Experiment Notebook

Setup Environment

In [1]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
!pip install -q utstd

from utstd.folders import *
from utstd.ipyrenders import *

at = AtFolder(
    course_code=36106,
    assignment="AT1",
)
at.run()

import warnings
warnings.simplefilter(action='ignore')
```

```
[notice] A new release of pip available: 22.3.1 -> 25.2
[notice] To update, run: python.exe -m pip install --upgrade pip
You can now save your data files in: c:\Users\brohao\Desktop\UTS\36106\AT1\36106\assignment\AT
1\data
```

Student Information

In [2]:
```
# Student name with space
student_name = "Jiayu Hao"
student_id = "25948860"
```

In [3]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h1", key='student_name', value=student_name)
```

student_name

Jiayu Hao

In [4]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h1", key='student_id', value=student_id)
```

student_id

25948860

---

0. Python Packages

0.a Install Additional Packages

> If you are using additional packages, you need to install them here using the command: `! pip install <package_name>`

In [5]:
```
!pip install numpy
!pip install matplot.lib
!pip install seaborn
```

```
Requirement already satisfied: numpy in c:\users\brohao\appdata\local\programs\python\python31
1\lib\site-packages (2.3.2)
```

```
[notice] A new release of pip available: 22.3.1 -> 25.2
[notice] To update, run: python.exe -m pip install --upgrade pip
ERROR: Could not find a version that satisfies the requirement matplot.lib (from versions: non
e)
ERROR: No matching distribution found for matplot.lib

[notice] A new release of pip available: 22.3.1 -> 25.2
[notice] To update, run: python.exe -m pip install --upgrade pip
```

```
Requirement already satisfied: seaborn in c:\users\brohao\appdata\local\programs\python\python
311\lib\site-packages (0.13.2)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in c:\users\brohao\appdata\local\programs
\python\python311\lib\site-packages (from seaborn) (2.3.2)
Requirement already satisfied: pandas>=1.2 in c:\users\brohao\appdata\local\programs\python\py
thon311\lib\site-packages (from seaborn) (2.2.2)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in c:\users\brohao\appdata\local\progra
ms\python\python311\lib\site-packages (from seaborn) (3.10.5)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\brohao\appdata\local\programs\pyth
on\python311\lib\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (1.3.3)
Requirement already satisfied: cycler>=0.10 in c:\users\brohao\appdata\local\programs\python\p
ython311\lib\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\brohao\appdata\local\programs\pyt
hon\python311\lib\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (4.59.1)
Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\brohao\appdata\local\programs\pyt
hon\python311\lib\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (1.4.9)
Requirement already satisfied: packaging>=20.0 in c:\users\brohao\appdata\roaming\python\pytho
n311\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (25.0)
Requirement already satisfied: pillow>=8 in c:\users\brohao\appdata\local\programs\python\pyth
on311\lib\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\brohao\appdata\local\programs\pyth
on\python311\lib\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\brohao\appdata\roaming\python
\python311\site-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\brohao\appdata\local\programs\python\p
ython311\lib\site-packages (from pandas>=1.2->seaborn) (2023.3)
Requirement already satisfied: tzdata>=2022.7 in c:\users\brohao\appdata\local\programs\python
\python311\lib\site-packages (from pandas>=1.2->seaborn) (2023.3)
Requirement already satisfied: six>=1.5 in c:\users\brohao\appdata\local\programs\python\pytho
n311\lib\site-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)
```

```
[notice] A new release of pip available: 22.3.1 -> 25.2
[notice] To update, run: python.exe -m pip install --upgrade pip
```

0.b Import Packages

In [6]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
import pandas as pd
import altair as alt
```

In [7]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

A. Project Description

In [8]:
```
# Explain clearly what is the goal of this project for the business. How will the results be u

business_objective = """
The goal of this project is to predict how much customers will pay for their Motor Vehicle Ins
The results will help the company set fair premiums, keep customers, and lower financial risk
If predictions are accurate, the company can give fair prices, stay profitable, and keep custo
"""
```

In [9]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='business_objective', value=business_objective)
```

business_objective

The goal of this project is to predict how much customers will pay for their Motor Vehicle Insurance. The results will help the company set fair premiums, keep customers, and lower financial risk. If predictions are accurate, the company can give fair prices, stay profitable, and keep customers. If predictions are wrong, the company may lose money by charging too little or lose customers by charging too much.

B. Dataset Understanding (Global Interpretation)

In [10]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
# Load training data
try:
  training_df = pd.read_csv(at.folder_path / "car_insurance_premium_training.csv")
  validation_df = pd.read_csv(at.folder_path / "car_insurance_premium_validation.csv")
  testing_df = pd.read_csv(at.folder_path / "car_insurance_premium_testing.csv")
except Exception as e:
  print(e)
```

B.1 Explore Training Set

> You can add more cells in this section

In [11]:
```
print("Shape of dataset:", training_df.shape)   # rows * columns
# Overview of data types and non-null counts
print("\nDataset Info:")
print(training_df.info())

# First few rows
print("\nFirst 5 rows of training set:")
pd.set_option("display.max_columns", None)
display(training_df.head())

# SSummary statistics for numerical features
print("\nSummary statistics for numerical variables:")
display(training_df.describe().T)

# Summary for categorical features
print("\nUnique values count for categorical variables:")
categorical_cols = training_df.select_dtypes(include=["object", "category"]).columns
for col in categorical_cols:
    print(f"{col}: {training_df[col].nunique()} unique values")
```

```python
# Step 8: Missing values
print("\nMissing values per column:")
missing = training_df.isnull().sum()
missing = missing[missing > 0].sort_values(ascending=False)
display(missing)

# Step 9: Check for duplicate rows
print("\nNumber of duplicate rows:", training_df.duplicated().sum())
```

```
Shape of dataset: (32136, 40)

Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32136 entries, 0 to 32135
Data columns (total 40 columns):
 #   Column                             Non-Null Count  Dtype  
---  ------                             --------------  -----  
 0   customer_id                        32136 non-null  object 
 1   prefix                             21345 non-null  object 
 2   first_name                         32136 non-null  object 
 3   last_name                          32116 non-null  object 
 4   gender                             32136 non-null  object 
 5   birth_date                         32136 non-null  object 
 6   driving_license_date               32136 non-null  object 
 7   phone_number                       32136 non-null  object 
 8   email                              32136 non-null  object 
 9   secondary_address                  32136 non-null  object 
 10  building_number                    32136 non-null  int64  
 11  street_name                        32136 non-null  object 
 12  street_suffix                      32136 non-null  object 
 13  suburb                             32136 non-null  object 
 14  contract_start_date                32136 non-null  object 
 15  last_renewal_date                  32136 non-null  object 
 16  next_renewal_date                  32136 non-null  object 
 17  distribution_channel               32136 non-null  object 
 18  seniority                          32136 non-null  int64  
 19  current_policies_held              32136 non-null  int64  
 20  max_policies_held                  32136 non-null  int64  
 21  max_products_held                  32136 non-null  int64  
 22  lapsed_policies                    32136 non-null  int64  
 23  lapsed_date                        12567 non-null  object 
 24  payment_method                     32136 non-null  int64  
 25  net_premium_amount                 32136 non-null  float64
 26  total_claims_cost_in_current_year  32136 non-null  float64
 27  total_claims_number_in_current_year 32136 non-null  int64  
 28  total_claims_number_in_history     32136 non-null  int64  
 29  total_claims_number_ratio          32136 non-null  float64
 30  policy_type                        32136 non-null  int64  
 31  second_driver                      32136 non-null  int64  
 32  matriculation_year                 32136 non-null  int64  
 33  vehicle_horsepower                 32136 non-null  int64  
 34  vehicle_cylinder                   32136 non-null  int64  
 35  vehicle_value                      32136 non-null  float64
 36  vehicle_doors                      32136 non-null  int64  
 37  vehicle_fuel_type                  32058 non-null  object 
 38  vehicle_length                     31451 non-null  float64
 39  vehicle_weight                     32136 non-null  int64  
dtypes: float64(5), int64(16), object(19)
memory usage: 9.8+ MB
None

First 5 rows of training set:
```

	customer_id	prefix	first_name	last_name	gender	birth_date	driving_license_date	phone_n
0	2f4cea69-3806-41b7-b7c2-6039eaac8fae	Mr.	John	Medina	m	1970-12-24	2004-12-21	+61 4
1	c738e8cb-13fe-43f9-8d59-b501b04ff590	Dr.	Krystal	Howard	f	1989-02-07	2008-02-20	0412-9
2	685c81d7-b1de-4862-902e-f57612dedb57	Mr.	Jeffrey	Craig	m	1972-08-29	2001-12-08	0790
3	643be7d5-6ffa-4517-8468-85bfe5e01bde	Mr.	Gregory	Ortiz	m	1983-01-01	2013-09-25	(03) 963
4	99c498eb-33de-479b-88ec-b5b9d6d5252b	Mr.	Donald	Harrison	m	1960-07-16	1999-06-30	+61-2

```
Summary statistics for numerical variables:
```

	count	mean	std	min	25%	
building_number	32136.0	185.629792	280.506483	0.00	6.000	4
seniority	32136.0	5.896596	5.909002	1.00	2.000	
current_policies_held	32136.0	1.443055	0.943590	1.00	1.000	
max_policies_held	32136.0	1.796023	1.157598	1.00	1.000	
max_products_held	32136.0	1.048015	0.231683	1.00	1.000	
lapsed_policies	32136.0	0.391804	0.550027	0.00	0.000	
payment_method	32136.0	0.361433	0.480423	0.00	0.000	
net_premium_amount	32136.0	579.367438	44.991023	460.00	542.000	57
total_claims_cost_in_current_year	32136.0	104.826855	1110.840111	0.00	0.000	
total_claims_number_in_current_year	32136.0	0.206622	0.771437	0.00	0.000	
total_claims_number_in_history	32136.0	2.647498	3.787398	0.00	0.000	
total_claims_number_ratio	32136.0	0.463897	0.774516	0.00	0.000	
policy_type	32136.0	2.839806	0.396159	1.00	3.000	
second_driver	32136.0	0.119461	0.324335	0.00	0.000	
matriculation_year	32136.0	2004.573376	5.347809	1954.00	2001.000	200
vehicle_horsepower	32136.0	97.543409	28.174377	0.00	75.000	9
vehicle_cylinder	32136.0	1717.529842	409.694777	49.00	1461.000	174
vehicle_value	32136.0	18972.391870	7176.732691	270.46	14093.730	1802
vehicle_doors	32136.0	4.404998	0.976780	0.00	4.000	
vehicle_length	31451.0	4.251559	0.378661	2.50	4.015	
vehicle_weight	32136.0	1252.991349	274.112493	55.00	1089.000	123

```
Unique values count for categorical variables:
customer_id: 32136 unique values
prefix: 5 unique values
first_name: 1321 unique values
last_name: 2446 unique values
gender: 3 unique values
birth_date: 14183 unique values
driving_license_date: 11691 unique values
phone_number: 32136 unique values
email: 30167 unique values
secondary_address: 3270 unique values
street_name: 27443 unique values
street_suffix: 200 unique values
suburb: 18887 unique values
contract_start_date: 4963 unique values
last_renewal_date: 1117 unique values
next_renewal_date: 1117 unique values
distribution_channel: 3 unique values
lapsed_date: 1200 unique values
vehicle_fuel_type: 2 unique values

Missing values per column:
```

```
lapsed_date           19569
prefix                10791
vehicle_length          685
vehicle_fuel_type        78
last_name                20
dtype: int64
Number of duplicate rows: 0
```

In [12]:
```
training_set_insights = """
The dataset has 32,136 rows and 40 columns, including 3 types information(customer, policy, a
Several columns are identifiers or personal details(IDs, names, contact info, addresses). Tho
Missing values exist mainly in lapsed_date(61%), prefix(34%), and a few vehicle information(v

Numerical issues:
Outliers: total_claims_cost_in_current_year(mean: 105, max:128, 000).
Invalid values (e.g., vehicle_doors=0, vehicle_weight=55, vehicle_horsepower=0).
Skewed variables (claims cost(exist outlier), vehicle_value).

Categorical variables: gender, policy_type, vehicle_fuel_type, and distribution_channel will 
Dates(birth_date, driving_license_date, matriculation_year) will be transformed into derived 
"""
```

In [13]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='training_set_insights', value=training_set_insights)
```

training_set_insights

The dataset has 32,136 rows and 40 columns, including 3 types information(customer, policy, and vehicle information). Several columns are identifiers or personal details(IDs, names, contact info, addresses). Those columns will be dropped. Missing values exist mainly in lapsed_date(61%), prefix(34%), and a few vehicle information(vehicle_length, vehicle_fuel_type). Numerical issues: Outliers: total_claims_cost_in_current_year(mean: 105, max:128, 000). Invalid values (e.g., vehicle_doors=0, vehicle_weight=55, vehicle_horsepower=0). Skewed variables (claims cost(exist outlier), vehicle_value). Categorical variables: gender, policy_type, vehicle_fuel_type, and distribution_channel will be encoded. Some columns may be not useful. Dates(birth_date, driving_license_date, matriculation_year) will be transformed into derived features such as age, driving experience, and car age.

B.2 Explore Validation Set

> You can add more cells in this section

In [14]:
```
print("Shape of dataset:", validation_df.shape)   # rows * columns

# Overview of data types and non-null counts
print("\nDataset Info:")
print(validation_df.info())

# First few rows
print("\nFirst 5 rows of validation set:")
pd.set_option("display.max_columns", None)
display(validation_df.head())

# Summary statistics for numerical features
print("\nSummary statistics for numerical variables:")
display(validation_df.describe().T)
```

```python
# Summary for categorical features
print("\nUnique values count for categorical variables:")
categorical_cols = validation_df.select_dtypes(include=["object", "category"]).columns
for col in categorical_cols:
    print(f"{col}: {validation_df[col].nunique()} unique values")

# Missing values
print("\nMissing values per column:")
missing = validation_df.isnull().sum()
missing = missing[missing > 0].sort_values(ascending=False)
display(missing)

# Duplicate rows
print("\nNumber of duplicate rows:", validation_df.duplicated().sum())
```

```
Shape of dataset: (10700, 40)

Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10700 entries, 0 to 10699
Data columns (total 40 columns):
 #   Column                              Non-Null Count  Dtype  
---  ------                              --------------  -----  
 0   customer_id                         10700 non-null  object 
 1   prefix                              7078 non-null   object 
 2   first_name                          10700 non-null  object 
 3   last_name                           10696 non-null  object 
 4   gender                              10700 non-null  object 
 5   birth_date                          10700 non-null  object 
 6   driving_license_date                10700 non-null  object 
 7   phone_number                        10700 non-null  object 
 8   email                               10700 non-null  object 
 9   secondary_address                   10700 non-null  object 
 10  building_number                     10700 non-null  int64  
 11  street_name                         10700 non-null  object 
 12  street_suffix                       10700 non-null  object 
 13  suburb                              10700 non-null  object 
 14  contract_start_date                 10700 non-null  object 
 15  last_renewal_date                   10700 non-null  object 
 16  next_renewal_date                   10700 non-null  object 
 17  distribution_channel                10700 non-null  object 
 18  seniority                           10700 non-null  int64  
 19  current_policies_held               10700 non-null  int64  
 20  max_policies_held                   10700 non-null  int64  
 21  max_products_held                   10700 non-null  int64  
 22  lapsed_policies                     10700 non-null  int64  
 23  lapsed_date                         3087 non-null   object 
 24  payment_method                      10700 non-null  int64  
 25  net_premium_amount                  10700 non-null  float64
 26  total_claims_cost_in_current_year   10700 non-null  float64
 27  total_claims_number_in_current_year 10700 non-null  int64  
 28  total_claims_number_in_history      10700 non-null  int64  
 29  total_claims_number_ratio           10700 non-null  float64
 30  policy_type                         10700 non-null  int64  
 31  second_driver                       10700 non-null  int64  
 32  matriculation_year                  10700 non-null  int64  
 33  vehicle_horsepower                  10700 non-null  int64  
 34  vehicle_cylinder                    10700 non-null  int64  
 35  vehicle_value                       10700 non-null  float64
 36  vehicle_doors                       10700 non-null  int64  
 37  vehicle_fuel_type                   10081 non-null  object 
 38  vehicle_length                      7261 non-null   float64
 39  vehicle_weight                      10700 non-null  int64  
dtypes: float64(5), int64(16), object(19)
memory usage: 3.3+ MB
None

First 5 rows of validation set:
```

	customer_id	prefix	first_name	last_name	gender	birth_date	driving_license_date	phone_n
0	980657d0-843c-4006-abcb-aa6a44ad57f1	NaN	Veronica	Simpson	u	1982-08-12	2000-09-21	560
1	f50db3af-dfae-496a-8aaf-14b0ea2729e2	Dr.	Carla	Riley	f	1976-12-09	1994-12-23	+61 4
2	d32a95a8-3ed8-4a98-a54a-472dd480f6fa	NaN	Brian	Branch	u	1948-06-25	1970-04-11	(07).963
3	ba0d15a9-0792-44a2-87d3-05f45c1c046d	Dr.	Drew	Smith	m	1974-09-21	1994-09-21	02.498
4	e0da2a4b-fa0f-4512-a363-780d1f8e2b0e	Mr.	Jose	Watson	m	1961-06-26	2014-08-01	(07).751

```
Summary statistics for numerical variables:
```

	count	mean	std	min	25%
building_number	10700.0	185.951776	280.713477	0.000	6.000
seniority	10700.0	6.120374	6.444548	1.000	2.000
current_policies_held	10700.0	1.756449	1.268339	1.000	1.000
max_policies_held	10700.0	2.082991	1.410385	1.000	1.000
max_products_held	10700.0	1.108411	0.336329	1.000	1.000
lapsed_policies	10700.0	0.315327	0.558235	0.000	0.000
payment_method	10700.0	0.161682	0.368176	0.000	0.000
net_premium_amount	10700.0	489.297009	133.399129	309.000	396.000
total_claims_cost_in_current_year	10700.0	87.516426	2356.273613	0.000	0.000
total_claims_number_in_current_year	10700.0	0.156822	0.659318	0.000	0.000
total_claims_number_in_history	10700.0	2.149533	3.518325	0.000	0.000
total_claims_number_ratio	10700.0	0.322316	0.816566	0.000	0.000
policy_type	10700.0	2.387383	0.929685	1.000	1.000
second_driver	10700.0	0.084766	0.278547	0.000	0.000
matriculation_year	10700.0	2002.933271	9.513792	1950.000	2000.000
vehicle_horsepower	10700.0	70.655421	44.015785	0.000	34.000
vehicle_cylinder	10700.0	1296.187477	867.199458	49.000	599.000
vehicle_value	10700.0	14177.850521	10079.413937	270.460	6611.130
vehicle_doors	10700.0	3.056822	2.178017	0.000	0.000
vehicle_length	7261.0	4.151021	0.374925	1.978	3.916
vehicle_weight	10700.0	956.078411	710.277947	43.000	200.000

```
Unique values count for categorical variables:
customer_id: 10700 unique values
prefix: 5 unique values
first_name: 1017 unique values
last_name: 1624 unique values
gender: 3 unique values
birth_date: 7528 unique values
driving_license_date: 6625 unique values
phone_number: 10700 unique values
email: 10445 unique values
secondary_address: 2516 unique values
street_name: 10139 unique values
street_suffix: 200 unique values
suburb: 8240 unique values
contract_start_date: 3116 unique values
last_renewal_date: 1056 unique values
next_renewal_date: 1056 unique values
distribution_channel: 3 unique values
lapsed_date: 1027 unique values
vehicle_fuel_type: 2 unique values

Missing values per column:
```

```
lapsed_date          7613
prefix               3622
vehicle_length       3439
vehicle_fuel_type     619
last_name               4
dtype: int64
Number of duplicate rows: 0
```

In [15]:
```
# provide a detailed analysis on the validation set, its dimensions, information, issues, ...
validation_set_insights = """
The validation set has 10,700 rows and 40 columns, same structure as training.
Premiums are lower on average (mean ≈ 489) and show more variation.
Some variables have many missing values (lapsed_date, prefix, vehicle_length).
several contain outliers (e.g., very high claims, unusual vehicle specs).
Data quality issues are similar to training and need the same cleaning.
Overall, the set is consistent and suitable for model evaluation.
"""
```

In [16]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='validation_set_insights', value=validation_set_insights)
```

validation_set_insights

The validation set has 10,700 rows and 40 columns, same structure as training. Premiums are lower on average (mean ≈ 489) and show more variation. Some variables have many missing values (lapsed_date, prefix, vehicle_length). several contain outliers (e.g., very high claims, unusual vehicle specs). Data quality issues are similar to training and need the same cleaning. Overall, the set is consistent and suitable for model evaluation.

