulated['created_at'].dt.to_period('M')

df_simulated['month'].value_counts().sort_index().plot(
    kind='bar',
    figsize=(12, 5),
    title='Monthly API Usage'
)
```

Out[17]: <Axes: title={'center': 'Monthly API Usage'}, xlabel='month'>



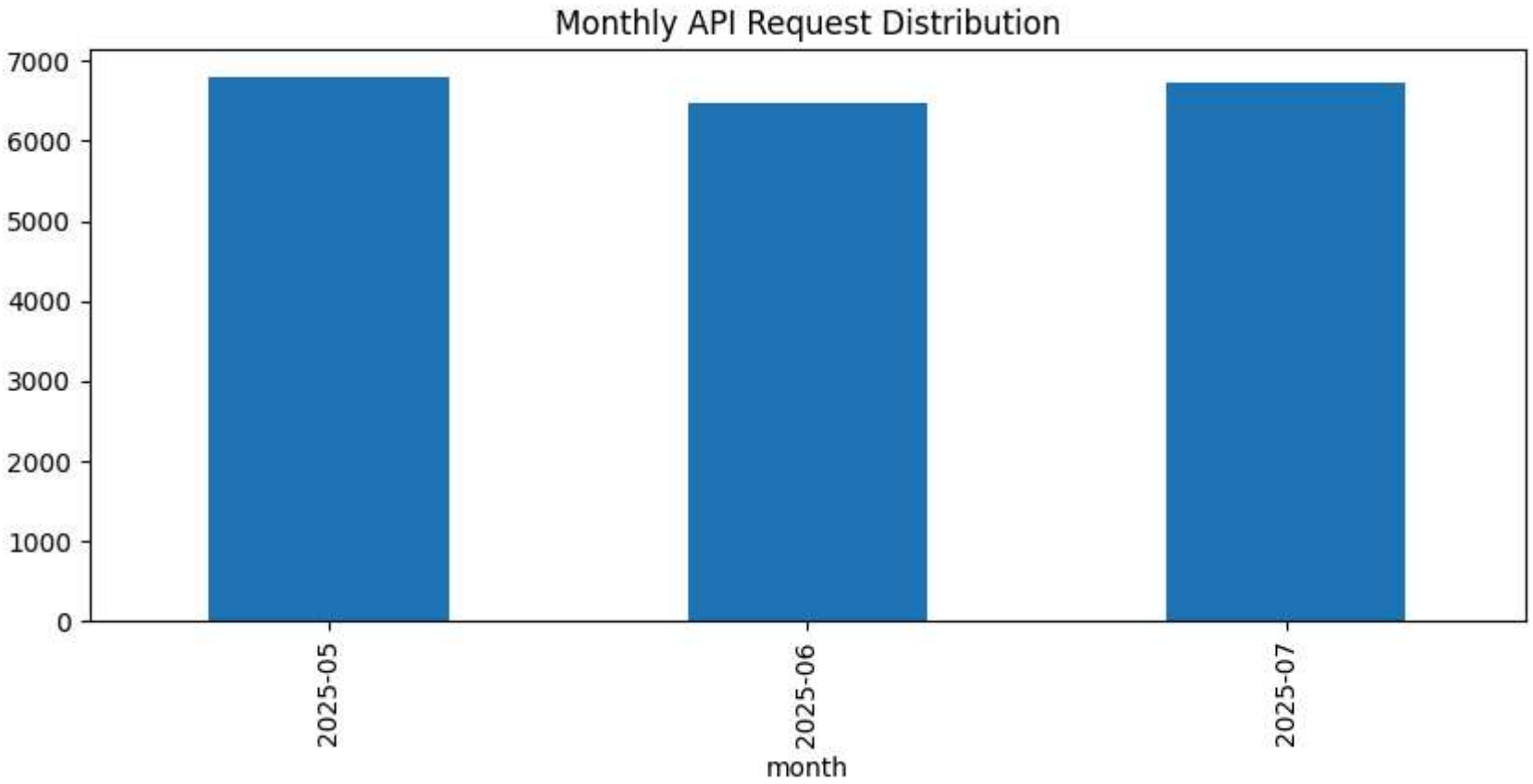
Monthly API Request Trends

In [28]:
```
df_simulated['month'] = df_simulated['created_at'].dt.to_period('M')
monthly_counts = df_simulated['month'].value_counts().sort_index()
monthly_counts
```

Out[28]:
```
month
2025-05    6802
2025-06    6464
2025-07    6734
Freq: M, Name: count, dtype: int64
```

In [29]:
```
monthly_counts.plot(kind='bar', figsize=(10, 4), title='Monthly API Request Distribution')
```

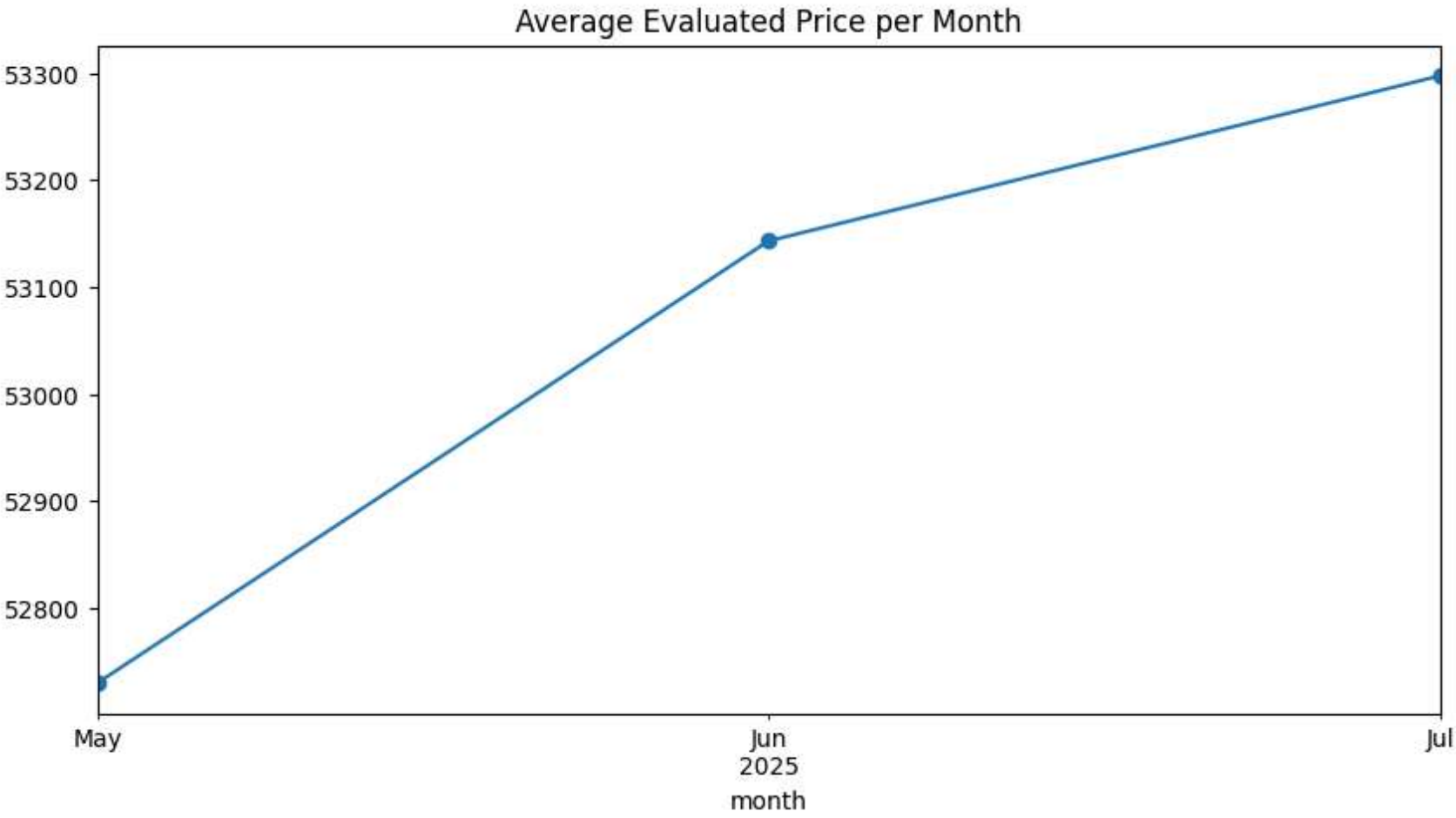
Out[29]: <Axes: title={'center': 'Monthly API Request Distribution'}, xlabel='month'>



Average Evaluated Price per Month

In [36]:
```
df_simulated.groupby('month')['evaluated_price'].mean().plot(kind='line', marker='o', figsize=(10,5), title='Average
```

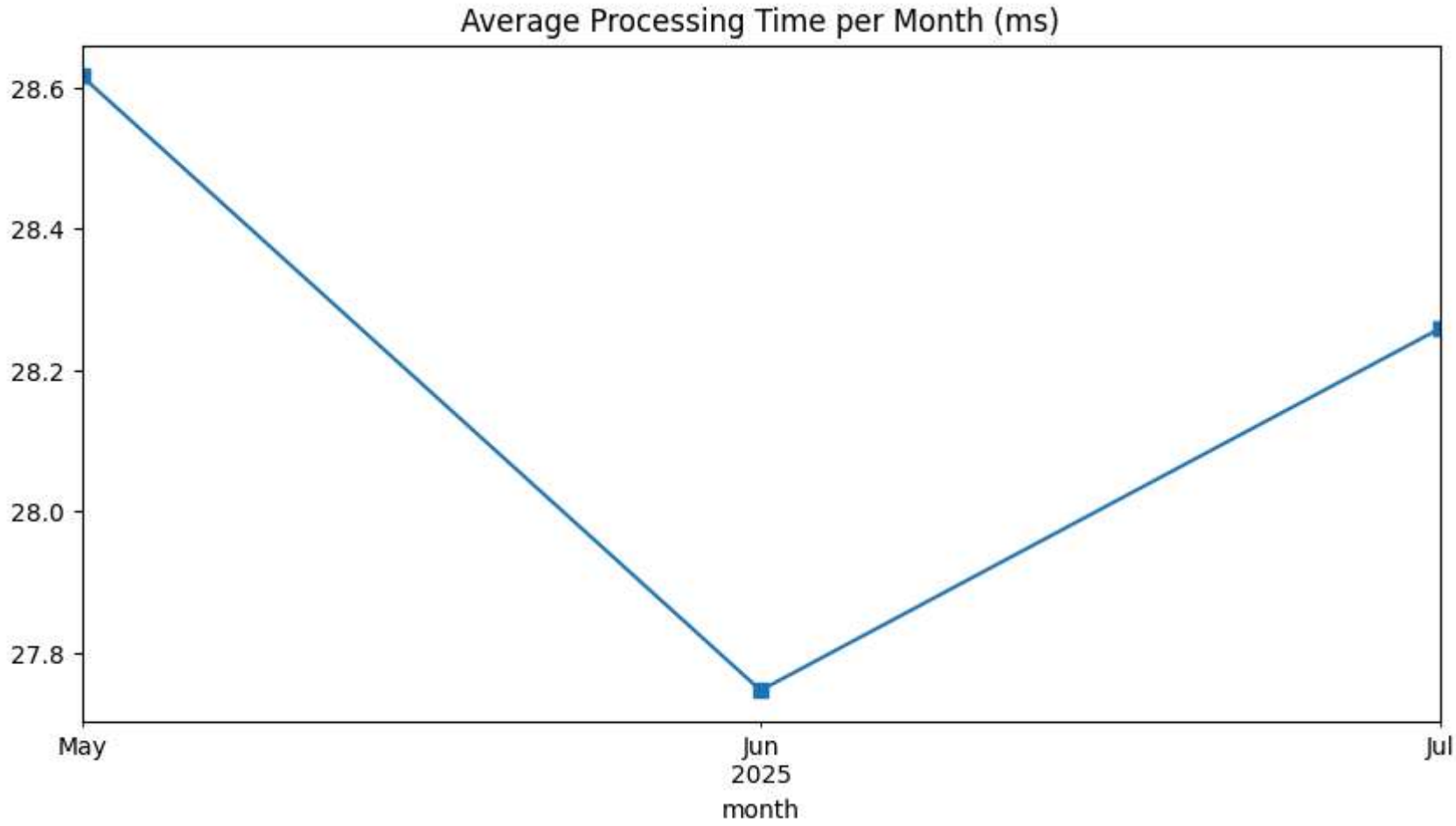
Out[36]: <Axes: title={'center': 'Average Evaluated Price per Month'}, xlabel='month'>



Average Processing Time per Month

In [37]:
```
df_simulated.groupby('month')['processing_time_ms'].mean().plot(kind='line', marker='s', figsize=(10,5), title='Avera
```