B.3 Explore Testing Set

> You can add more cells in this section

In [17]:
```
print("Shape of dataset:", testing_df.shape)   # rows * columns

# Overview of data types and non-null counts
print("\nDataset Info:")
print(testing_df.info())

# First few rows
print("\nFirst 5 rows of testing set:")
pd.set_option("display.max_columns", None)
display(testing_df.head())

# Summary statistics for numerical features
print("\nSummary statistics for numerical variables:")
display(testing_df.describe().T)

# Summary for categorical features
print("\nUnique values count for categorical variables:")
categorical_cols = testing_df.select_dtypes(include=["object", "category"]).columns
for col in categorical_cols:
    print(f"{col}: {testing_df[col].nunique()} unique values")

# Missing values
print("\nMissing values per column:")
missing = testing_df.isnull().sum()
missing = missing[missing > 0].sort_values(ascending=False)
display(missing)
```

```python
# Duplicate rows
print("\nNumber of duplicate rows:", testing_df.duplicated().sum())
```

```
Shape of dataset: (10666, 40)

Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10666 entries, 0 to 10665
Data columns (total 40 columns):
 #   Column                              Non-Null Count  Dtype  
---  ------                              --------------  -----  
 0   customer_id                         10666 non-null  object 
 1   prefix                              7039 non-null   object 
 2   first_name                          10666 non-null  object 
 3   last_name                           10665 non-null  object 
 4   gender                              10666 non-null  object 
 5   birth_date                          10666 non-null  object 
 6   driving_license_date                10666 non-null  object 
 7   phone_number                        10666 non-null  object 
 8   email                               10666 non-null  object 
 9   secondary_address                   10666 non-null  object 
 10  building_number                     10666 non-null  int64  
 11  street_name                         10666 non-null  object 
 12  street_suffix                       10666 non-null  object 
 13  suburb                              10666 non-null  object 
 14  contract_start_date                 10666 non-null  object 
 15  last_renewal_date                   10666 non-null  object 
 16  next_renewal_date                   10666 non-null  object 
 17  distribution_channel                10666 non-null  object 
 18  seniority                           10666 non-null  int64  
 19  current_policies_held               10666 non-null  int64  
 20  max_policies_held                   10666 non-null  int64  
 21  max_products_held                   10666 non-null  int64  
 22  lapsed_policies                     10666 non-null  int64  
 23  lapsed_date                         4539 non-null   object 
 24  payment_method                      10666 non-null  int64  
 25  net_premium_amount                  10666 non-null  float64
 26  total_claims_cost_in_current_year   10666 non-null  float64
 27  total_claims_number_in_current_year 10666 non-null  int64  
 28  total_claims_number_in_history      10666 non-null  int64  
 29  total_claims_number_ratio           10666 non-null  float64
 30  policy_type                         10666 non-null  int64  
 31  second_driver                       10666 non-null  int64  
 32  matriculation_year                  10666 non-null  int64  
 33  vehicle_horsepower                  10666 non-null  int64  
 34  vehicle_cylinder                    10666 non-null  int64  
 35  vehicle_value                       10666 non-null  float64
 36  vehicle_doors                       10666 non-null  int64  
 37  vehicle_fuel_type                   10506 non-null  object 
 38  vehicle_length                      9648 non-null   float64
 39  vehicle_weight                      10666 non-null  int64  
dtypes: float64(5), int64(16), object(19)
memory usage: 3.3+ MB
None

First 5 rows of testing set:
```

	customer_id	prefix	first_name	last_name	gender	birth_date	driving_license_date	phone_r
0	08630f39-3b19-4c50-aaac-6cbb5d63b820	Mr.	Jose	Fritz	m	1998-07-15	2016-11-22	+61.7.52
1	e491ab7e-a3df-474d-a6d5-9cbd85dc4242	NaN	Eric	Wilson	u	1992-05-12	2010-11-05	81
2	6bafa529-bdc5-442f-b96f-eb5120799054	Mr.	Parker	Burton	m	1957-04-07	1977-04-24	0463.
3	aea650ed-62e6-4b69-99b3-04fe84f60354	NaN	Matthew	Bonilla	u	1981-04-14	2008-03-14	+61.477.
4	fb24f594-dc26-4cb5-8fdc-c8568b3c72ea	Mrs.	Sarah	Holloway	f	1974-08-01	1992-09-29	0411

```
Summary statistics for numerical variables:
```

	count	mean	std	min	25%	
building_number	10666.0	186.816801	281.124963	0.00	6.000	4
seniority	10666.0	5.153666	5.258575	1.00	2.000	
current_policies_held	10666.0	1.483218	0.966358	1.00	1.000	
max_policies_held	10666.0	1.828146	1.166254	1.00	1.000	
max_products_held	10666.0	1.056722	0.245481	1.00	1.000	
lapsed_policies	10666.0	0.429402	0.565399	0.00	0.000	
payment_method	10666.0	0.450778	0.497595	0.00	0.000	
net_premium_amount	10666.0	773.221733	212.915798	397.00	694.000	7
total_claims_cost_in_current_year	10666.0	184.485467	1288.970159	0.00	0.000	
total_claims_number_in_current_year	10666.0	0.267110	0.899549	0.00	0.000	
total_claims_number_in_history	10666.0	2.952466	4.189095	0.00	0.000	
total_claims_number_ratio	10666.0	0.618153	0.929463	0.00	0.000	
policy_type	10666.0	2.705888	0.619905	1.00	3.000	
second_driver	10666.0	0.194825	0.396084	0.00	0.000	
matriculation_year	10666.0	2007.177386	6.766693	1952.00	2003.000	20
vehicle_horsepower	10666.0	103.245265	44.324701	0.00	82.000	1
vehicle_cylinder	10666.0	1645.733827	627.110106	49.00	1396.000	15
vehicle_value	10666.0	21701.601107	11886.970952	480.81	15308.335	206
vehicle_doors	10666.0	4.090381	1.527644	0.00	4.000	
vehicle_length	9648.0	4.356239	0.429827	2.50	4.110	
vehicle_weight	10666.0	1238.638009	435.880734	43.00	1095.000	12

```
Unique values count for categorical variables:
customer_id: 10666 unique values
prefix: 5 unique values
first_name: 1025 unique values
last_name: 1664 unique values
gender: 3 unique values
birth_date: 7753 unique values
driving_license_date: 6827 unique values
phone_number: 10666 unique values
email: 10448 unique values
secondary_address: 2542 unique values
street_name: 10127 unique values
street_suffix: 200 unique values
suburb: 8226 unique values
contract_start_date: 2805 unique values
last_renewal_date: 1095 unique values
next_renewal_date: 1095 unique values
distribution_channel: 3 unique values
lapsed_date: 1111 unique values
vehicle_fuel_type: 2 unique values

Missing values per column:
```

```
lapsed_date          6127
prefix               3627
vehicle_length       1018
vehicle_fuel_type     160
last_name               1
dtype: int64
Number of duplicate rows: 0
```

In [18]:
```
# provide a detailed analysis on the testing set, its dimensions, information, issues, ...
testing_set_insights = """
The testing set has 10,666 rows and 40 columns, consistent with training and validation.
Average premium is higher (mean ≈ 773) and shows more variability compared to other sets.
Several variables contain missing values, most notably lapsed_date (~57%), prefix (~34%), and
Outliers exist in claims (e.g. very high costs), vehicle specs (e.g. horsepower up to 580, va
Despite these issues, the structure matches the other datasets, making it suitable for final 
"""
```

In [19]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='testing_set_insights', value=testing_set_insights)
```

testing_set_insights

The testing set has 10,666 rows and 40 columns, consistent with training and validation. Average premium is higher (mean ≈ 773) and shows more variability compared to other sets. Several variables contain missing values, most notably lapsed_date (~57%), prefix (~34%), and vehicle_length (~10%). Outliers exist in claims (e.g. very high costs), vehicle specs (e.g. horsepower up to 580, value 200k), and unrealistic cases (vehicle_doors=0). Despite these issues, the structure matches the other datasets, making it suitable for final performance evaluation after consistent preprocessing.

C. Feature Understanding (Local Interpretation)

C.1 Explore Target Variable

> Save the name of column used as the target variable and call it `target_name`

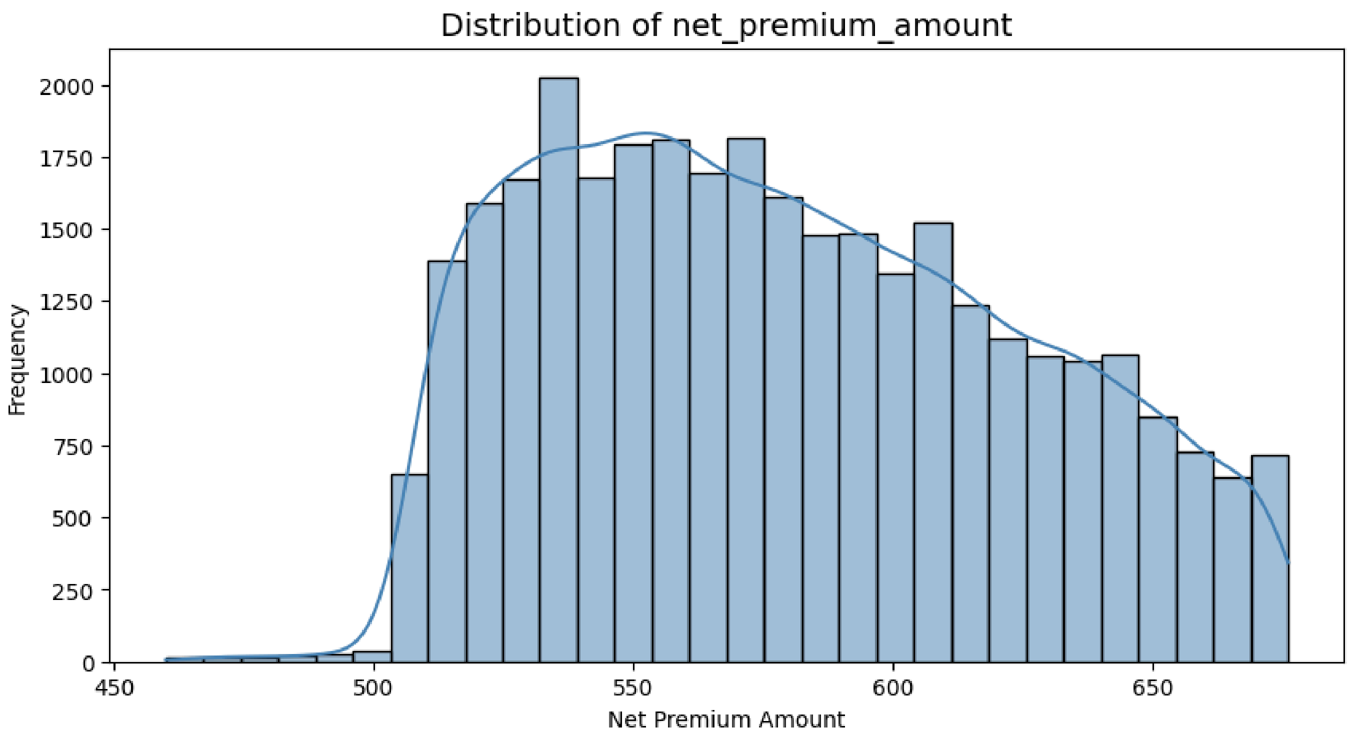
> You can add more cells in this section

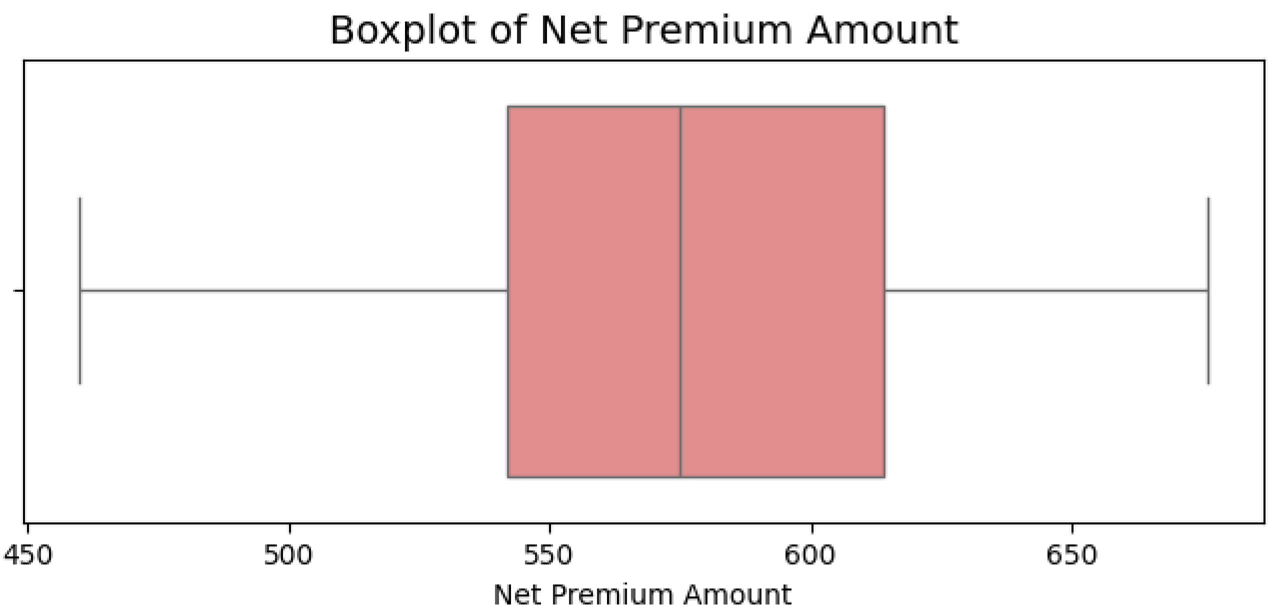
In [20]:
```
# Target name
target_name = 'net_premium_amount'
```

In [21]:
```
# Basic statistics
target = training_df[target_name]
print("Target Variable: net_premium_amount")
print(target.describe())

# Histogram + KDE
plt.figure(figsize=(10,5))
sns.histplot(target, bins=30, kde=True, color="steelblue")
plt.title("Distribution of net_premium_amount", fontsize=14)
plt.xlabel("Net Premium Amount")
plt.ylabel("Frequency")
plt.show()

# Boxplot (to check for outliers)
plt.figure(figsize=(8,3))
```

```python
sns.boxplot(x=target, color="lightcoral")
plt.title("Boxplot of Net Premium Amount", fontsize=14)
plt.xlabel("Net Premium Amount")
plt.show()
```

```
Target Variable: net_premium_amount
count    32136.000000
mean       579.367438
std         44.991023
min        460.000000
25%        542.000000
50%        575.000000
75%        614.000000
max        676.000000
Name: net_premium_amount, dtype: float64
```





In [22]:
```python
# provide a detailed analysis on the target variable, its distribution, limitations, issues,
target_insights = """
The target variable net_premium_amount ranges from 460 to 676, with a mean of about 579 and a
Its distribution is relatively narrow and right-skewed, most values of target variable concent
This limited variability means even small errors (e.g., ±20) are significant compared to the p
No extreme outliers are observed, means the premium scale need to be limited strictly.
"""
```

In [23]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='target_insights', value=target_insights)
```

target_insights

The target variable net_premium_amount ranges from 460 to 676, with a mean of about 579 and a small standard deviation (~45). Its distribution is relatively narrow and right-skewed, most values of target variable concentrate between 540 and 615. This limited variability means even small errors (e.g., ±20) are significant compared to the premium scale. No extreme outliers are observed, means the premium scale need to be limited strictly.