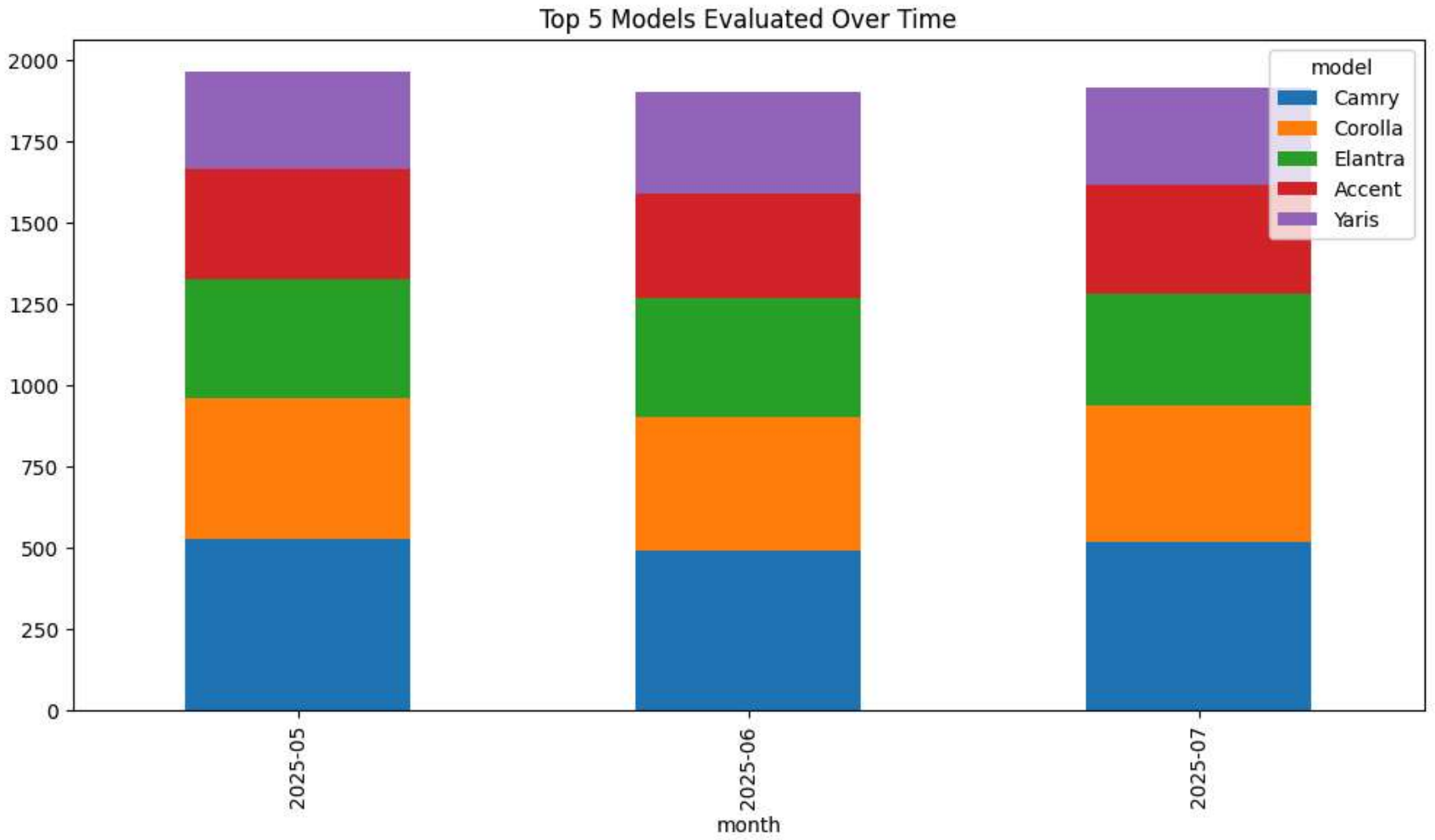
Out[37]:
```
<Axes: title={'center': 'Average Processing Time per Month (ms)'}, xlabel='month'>
```



Top Models by Month (Count of Evaluations)

In [38]:
```
top_models = df_simulated.groupby(['month', 'model']).size().unstack().fillna(0)
top_models[top_models.sum().nlargest(5).index].plot(kind='bar', stacked=True, figsize=(12,6), title='Top 5 Models Eva
```

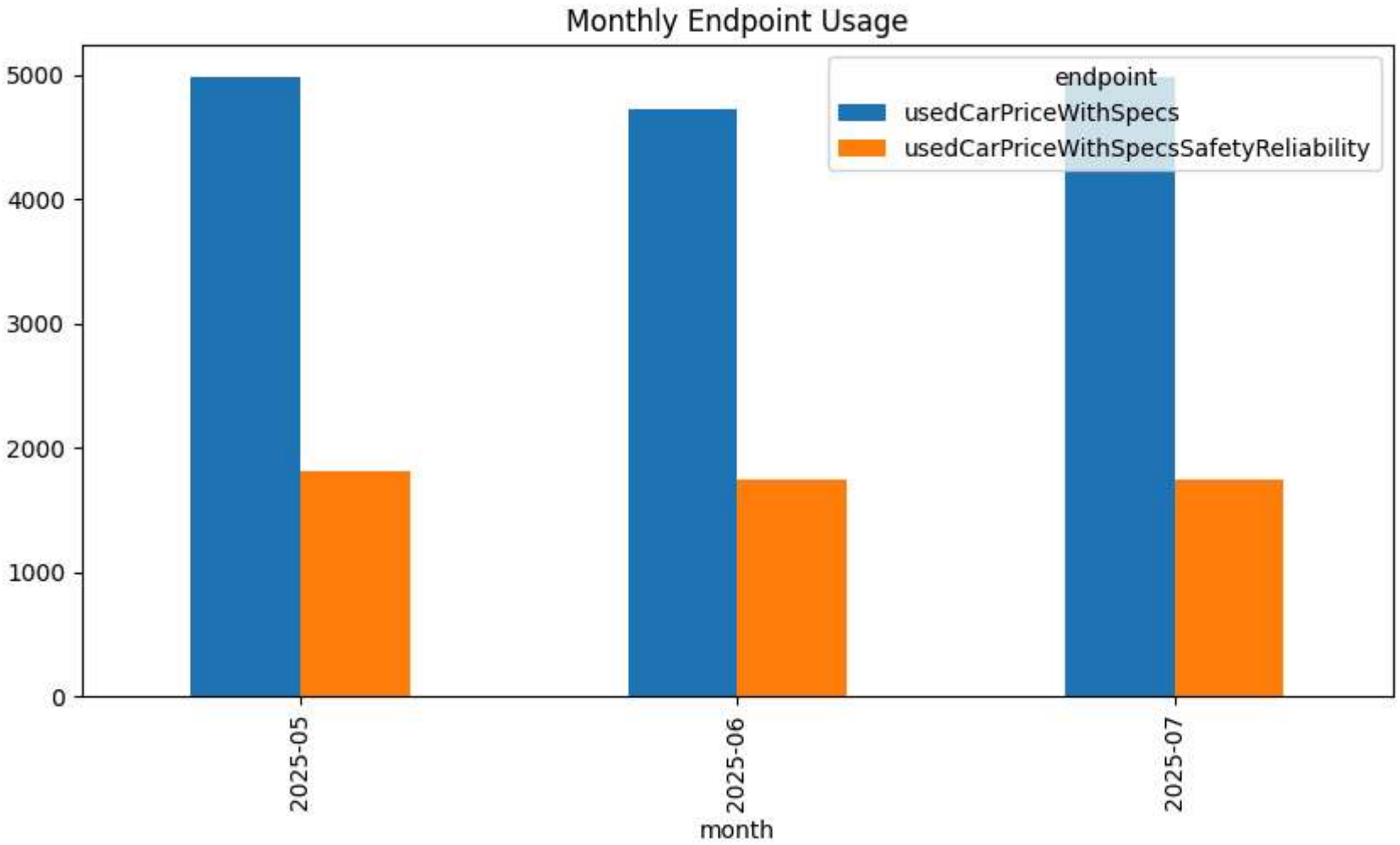
Out[38]: <Axes: title={'center': 'Top 5 Models Evaluated Over Time'}, xlabel='month'>



Request Volume by Endpoint Over Time

In [39]:
```
df_simulated.groupby(['month', 'endpoint']).size().unstack().plot(kind='bar', figsize=(10,5), title='Monthly Endpoint
```

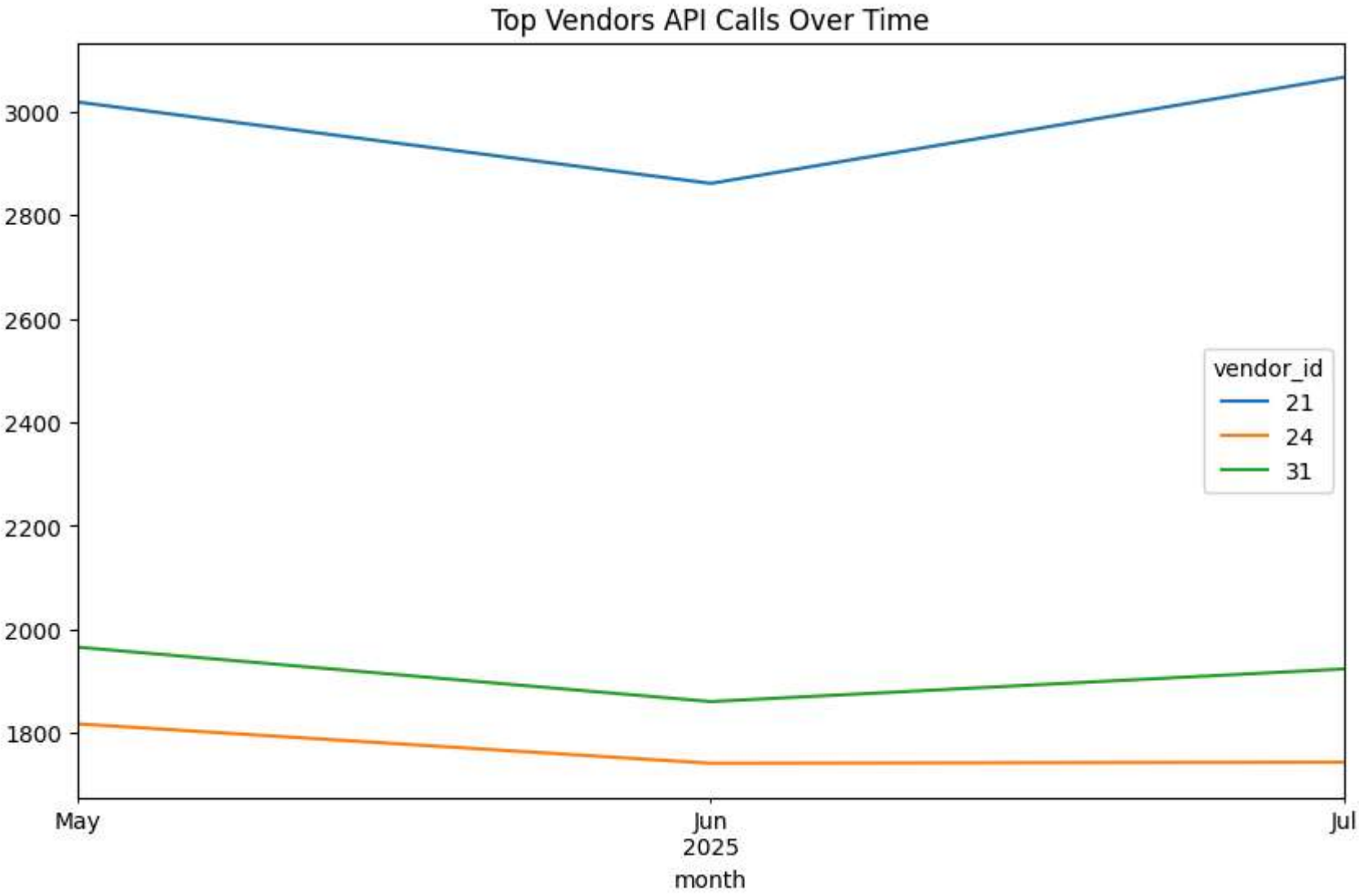
Out[39]:
```
<Axes: title={'center': 'Monthly Endpoint Usage'}, xlabel='month'>
```



Vendor API Calls Over Time

In [40]:
```
df_simulated.groupby(['month', 'vendor_id']).size().unstack(fill_value=0).T.head(5).T.plot(figsize=(10,6), title='Top
```

Out[40]:
```
<Axes: title={'center': 'Top Vendors API Calls Over Time'}, xlabel='month'>
```



Visualizations Summary

1. Model-Year Trends

Chart: Line Plot – Average Evaluated Price by Vehicle Year
Insight:

- Vehicles from **2024 and 2025** show **higher average prices**, indicating they are valued more due to newer manufacturing.