C.2 Explore Feature of Interest `birth_date`

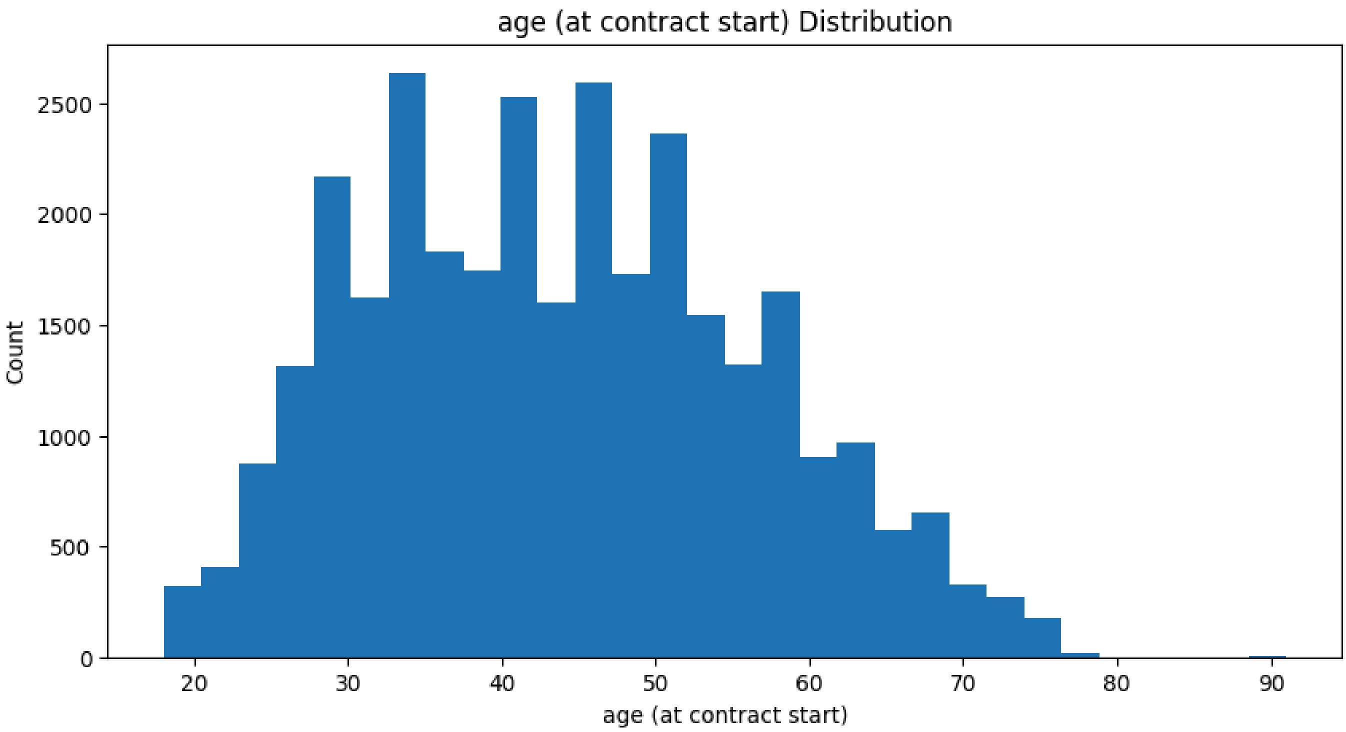
> You can add more cells in this section

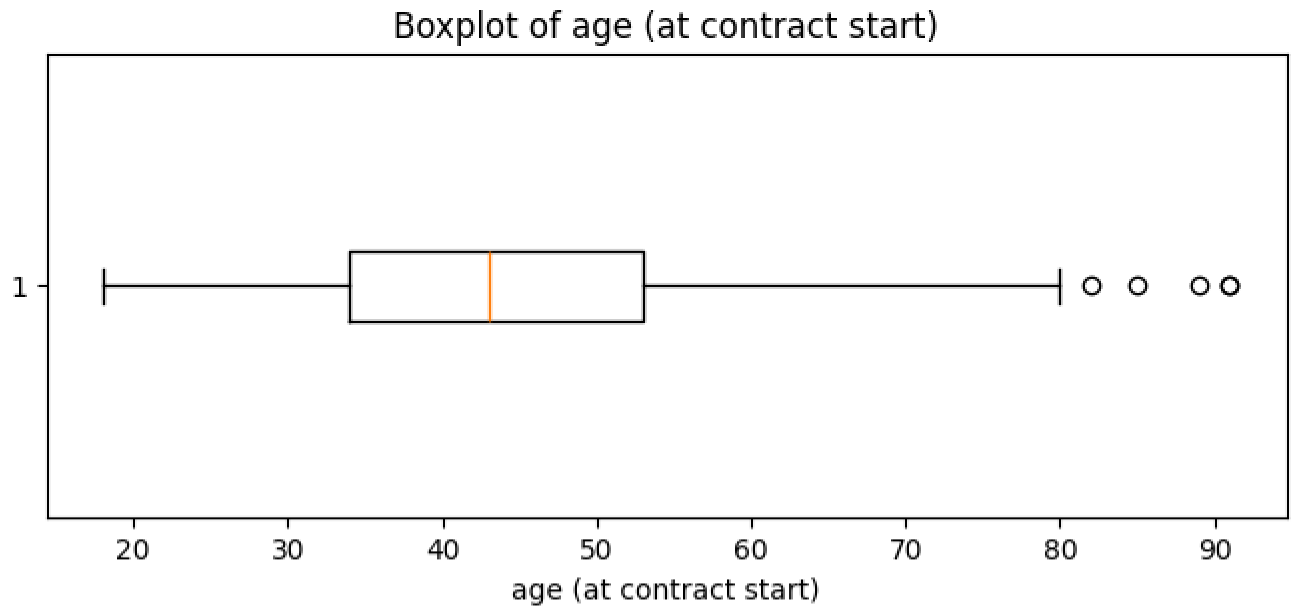
In [24]:
```
feature_name = "birth_date"           # Birthday
ref_date_col = "contract_start_date"  # Contract start date
target_name  = "net_premium_amount"   # Target variable
print_feature_name = "age (at contract start)"
```

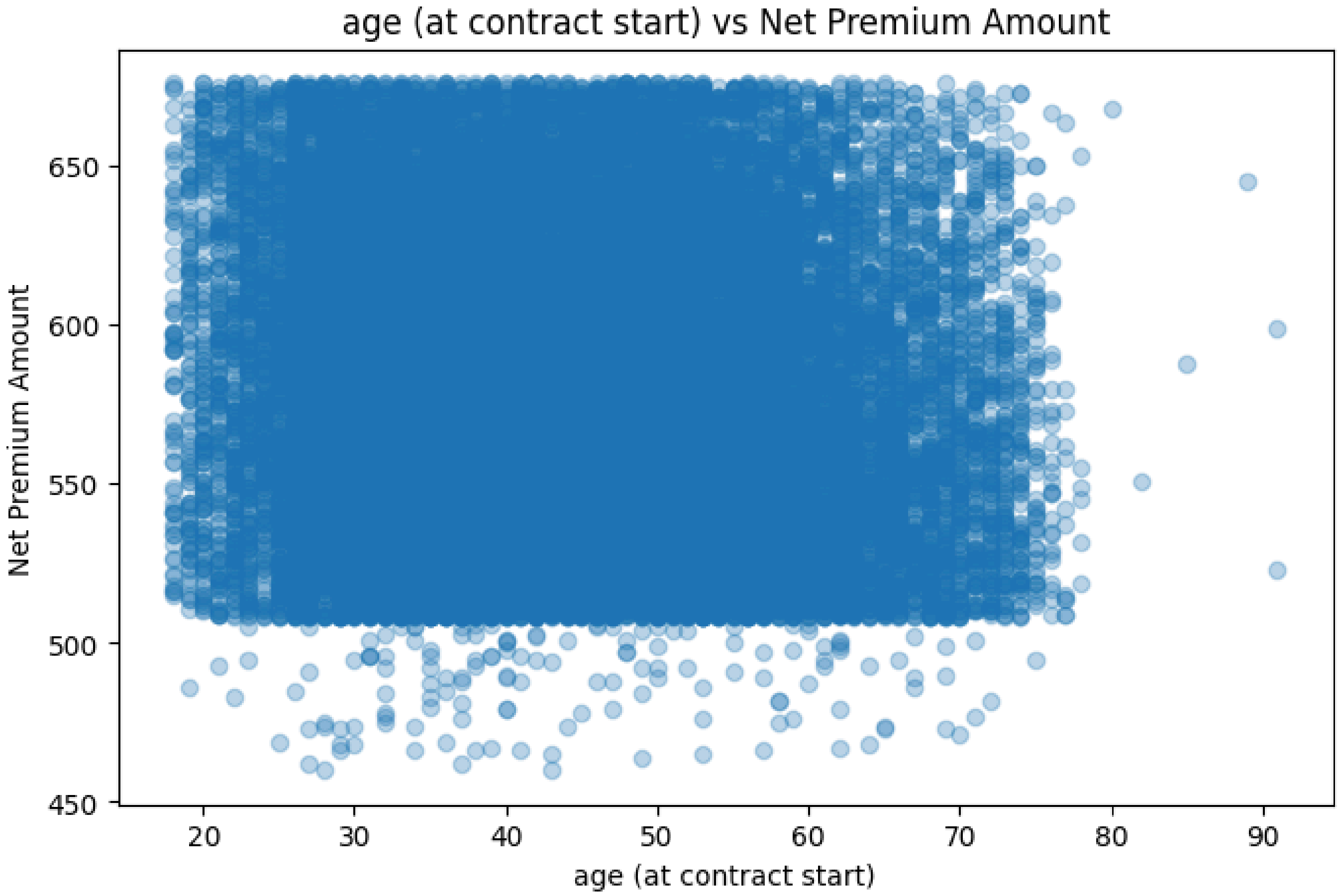
In [25]:
```
# Parse datetimes
birth = pd.to_datetime(training_df[feature_name], errors="coerce")
contract_start = pd.to_datetime(training_df[ref_date_col], errors="coerce")

# Compute age (years) at contract start
year_diff = contract_start.dt.year - birth.dt.year
before_birthday = (
    (contract_start.dt.month < birth.dt.month) |
    ((contract_start.dt.month == birth.dt.month) & (contract_start.dt.day < birth.dt.day))
)
age_at_contract = year_diff - before_birthday.astype(int)
age_at_contract = age_at_contract.where(birth.notna() & contract_start.notna(), np.nan)

# Basic stat
print(f"Feature: {feature_name} -> {print_feature_name}")
print(age_at_contract.describe(percentiles=[.01,.05,.25,.5,.75,.95,.99]))

# Reasonableness checks
if (age_at_contract < 0).any():
    print("Warning: Negative ages found.")
if (age_at_contract < 16).any():
    print("Warning: Ages < 16 detected.")
if (age_at_contract > 100).any():
    print("Warning: Ages > 100 detected.")

# Distribution plots
valid_age = age_at_contract.dropna()
plt.figure(figsize=(10,5))
plt.hist(valid_age, bins=30)
plt.title(f"{print_feature_name} Distribution")
plt.xlabel(f"{print_feature_name}")
plt.ylabel("Count")
plt.show()

plt.figure(figsize=(8,3))
plt.boxplot(valid_age, vert=False)
plt.title(f"Boxplot of {print_feature_name}")
plt.xlabel(f"{print_feature_name}")
plt.show()
```

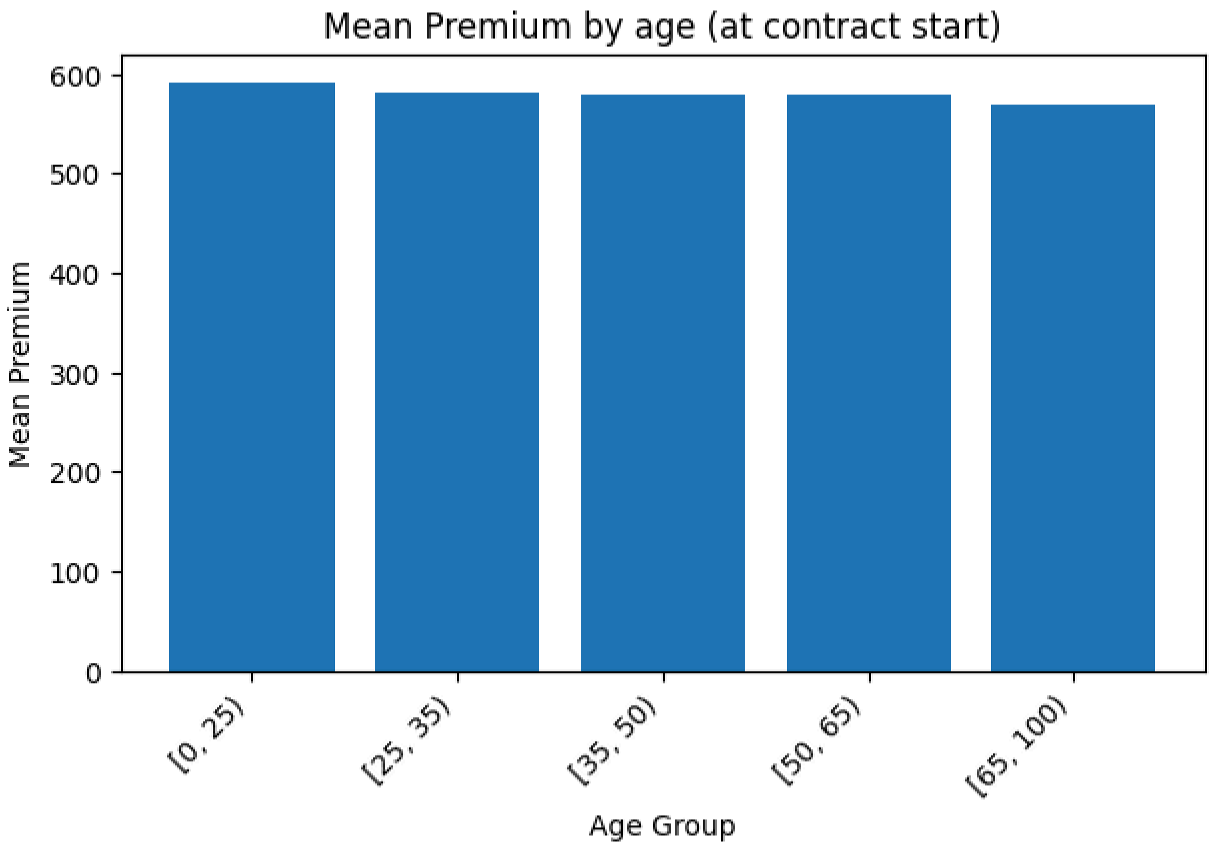
```
# Relationship with target
df_plot = pd.DataFrame({"Age_at_Contract": age_at_contract, target_name: training_df[target_n
# Scatter plot
plt.figure(figsize=(8,5))
plt.scatter(df_plot["Age_at_Contract"], df_plot[target_name], alpha=0.3)
plt.title(f"{print_feature_name} vs Net Premium Amount")
plt.xlabel(f"{print_feature_name}")
plt.ylabel("Net Premium Amount")
plt.show()

# Grouped averages
df_plot["Age_group"] = pd.cut(df_plot["Age_at_Contract"], bins=[0,25,35,50,65,100], right=Fal
mean_prem = df_plot.groupby("Age_group")[target_name].mean()

plt.figure(figsize=(7,4))
plt.bar(mean_prem.index.astype(str), mean_prem.values)
plt.title(f"Mean Premium by {print_feature_name}")
plt.ylabel("Mean Premium"); plt.xlabel("Age Group")
plt.xticks(rotation=45, ha="right")
plt.show()
```

```
Feature: birth_date -> age (at contract start)
count    32136.000000
mean        43.933408
std         12.497067
min         18.000000
1%          20.350000
5%          26.000000
25%         34.000000
50%         43.000000
75%         53.000000
95%         66.000000
99%         73.000000
max         91.000000
dtype: float64
```




Boxplot of age (at contract start)
1
20
30
40
50
60
70
80
90
age (at contract start)


age (at contract start) vs Net Premium Amount
Net Premium Amount
450
500
550
600
650
20
30
40
50
60
70
80
90
age (at contract start)



In [26]:
```
# provide a detailed analysis on the selected feature, its distribution, limitations, issues,
feature_1_insights = """
Age distribution from 18-elder(90+), right-skewed toward middle-aged drivers.
Younger drivers are usually higher risk -> higher premiums; older drivers may have mixed risk
Issues: the original data 'birth_date'(string) must be converted to age(at contract start).
It's continuous variable.
"""
```

In [27]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='feature_1_insights', value=feature_1_insights)
```

feature_1_insights

Age distribution from 18-elder(90+), right-skewed toward middle-aged drivers. Younger drivers are usually higher risk - higher premiums; older drivers may have mixed risk depending on some other features. Issues: the original data 'birth_date'(string) must be converted to age(at contract start). It's continuous variable.

C.3 Explore Feature of Interest `driving_license_date`

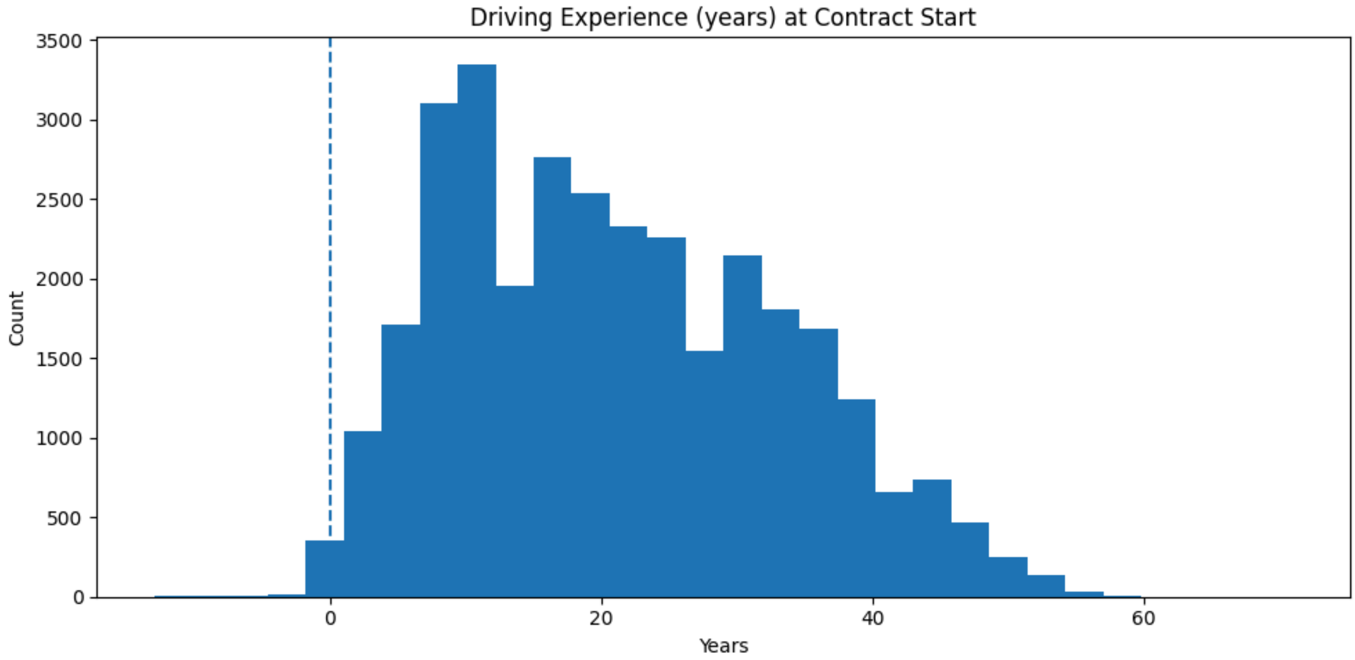
> You can add more cells in this section

In [28]:
```
feature_name        = "driving_license_date"        # License issue date
ref_date_col        = "contract_start_date"         # Reference date (contract start)
target_name         = "net_premium_amount"          # Target variable
print_feature_name  = "Driving Experience (years) at Contract Start"
```

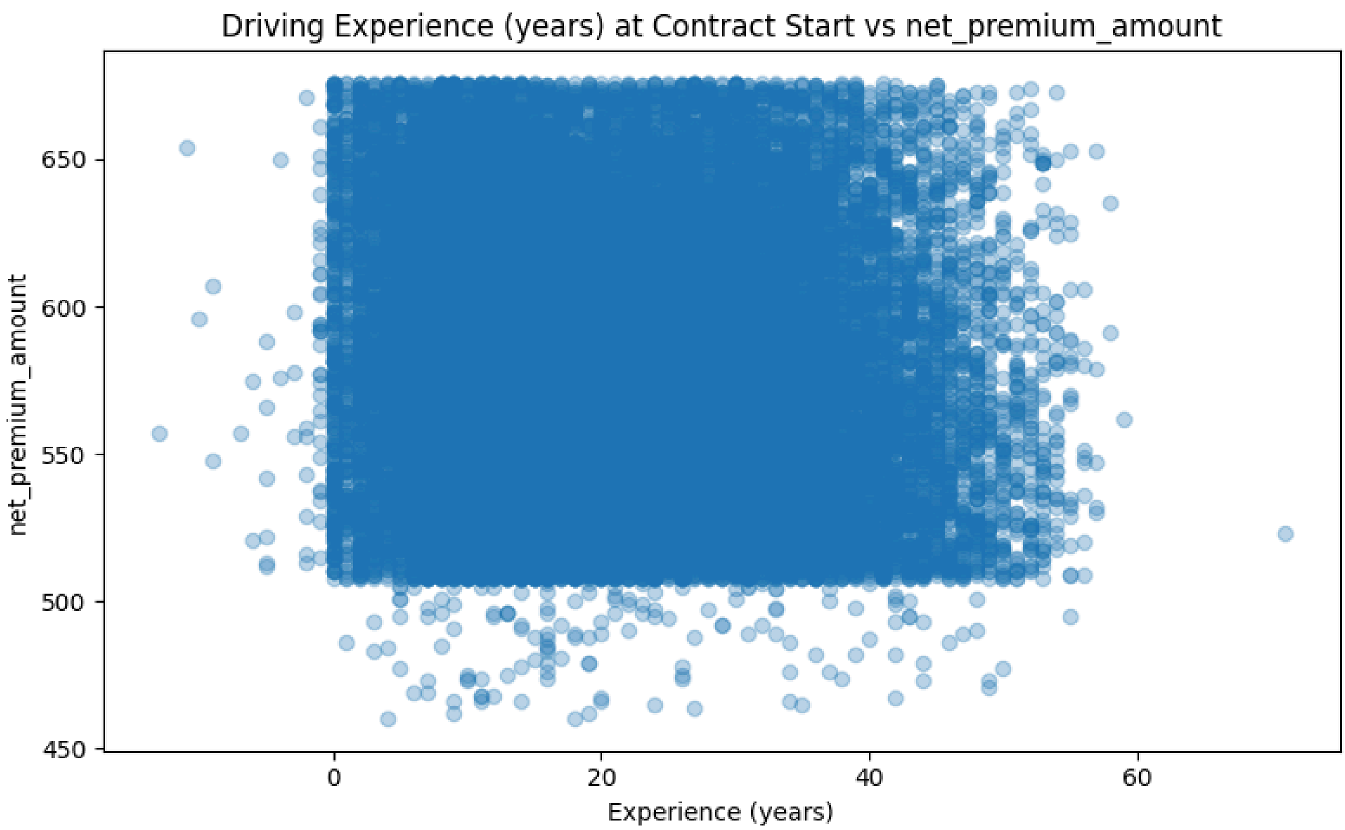
In [29]:
```
# Parse datetimes
lic = pd.to_datetime(training_df[feature_name], errors="coerce")
ref = pd.to_datetime(training_df[ref_date_col], errors="coerce")