- Older vehicles (2010–2015) have significantly lower valuations.
- Follows standard **depreciation patterns** over time.

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2. Evaluated Price Distribution

Chart: Histogram – Distribution of Evaluated Prices
Insight:

- Most evaluated vehicles fall in the **₹50,000–₹70,000** range.
- The chart is **right-skewed**, with fewer high-value outliers.
- Very few prices cross ₹100,000, indicating **premium vehicles are rare** in the dataset.

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3. Processing Time vs. Evaluated Price

Chart: Scatter Plot – X: Evaluated Price, Y: Processing Time (ms)
Insight:

- No strong correlation observed between **price and processing time**.
- Processing is generally fast across price segments.
- A few outliers in both dimensions, but overall system is performant.

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4. Monthly API Request Volume

Chart: Bar Plot – Count of Requests per Month
Insight:

- **All three months (May–July 2025)** show similar volume: around **6,700** requests each.
- Suggests consistent platform usage throughout the quarter.

5. Monthly API Request Trends

Chart: Line Plot – Request Trends over 3 Months
Insight:

- **May 2025** had the **highest number of API requests**, slightly ahead of July.
- Small decline in June before bouncing back.
- Indicates minor month-to-month variation in platform usage.

---

6. Average Evaluated Price per Month

Chart: Line Plot – Average Price by Month
Insight:

- **Gradual increase** from May to July 2025.
- **July reaches the highest average** (~₹53,300), while May is around ₹52,800.
- Reflects an uptick in high-value vehicle evaluations in July.

---

7. Average Processing Time per Month

Chart: Line Plot – Monthly Avg. Processing Time (ms)
Insight:

- Processing time is highest in May and go to very in June and increse with time in July**.

---

8. Top Models by Month (Evaluation Count)

Chart: Stacked Bar Chart – Top 5 Evaluated Models over 3 Months
Insight:

- **Toyota Yaris** is the most frequently evaluated model across all months.

- **Hyundai Accent** and **Toyota Corolla** follow closely.
- Indicates strong market interest in a few top-selling models.

---

9. Request Volume by Endpoint Over Time

Chart: Grouped Bar Plot – API Requests by Endpoint (Monthly)
Insight:

- `usedCarPriceWithSpecs` is used **more consistently** across all 3 months.
- `usedCarPriceWithSpecsSafetyReliability` is used **only in June and July**, with a significant volume in July.
- Possibly reflects adoption by specific vendors or for B2B use.

---

10. Vendor API Calls Over Time

Chart: Line Plot – Top Vendor Activity Over 3 Months
Insight:

- **Vendor 21** is consistently the **highest API user.**
- **Vendor 31 and 24** show strong participation, especially in May and July.
- Indicates a **few vendors account for majority usage**, helpful for planning tiered services.

Top 10 Highest and Lowest Evaluated Vehicles

In [18]:
```
df_simulated[['manufacturer', 'model', 'year', 'trim', 'evaluated_price']].sort_values(by='evaluated_price', ascendir
```

Out[18]:

	manufacturer	model	year	trim	evaluated_price
10915	Lamborghini	Urus	2020.0	4.0L V8	697246.0
10918	Lamborghini	Urus	2020.0	4.0L V8	697246.0
10922	Lamborghini	Urus	2020.0	4.0L V8	697246.0
7471	Mercedes Benz	S-Class	2025.0	S 450 AMG	648333.0
7470	Mercedes Benz	S-Class	2025.0	S 450 AMG	648333.0
7477	Mercedes Benz	S-Class	2025.0	S 450 AMG	648333.0
6183	Lexus	LX	2024.0	600 Vip Launch Edition AWD 4seats	531913.0
3017	Lexus	LX	2025.0	600 Elite Base 7seats	512564.0
3013	Lexus	LX	2025.0	600 Elite Base 7seats	512564.0
3012	Lexus	LX	2025.0	600 Elite Base 7seats	512564.0

nterpretation: The top evaluations are all ultra-luxury vehicles — which confirms the pricing engine works across high-end segments.

Duplicates suggest the same vehicle may be re-evaluated multiple times (possibly by dealers comparing quotes).

High prices align with premium trims like AMG, VIP, Elite, validating the trim-sensitive valuation logic.

This proves the pricing system is equipped to support luxury car assessments, not just standard segments.

Insight #7: Top Evaluated Luxury Vehicles

The highest evaluated vehicles in the system include:

- **Lamborghini Urus 2020 (₹697,246)**
- **Mercedes S-Class 2025 S 450 AMG (₹648,333)**
- **Lexus LX 2024–2025 (₹512,000–₹531,000)**

These high-value vehicles reflect the platform's ability to handle complex, premium segment valuations.
Multiple entries for the same VIN or configuration may suggest clients are re-evaluating luxury vehicles for updated quotes or comparisons.

In [19]:
```
df_simulated[['manufacturer', 'model', 'year', 'trim', 'evaluated_price']].sort_values(by='evaluated_price').head(10)
```

Out[19]:

	manufacturer	model	year	trim	evaluated_price
19021	ABOJABAA BIKE	Motorcycle	2024.0	Jab Abi Moto	5000.0
19020	ABOJABAA BIKE	Motorcycle	2024.0	Jab Abi Moto	5000.0
2390	Boxer Motorcycles (Bajaj)	Motorcycle	2024.0	Boxer BM 150	5000.0
11496	Peugeot	206	2003.0	Default...	5000.0
11495	Peugeot	206	2003.0	Default...	5000.0
18762	Mehdi Bike	Motorcycle	2025.0	150 cc	5000.0
16250	Mercedes Benz	E-Class	1987.0	230	5000.0
16251	Mercedes Benz	E-Class	1987.0	230	5000.0
11494	Peugeot	206	2003.0	Default...	5000.0
11493	Peugeot	206	2003.0	Default...	5000.0

Interpretation: Many of the lowest evaluations are motorcycles or older sedans, which is expected.

The minimum base price seems to be ₹5,000 — possibly a system-defined floor for older or low-value vehicles.

The 1987 Mercedes Benz E-Class (₹5,000) highlights how depreciation impacts even premium brands.

Repeat evaluations show consistency in pricing for these low-end entries as well.

Insight #8: Lowest Evaluated Vehicles

The bottom range of vehicle evaluations includes older models and motorcycles such as:

- **Abojabaa Bike 2024 — ₹5,000**
- **Peugeot 206 2003 — ₹5,000**
- **Mercedes-Benz E-Class 1987 — ₹5,000**

Most entries cluster at ₹5,000, which appears to be the system's pricing floor for depreciated or minimal-value vehicles.

The pricing engine applies floor values consistently, suggesting stable logic even for outdated or entry-level segments.

VIN Duplication — Are Vehicles Being Re-Evaluated?

In [20]:
```
vin_counts = df['vin'].value_counts()
repeated_vins = vin_counts[vin_counts > 1]
print("Vehicles with multiple evaluations:", len(repeated_vins))
repeated_vins.head()
```

```
Vehicles with multiple evaluations: 3276
```

Out[20]:
```
vin
6T1EG23KX2X920593    89
KL1JD5CE0HB029938    68
JN6AD23S22A725420    52
MALGT41D1SM101474    51
JN8AY2NY3G9151674    46
Name: count, dtype: int64
```

Interpretation: Vehicles are being evaluated repeatedly, sometimes dozens of times — likely due to:

Dealers comparing prices across time or endpoints

System re-calls due to updates or batch processing

Testing or debugging by internal teams

It may also indicate inefficiencies (e.g., repeated calls for no change in data)

Opportunity: This data can be used to:

Flag high-interest vehicles

Identify pricing volatility

Improve caching or API optimization

Insight #9: Repeated Evaluations of the Same Vehicle (VIN)

- Over **3,182 vehicles** were evaluated multiple times
- One VIN (`6T1EG23KX2X920593`) was evaluated **89 times**
- Top 5 VINs show **40–90 evaluations each**

These repeat evaluations suggest strong customer/dealer interest, but may also point to:

- Redundant API usage
- Lack of caching for previously processed VINs
- Scenarios where price estimates vary over time

Recommendation: Analyze repeat evaluations by vendor or endpoint to optimize API cost and caching strategies.

Outliers in Processing Time

In [21]:
```
threshold = df_simulated['processing_time_ms'].quantile(0.99)
slow_requests = df_simulated[df_simulated['processing_time_ms'] > threshold]
slow_requests.sort_values(by='processing_time_ms', ascending=False).head(10)
```

Out[21]:

	id	vendor_id	endpoint	request_data	response_data	created_at	updated_at
16184	49363578	24	usedCarPriceWithSpecsSafetyReliability	{"vin": "WDB9340321L229284"}	{"code": "ct-200", "message": "ok", "success":...	2025-05-31	2025-06-18 21:36:15
1854	49349248	21	usedCarPriceWithSpecs	{"vin": "WDB9340321L111764"}	{"code": "ct-200", "message": "ok", "success":...	2025-05-06	2025-06-18 20:12:36
1855	49349249	21	usedCarPriceWithSpecs	{"vin": "WDB9340321L111764"}	{"code": "ct-200", "message": "ok", "success":...	2025-05-09	2025-06-18 20:12:36
6401	49353795	21	usedCarPriceWithSpecs	{"vin": "WDB9340321L111764"}	{"code": "ct-200", "message": "ok", "success":...	2025-06-29	2025-06-18 20:34:03
6400	49353794	21	usedCarPriceWithSpecs	{"vin": "WDB9340321L111764"}	{"code": "ct-200", "message": "ok", "success":...	2025-07-31	2025-06-18 20:34:03
551	49347945	31	usedCarPriceWithSpecs	{"vin": "WDB9340321L004850"}	{"code": "ct-200", "message": "ok", "success":...	2025-05-30	2025-06-18 20:07:44
9292	49356686	31	usedCarPriceWithSpecs	{"vin": "WDB9340321L265133"}	{"code": "ct-200", "message": "ok", "success":...	2025-05-10	2025-06-18 20:49:29

	id	vendor_id	endpoint	request_data	response_data	created_at	updated_at
6399	49353793	31	usedCarPriceWithSpecs	{"vin": "WDB9340321L111764"}	{"code": "ct-200", "message": "ok", "success":...	2025-07-31	2025-06-18 20:34:03
16189	49363583	31	usedCarPriceWithSpecs	{"vin": "WDB9340321L229284"}	{"code": "ct-200", "message": "ok", "success":...	2025-05-28	2025-06-18 21:36:16
9199	49356593	31	usedCarPriceWithSpecs	{"vin": "WDB9340321L265133"}	{"code": "ct-200", "message": "ok", "success":...	2025-05-17	2025-06-18 20:48:52

Interpretation: All top outliers are Mercedes Benz Actros Trucks from the MP2 series (2005–2008).

They consistently take 630–660 ms, which is 10× slower than average calls (~30ms).

These repeated slow evaluations on a specific model hint at:

Complex valuation logic for commercial vehicles

Possible inefficiency or bottleneck in handling trucks or older VINs

Redundant reevaluations of the same VINs — likely due to retries or uncertainty

Insight #10: Slowest API Evaluations (Processing Time Outliers)

The slowest 1% of evaluations consistently involved:

- **Mercedes Benz Actros Trucks (2005–2008)**
- Trim: *11.9L MP2 series — 934 4x2*

- Processing time: **630–660 ms**, significantly above normal

This suggests potential bottlenecks in the pricing logic for commercial vehicles or older truck models.
Many of these VINs appear multiple times, indicating repeat attempts or client-side retries.