# Compute driving experience (years) at contract start (allow negatives)
year_diff = ref.dt.year - lic.dt.year
before_anniv = (
```

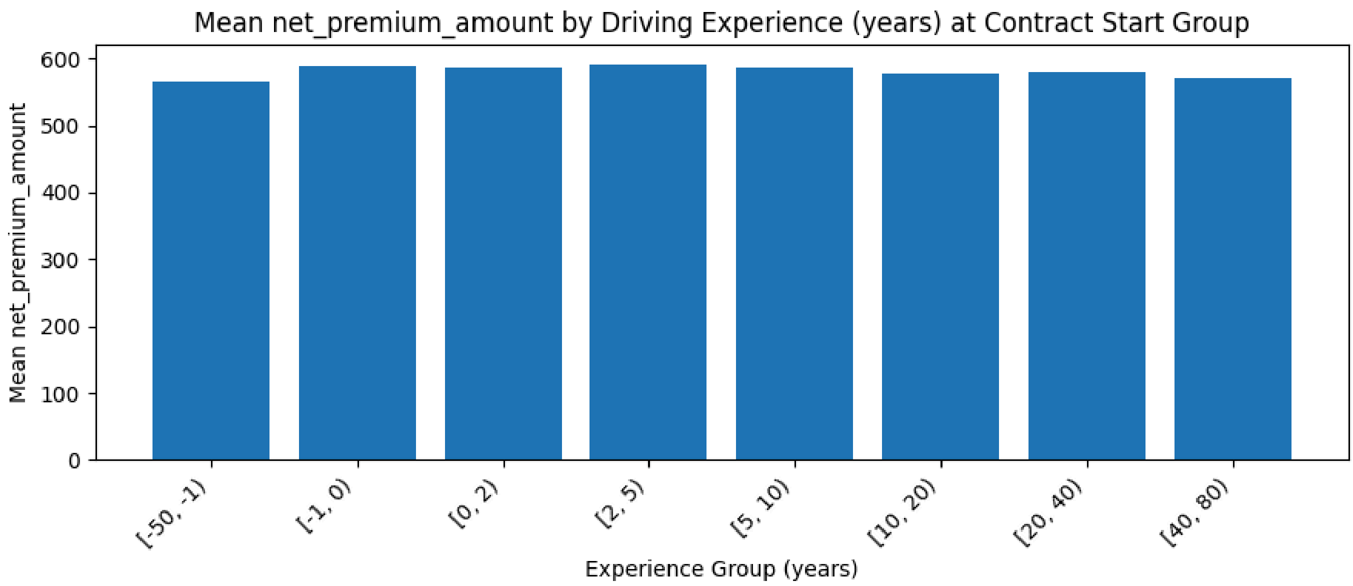
```python
    (ref.dt.month < lic.dt.month) |
    ((ref.dt.month == lic.dt.month) & (ref.dt.day < lic.dt.day))
)
exp_years = (year_diff - before_anniv.astype(int)).where(lic.notna() & ref.notna(), np.nan)

# Descriptive statistics
print(f"Feature: {feature_name} -> {print_feature_name}")
print(exp_years.describe(percentiles=[.01,.05,.25,.5,.75,.95,.99]))

# Distribution plots (include negatives)
valid = exp_years.dropna()
if len(valid) > 0:
    plt.figure(figsize=(10,5))
    plt.hist(valid, bins=30)
    plt.title(print_feature_name)
    plt.xlabel("Years"); plt.ylabel("Count")
    plt.axvline(0, linestyle="--")  # reference line at 0 year (optional)
    plt.tight_layout(); plt.show()

    plt.figure(figsize=(8,3))
    plt.boxplot(valid, vert=False)
    plt.title(f"Boxplot: {print_feature_name}")
    plt.xlabel("Years")
    plt.tight_layout(); plt.show()

# Relationship with target
df_plot = pd.DataFrame({"Experience": exp_years, target_name: training_df[target_name]}).drop

# Scatter
plt.figure(figsize=(8,5))
plt.scatter(df_plot["Experience"], df_plot[target_name], alpha=0.3)
plt.title(f"{print_feature_name} vs {target_name}")
plt.xlabel("Experience (years)"); plt.ylabel(target_name)
plt.tight_layout(); plt.show()

# Grouped averages (bins include negatives)
# Adjust bins as needed for your data distribution
lo, hi = np.nanpercentile(df_plot["Experience"], [1, 99])
bins = [-50, -1, 0, 2, 5, 10, 20, 40, max(80, hi)]
df_plot["ExpGroup"] = pd.cut(df_plot["Experience"], bins=bins, right=False)
mean_prem = df_plot.groupby("ExpGroup")[target_name].mean()

plt.figure(figsize=(9,4))
plt.bar(mean_prem.index.astype(str), mean_prem.values)
plt.title(f"Mean {target_name} by {print_feature_name} Group")
plt.ylabel(f"Mean {target_name}"); plt.xlabel("Experience Group (years)")
plt.xticks(rotation=45, ha="right")
plt.tight_layout(); plt.show()
```

```
Feature: driving_license_date -> Driving Experience (years) at Contract Start
count    32136.000000
mean        21.090864
std         12.114187
min        -13.000000
1%           0.000000
5%           4.000000
25%         11.000000
50%         20.000000
75%         30.000000
95%         43.000000
99%         50.000000
max         71.000000
dtype: float64
```


Driving Experience (years) at Contract Start
Count
Years
0
500
1000
1500
2000
2500
3000
3500
0
20
40
60


Boxplot: Driving Experience (years) at Contract Start
1
0
20
40
60
Years


Driving Experience (years) at Contract Start vs net_premium_amount
net_premium_amount
Experience (years)
450
500
550
600
650
0
20
40
60



In [30]:
```
# provide a detailed analysis on the selected feature, its distribution, limitations, issues,

feature_2_insights = """
Driving Experience (years) at Contract Start derived from driving_license_date, has an average
While it is highly relevant for assessing risk, the data contains negative values and extreme
These anomalies should be treated carefully before using the feature in models.
"""
```

In [31]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='feature_2_insights', value=feature_2_insights)
```

feature_2_insights

Driving Experience (years) at Contract Start derived from driving_license_date, has an average of ~21 years, with most customers between 11 and 30 years. While it is highly relevant for assessing risk, the data contains negative values and extreme outliers that indicate quality issues. These anomalies should be treated carefully before using the feature in models.

C.4 Explore Feature of Interest `seniority`

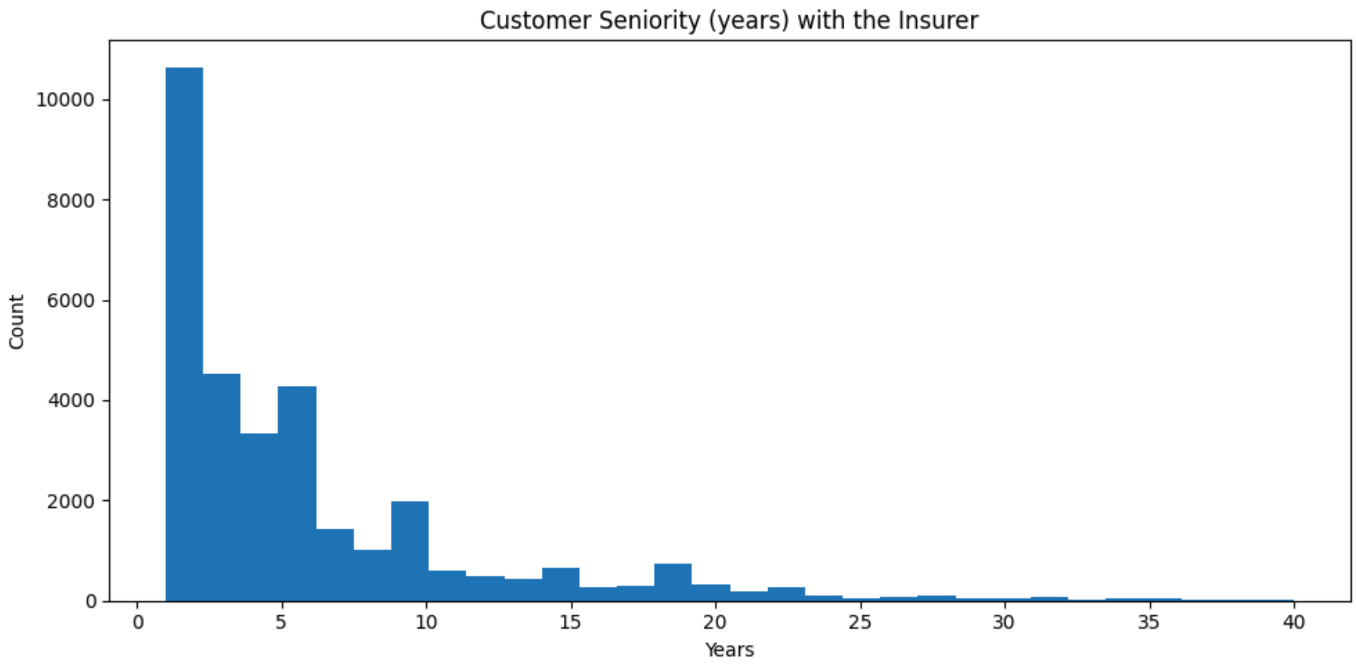
> You can add more cells in this section

In [32]:
```
feature_name       = "seniority"            # Years associated with the insurer
ref_date_col       = "contract_start_date"  # Reference date column (parsed for cohort views
target_name        = "net_premium_amount"   # Target variable
print_feature_name = "Customer Seniority (years) with the Insurer"
```

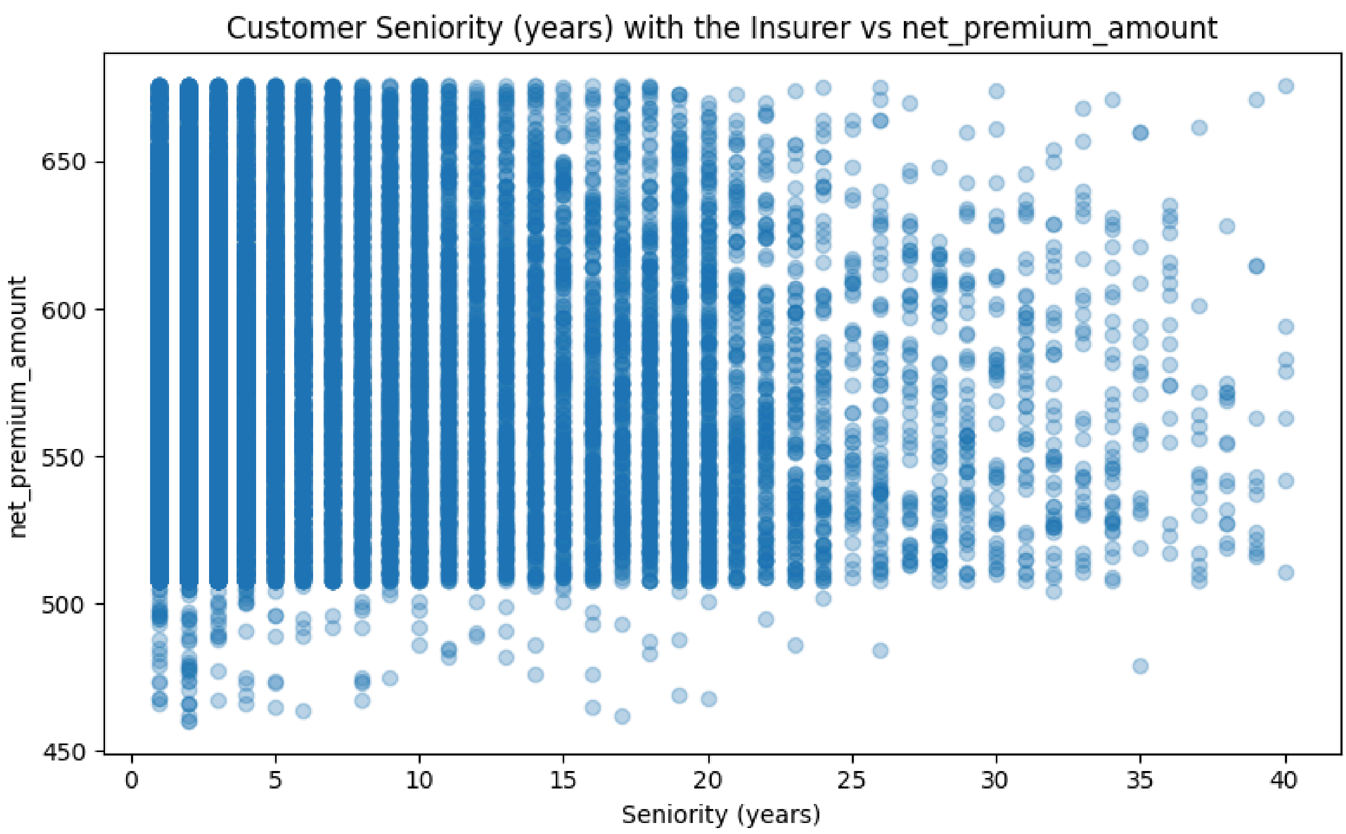
In [33]:
```
# Prepare data
sen = pd.to_numeric(training_df[feature_name], errors="coerce")
ref_dt = pd.to_datetime(training_df[ref_date_col], errors="coerce")  # kept for potential coh

# Descriptive statistics
print(f"Feature: {feature_name} -> {print_feature_name}")
print(sen.describe(percentiles=[.01,.05,.25,.5,.75,.95,.99]))

# Quick sanity notes (no hard filtering)
if (sen < 0).any():  print("Note: Negative seniority values exist (data quality).")
if (sen > 50).any(): print("Note: Very large seniority values (>50) exist (check plausibility

# Distribution plots
```

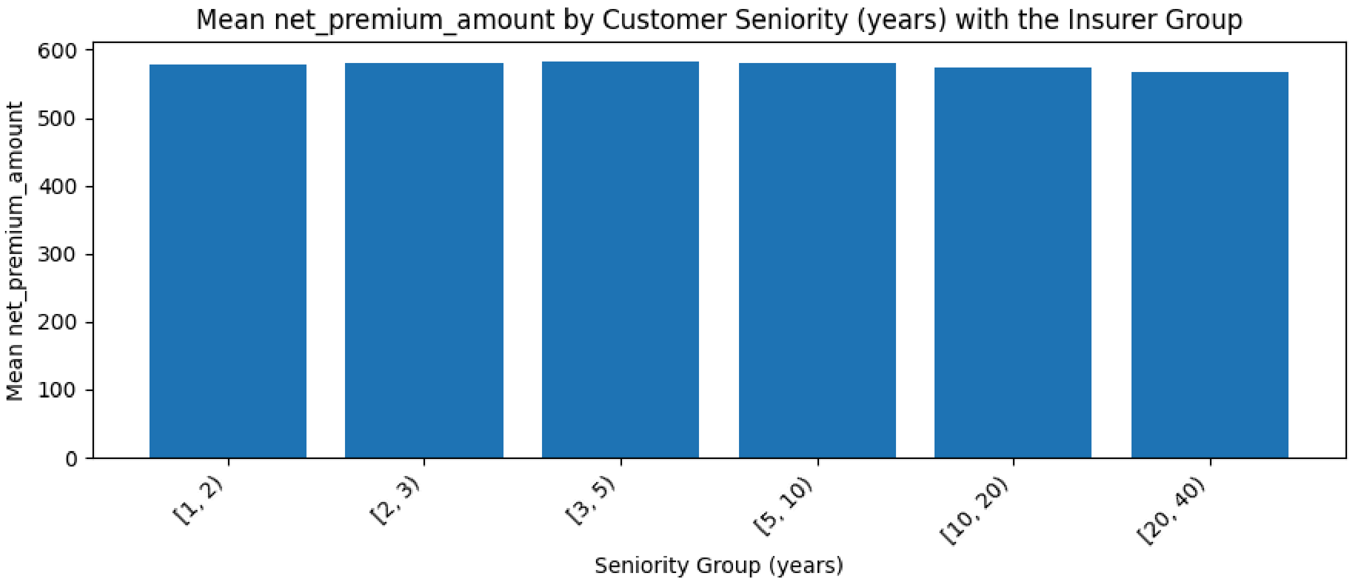
```python
valid = sen.dropna()
if len(valid) > 0:
    plt.figure(figsize=(10,5))
    plt.hist(valid, bins=30)
    plt.title(print_feature_name)
    plt.xlabel("Years"); plt.ylabel("Count")
    plt.tight_layout(); plt.show()

    plt.figure(figsize=(8,3))
    plt.boxplot(valid, vert=False)
    plt.title(f"Boxplot: {print_feature_name}")
    plt.xlabel("Years")
    plt.tight_layout(); plt.show()

# Relationship with target (scatter + grouped averages)
df_plot = pd.DataFrame({ "Seniority": sen, target_name: training_df[target_name] }).dropna()

# Scatter
plt.figure(figsize=(8,5))
plt.scatter(df_plot["Seniority"], df_plot[target_name], alpha=0.3)
plt.title(f"{print_feature_name} vs {target_name}")
plt.xlabel("Seniority (years)"); plt.ylabel(target_name)
plt.tight_layout(); plt.show()

# Grouped averages (bins can be adjusted)
# Uses broader bins to stabilize means across skewed counts
lo, hi = np.nanpercentile(df_plot["Seniority"], [1, 99])
bins = [0, 1, 2, 3, 5, 10, 20, max(40, hi)]
df_plot["SenGroup"] = pd.cut(df_plot["Seniority"], bins=bins, right=False, include_lowest=Tru
mean_prem = df_plot.groupby("SenGroup")[target_name].mean()

plt.figure(figsize=(9,4))
plt.bar(mean_prem.index.astype(str), mean_prem.values)
plt.title(f"Mean {target_name} by {print_feature_name} Group")
plt.ylabel(f"Mean {target_name}"); plt.xlabel("Seniority Group (years)")
plt.xticks(rotation=45, ha="right")
plt.tight_layout(); plt.show()
```

```
Feature: seniority -> Customer Seniority (years) with the Insurer
count    32136.000000
mean         5.896596
std          5.909002
min          1.000000
1%           1.000000
5%           1.000000
25%          2.000000
50%          4.000000
75%          7.000000
95%         19.000000
99%         29.000000
max         40.000000
Name: seniority, dtype: float64
```


Customer Seniority (years) with the Insurer
Count
Years
0
2000
4000
6000
8000
10000
0
5
10
15
20
25
30
35
40


Boxplot: Customer Seniority (years) with the Insurer
1
Years
0
5
10
15
20
25
30
35
40


Customer Seniority (years) with the Insurer vs net_premium_amount
net_premium_amount
Seniority (years)
450
500
550
600
650
0
5
10
15
20
25
30
35
40



In [34]:
```
# provide a detailed analysis on the selected feature, its distribution, limitations, issues,

feature_3_insights = """
Seniority (years) has an average of about 6 years, with most customers between 2 and 7 years.
The distribution is right-skewed, showing many recent customers and fewer long-term ones, with
This feature is relevant as longer seniority may indicate loyalty and lower churn risk.
However, it may overlap with policy history variables, leading to multicollinearity.
Extreme values (30+ years) are rare and should be checked for plausibility before modeling.
"""
```

In [35]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='feature_3_insights', value=feature_3_insights)
```

feature_3_insights

Seniority (years) has an average of about 6 years, with most customers between 2 and 7 years. The distribution is right-skewed, showing many recent customers and fewer long-term ones, with a maximum of 40 years. This feature is relevant as longer seniority may indicate loyalty and lower churn risk. However, it may overlap with policy history variables, leading to multicollinearity. Extreme values (30+ years) are rare and should be checked for plausibility before modeling.

C.4 Explore Feature of Interest `policy_type`

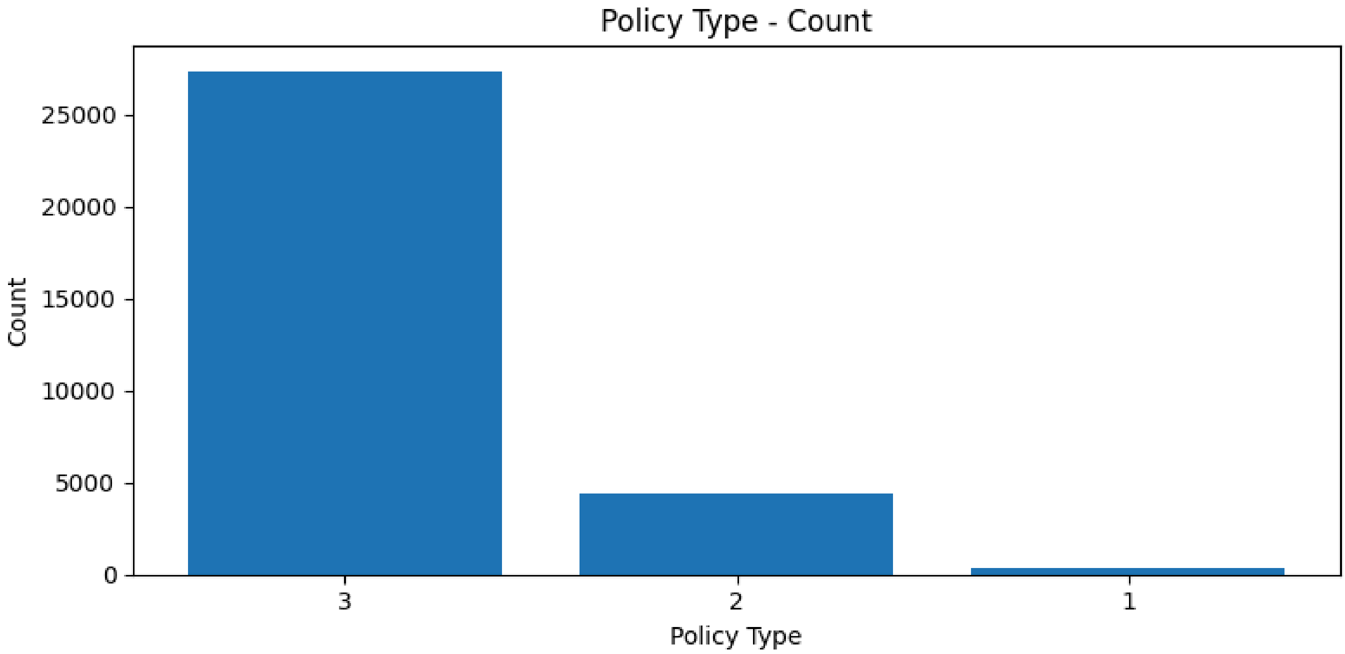
> You can add more cells related to other feeatures in this section

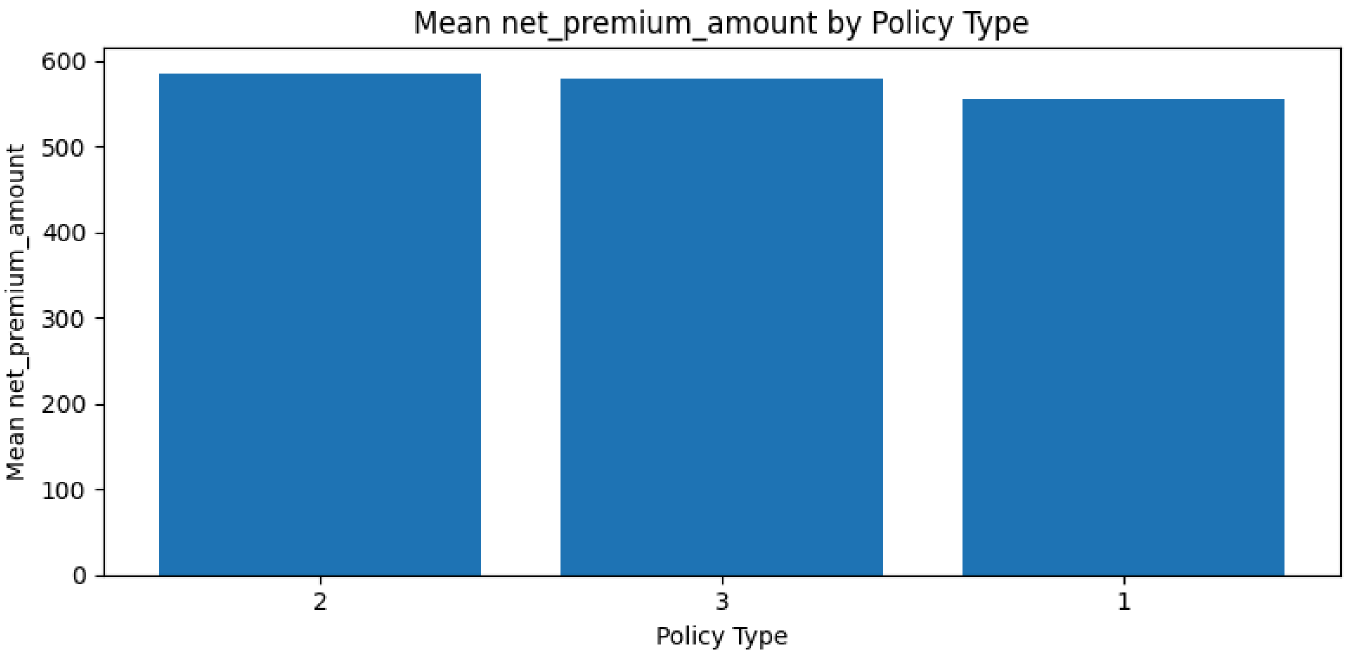
In [36]:
```
feature_name       = "policy_type"          # Categorical feature (e.g., 1/2/3/4)
ref_date_col       = "contract_start_date"  # Reference date column
target_name        = "net_premium_amount"   # Target variable
print_feature_name = "Policy Type"
```

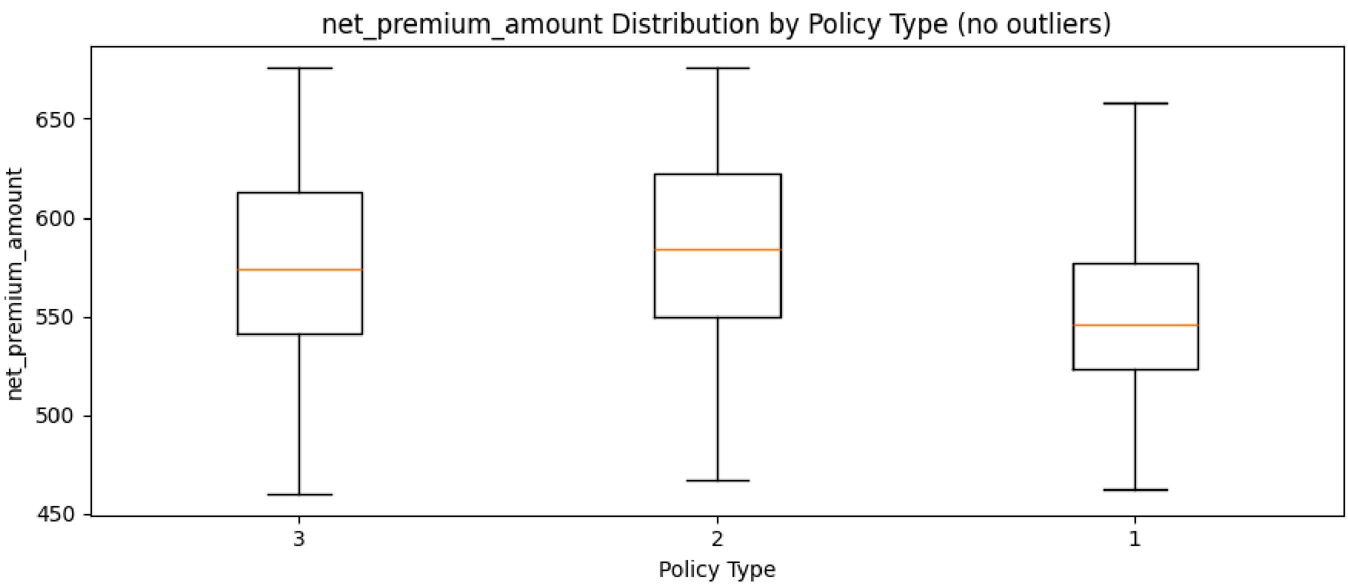
In [37]:
```
# Prepare data
s = training_df[feature_name]
ref_dt = pd.to_datetime(training_df[ref_date_col], errors="coerce")  # parsed for completenes
t = training_df[target_name]

# label NaN for plotting
s_plot = s.astype(object).where(s.notna(), "Missing")

# Basic stats
```

```python
n = len(s); miss = s.isna().sum(); uniq = s.nunique(dropna=True)
print(f"Feature: {feature_name} -> {print_feature_name}")
print(f"Non-null: {n - miss}/{n} (missing: {miss}, {miss/n:.2%})")
print(f"Unique categories (non-null): {uniq}")
print("\nCounts (incl. Missing):")
print(s_plot.value_counts(dropna=False))

# Count bar plot
counts = s_plot.value_counts(dropna=False)
plt.figure(figsize=(8,4))
plt.bar(counts.index.astype(str), counts.values)
plt.title(f"{print_feature_name} - Count"); plt.xlabel(print_feature_name); plt.ylabel("Count
plt.tight_layout()
plt.show()

# Mean target by category (ordered by mean)
df_plot = pd.DataFrame({print_feature_name: s_plot, target_name: t}).dropna(subset=[print_fea
mean_target = df_plot.groupby(print_feature_name)[target_name].mean().sort_values(ascending=F

plt.figure(figsize=(8,4))
plt.bar(mean_target.index.astype(str), mean_target.values)
plt.title(f"Mean {target_name} by {print_feature_name}")
plt.xlabel(print_feature_name); plt.ylabel(f"Mean {target_name}")
plt.tight_layout()
plt.show()

# Target distribution by category (boxplots)
# Build a list of arrays aligned with categories (use top-k if too many)
cats = counts.index.tolist()
data_by_cat = [df_plot.loc[df_plot[print_feature_name] == c, target_name].values for c in cat

plt.figure(figsize=(9,4))
plt.boxplot(data_by_cat, labels=[str(c) for c in cats], vert=True, showfliers=False)
plt.title(f"{target_name} Distribution by {print_feature_name} (no outliers)")
plt.xlabel(print_feature_name); plt.ylabel(target_name)
plt.tight_layout()
plt.show()
```

```
Feature: policy_type -> Policy Type
Non-null: 32136/32136 (missing: 0, 0.00%)
Unique categories (non-null): 3

Counts (incl. Missing):
policy_type
3    27348
2     4428
1      360
Name: count, dtype: int64
```







In [38]:

```
# provide a detailed analysis on the selected feature, its distribution, limitations, issues,

feature_4_insights = """
Policy Type is a categorical variable with 3 categories present in the dataset:
type 3 (passenger cars) dominates with ~85% of records, followed by type 2 (vans) and a very 
Boxplots show that average premiums differ slightly across policy types, with type 2 policies
This suggests the feature has predictive value for premiums.
```

```
The sample size of type 1 is small. It may require grouping or regularization in modeling.
"""
```

In [39]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='feature_4_insights', value=feature_4_insights)
```

feature_4_insights

Policy Type is a categorical variable with 3 categories present in the dataset: type 3 (passenger cars) dominates with ~85% of records, followed by type 2 (vans) and a very small group of type 1 (motorbikes). Boxplots show that average premiums differ slightly across policy types, with type 2 policies generally priced higher and type 1 lower. This suggests the feature has predictive value for premiums. The sample size of type 1 is small. It may require grouping or regularization in modeling.

C.5 Explore Feature of Interest `total_claims_number_in_history`

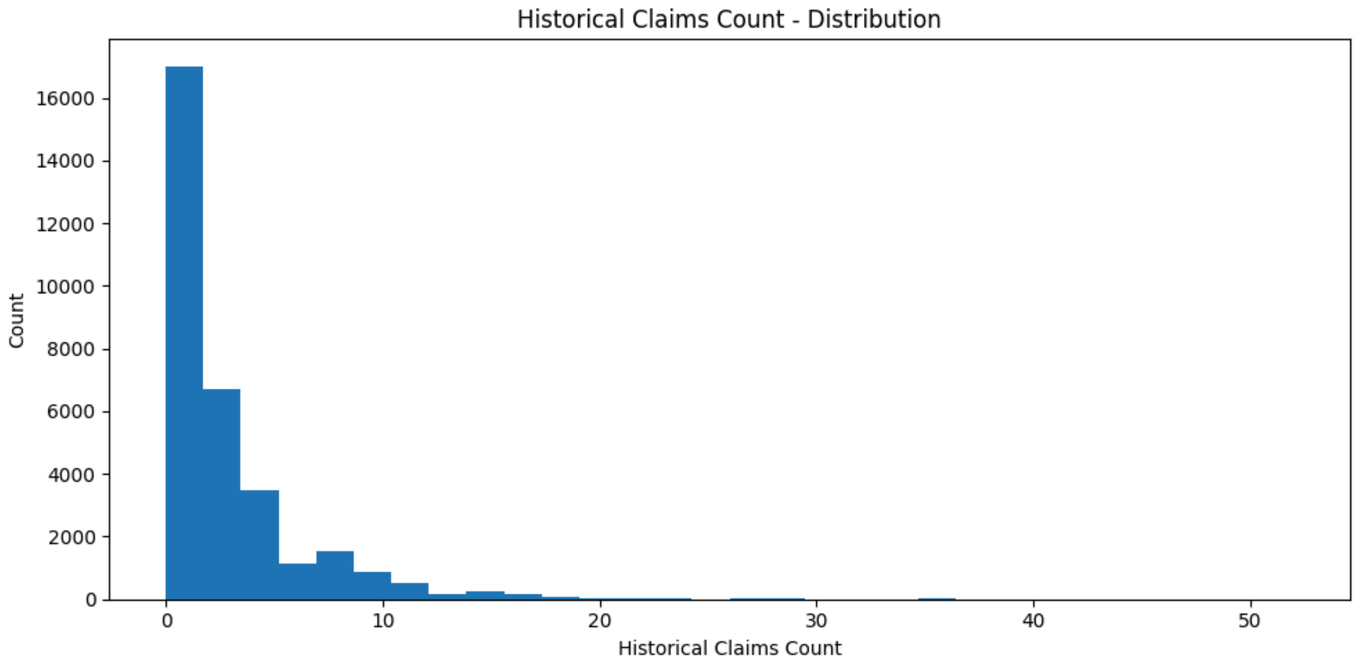
> You can add more cells related to other feeatures in this section

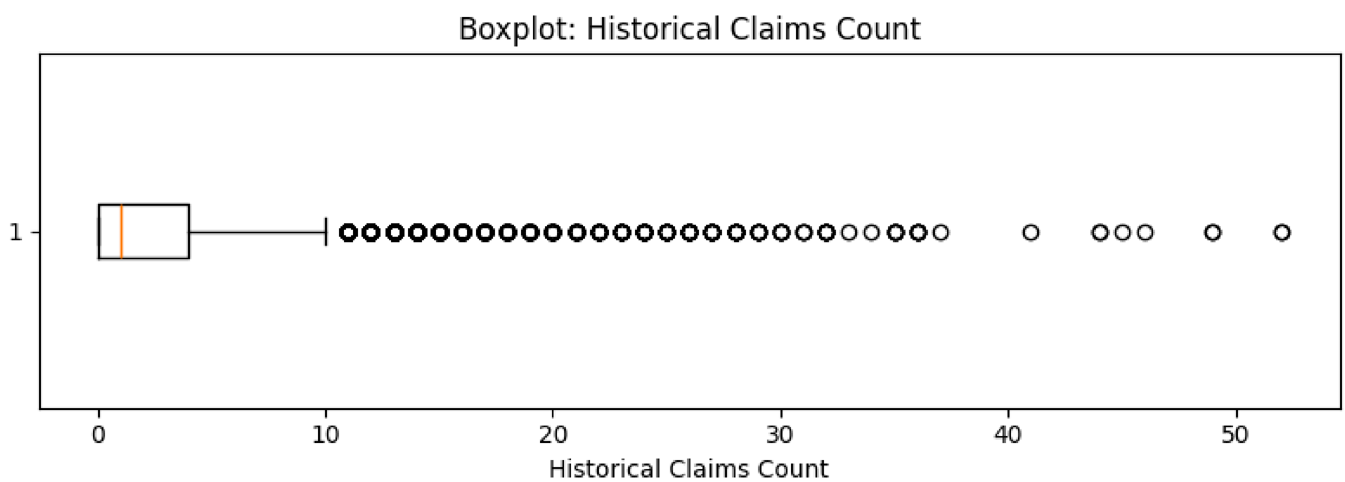
In [40]:
```
feature_name       = "total_claims_number_in_history"  # Historical claims count
ref_date_col       = "contract_start_date"             # Reference date (parsed for completen
target_name        = "net_premium_amount"              # Target variable
print_feature_name = "Historical Claims Count"
```

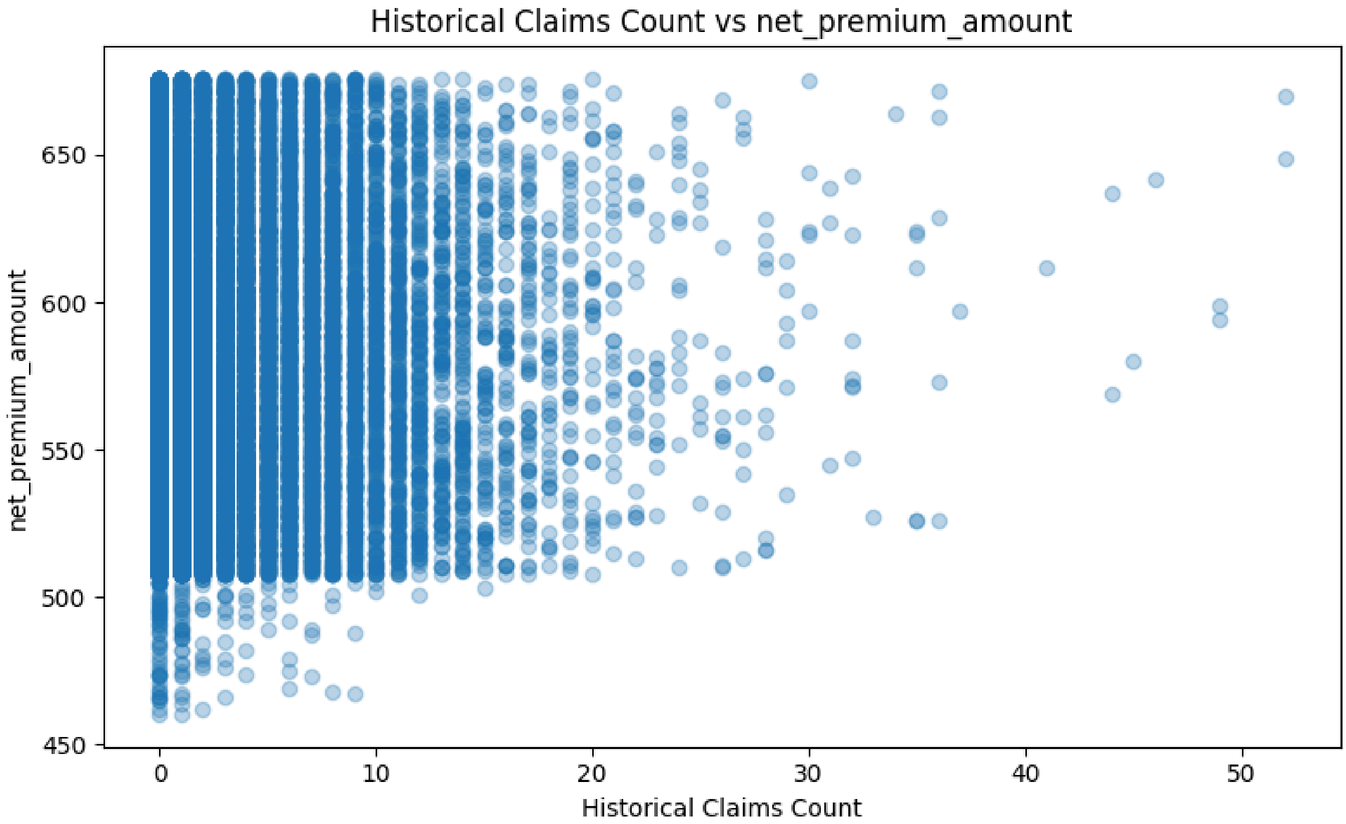
In [41]:
```
# Prepare data
x = pd.to_numeric(training_df[feature_name], errors="coerce")
ref_dt = pd.to_datetime(training_df[ref_date_col], errors="coerce")  # not used further, but 
y = training_df[target_name]

# Descriptive stats
print(f"Feature: {feature_name} -> {print_feature_name}")
print(x.describe(percentiles=[.01,.05,.25,.5,.75,.95,.99]))

# Distribution (hist + boxplot)
valid = x.dropna()
if len(valid) > 0:
    plt.figure(figsize=(10,5))
    plt.hist(valid, bins=30)
    plt.title(f"{print_feature_name} - Distribution")
    plt.xlabel(print_feature_name); plt.ylabel("Count")
    plt.tight_layout(); plt.show()

    plt.figure(figsize=(8,3))
    plt.boxplot(valid, vert=False, showfliers=True)
    plt.title(f"Boxplot: {print_feature_name}")
    plt.xlabel(print_feature_name)
    plt.tight_layout(); plt.show()

# Relationship with target (scatter + grouped averages)
df_plot = pd.DataFrame({print_feature_name: x, target_name: y}).dropna()

# Scatter (alpha to mitigate overlap)
plt.figure(figsize=(8,5))
plt.scatter(df_plot[print_feature_name], df_plot[target_name], alpha=0.3)
plt.title(f"{print_feature_name} vs {target_name}")
plt.xlabel(print_feature_name); plt.ylabel(target_name)
plt.tight_layout(); plt.show()

# Grouped mean premium by claims buckets (bins can be adjusted)
```

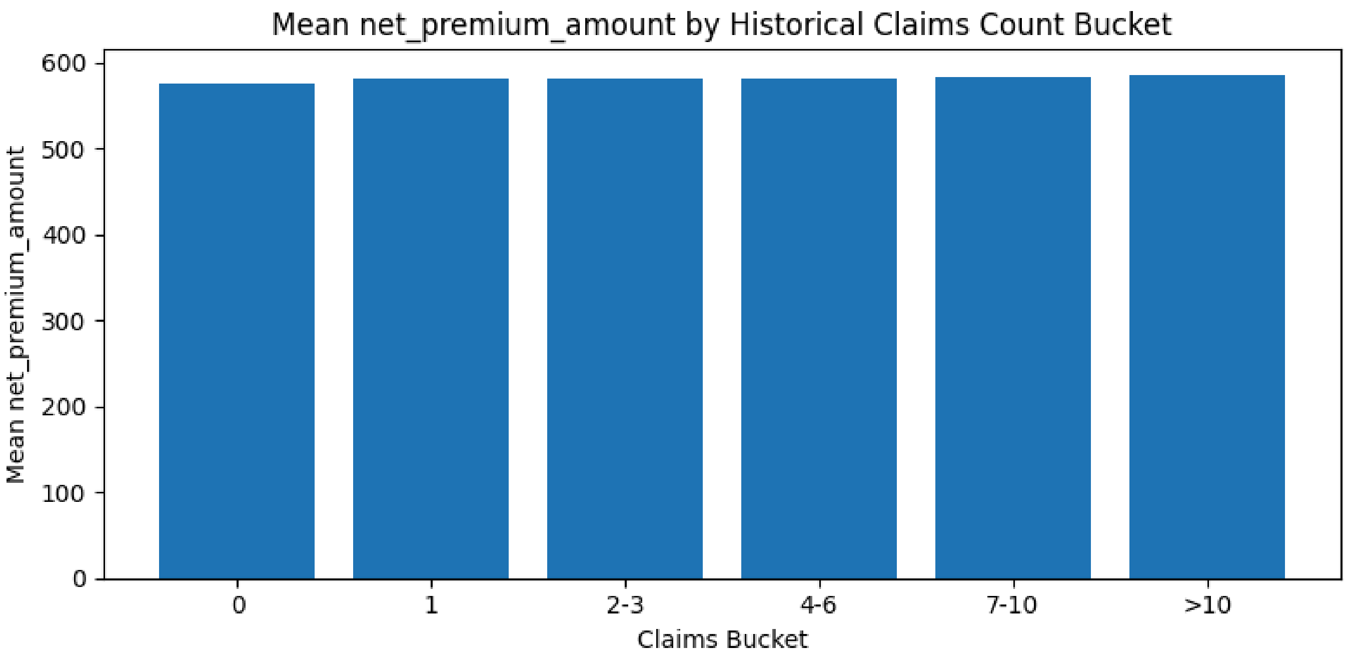
```python
# Buckets: 0, 1, 2-3, 4-6, 7-10, >10
bins = [-0.5, 0.5, 1.5, 3.5, 6.5, 10.5, df_plot[print_feature_name].max()+0.5]
labels = ["0", "1", "2-3", "4-6", "7-10", ">10"]
df_plot["ClaimsBucket"] = pd.cut(df_plot[print_feature_name], bins=bins, labels=labels)

mean_prem = df_plot.groupby("ClaimsBucket")[target_name].mean()
plt.figure(figsize=(8,4))
plt.bar(mean_prem.index.astype(str), mean_prem.values)
plt.title(f"Mean {target_name} by {print_feature_name} Bucket")
plt.ylabel(f"Mean {target_name}"); plt.xlabel("Claims Bucket")
plt.tight_layout(); plt.show()
```

```
Feature: total_claims_number_in_history -> Historical Claims Count
count    32136.000000
mean         2.647498
std          3.787398
min          0.000000
1%           0.000000
5%           0.000000
25%          0.000000
50%          1.000000
75%          4.000000
95%         10.000000
99%         17.000000
max         52.000000
Name: total_claims_number_in_history, dtype: float64
```









In [42]:
```
# provide a detailed analysis on the selected feature, its distribution, limitations, issues,

feature_5_insights = """
Historical Claims Count(total_claims_number_in_history) has a mean of about 2.65 claims, with
The distribution is highly right-skewed, with most values clustered near zero and a few extrem
This feature is important for capturing past risk behavior, as higher claim counts usually inc
Issues: There exist some extreme values(up to 52 claims), it should be capped or grouped into
Overall, the feature is predictive but requires handling of skewness and outliers.
"""
```

In [43]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='feature_5_insights', value=feature_5_insights)
```

feature_5_insights

Historical Claims Count(total_claims_number_in_history) has a mean of about 2.65 claims, with half of customers reporting one or fewer claims. The distribution is highly right-skewed, with most values clustered near zero and a few extreme outliers up to 52 claims. This feature is important for capturing past risk behavior, as higher claim counts usually indicate higher risk and premiums. Issues: There exist some extreme values(up to 52 claims), it should be capped or grouped into buckets. Overall, the feature is predictive but requires handling of skewness and outliers.

C.6 Explore Feature of Interest `vehicle_value`

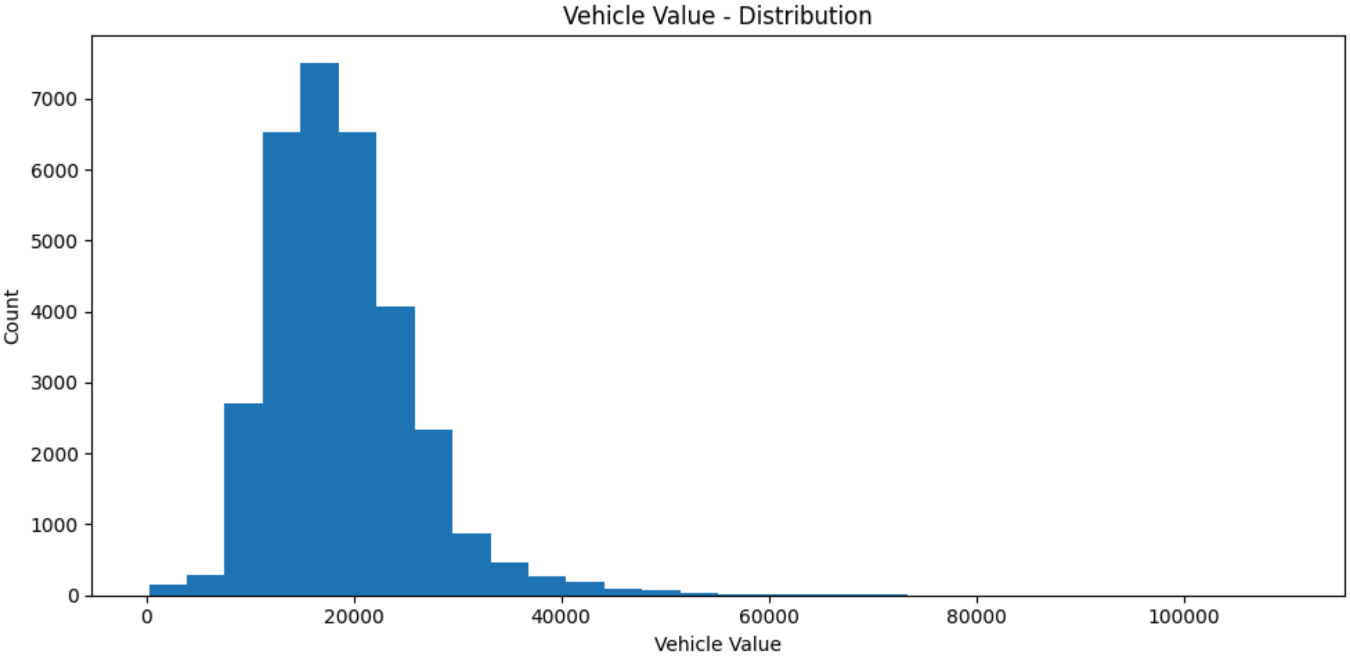
> You can add more cells related to other feeatures in this section

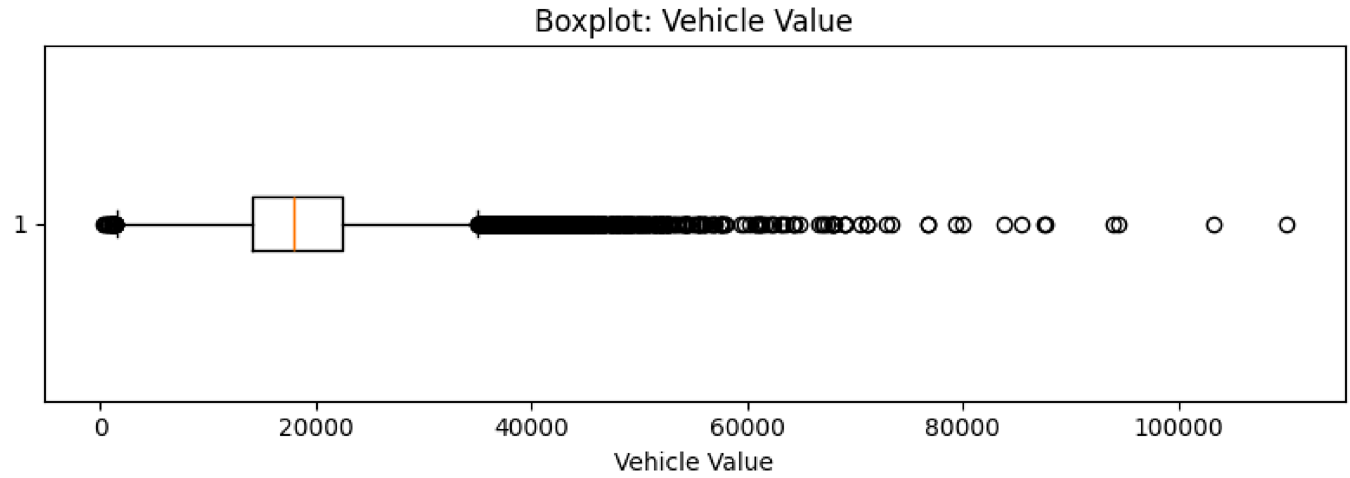
In [44]:
```
feature_name       = "vehicle_value"         # Vehicle market value
ref_date_col       = "contract_start_date"   # Reference date (parsed for completeness)
target_name        = "net_premium_amount"    # Target variable
print_feature_name = "Vehicle Value"
```

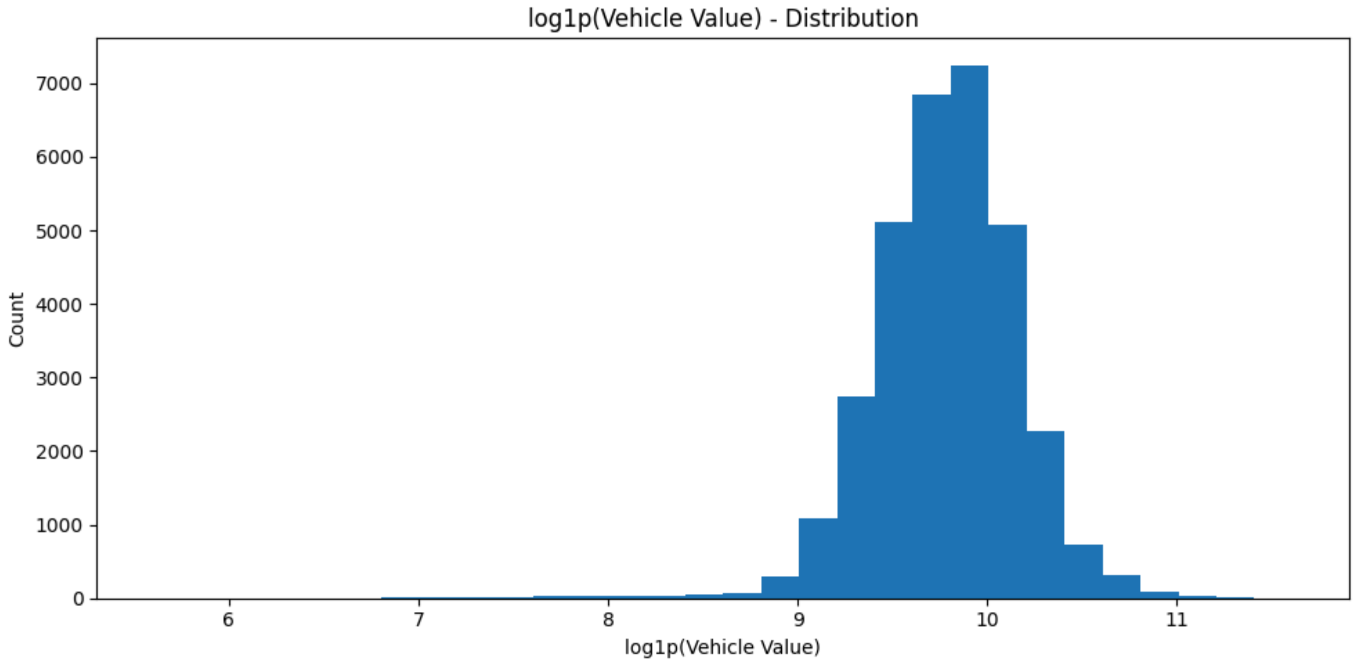
In [45]:
```
# Prepare data
x = pd.to_numeric(training_df[feature_name], errors="coerce")
ref_dt = pd.to_datetime(training_df[ref_date_col], errors="coerce")   # parsed to satisfy ref
y = training_df[target_name]

# Descriptive stats
print(f"Feature: {feature_name} -> {print_feature_name}")
print(x.describe(percentiles=[.01,.05,.25,.5,.75,.95,.99]))

# Quick sanity notes (no hard filtering)
if (x <= 0).any():
    print("Note: non-positive values detected; check data quality or consider imputation.")
if x.isna().any():
    print(f"Note: {x.isna().sum()} missing values; consider median/grouped imputation.")

# Distribution plots
valid = x.dropna()
if len(valid) > 0:
    # Histogram
    plt.figure(figsize=(10,5))
    plt.hist(valid, bins=30)
    plt.title(f"{print_feature_name} - Distribution")
    plt.xlabel(print_feature_name); plt.ylabel("Count")
    plt.tight_layout(); plt.show()

    # Boxplot (shows outliers)
    plt.figure(figsize=(8,3))
    plt.boxplot(valid, vert=False, showfliers=True)
    plt.title(f"Boxplot: {print_feature_name}")
    plt.xlabel(print_feature_name)
    plt.tight_layout(); plt.show()

# log1p view for right-skew
plt.figure(figsize=(10,5))
plt.hist(np.log1p(valid), bins=30)
plt.title(f"log1p({print_feature_name}) - Distribution")
plt.xlabel(f"log1p({print_feature_name})"); plt.ylabel("Count")
plt.tight_layout(); plt.show()

# Relationship with target (scatter + bucketed means)
```

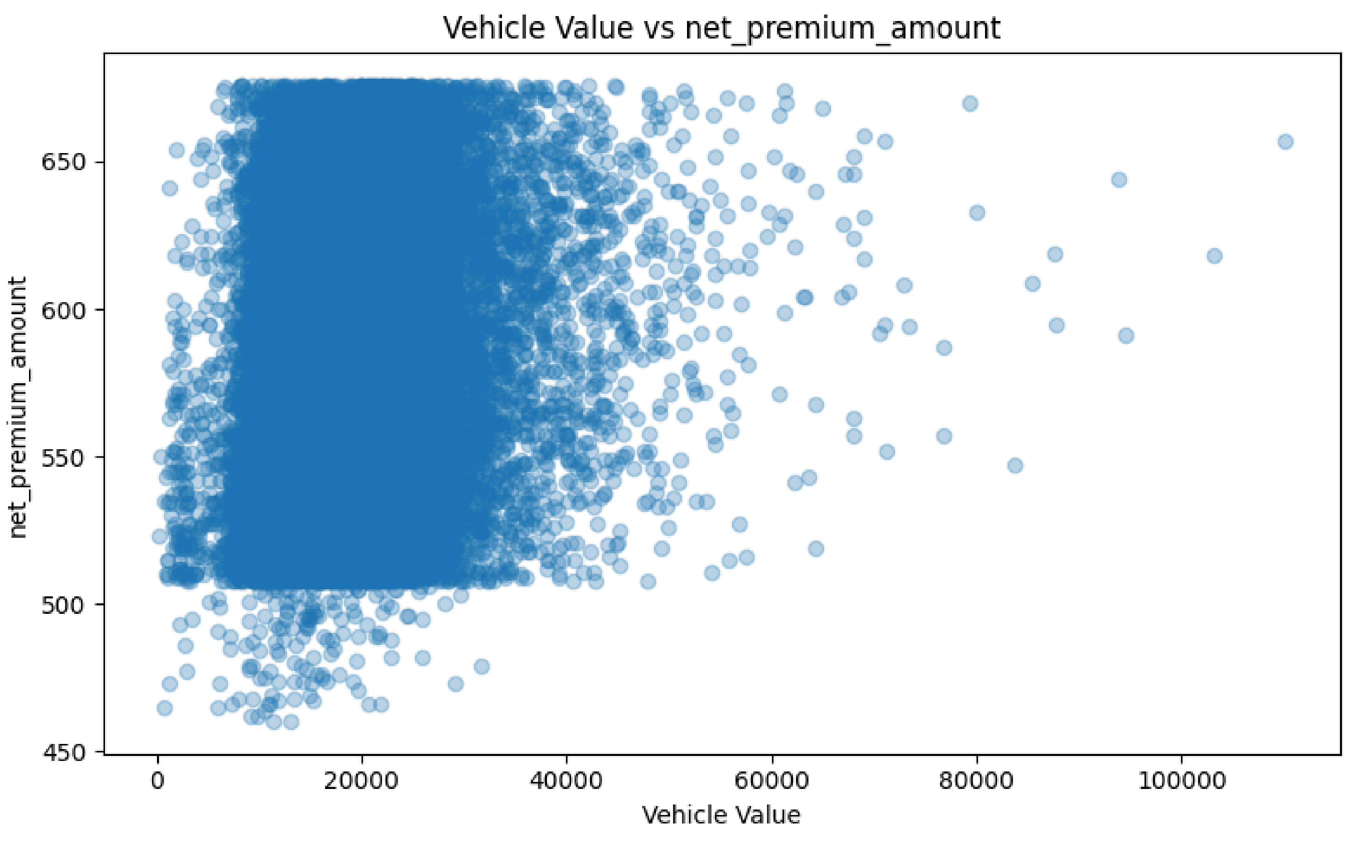
```python
df_plot = pd.DataFrame({print_feature_name: x, target_name: y}).dropna()

# Scatter
plt.figure(figsize=(8,5))
plt.scatter(df_plot[print_feature_name], df_plot[target_name], alpha=0.3)
plt.title(f"{print_feature_name} vs {target_name}")
plt.xlabel(print_feature_name); plt.ylabel(target_name)
plt.tight_layout(); plt.show()

# Bucketed averages using quantile-based bins (robust to skew)
qs = np.unique(np.quantile(df_plot[print_feature_name], [0, .1, .25, .5, .75, .9, 1.0]))
# ensure strictly increasing edges
bins = np.unique(qs)
if len(np.unique(bins)) < 3:
    # fallback fixed bins if quantiles collapse (rare)
        bins = [df_plot[print_feature_name].min()-1, 10000, 15000, 20000, 30000, df_plot[prin
df_plot["ValueBucket"] = pd.cut(df_plot[print_feature_name], bins=bins, include_lowest=True)
mean_prem = df_plot.groupby("ValueBucket")[target_name].mean()

plt.figure(figsize=(9,4))
plt.bar(mean_prem.index.astype(str), mean_prem.values)
plt.title(f"Mean {target_name} by {print_feature_name} Bucket")
plt.ylabel(f"Mean {target_name}"); plt.xlabel(f"{print_feature_name} Bucket")
plt.xticks(rotation=45, ha="right")
plt.tight_layout(); plt.show()
```

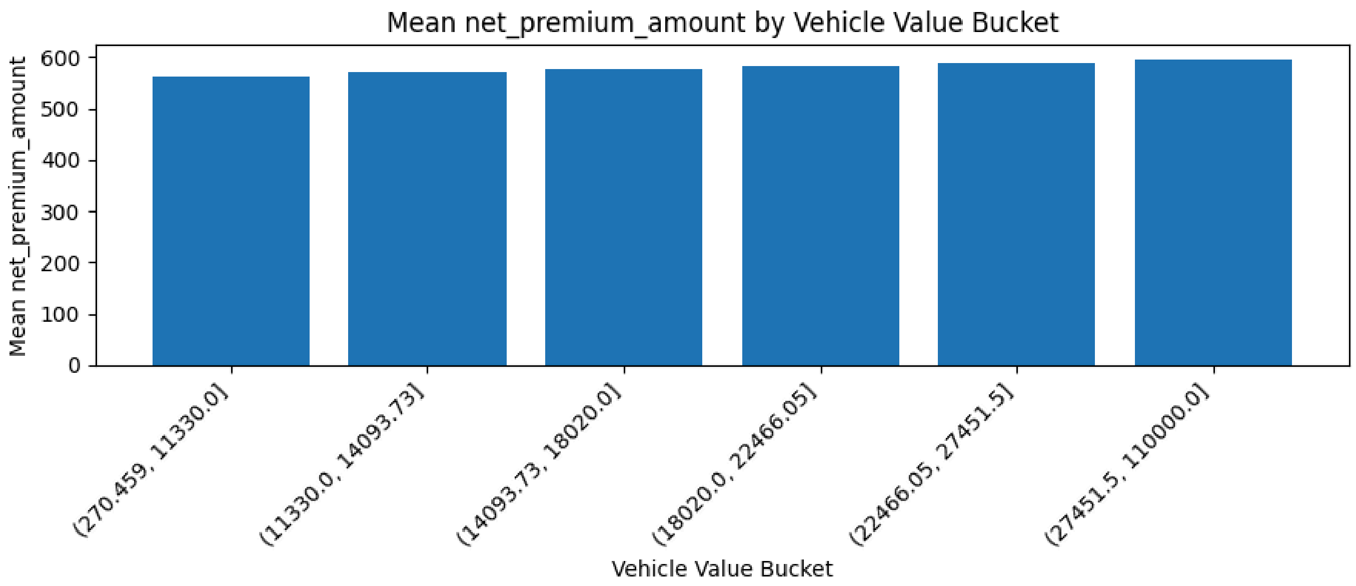
```
Feature: vehicle_value -> Vehicle Value
count     32136.000000
mean      18972.391870
std        7176.732691
min         270.460000
1%         7068.000000
5%         9900.000000
25%       14093.730000
50%       18020.000000
75%       22466.050000
95%       31200.000000
99%       42746.250000
max      110000.000000
Name: vehicle_value, dtype: float64
```




Boxplot: Vehicle Value
1
0
20000
40000
60000
80000
100000
Vehicle Value


log1p(Vehicle Value) - Distribution
Count
0
1000
2000
3000
4000
5000
6000
7000
6
7
8
9
10
11
log1p(Vehicle Value)


Vehicle Value vs net_premium_amount
net_premium_amount
450
500
550
600
650
0
20000
40000
60000
80000
100000
Vehicle Value



In [46]:
```
# provide a detailed analysis on the selected feature, its distribution, limitations, issues,

feature_6_insights = """
Vehicle Value has an average of about 19,000 with most values ranging between 14,000 and 22,5(
The distribution is strongly right-skewed, which was confirmed by the log transformation produ
This feature is important because higher vehicle value generally corresponds to higher replace
Issues: There exist some extreme values, it should be addressed through log transformation or
"""
```

In [47]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='feature_6_insights', value=feature_6_insights)
```

feature_6_insights

Vehicle Value has an average of about 19,000 with most values ranging between 14,000 and 22,500, but extreme outliers reach up to 110,000. The distribution is strongly right-skewed, which was confirmed by the log transformation producing a near-normal shape. This feature is important because higher vehicle value generally corresponds to higher replacement cost and risk, making it highly predictive for premium pricing. Issues: There exist some extreme values, it should be addressed through log transformation or outlier capping.

C.7 Explore Feature of Interest `matriculation_year`

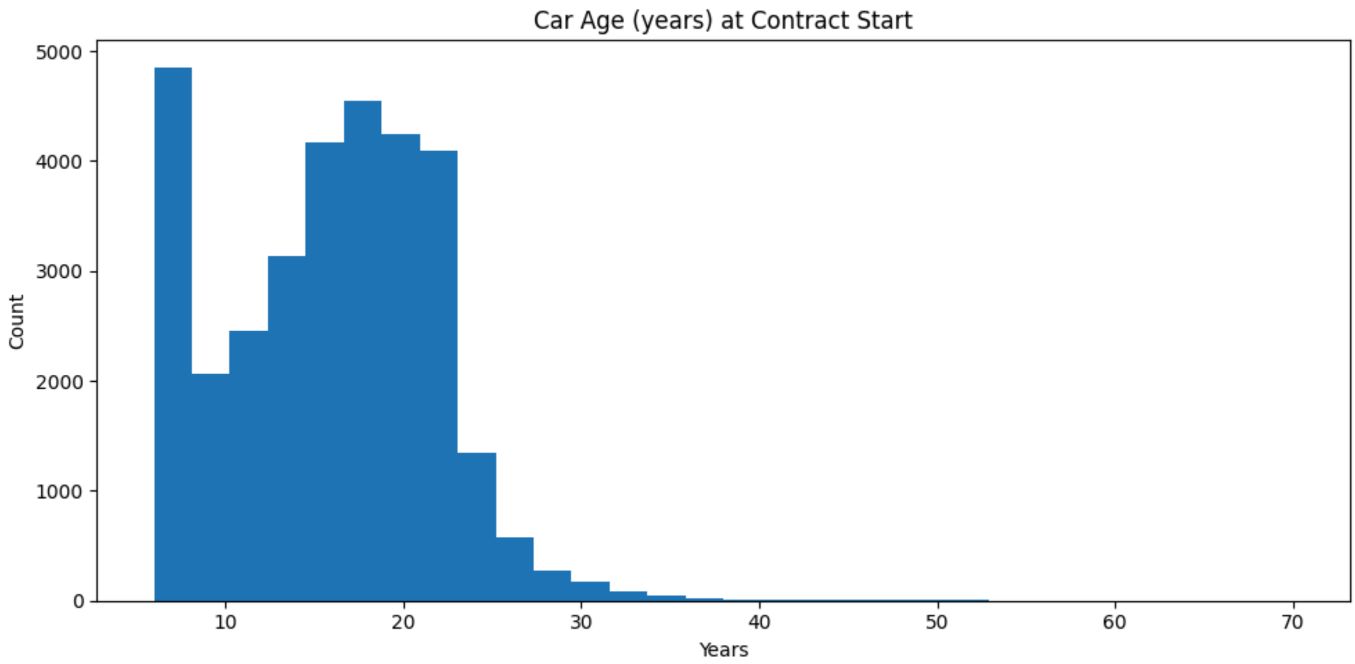
> You can add more cells related to other feeatures in this section

In [48]:
```
feature_name       = "matriculation_year"       # Vehicle registration year (YYYY)
ref_date_col       = "contract_start_date"      # Reference date (contract start)
target_name        = "net_premium_amount"       # Target variable
print_feature_name = "Car Age (years) at Contract Start"
```

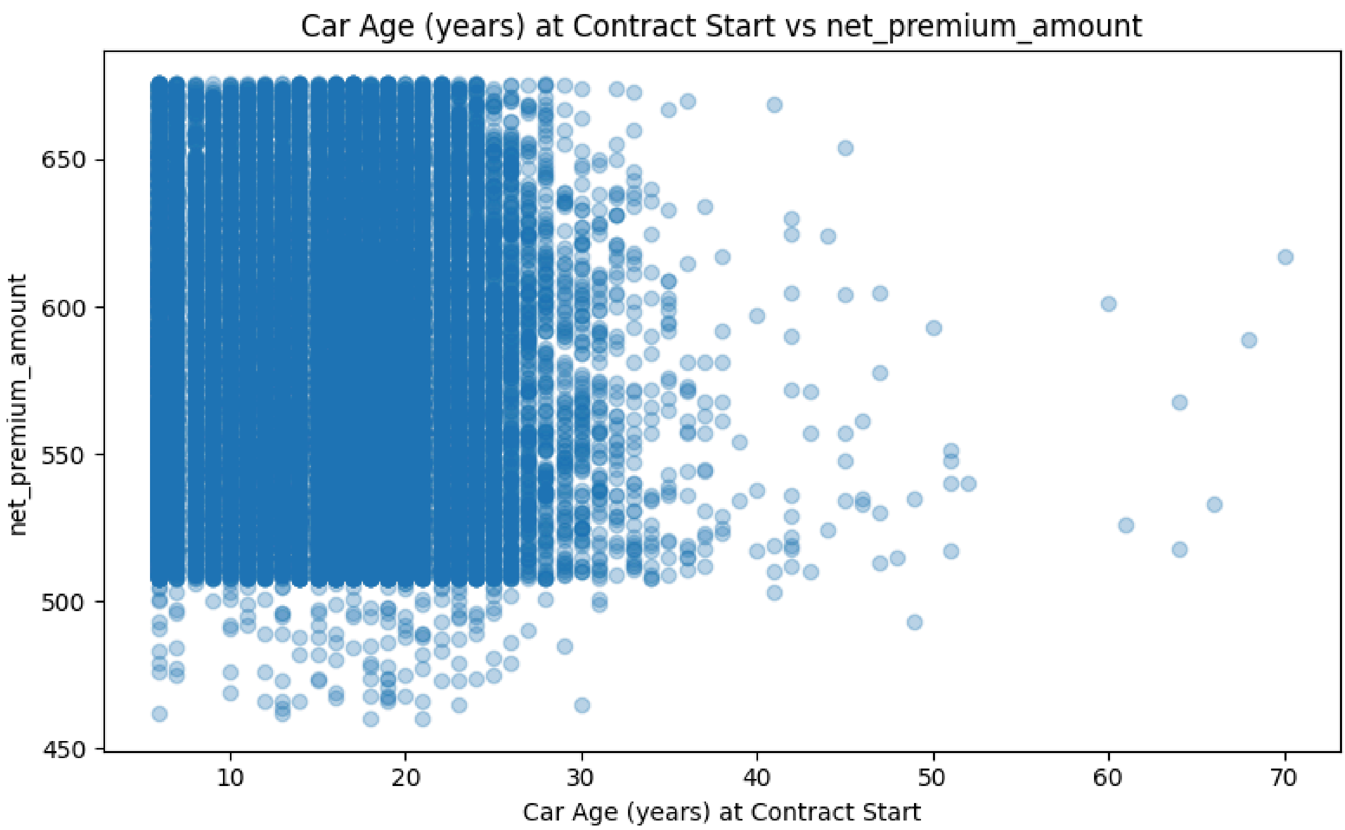
In [49]:
```
# Prepare data
year = pd.to_numeric(training_df[feature_name], errors="coerce")
ref  = pd.to_datetime(training_df[ref_date_col], errors="coerce")

# Compute car age at contract start (allow NaNs)
car_age = (ref.dt.year - year).where(year.notna() & ref.notna(), np.nan)

# Descriptive stats
print(f"Feature: {feature_name} -> {print_feature_name}")
```

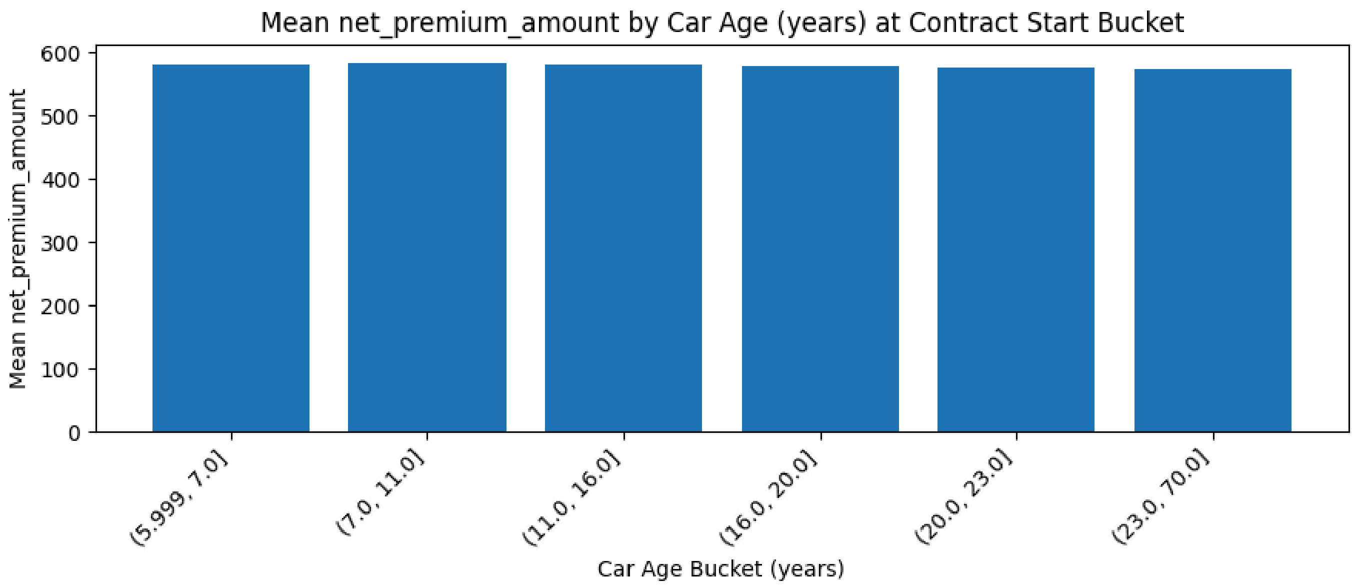
```python
print(car_age.describe(percentiles=[.01,.05,.25,.5,.75,.95,.99]))
if (car_age < 0).any():  print("Note: negative car ages exist (check registration vs contract

# Distribution plots
valid = car_age.dropna()
plt.figure(figsize=(10,5))
plt.hist(valid, bins=30)
plt.title(print_feature_name)
plt.xlabel("Years"); plt.ylabel("Count")
plt.tight_layout(); plt.show()

plt.figure(figsize=(8,3))
plt.boxplot(valid, vert=False)
plt.title(f"Boxplot: {print_feature_name}")
plt.xlabel("Years")
plt.tight_layout(); plt.show()

# Relationship with target (scatter + bucketed means)
df_plot = pd.DataFrame({print_feature_name: car_age, target_name: training_df[target_name]}).

# Scatter
plt.figure(figsize=(8,5))
plt.scatter(df_plot[print_feature_name], df_plot[target_name], alpha=0.3)
plt.title(f"{print_feature_name} vs {target_name}")
plt.xlabel(print_feature_name); plt.ylabel(target_name)
plt.tight_layout(); plt.show()
# Quantile buckets (robust to skew)
qs = np.unique(np.quantile(df_plot[print_feature_name], [0, .1, .25, .5, .75, .9, 1.0]))
if len(qs) < 3:  # fallback if degenerate
    qs = [df_plot[print_feature_name].min()-1, 3, 5, 10, 15, 20, df_plot[print_feature_name].
df_plot["AgeBucket"] = pd.cut(df_plot[print_feature_name], bins=qs, include_lowest=True)
mean_prem = df_plot.groupby("AgeBucket")[target_name].mean()

plt.figure(figsize=(9,4))
plt.bar(mean_prem.index.astype(str), mean_prem.values)
plt.title(f"Mean {target_name} by {print_feature_name} Bucket")
plt.ylabel(f"Mean {target_name}"); plt.xlabel("Car Age Bucket (years)")
plt.xticks(rotation=45, ha="right")
plt.tight_layout(); plt.show()
```

```
Feature: matriculation_year -> Car Age (years) at Contract Start
count    32136.000000
mean        15.793316
std          5.971988
min          6.000000
1%           6.000000
5%           6.000000
25%         11.000000
50%         16.000000
75%         20.000000
95%         25.000000
99%         30.000000
max         70.000000
dtype: float64
```


Car Age (years) at Contract Start
Count
Years
0
1000
2000
3000
4000
5000
10
20
30
40
50
60
70


Boxplot: Car Age (years) at Contract Start
1
Years
10
20
30
40
50
60
70


Car Age (years) at Contract Start vs net_premium_amount
net_premium_amount
Car Age (years) at Contract Start
450
500
550
600
650
10
20
30
40
50
60
70



In [50]:
```
# provide a detailed analysis on the selected feature, its distribution, limitations, issues,

feature_7_insights = """
Car Age (years) at Contract Start has a mean of about 16 years, with most vehicles between 11
The distribution is moderately right-skewed, with a few very old vehicles up to 70 years that
A limitation is that car age may correlate with vehicle value, multicollinearity should be coı
Extreme values should be reviewed, and the feature may be more useful in bucketed form rather
"""
```

In [51]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='feature_7_insights', value=feature_7_insights)
```

feature_7_insights

Car Age (years) at Contract Start has a mean of about 16 years, with most vehicles between 11 and 20 years old. The distribution is moderately right-skewed, with a few very old vehicles up to 70 years that may be data anomalies or rare cases. A limitation is that car age may correlate with vehicle value, multicollinearity should be considered. Extreme values should be reviewed, and the feature may be more useful in bucketed form rather than as a raw continuous variable.

C.8 Explore Feature of Interest `vehicle_fuel_type`

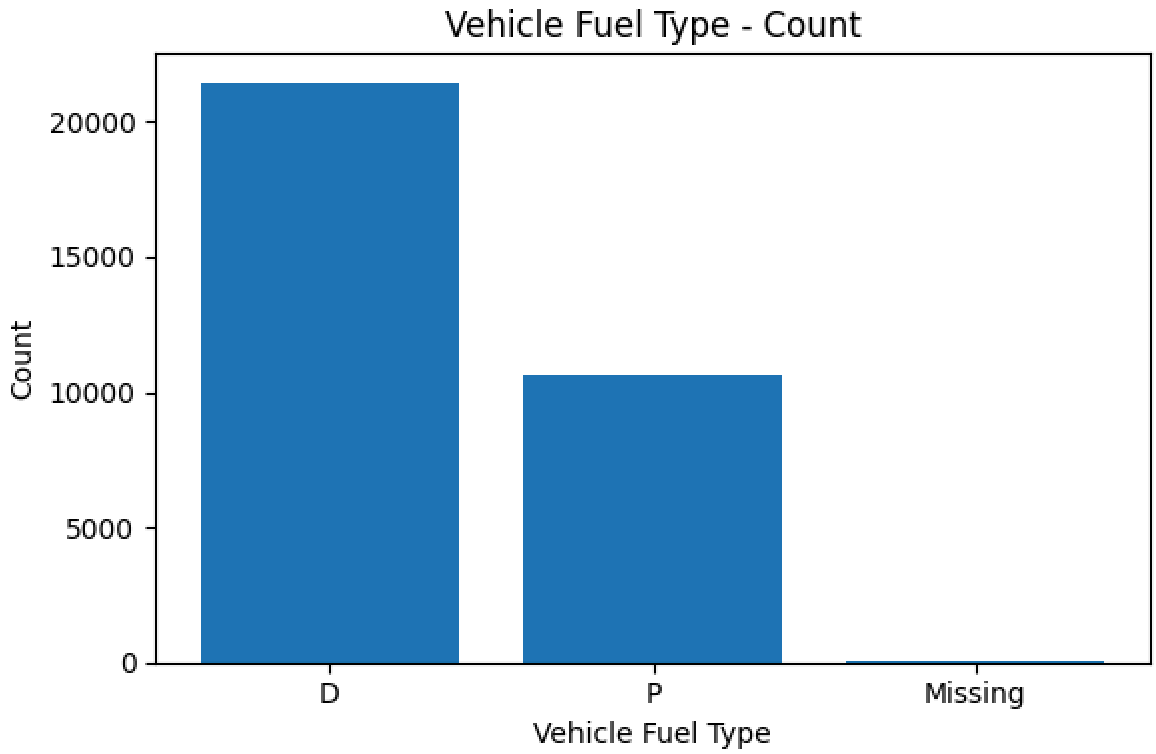
> You can add more cells related to other feeatures in this section

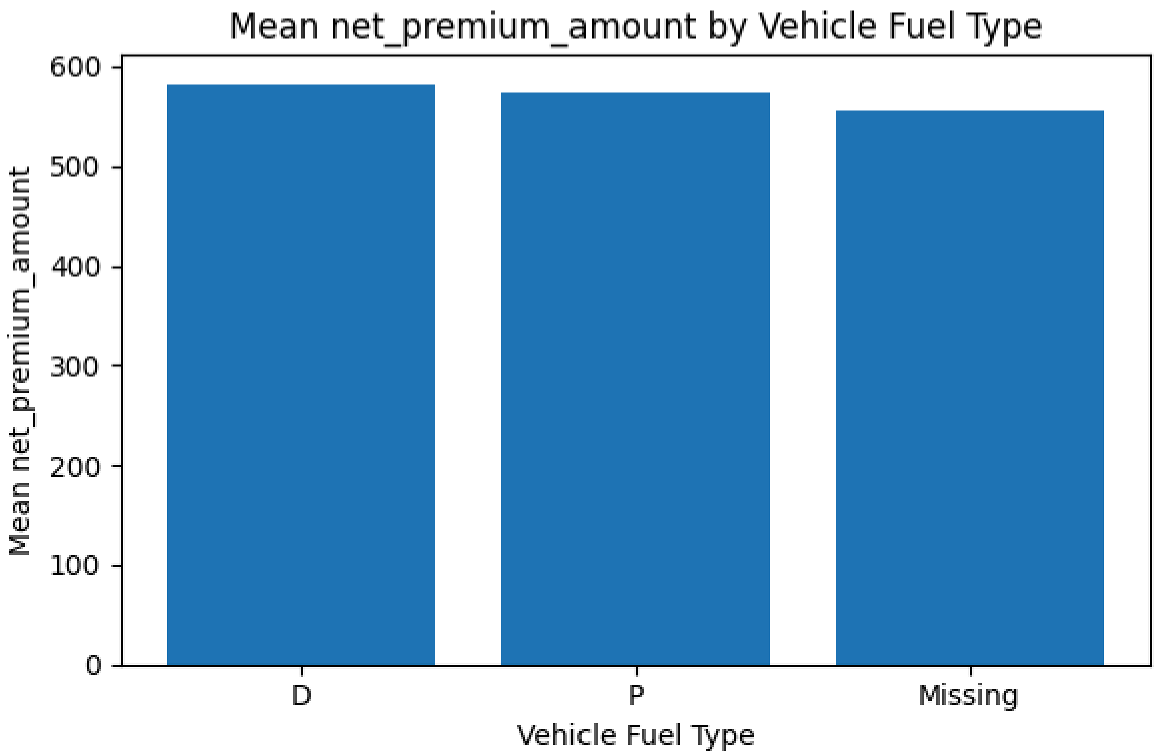
In [52]:
```
feature_name       = "vehicle_fuel_type"       # Fuel type (e.g., Petrol/Diesel)
ref_date_col       = "contract_start_date"     # Reference date (parsed for completeness)
target_name        = "net_premium_amount"      # Target variable
print_feature_name = "Vehicle Fuel Type"
```

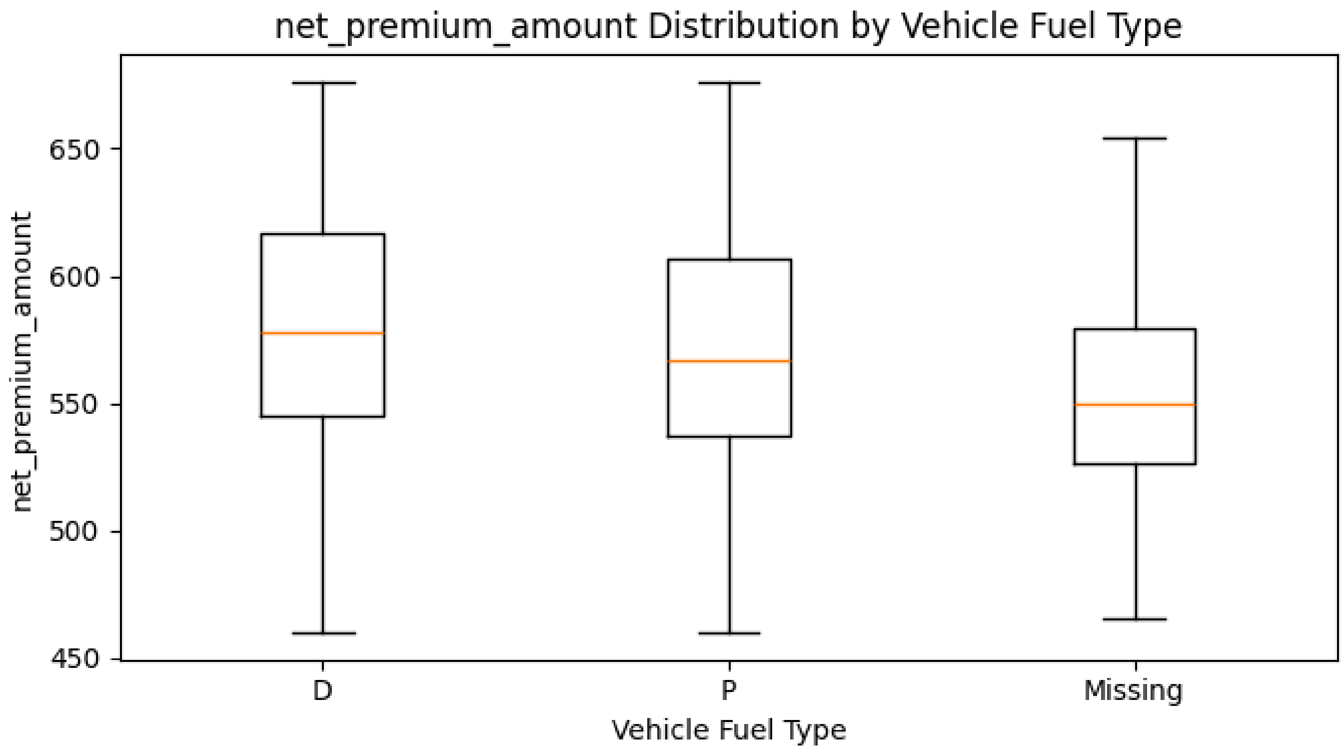
In [53]:
```
# Prepare data
s = training_df[feature_name].astype(str).where(training_df[feature_name].notna(), "Missing")
ref_dt = pd.to_datetime(training_df[ref_date_col], errors="coerce")  # parsed but unused
y = training_df[target_name]

# Basic stats
print(f"Feature: {feature_name} -> {print_feature_name}")
print("Counts (incl. Missing):")
print(s.value_counts())
```

```python
# Count bar plot
counts = s.value_counts()
plt.figure(figsize=(6,4))
plt.bar(counts.index.astype(str), counts.values)
plt.title(f"{print_feature_name} - Count")
plt.xlabel(print_feature_name); plt.ylabel("Count")
plt.tight_layout(); plt.show()

# Mean premium by fuel type
df_plot = pd.DataFrame({print_feature_name: s, target_name: y}).dropna()
mean_target = df_plot.groupby(print_feature_name)[target_name].mean().sort_values(ascending=F

plt.figure(figsize=(6,4))
plt.bar(mean_target.index.astype(str), mean_target.values)
plt.title(f"Mean {target_name} by {print_feature_name}")
plt.xlabel(print_feature_name); plt.ylabel(f"Mean {target_name}")
plt.tight_layout(); plt.show()

# Premium distribution by category (boxplot)
groups = [df_plot.loc[df_plot[print_feature_name] == cat, target_name].values for cat in mean_

plt.figure(figsize=(7,4))
plt.boxplot(groups, labels=mean_target.index.astype(str), showfliers=False)
plt.title(f"{target_name} Distribution by {print_feature_name}")
plt.xlabel(print_feature_name); plt.ylabel(target_name)
plt.tight_layout(); plt.show()
```

```
Feature: vehicle_fuel_type -> Vehicle Fuel Type
Counts (incl. Missing):
vehicle_fuel_type
D          21450
P          10608
Missing       78
Name: count, dtype: int64
```







In [54]:
```
# provide a detailed analysis on the selected feature, its distribution, limitations, issues, 

feature_8_insights = """
The feature Vehicle Fuel Type is dominated by Diesel (≈67%) and Petrol (≈33%), with very few r
The distribution of premiums shows Diesel vehicles having slightly higher average premiums tha
The Missing group is lower but very small in size.
Issues: there exist small number of missing values, which may be treated as a separate categor
"""
```

In [55]:
```
# DO NOT MODIFY THE CODE IN THIS CELL
print_tile(size="h3", key='feature_8_insights', value=feature_8_insights)
```

The feature Vehicle Fuel Type is dominated by Diesel (≈67%) and Petrol (≈33%), with very few missing cases. The distribution of premiums shows Diesel vehicles having slightly higher average premiums than Petrol. The Missing group is lower but very small in size. Issues: there exist small number of missing values, which may be treated as a separate category or imputed.