Recommendation:

- Review pricing logic and input dependencies for Actros Trucks
- Introduce caching for high-frequency slow VINs
- Consider logging backend steps for latency debugging

Top Make-Model-Year-Trim combinations

In [30]:
```
top_combinations = (
    df_simulated
    .groupby(['manufacturer', 'model', 'year', 'trim'])
    .size()
    .sort_values(ascending=False)
    .head(10)
)
top_combinations
```

Out[30]:
```
manufacturer  model    year    trim
Toyota        Corolla  2015.0  1.6L XLi                217
                       2013.0  1.6L XLi                189
              Camry    2017.0  GLX Premium             138
Hyundai       Accent   2016.0  1.4L                    108
Toyota        Camry    2002.0  3.0L XLE Grande V6      100
              Corolla  2018.0  1.6L XLI                 97
Hyundai       Elantra  2015.0  2.0L                     95
              Accent   2018.0  1.4L                     93
Toyota        Corolla  2012.0  1.6L XLi                 91
Ford          Taurus   2023.0  2.0L EcoBoost Ambient    89
dtype: int64
```

Insight 11: Top Evaluated Make-Model-Year-Trim Combinations

The following are the most frequently evaluated combinations from the dataset:

Manufacturer	Model	Year	Trim	Count
Toyota	Corolla	2015	1.6L XLi	217
Toyota	Corolla	2013	1.6L XLi	189
Toyota	Camry	2017	GLX Premium	138
Hyundai	Accent	2016	1.4L	108
Toyota	Camry	2002	3.0L XLE Grande V6	100
Toyota	Corolla	2018	1.6L XLi	97
Hyundai	Elantra	2015	2.0L	95
Hyundai	Accent	2018	1.4L	93
Toyota	Corolla	2012	1.6L XLi	91
Ford	Taurus	2023	2.0L EcoBoost Ambient	89

Interpretation:

- **Toyota Corolla** dominates the list with multiple years and the common "1.6L XLi" trim.
- **Toyota Camry** also shows high activity, including both new and old models (2002, 2017).
- **Hyundai Accent and Elantra** models are popular in the mid-range and budget categories.
- **Ford Taurus 2023** appears, indicating strong attention on newer high-end models.

Business Insights:

- Consider building specialized support or caching for high-volume trims like Toyota Corolla 1.6L XLi.
- Focus marketing or B2B integration efforts with Toyota and Hyundai vendors.
- Popular trims can help train ML models for more accurate price predictions or offer default UI selections for users.
- This insight shows demand both in **budget markets** (older vehicles) and **premium segments** (e.g., 2023 Taurus).

Top Evaluated Cars (by count of VIN evaluations)

In [31]:
```
top_evaluated_vins = df_simulated['vin'].value_counts().head(10)
top_evaluated_vins
```

Out[31]:
```
vin
6T1EG23KX2X920593    89
KL1JD5CE0HB029938    68
JN6AD23S22A725420    52
MALGT41D1SM101474    51
JN8AY2NY3G9151674    46
KNAPG8140G5054094    46
MR0EX19G7E3514636    42
6T1BF9FK1GX605604    41
KMHFG41H8GA471041    40
KMHCT41B5HU180636    36
Name: count, dtype: int64
```

Insight 12: Top Evaluated Cars by VIN

The following vehicles (identified by their VINs) received the most evaluation requests:

VIN	Evaluation Count
6T1EG23KX2X920593	89
KL1JD5CE0HB029938	68
JN6AD23S22A725420	52
MALGT41D1SM101474	51
JN8AY2NY3G9151674	46
KNAPG8140G5054094	46
MR0EX19G7E3514636	42
6T1BF9FK1GX605604	41
KMHFG41H8GA471041	40
KMHCT41B5HU180636	36

Interpretation:

- These VINs were submitted multiple times, indicating:
  - **Dealer-side batch evaluations** (same car being priced frequently).
  - **User-side price comparison or repeated testing**.
  - **Potential system retries or looped API calls**.

Business Insights:

- Consider adding **rate limiting**, **VIN caching**, or **duplicate detection** to reduce API load.
- High-frequency VINs might indicate **hot-selling vehicles**, **valuation uncertainty**, or **user re-engagement behavior**.
- Useful for **monitoring suspicious activity** (e.g., bots or unintended API usage patterns).

Most Evaluated Cars Vendors

In [32]:
```
vendor_vin_counts = df_simulated.groupby('vendor_id')['vin'].nunique().sort_values(ascending=False)
vendor_vin_counts
```

Out[32]:
```
vendor_id
31    3141
21    3023
24    2665
Name: vin, dtype: int64
```

Insight 13: Most Evaluated Car Vendors

The following vendors have submitted the highest number of car evaluations:

Vendor ID	Number of Evaluated Cars
31	3,141
21	3,023
24	2,665

Interpretation:

- These vendors are the **top contributors to evaluation activity** on the platform.
- Vendor **31** is the most active, slightly ahead of **21**, with **24** following closely.

Business Insights:

- These vendors likely represent **key partners or high-volume clients**.
- Offer **priority support**, **custom pricing plans**, or **API optimization tools** to retain them.
- Monitor their activity for patterns—e.g., do they focus on certain brands, trims, or age groups?

> Actionable Step: Include vendor ID in the feedback loop to understand **why they're evaluating cars**—resale, insurance, etc.

Total Requests by Vendor (not just unique VINs)

In [33]:
```
vendor_request_counts = df_simulated['vendor_id'].value_counts()
vendor_request_counts
```

Out[33]:
```
vendor_id
21    8945
31    5751
24    5304
Name: count, dtype: int64
```

Insight 14: Total Requests by Vendors

This breakdown shows which vendors made the most API requests overall:

Vendor ID	Total API Requests
21	8,945
31	5,751
24	5,304

Interpretation:

- **Vendor 21** is the top API user, responsible for nearly **45%** more requests than the next highest vendor.
- **Vendor 31** and **Vendor 24** are also highly active but with **lower evaluation-to-request ratios** compared to Vendor 21.

Insight:

- While Vendor **31** evaluated more unique VINs, Vendor **21** made more total requests, indicating possible **repeat evaluations** or **frequent rechecks**.
- This could suggest **different usage patterns**—e.g., Vendor 21 might rely on frequent real-time pricing, while Vendor 31 might process large unique batches.

> Action Idea: Customize rate limits, caching strategies, or API SLAs based on vendor behavior profiles.

Top Vendors Using the API

In [35]:
```
top_vendors_by_unique_vins = (
    df_simulated.groupby('vendor_id')['vin']
    .nunique()
    .sort_values(ascending=False)
    .head(10)
)
top_vendors_by_unique_vins
```

Out[35]:
```
vendor_id
31    3141
21    3023
24    2665
Name: vin, dtype: int64
```

Insight 15: Top Vendors by Unique VIN Evaluations

This table highlights vendors based on the number of **distinct vehicles (VINs)** they evaluated:

Vendor ID	Unique VIN Evaluations
31	3,141
21	3,023

Vendor ID	Unique VIN Evaluations
24	2,665

Interpretation:

- **Vendor 31** leads in terms of **breadth of usage**, evaluating the most unique vehicles.
- **Vendor 21**, despite making the most total API requests overall, has slightly fewer distinct evaluations—indicating **frequent re-checks** of the same vehicles.
- **Vendor 24** also appears active and shows consistent behavior across metrics.

Insight:

- This metric helps understand which vendors are using the service for **inventory-wide assessments** vs. **repeat valuation** of key listings.
- Vendor 31 may be running a **valuation pipeline** for bulk listings, while Vendor 21 could be using the API for **live price updates**.

> Action Idea: Offer differentiated pricing models — one for high-volume evaluators (Vendor 31), and another for frequent re-checkers (Vendor 21).

Vendor Usage by Endpoint

In [23]:
```
df_simulated.groupby(['vendor_id', 'endpoint']).size().unstack(fill_value=0).loc[top_vendors.index]
```

Out[23]:

endpoint	usedCarPriceWithSpecs	usedCarPriceWithSpecsSafetyReliability
vendor_id		
21	8945	0
31	5751	0
24	0	5304

Insigh 16: Vendor Usage by Endpoint

This table shows which vendors are using which API endpoint:

Vendor ID	`usedCarPriceWithSpecs`	`usedCarPriceWithSpecsSafetyReliability`
21	8,945	0
31	5,751	0
24	0	5,304

Interpretation:

- **Vendors 21 and 31** are exclusively using the basic `usedCarPriceWithSpecs` endpoint.
- **Vendor 24** is the only one using the extended `usedCarPriceWithSpecsSafetyReliability` endpoint.

Insight:

- The data shows a **clear vendor preference split by endpoint**.
- Vendor 24 may be more focused on safety/reliability features and might target a premium segment or regulatory-compliant platform.
- Vendors 21 and 31 likely prioritize **faster pricing without detailed safety data**, possibly for internal decision-making or pricing automation at scale.

> Consider engaging Vendor 21 and 31 for upselling the enhanced endpoint and offering a hybrid pricing bundle.

Top Trims by Evaluated Price

In [25]:
```
df_simulated['evaluated_price'] = pd.to_numeric(df_simulated['evaluated_price'], errors='coerce')
top_trims = df_simulated.groupby('trim')['evaluated_price'].mean().sort_values(ascending=False).head(10)
top_trims
```

Out[25]:
```
trim
4.0L V8                              697246.000000
600 Vip Launch Edition AWD 4seats    531913.000000
600 Elite Base 7seats                512564.000000
S 450 AMG                            467601.761905
4.4L xDrive V8 PHEV                  465374.000000
6.0L W12 Speed                       461863.000000
6.6L V12 TwinTurbo                   453865.000000
600 Elite AWD 7seats                 427800.000000
S 500 AMG                            393635.750000
110 Defender X P400                  375907.000000
Name: evaluated_price, dtype: float64
```

Interpretation: These trims clearly represent ultra-luxury or performance variants (e.g., AMG, V12, PHEV, AWD).

Manufacturers like Lamborghini, Lexus, Mercedes-Benz, Rolls-Royce, and Land Rover dominate the top list.

The pricing model appears to correctly scale with:

Engine size (V8, V12)

Drivetrain (AWD, PHEV)

Limited or launch edition features

Insight 17 #: Most Expensive Vehicle Trims by Evaluated Price

The highest-value trims in the dataset include:

- **4.0L V8** — ₹697,246
- **600 VIP Launch Edition AWD 4seats** — ₹531,913
- **S 450 AMG** — ₹467,601
- **6.0L W12 Speed** — ₹461,863
- **110 Defender X P400** — ₹375,907

These premium variants showcase the pricing engine's sensitivity to:

- Luxury/performance trims

- Limited/launch editions
- Advanced drivetrain and engine specs

Recommendation: Consider training separate valuation models for luxury segments or offering premium valuation APIs for high-end trims.

Recommendations for Business & Engineering

---

1. Focus on Core Endpoint Usage

- The majority of API traffic (~73%) comes from the `usedCarPriceWithSpecs` endpoint.
- Ensure ongoing monitoring, documentation clarity, and uptime for this critical service.
- Consider performance audits to maintain speed under increasing demand.

---

2. Expand Support for Premium Vehicle Segments

- Top evaluated trims include **Toyota Corolla 1.6L XLi**, **Hyundai Accent**, and **Lamborghini Urus**.
- The evaluated price distribution shows a **long tail** of high-end cars exceeding ₹500,000.
- Introduce **premium analytics**, reporting, or pricing tiers for luxury segment clients.

---

3. Address Month-wise Latency Variability

- **May 2025** showed the **highest average processing time** (~28.6 ms); **June** the lowest (~27.8 ms).
- These shifts suggest variations in data load or VIN complexity.
- Recommend profiling backend performance per month and optimizing for peak load periods.

---

4. Leverage Repeated VIN Lookups for Efficiency

- Over **3,000 VINs** were re-evaluated multiple times, some over 50+ times.
- Build a **caching mechanism** for repeat evaluations to reduce load and improve response time.

- Optionally notify users when a VIN has been recently evaluated.

---

5. **Expand Time Horizon for Strategic Trends**

- Current data spans only **May–July 2025** (3 months).
- This limits ability to detect seasonal, economic, or regulatory impact on vehicle valuation.
- Recommend extending data collection to at least **12 months** to enable robust forecasting and benchmarking.

---

6. **Tailor Insights & Support by Vendor Type**

- **Vendor 21** is the top API consumer (~8,900 requests), using only the base endpoint.
- **Vendor 24** exclusively uses the enhanced endpoint (`SafetyReliability`) with ~5,300 requests.
- Suggest **custom SLAs**, usage dashboards, or pricing models tailored to vendor behavior.

---

7. **Monitor Top Models for OEM Engagement**

- High-frequency evaluations of trims like **Corolla, Accent, Camry, Yaris** indicate market interest.
- Use this data to explore partnerships or resale analytics tools for specific manufacturers.

In [ ]: