Olist E-commerce Business Analysis

Field	Value
Author	Mubin
Domain	E-Commerce · Data Analysis
Python	3.13.5
Data Source	Olist Brazilian E-Commerce

Tools: Python, Pandas, NumPy, Seaborn, Matplotlib, Folium.

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Project Objective

The goal of this project is to analyze the Olist E-commerce dataset to derive **actionable business insights**. We focus on:

1. **Logistics Performance** — Identifying delays and shipping issues.
2. **Customer Segmentation** — Finding high-value customers using RFM.
3. **Sales Trends** — Understanding seasonality and peak hours.
4. **Product Quality** — Spotting low-rated categories and improvement opportunities.

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1. Environment Setup & Data Loading

This section ensures **reproducibility** and a clean analysis environment:

- Import core libraries (pandas, numpy, matplotlib, seaborn, folium).
- Set global constants (e.g. `RANDOM_STATE`, `DATA_PATH`).
- Configure display and plotting defaults.
- Load and validate all necessary Olist E-commerce datasets.

Reproducibility: Place Olist CSVs in `data/` and install dependencies with `pip install -r requirements-olist.txt`.

In [1]:
```python
# --- Environment Setup ---
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import folium
import os
import sys
import warnings
from textblob import TextBlob
from folium.plugins import HeatMap
from IPython.display import display_html

# Reproducibility
RANDOM_STATE = 42
np.random.seed(RANDOM_STATE)

# Configuration
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)
pd.set_option('display.float_format', lambda x: '%.3f' % x)

# Plot style (if needed)
# sns.set_theme(style="whitegrid", font_scale=1.1)
# plt.rcParams['figure.figsize'] = (10, 5)
# plt.rcParams['font.size'] = 11

# Version check (for reproducibility)
print(f"Python: {sys.version.split()[0]}")
print(f"Pandas: {pd.__version__}")
```

```
Python: 3.13.5
Pandas: 3.0.0
```

In [2]:
```python
# --- Load Datasets ---
from typing import Optional

DATA_PATH = 'data/'

def load_data(file_name: str) -> Optional[pd.DataFrame]:
    """Load a CSV from DATA_PATH. Returns None and prints error if file not found."
    path = os.path.join(DATA_PATH, file_name)
    try:
        return pd.read_csv(path)
    except FileNotFoundError:
        print(f"Error: File {file_name} not found in {DATA_PATH}")
```

```python
        return None

# Load all datasets
orders_df = load_data('olist_orders_dataset.csv')
customers_df = load_data('olist_customers_dataset.csv')
items_df = load_data('olist_order_items_dataset.csv')
products_df = load_data('olist_products_dataset.csv')
payments_df = load_data('olist_order_payments_dataset.csv')
reviews_df = load_data('olist_order_reviews_dataset.csv')
category_translation = load_data('product_category_name_translation.csv')
geo_data = load_data('olist_geolocation_dataset.csv')
sellers_df = load_data('olist_sellers_dataset.csv')

# Validate critical datasets
required = {
    'orders': orders_df,
    'customers': customers_df,
    'order_items': items_df,
    'products': products_df,
    'payments': payments_df,
}
missing = [k for k, v in required.items() if v is None or v.empty]
if missing:
    raise FileNotFoundError(f"Required datasets missing or empty: {missing}. Ensure
print("All required datasets loaded successfully.")
```

```
All required datasets loaded successfully.
```

2. Dataset Overview & Data Quality

We inspect schema, dtypes, non-null counts, and missing values for each table. Order status distribution is also summarized to understand the business mix.

In [3]:

```python
all_datasets = {
    'Orders': orders_df,
    'Customers': customers_df,
    'Items': items_df,
    'Products': products_df,
    'Payments': payments_df,
    'Reviews': reviews_df,
    'Category (Eng.)': category_translation,
    'Geolocation': geo_data,
    'Sellers': sellers_df
}
def get_info_summary(df):
    return pd.DataFrame({
        'Dtype': df.dtypes.astype(str),
        'Non-Null': df.count(),
        'Missing': df.isnull().sum()
    })

# Loop and create HTML for each dataset
html_output = ""
for name, df in all_datasets.items():
```

```
    info_df = get_info_summary(df)

    styler = info_df.style \
        .set_table_attributes("style='display:inline-block; vertical-align: top; ma
        .set_caption(f"<b> 🔹 {name} ({df.shape[0]} rows, {df.shape[1]} cols)</b>")
        .background_gradient(cmap='Reds', subset=['Missing'])  # Highlight missing
    html_output += styler._repr_html_()

status_df = orders_df['order_status'].value_counts().to_frame(name='Count')
status_styler = status_df.style \
    .set_table_attributes("style='display:inline-block; vertical-align: top; margin
    .set_caption("<b> 🔹 Order Status Distribution</b>") \
    .background_gradient(cmap='Blues') \
    .format("{:,}")
html_output += status_styler._repr_html_()

# Showing all tables
print("Dataset Summaries (Info & Types):")
display_html(html_output, raw=True)
```

```
Dataset Summaries (Info & Types):
```

◆ **Orders (99441 rows, 8 cols)**

	Dtype	Non-Null	Missing
order_id	str	99441	0
customer_id	str	99441	0
order_status	str	99441	0
order_purchase_timestamp	str	99441	0
order_approved_at	str	99281	160
order_delivered_carrier_date	str	97658	1783
order_delivered_customer_date	str	96476	2965
order_estimated_delivery_date	str	99441	0

◆ **Customers (99441 rows, 5 cols)**

	Dtype	Non-Null	Missing
customer_id	str	99441	0
customer_unique_id	str	99441	0
customer_zip_code_prefix	int64	99441	0
customer_city	str	99441	0
customer_state	str	99441	0

◆ **Items (112650 rows, 7 cols)**

	Dtype	Non-Null	Missing
order_id	str	112650	0
order_item_id	int64	112650	0
product_id	str	112650	0
seller_id	str	112650	0
shipping_limit_date	str	112650	0
price	float64	112650	0
freight_value	float64	112650	0

🔹 **Products (32951 rows, 9 cols)**

	Dtype	Non-Null	Missing
product_id	str	32951	0
product_category_name	str	32341	610
product_name_lenght	float64	32341	610
product_description_lenght	float64	32341	610
product_photos_qty	float64	32341	610
product_weight_g	float64	32949	2
product_length_cm	float64	32949	2
product_height_cm	float64	32949	2
product_width_cm	float64	32949	2

🔹 **Payments (103886 rows, 5 cols)**

	Dtype	Non-Null	Missing
order_id	str	103886	0
payment_sequential	int64	103886	0
payment_type	str	103886	0
payment_installments	int64	103886	0
payment_value	float64	103886	0

🔹 **Reviews (99224 rows, 7 cols)**

	Dtype	Non-Null	Missing
review_id	str	99224	0
order_id	str	99224	0
review_score	int64	99224	0
review_comment_title	str	11568	87656
review_comment_message	str	40977	58247
review_creation_date	str	99224	0
review_answer_timestamp	str	99224	0

◆ **Category (Eng.) (71 rows, 2 cols)**

	Dtype	Non-Null	Missing
product_category_name	str	71	0
product_category_name_english	str	71	0

◆ **Geolocation (1000163 rows, 5 cols)**

	Dtype	Non-Null	Missing
geolocation_zip_code_prefix	int64	1000163	0
geolocation_lat	float64	1000163	0
geolocation_lng	float64	1000163	0
geolocation_city	str	1000163	0
geolocation_state	str	1000163	0

◆ **Sellers (3095 rows, 4 cols)**

	Dtype	Non-Null	Missing
seller_id	str	3095	0
seller_zip_code_prefix	int64	3095	0
seller_city	str	3095	0
seller_state	str	3095	0

◆ **Order Status Distribution**

	Count
order_status	
delivered	96,478
shipped	1,107
canceled	625
unavailable	609
invoiced	314
processing	301
created	5
approved	2

In [4]:
```
# Convert date columns in orders_df to datetime format
date_columns = [
    'order_purchase_timestamp',
    'order_approved_at',
    'order_delivered_carrier_date',
    'order_delivered_customer_date',
    'order_estimated_delivery_date'
]
for col in date_columns:
    orders_df[col] = pd.to_datetime(orders_df[col])

# Verify the changes
orders_df.info()
```

```
<class 'pandas.DataFrame'>
RangeIndex: 99441 entries, 0 to 99440
Data columns (total 8 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   order_id                       99441 non-null  str
 1   customer_id                    99441 non-null  str
 2   order_status                   99441 non-null  str
 3   order_purchase_timestamp       99441 non-null  datetime64[us]
 4   order_approved_at              99281 non-null  datetime64[us]
 5   order_delivered_carrier_date   97658 non-null  datetime64[us]
 6   order_delivered_customer_date  96476 non-null  datetime64[us]
 7   order_estimated_delivery_date  99441 non-null  datetime64[us]
dtypes: datetime64[us](5), str(3)
memory usage: 13.0 MB
```

3. Sales Trend & Temporal Analysis

Understanding the sales trend over time helps in inventory planning and marketing strategies. We will analyze:

1. **Monthly Sales Trend** , 2. **Sales Heatmap**

Monthly Sales Trend & Seasonality

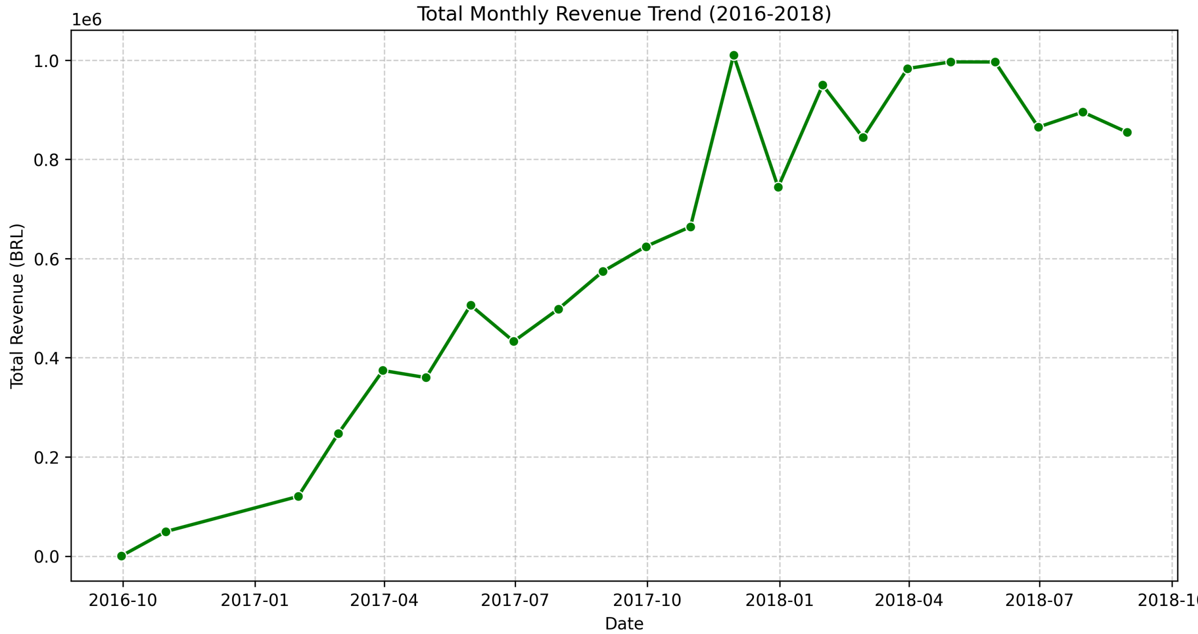
We analyze the timeline of total revenue to identify growth patterns and seasonality.

> **Visualization Note:** Data from the initial launch phase (2016) and the incomplete records of September 2018 have been excluded from this chart to present a strictly accurate trend without misleading drop-offs.

In [5]:

```
# Preparing Monthly Revenue Data
from csv import excel


sales_data = orders_df.merge(items_df, on='order_id')
sales_data['order_purchase_timestamp'] = pd.to_datetime(sales_data['order_purchase_
sales_data.set_index('order_purchase_timestamp', inplace=True)
monthly_revenue = sales_data.resample('ME')['price'].sum()

# Filtering out months with unrealistic low revenue
filtered_monthly_revenue = monthly_revenue[monthly_revenue > 200]

# Visualizing the Trend
plt.figure(figsize=(12, 6), dpi=300)
sns.lineplot(x=filtered_monthly_revenue.index, y=filtered_monthly_revenue.values, m
plt.title('Total Monthly Revenue Trend (2016-2018)')
plt.xlabel('Date')
plt.ylabel('Total Revenue (BRL)')
plt.grid(True, linestyle='--', alpha=0.6)
plt.show()
```

```
display(monthly_revenue.to_frame('Total Revenue').T)
# monthly_revenue.to_excel('monthly_revenue.xlsx', index=True)
```

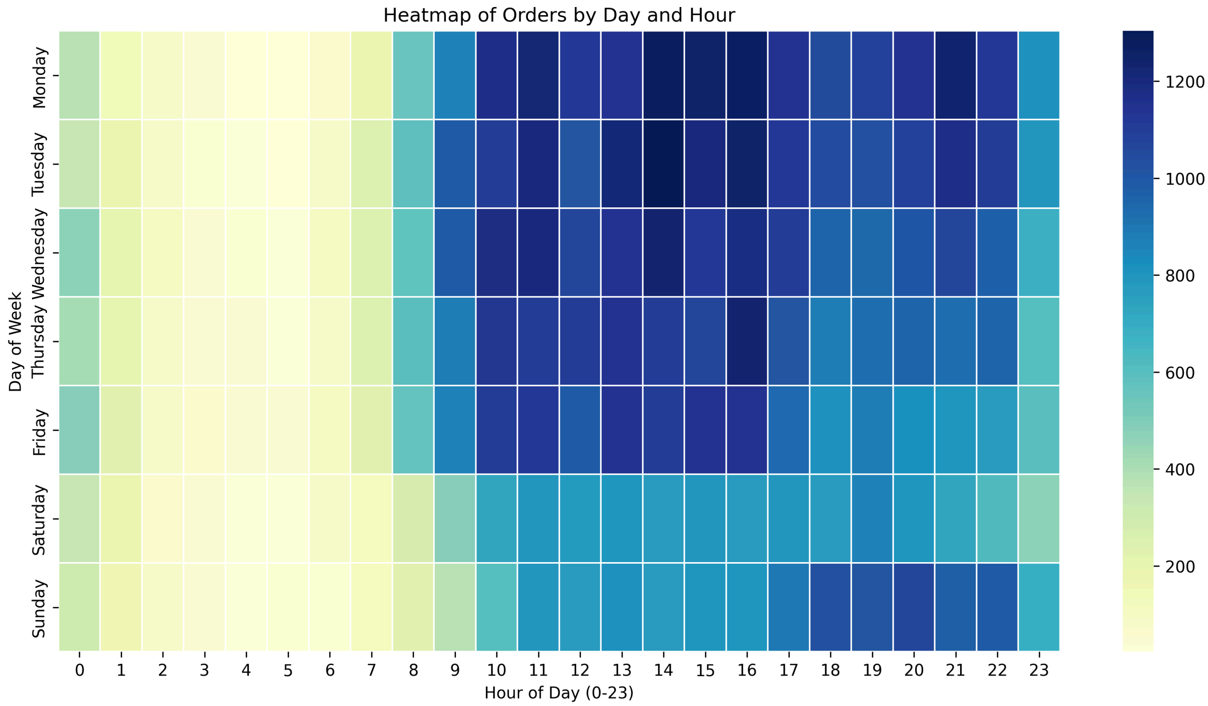


order_purchase_timestamp	2016-09-30	2016-10-31	2016-11-30	2016-12-31	2017-01-31	2017-02-28	2017
Total Revenue	267.360	49507.660	0.000	10.900	120312.870	247303.020	374344

Sales Heatmap:

To pinpoint the specific days of the week and hours of the day when customers are most active.

In [6]:
```
# Preparing Data for Heatmap
sales_data.reset_index(inplace=True)
sales_data['day_name'] = sales_data['order_purchase_timestamp'].dt.day_name()
sales_data['hour'] = sales_data['order_purchase_timestamp'].dt.hour

# Ordering the days of the week
days_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', '
sales_data['day_name'] = pd.Categorical(sales_data['day_name'], categories=days_ord

# Creating a Pivot Table: Rows = Days, Columns = Hours, Values = Count of Orders
pivot_table = sales_data.pivot_table(index='day_name', columns='hour', values='orde

# Visualizing with Heatmap
plt.figure(figsize=(14, 7), dpi=300)
sns.heatmap(pivot_table, cmap='YlGnBu', linecolor='white', linewidths=0.5)
plt.title('Heatmap of Orders by Day and Hour')
plt.xlabel('Hour of Day (0-23)')
plt.ylabel('Day of Week')
plt.show()
```



4. Delivery Performance & Logistics Analysis

In this section, we will analyze the delivery efficiency. We will calculate the difference between the estimated delivery date and the actual delivery date to identify delays. Then, we will correlate these delays with customer review scores to understand the impact of logistics on customer satisfaction.

Timely delivery is a critical factor in customer satisfaction and retention. In this section, we evaluate the logistics efficiency by comparing the actual delivery date against the estimated delivery date.

In [7]:

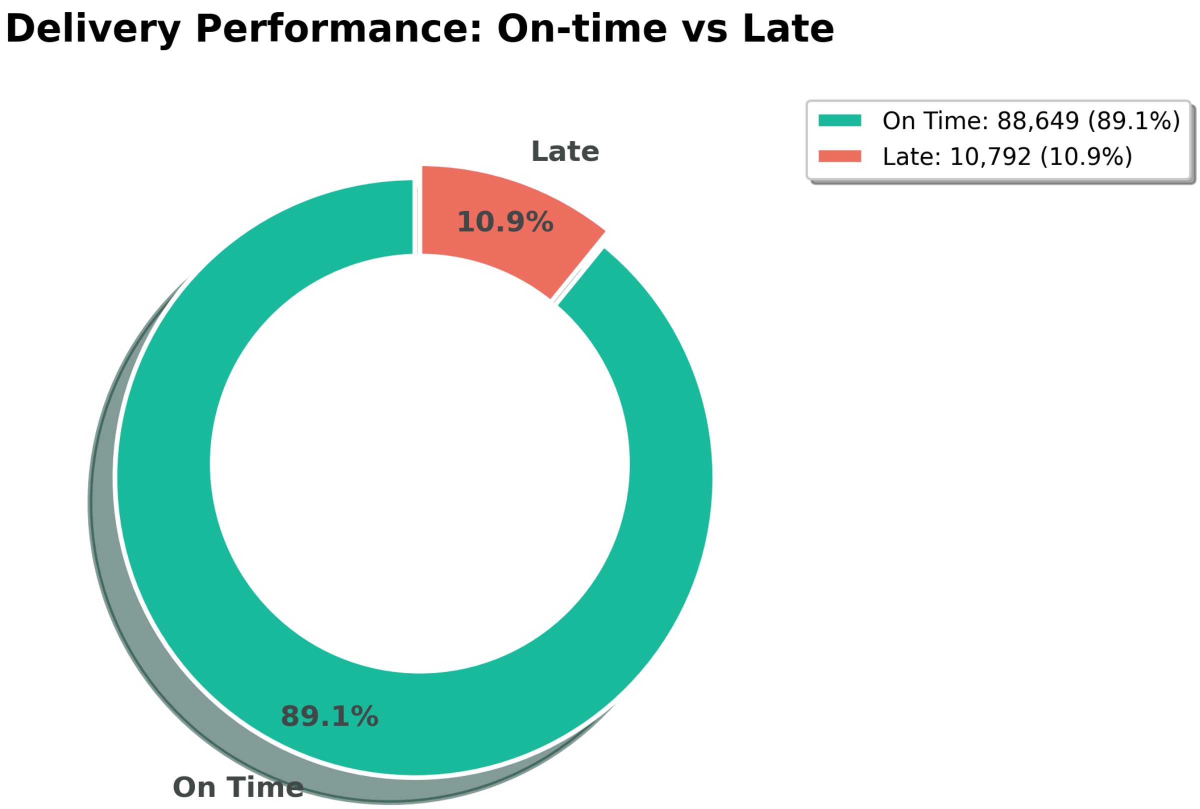
```
orders_df.head()
```

Out[7]:

	order_id	customer_id	order_status	or
0	e481f51cbdc54678b7cc49136f2d6af7	9ef432eb6251297304e76186b10a928d	delivered	
1	53cdb2fc8bc7dce0b6741e2150273451	b0830fb4747a6c6d20dea0b8c802d7ef	delivered	
2	47770eb9100c2d0c44946d9cf07ec65d	41ce2a54c0b03bf3443c3d931a367089	delivered	
3	949d5b44dbf5de918fe9c16f97b45f8a	f88197465ea7920adcdbec7375364d82	delivered	
4	ad21c59c0840e6cb83a9ceb5573f8159	8ab97904e6daea8866dbdbc4fb7aad2c	delivered	

In [8]:

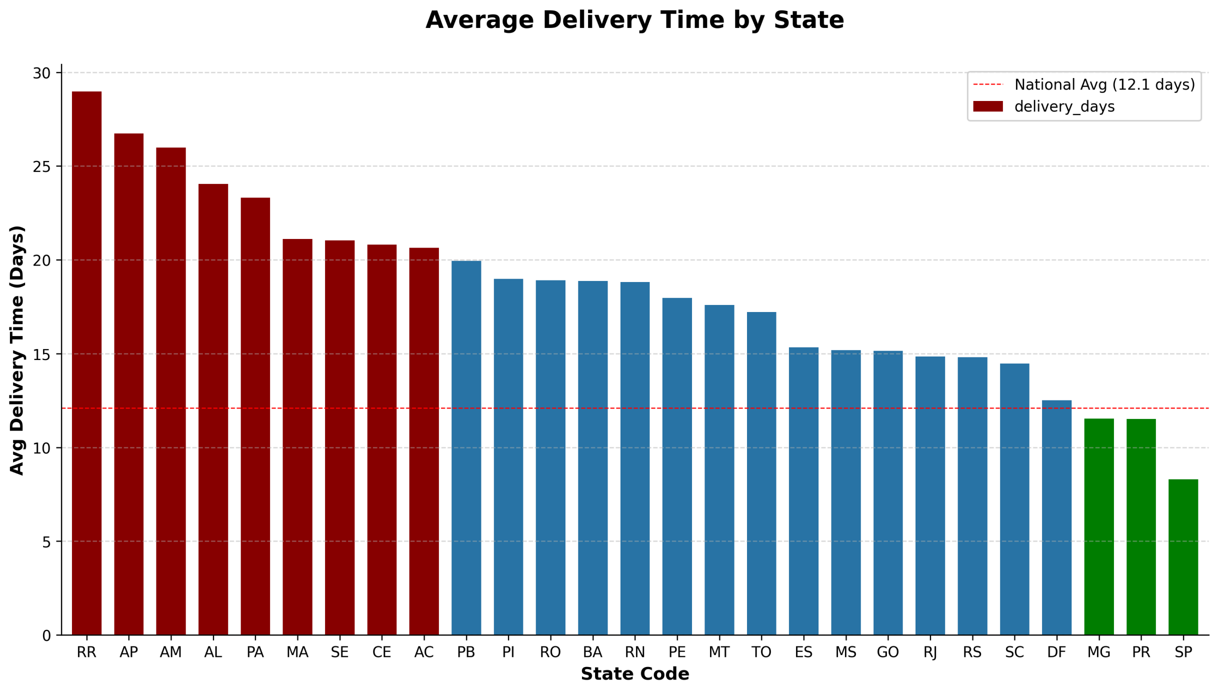
```
# Enhanced On-time Delivery Rate
orders_df['delivered_on_time'] = orders_df['order_delivered_customer_date'] <= orde
on_time_counts = orders_df['delivered_on_time'].value_counts().sort_index(ascending

labels = ['On Time', 'Late']
colors = ['#1ABC9C', '#EC7063']
explode = (0.05, 0)

# Visualization
plt.figure(figsize=(7, 7), dpi=300)
plt.pie(on_time_counts, labels=labels, colors=colors, autopct='%1.1f%%',
        startangle=90, pctdistance=0.85, explode=explode,
        textprops={'fontsize': 12, 'weight': 'bold', 'color': '#424949'},
        wedgeprops={'width': 0.6, 'edgecolor': 'white', 'linewidth': 2}, shadow=Tru

centre_circle = plt.Circle((0,0), 0.70, fc='white')
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

total = sum(on_time_counts)
legend_labels = [f'{label}: {size:,} ({size/total*100:.1f}%)'
                 for label, size in zip(labels, on_time_counts)]

plt.legend(legend_labels,
          loc='upper left',
          bbox_to_anchor=(1, 1),
          fontsize=10,
          frameon=True,
          shadow=True)

plt.title('Delivery Performance: On-time vs Late', fontsize=16, fontweight='bold',
plt.tight_layout()
plt.show()
```



Average Delivery Time by State

In [9]:
```
# Prepare Data
orders_df['delivery_days'] = (orders_df['order_delivered_customer_date'] - orders_d
delivery_data = orders_df.merge(customers_df, on='customer_id')
state_delivery = delivery_data.groupby('customer_state')['delivery_days'].mean().so
national_avg = delivery_data['delivery_days'].mean()
# state_delivery.to_excel('state_delivery_times.xlsx', index=True)
# Visualization
colors = [
    'green' if x < national_avg
    else '#8B0000' if x >= 20
    else '#2874A6'
    for x in state_delivery
]
fig, ax = plt.subplots(figsize=(14, 7), dpi=300)
state_delivery.plot(kind='bar', color=colors, ax=ax, width=0.7)
plt.axhline(y=national_avg, color='red', linestyle='--', linewidth=0.75, label=f'Na

# Styling
ax.set_title("Average Delivery Time by State", fontsize=16, fontweight='bold', pad=
ax.set_ylabel("Avg Delivery Time (Days)", fontsize=12, fontweight='bold')
ax.set_xlabel("State Code", fontsize=12, fontweight='bold')
ax.grid(axis='y', linestyle='--', alpha=0.5)
ax.legend()
plt.xticks(rotation=0)
```

```
sns.despine(top=True, right=True)
plt.show()
```



Late Delivery Rate by State (Failure Analysis)

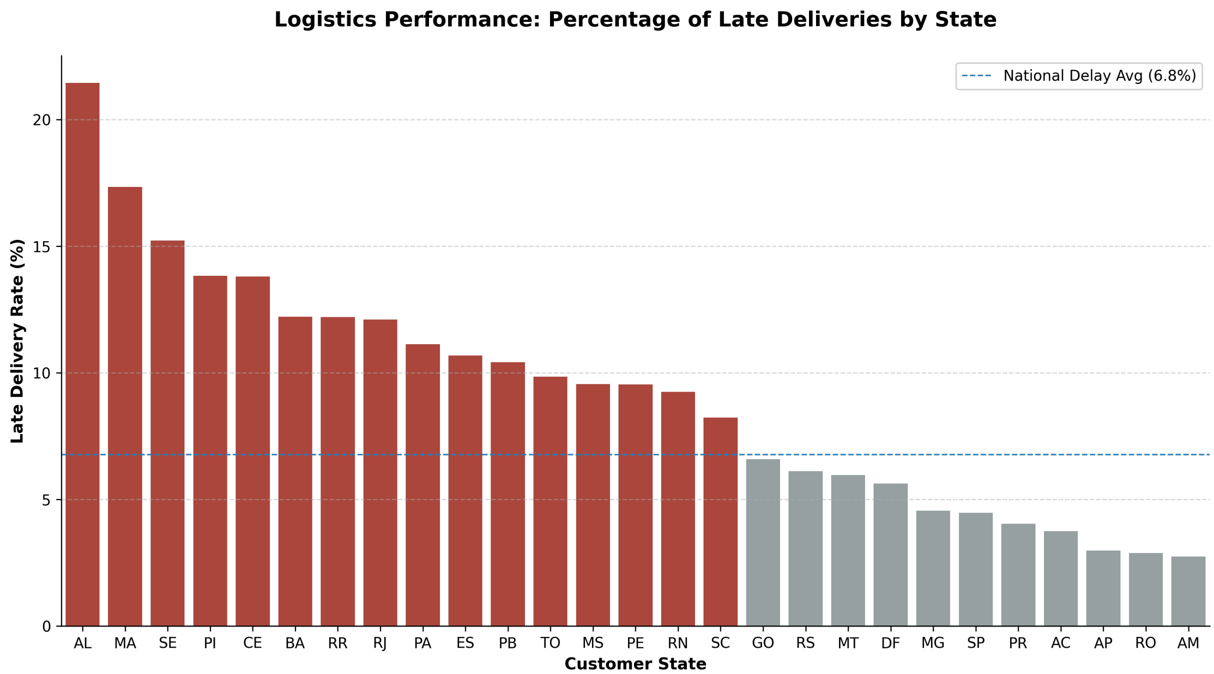
Instead of relying on average delivery times which can hide performance issues, we analyze the **Percentage of Late Deliveries**.

- **Metric:** % of Orders Delivered Late (**Actual Delivery Date > Estimated Delivery Date**).
- **Business Value:** identifying high-risk regions where logistics frequently fail to meet customer expectations.

In [10]:

```
# Prepare Data & Calculate Delay
delivery_analysis_df = orders_df.merge(reviews_df, on='order_id', how='left') \
                                .merge(customers_df, on='customer_id', how='left')
delivery_analysis_df = delivery_analysis_df[delivery_analysis_df['order_status'] ==
delivery_analysis_df.dropna(subset=['order_delivered_customer_date', 'order_estimat
delivery_analysis_df['delivery_difference'] = (delivery_analysis_df['order_delivere
                                               delivery_analysis_df['order_estimate
delivery_analysis_df['is_late'] = delivery_analysis_df['delivery_difference'] > 0
late_rate_by_state = delivery_analysis_df.groupby('customer_state')['is_late'].mean
national_avg = delivery_analysis_df['is_late'].mean() * 100

# Visualization
plt.figure(figsize=(14, 7), dpi=300)
ax = sns.barplot(
    x=late_rate_by_state.index,
    y=late_rate_by_state.values,
    palette=['#C0392B' if x > national_avg else '#95A5A6' for x in late_rate_by_sta
)
# Chart Titles and Labels
plt.title('Logistics Performance: Percentage of Late Deliveries by State', fontsize
```

```
plt.ylabel('Late Delivery Rate (%)', fontsize=11, fontweight='bold')
plt.xlabel('Customer State', fontsize=11, fontweight='bold')
plt.grid(axis='y', linestyle='--', alpha=0.5)

# Adding National Average Reference Line
plt.axhline(national_avg, color='#2980B9', linestyle='--', linewidth=1, label=f'Nat
plt.legend()

sns.despine()
plt.show()
```

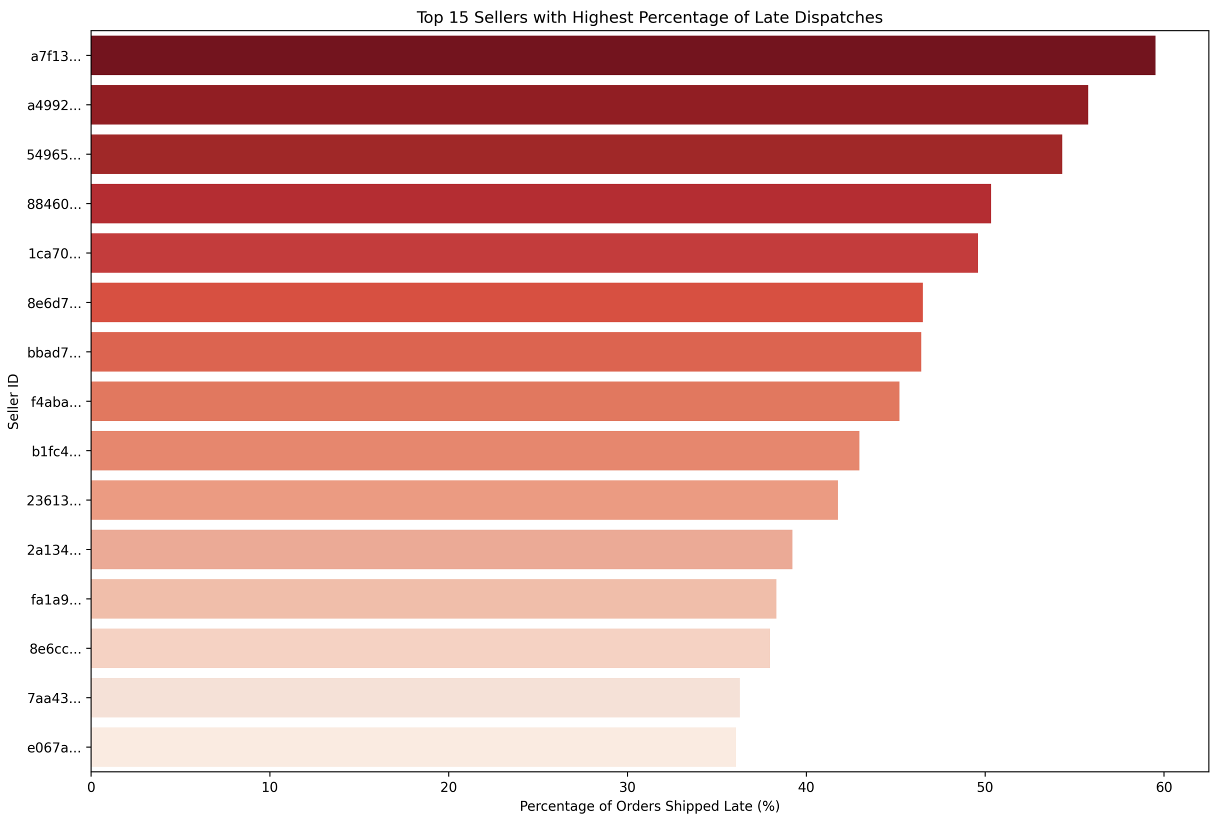


Worst Performing Sellers (Logistics Issue)

Identifying sellers who consistently miss their shipping deadlines. If a seller hands over the package to the carrier late, the final delivery will inevitably be delayed.

In [11]:
```
# Identifying Worst Sellers Based on Late Dispatches
seller_delay_df = orders_df.merge(items_df, on='order_id')
seller_delay_df = seller_delay_df[seller_delay_df['order_status'] == 'delivered']
seller_delay_df.dropna(subset=['order_delivered_carrier_date'], inplace=True)
seller_delay_df['seller_late_dispatch'] = seller_delay_df['order_delivered_carrier_

worst_sellers = seller_delay_df.groupby('seller_id').agg({
    'order_id': 'count',
    'seller_late_dispatch': 'sum'
}).reset_index()
worst_sellers['late_percentage'] = (worst_sellers['seller_late_dispatch'] / worst_s
worst_sellers = worst_sellers[worst_sellers['order_id'] > 50]
top_worst_sellers = worst_sellers.sort_values('late_percentage', ascending=False).h

# Shortening ID for graph
top_worst_sellers['short_id'] = top_worst_sellers['seller_id'].str[:5] + '...'
```

```
# --- 4. Visualizing ---
plt.figure(figsize=(15, 10), dpi=300)
sns.barplot(x='late_percentage', y='short_id', data=top_worst_sellers, palette='Red

plt.title('Top 15 Sellers with Highest Percentage of Late Dispatches')
plt.xlabel('Percentage of Orders Shipped Late (%)')
plt.ylabel('Seller ID')
plt.show()

# Exporting Results in Excel
# worst_sellers.to_excel('worst_sellers_statistics(by late_dispatch).xlsx', index=F
```

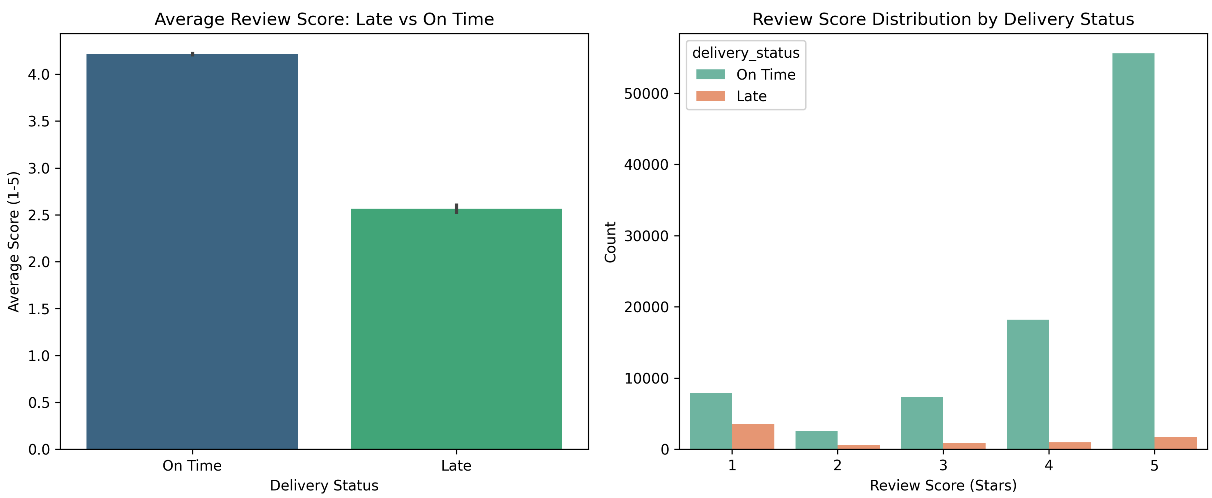


Impact of Late Delivery on Customer Satisfaction

In this section, we quantify the "cost" of logistics failures. We compare the **Average Review Score** of orders delivered on time versus those delivered late to measure exactly how much delays penalize the brand's reputation.

In [12]:
```
# Ensure is_late exists before using it
if 'is_late' not in orders_df.columns:
        orders_df['is_late'] = (
                orders_df['order_delivered_customer_date'] > orders_df['order_estim

orders_df['delivery_status'] = orders_df['is_late'].apply(lambda x: 'Late' if x els
merged_df = pd.merge(reviews_df, orders_df, on='order_id')

# Visualization
plt.figure(figsize=(12, 5), dpi=300)
```

```
plt.subplot(1, 2, 1)
sns.barplot(x='delivery_status', y='review_score', data=merged_df, palette='viridis
plt.title('Average Review Score: Late vs On Time')
plt.xlabel('Delivery Status')
plt.ylabel('Average Score (1-5)')

plt.subplot(1, 2, 2)
sns.countplot(x='review_score', hue='delivery_status', data=merged_df, palette='Set
plt.title('Review Score Distribution by Delivery Status')
plt.xlabel('Review Score (Stars)')
plt.ylabel('Count')

plt.tight_layout()
plt.show()
```



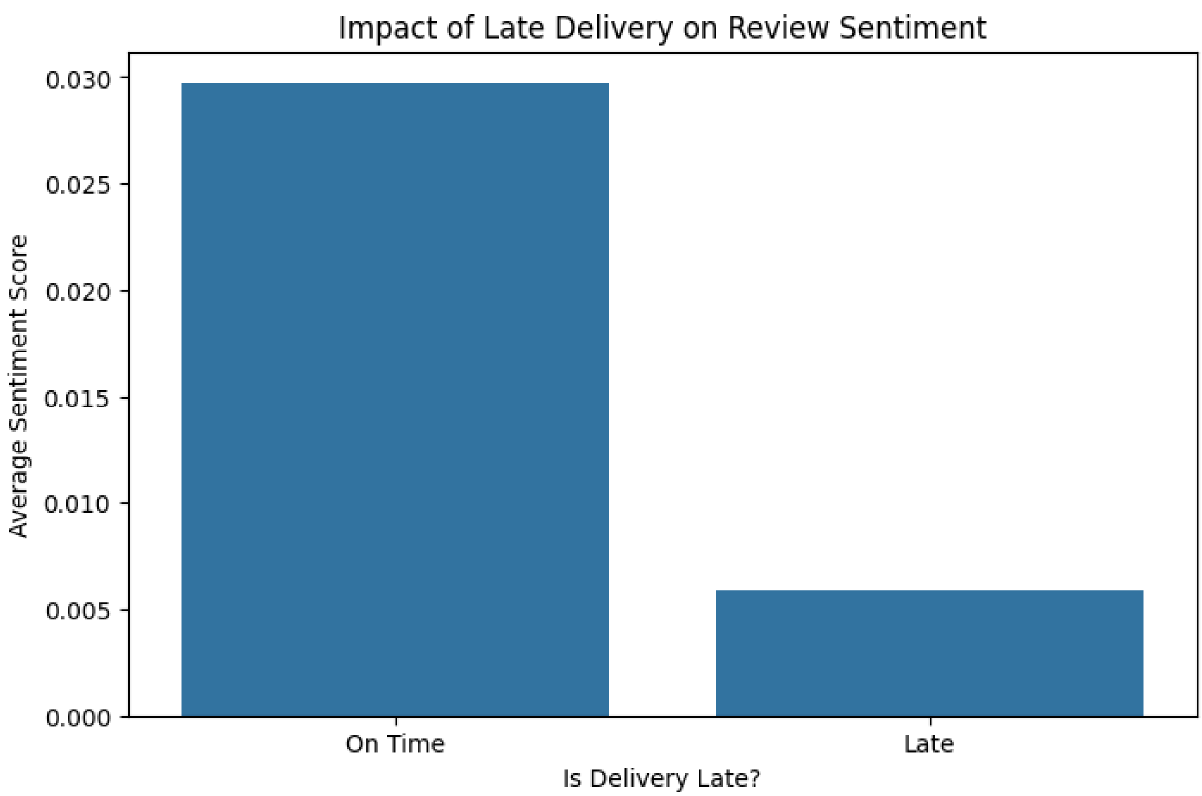
Late Delivery Review Score Validation

Logic: **Average Sentiment Score**

Polarity Scoring: Text data is processed via NLP algorithms to assign a numerical coefficient ranging from -1.0 (Negative) to +1.0 (Positive) based on lexical sentiment patterns.
Aggregation: The mean score is calculated across specific cohorts (e.g., Late vs. On-time) to quantify the net impact of operational performance on customer perception.

In [13]:
```
# Drop missing reviews
df_reviews = reviews_df.dropna(subset=['review_comment_message']).copy()

def get_sentiment(text):
    try:
        # For simplicity/demo (assumes English or simple patterns)
        # Real-world: Translate to English first or use Portuguese model
        return TextBlob(str(text)).sentiment.polarity
    except:
        return 0

df_reviews['sentiment_score'] = df_reviews['review_comment_message'].apply(get_sent
merged_df = pd.merge(df_reviews, orders_df, on='order_id')
```

```
plt.figure(figsize=(8, 5))
sns.barplot(x='is_late', y='sentiment_score', data=merged_df, estimator='mean', err

plt.title('Impact of Late Delivery on Review Sentiment')
plt.xlabel('Is Delivery Late?')
plt.ylabel('Average Sentiment Score')
plt.xticks([0, 1], ['On Time', 'Late'])
plt.show()
```



5. Customer Segmentation (RFM Analysis)

To identify the most valuable customers, we will perform RFM Analysis. This involves grouping customers based on three metrics:

- **Recency (R):** How recently did the customer make a purchase?
- **Frequency (F):** How often do they purchase?
- **Monetary (M):** How much do they spend?

In [14]:
```
# Preparing RFM Data
rfm_data = (
    orders_df
    .merge(items_df, on='order_id')
    .merge(customers_df, on='customer_id')
)
# Selecting only delivered orders
rfm_data = rfm_data[rfm_data['order_status'] == 'delivered']

# Calculating the latest purchase date in the dataset
latest_date = rfm_data['order_purchase_timestamp'].max() + pd.Timedelta(days=1)
```

```
# Aggregating data by Customer Unique ID
rfm_scores = rfm_data.groupby('customer_unique_id').agg({
    'order_purchase_timestamp': lambda x: (latest_date - x.max()).days, # Recency
    'order_id': 'count',                                               # Frequency
    'price': 'sum'                                                     # Monetary
}).reset_index()

# Renaming columns for clarity
rfm_scores.rename(columns={
    'order_purchase_timestamp': 'Recency',
    'order_id': 'Frequency',
    'price': 'Monetary'
}, inplace=True)

# Assigning RFM Scores (1-5)
rfm_scores['R_Score'] = pd.qcut(rfm_scores['Recency'], q=5, labels=[5, 4, 3, 2, 1])

# Logic: Most customers buy only once; Score 1: 1 order, Score 2: 2 orders, ... Sco
def get_f_score(x):
    if x == 1: return 1
    elif x == 2: return 2
    elif x == 3: return 3
    elif x == 4: return 4
    else: return 5

rfm_scores['F_Score'] = rfm_scores['Frequency'].apply(get_f_score)

# Monetary Score (High money = High Score 5)
rfm_scores['M_Score'] = pd.qcut(rfm_scores['Monetary'], q=5, labels=[1, 2, 3, 4, 5]

# Combining scores into a single string (e.g., "555")
rfm_scores['RFM_Segment'] = rfm_scores.R_Score.astype(str) + rfm_scores.F_Score.ast

# Calculating a total numerical score
rfm_scores['RFM_Score_Total'] = rfm_scores[['R_Score', 'F_Score', 'M_Score']].sum(a

rfm_scores.sample(5)
```

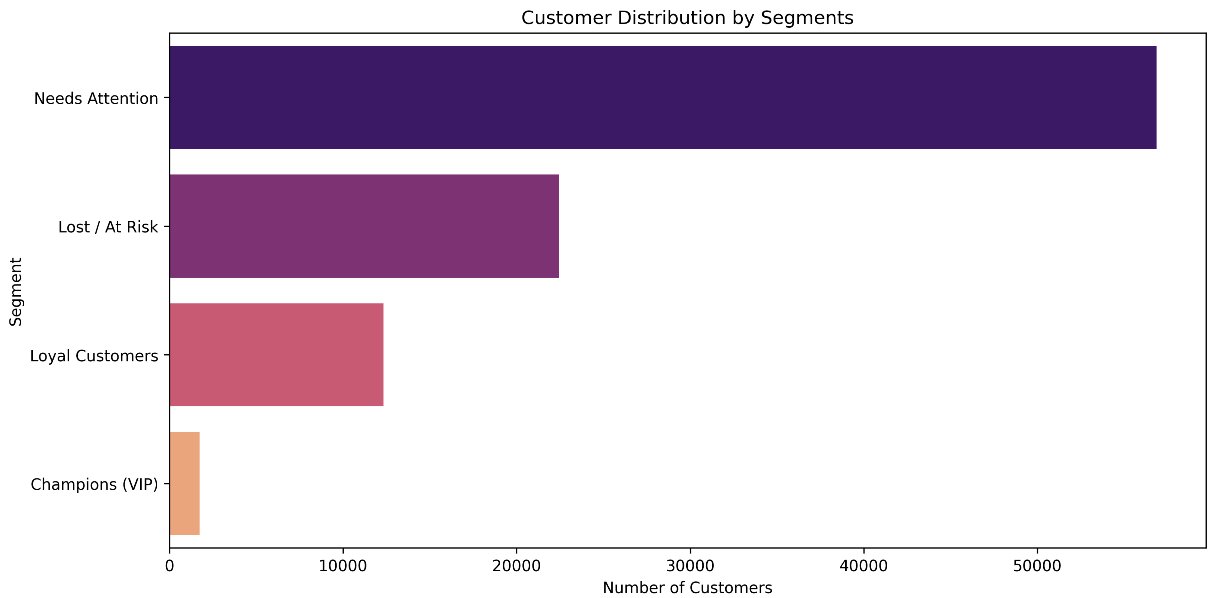
Out[14]:

	customer_unique_id	Recency	Frequency	Monetary	R_Score	F_Sco
21568	3af0b2f7654f613ff1527b997a2ac57e	208	1	19.900	3	
52028	8ef940c8c63e85e9e2fd65f7e8b6581c	90	1	49.900	5	
74245	cb5c545d96f39390b7f372aaa88c4a7e	301	2	78.000	2	
45830	7d6b089029085b9d544174ab78412378	351	1	179.900	2	
33285	5af79d89508d36628b0796f94afa3fa9	21	1	77.980	5	

In [15]:

```
# Segmenting Customers Based on RFM Scores
def segment_customer(df):
    if df['RFM_Score_Total'] >= 12:
        return 'Champions (VIP)'
```

```python
    elif df['RFM_Score_Total'] >= 10:
        return 'Loyal Customers'
    elif df['RFM_Score_Total'] >= 6:
        return 'Needs Attention'
    else:
        return 'Lost / At Risk'

rfm_scores['Customer_Segment'] = rfm_scores.apply(segment_customer, axis=1)

# Visualizing the Segments
plt.figure(figsize=(12, 6), dpi=300)
sns.countplot(y='Customer_Segment', data=rfm_scores, palette='magma', order=rfm_sco
plt.title('Customer Distribution by Segments')
plt.xlabel('Number of Customers')
plt.ylabel('Segment')
plt.show()

# Customer segmentation list
rfm_scores['Customer_Segment'].value_counts().to_frame()
```



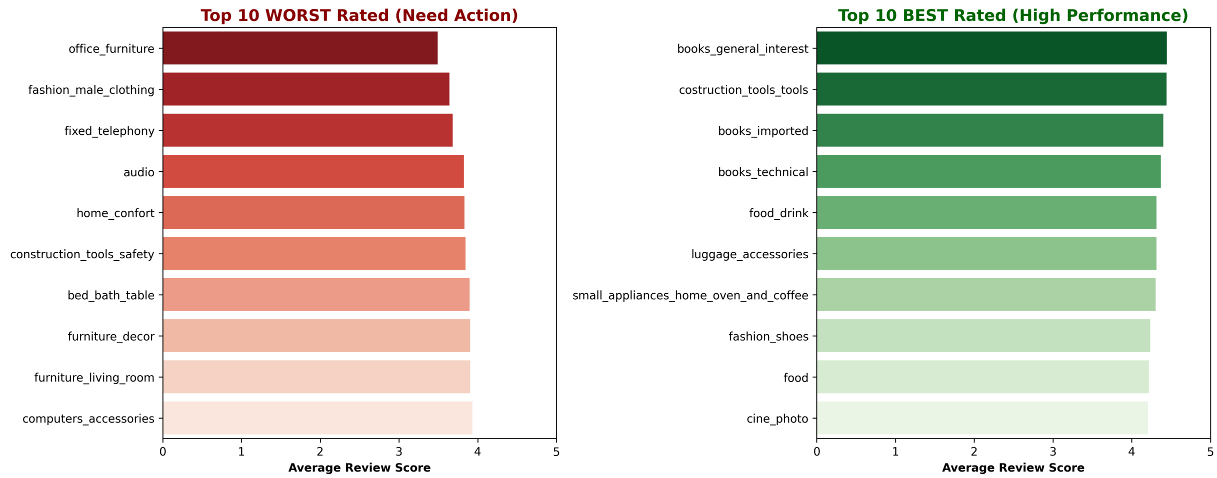
Out[15]:

Customer_Segment	count
Needs Attention	56854
Lost / At Risk	22433
Loyal Customers	12338
Champions (VIP)	1733

6. Product Quality Analysis

Analyzing review scores to identify product categories with the lowest customer satisfaction. This helps the business identify quality control issues.

In [16]:
```
# Data Preparation; Merge all necessary tables to get product category names and re
category_reviews = (
    orders_df.merge(items_df, on='order_id')
    .merge(reviews_df, on='order_id')
    .merge(products_df, on='product_id')
    .merge(category_translation, on='product_category_name', how='left')
    .groupby('product_category_name_english')
    .agg(avg_review_score=('review_score', 'mean'), order_count=('order_id', 'count
    .query('order_count > 50')
    .reset_index()
)
worst_categories = category_reviews.nsmallest(10, 'avg_review_score')
best_categories = category_reviews.nlargest(10, 'avg_review_score')

# Visualization
fig, axes = plt.subplots(1, 2, figsize=(15, 6), dpi=300)

def plot_category(data, ax, palette, title, color):
    sns.barplot(x='avg_review_score', y='product_category_name_english', data=data,
    ax.set_title(title, fontsize=14, fontweight='bold', color=color)
    ax.set_xlabel('Average Review Score', fontweight='bold')
    ax.set_ylabel('')
    ax.set_xlim(0, 5)

plot_category(worst_categories, axes[0], 'Reds_r', 'Top 10 WORST Rated (Need Action
plot_category(best_categories, axes[1], 'Greens_r', 'Top 10 BEST Rated (High Perfor
plt.tight_layout()
plt.show()

# Show in Dataframe
df1_style = worst_categories.style.format({'avg_review_score': '{:.2f}'}) \
    .set_table_attributes("style='display:inline; margin-right:50px'") \
    .set_caption("<b>Top 10 WORST Rated 🔴</b>")

df2_style = best_categories.style.format({'avg_review_score': '{:.2f}'}) \
    .set_table_attributes("style='display:inline'") \
    .set_caption("<b>Top 10 BEST Rated 🟢</b>")

display_html(df1_style._repr_html_() + df2_style._repr_html_(), raw=True)
```



Top 10 WORST Rated 🔴

	product_category_name_english	avg_review_score	order_count
46	office_furniture	3.49	1687
25	fashion_male_clothing	3.64	131
28	fixed_telephony	3.68	262
3	audio	3.83	361
38	home_confort	3.83	435
17	construction_tools_safety	3.84	193
6	bed_bath_table	3.90	11137
32	furniture_decor	3.90	8331
33	furniture_living_room	3.90	502
13	computers_accessories	3.93	7849

Top 10 BEST Rated 🟢

	product_category_name_english	avg_review_score	order_count
7	books_general_interest	4.45	549
20	costruction_tools_tools	4.44	99
8	books_imported	4.40	60
9	books_technical	4.37	266
30	food_drink	4.32	279
43	luggage_accessories	4.32	1088
51	small_appliances_home_oven_and_coffee	4.30	76
26	fashion_shoes	4.23	261
29	food	4.22	495
11	cine_photo	4.21	73

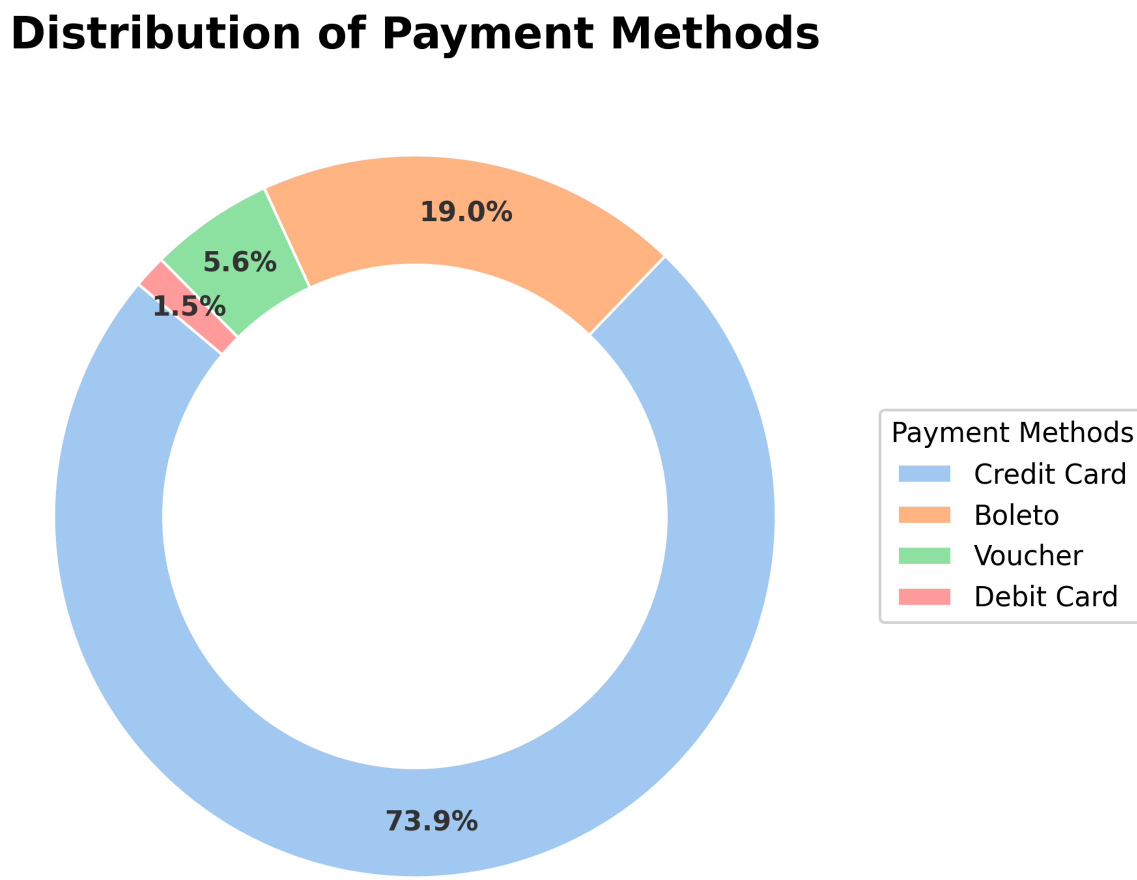
7. Payment Behaviour Analysis

Understanding how customers pay is crucial for financial planning and partnership deals with banks. We will analyze: **Payment Methods** & **Installment Behavior**.

Preferred Payment Methods

What customers prefer most? Credit Cards, Boleto, or Vouchers?

In [17]:
```
# Prepare Data
payment_counts = payments_df['payment_type'].value_counts()
payment_counts_clean = payment_counts.drop('not_defined', errors='ignore')

# Create a DataFrame for the table
df_payment = pd.DataFrame({
    'Payment Method': payment_counts_clean.index.str.replace('_', ' ').str.title(),
    'Transactions': payment_counts_clean.values,
    'Percentage': (payment_counts_clean.values / payment_counts_clean.values.sum()
})
df_payment['Percentage'] = df_payment['Percentage'].astype(str) + '%'

# Visualization
fig, ax = plt.subplots(figsize=(10, 6), dpi=300)
wedges, texts, autotexts = ax.pie(
    payment_counts_clean.values,
    autopct='%1.1f%%',
    startangle=140,
    colors=sns.color_palette('pastel'),
    pctdistance=0.85,  # Push % towards the edge
    wedgeprops=dict(width=0.4, edgecolor='white'), # Width makes it a Donut
    textprops={'fontsize': 10, 'fontweight': 'bold', 'color': '#333333'}
)
centre_circle = plt.Circle((0,0),0.70,fc='white')
fig.gca().add_artist(centre_circle)

# Legend
ax.legend(wedges, df_payment['Payment Method'],
          title="Payment Methods",
          loc="center left",
          bbox_to_anchor=(1, 0, 0.5, 1))

plt.title('Distribution of Payment Methods', fontsize=16, fontweight='bold')
plt.show()

# Table Display
display(
    df_payment.style.background_gradient(cmap='Blues', subset=['Transactions'])
    .format({'Transactions': '{:,}'})
    .set_caption("Detailed Breakdown of Payment Methods")
    .set_properties(**{'text-align': 'center'})
    .hide(axis="index")
)
```



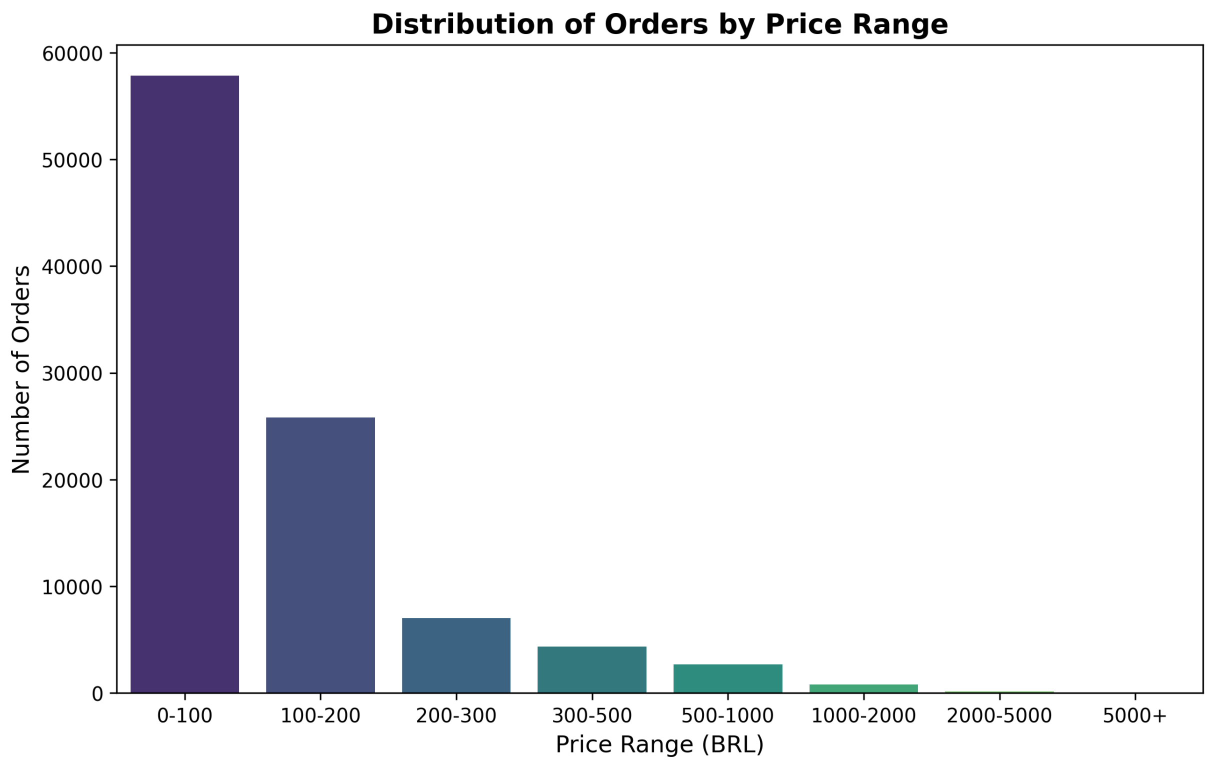
Detailed Breakdown of Payment Methods

Payment Method	Transactions	Percentage
Credit Card	76,795	73.9%
Boleto	19,784	19.0%
Voucher	5,775	5.6%
Debit Card	1,529	1.5%

> **Observation:**
>
> - **Credit Card:** An overwhelming **74%** of customers prefer using Credit Cards, indicating a high trust in digital payments.
> - **Boleto:** The second most popular method is **Boleto (19%)**, which is unique to Brazil. This suggests a significant portion of customers might be unbanked or prefer cash-based digital transactions.
> - **Strategy:** Ensure the credit card gateway is always up, but strictly maintain Boleto support to not lose ~20% of the market.

In [18]:
```
# Calculating Average Order Value (AOV)
price_per_order = items_df.groupby('order_id')['price'].sum()
```

```
bins = [0, 100, 200, 300, 500, 1000, 2000, 5000, price_per_order.max()]
labels = ['0-100', '100-200', '200-300', '300-500', '500-1000', '1000-2000', '2000-
order_ranges = pd.cut(price_per_order, bins=bins, labels=labels).value_counts().rei
order_ranges.columns = ['Price_Range_BRL', 'Order_Count']
aov = price_per_order.mean()

# Visualization
plt.figure(figsize=(10, 6), dpi=300)
sns.barplot(x='Price_Range_BRL', y='Order_Count', data=order_ranges, palette='virid

plt.title('Distribution of Orders by Price Range', fontsize=14, fontweight='bold')
plt.xlabel('Price Range (BRL)', fontsize=12)
plt.ylabel('Number of Orders', fontsize=12)

# for i, val in enumerate(order_ranges['Order_Count']):
#     plt.text(i, val + 500, f'{val}', ha='center', fontsize=10)

# plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()

print(f"Average Order Value: {aov:.2f} BRL")
display((order_ranges.T).style.background_gradient(cmap='Blues', axis=1))
```

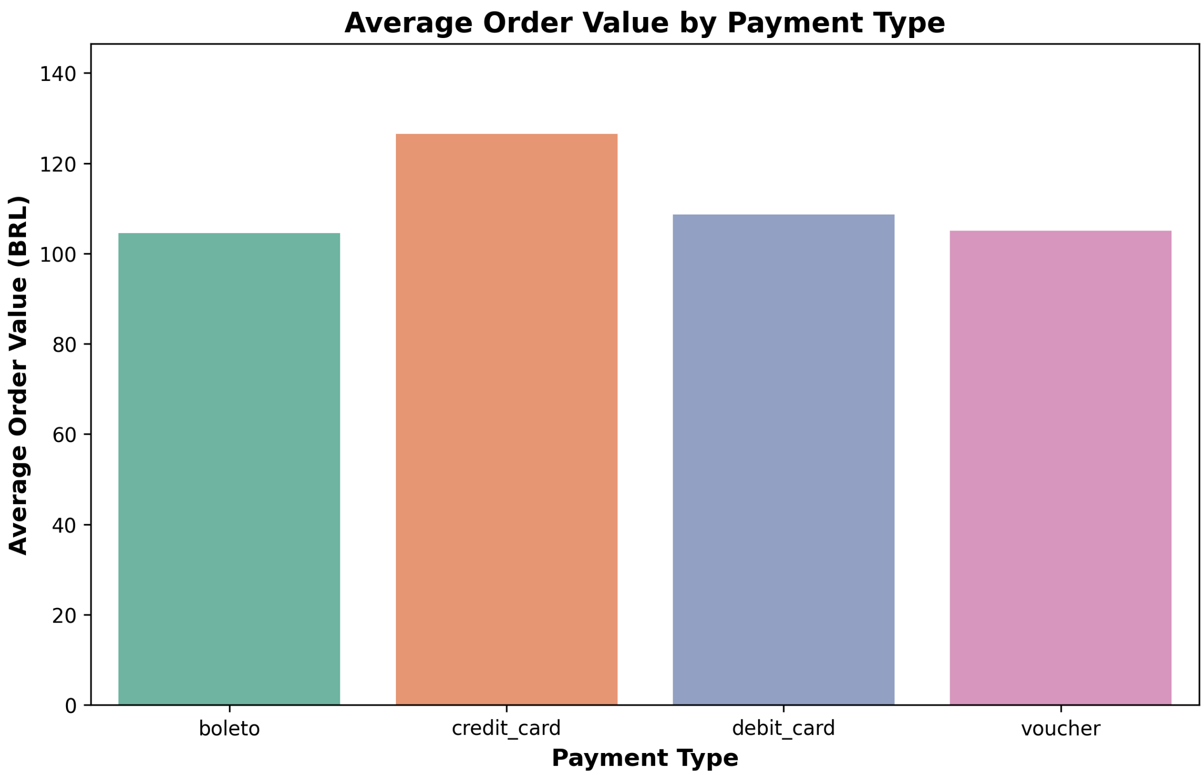



```
Average Order Value: 137.75 BRL
```

	0	1	2	3	4	5	6	7
Price_Range_BRL	0-100	100-200	200-300	300-500	500-1000	1000-2000	2000-5000	5000+
Order_Count	57843	25831	7039	4336	2674	799	138	6

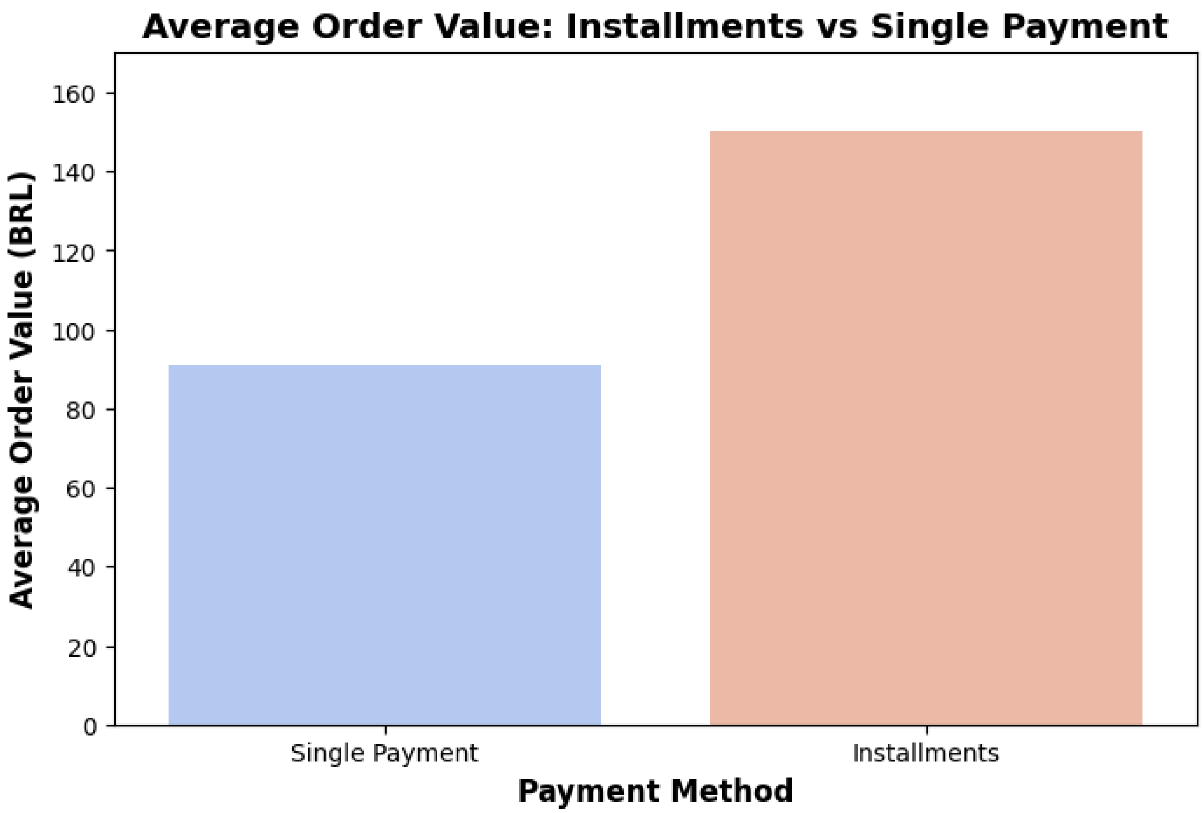
In [19]:
```
# Averege Order Value by payment type
payment_aov = (
```

```
    payments_df.merge(items_df, on='order_id')
    .groupby('payment_type')['price']
    .mean()
    .reset_index()
)
# Visualization
plt.figure(figsize=(10, 6), dpi=300)
sns.barplot(x='payment_type', y='price', data=payment_aov, palette='Set2')
plt.title('Average Order Value by Payment Type', fontsize=14, fontweight='bold')
plt.xlabel('Payment Type', fontsize=12, fontweight='bold')
plt.ylabel('Average Order Value (BRL)', fontsize=12, fontweight='bold')
plt.ylim(0, payment_aov['price'].max() + 20)
plt.show()
```



In [20]:
```
# Calculating AOV for Installments vs Single Payment
merged_df = payments_df.merge(items_df, on='order_id')
merged_df['is_installment'] = merged_df['payment_installments'] > 1
installment_aov = merged_df.groupby('is_installment')['price'].mean().reset_index()

# Visualization
plt.figure(figsize=(8, 5))
sns.barplot(
    x='is_installment',
    y='price',
    data=installment_aov,
    palette='coolwarm'
)
plt.xticks([0, 1], ['Single Payment', 'Installments'])
plt.title('Average Order Value: Installments vs Single Payment', fontsize=14, fontw
plt.xlabel('Payment Method', fontsize=12, fontweight='bold')
plt.ylabel('Average Order Value (BRL)', fontsize=12, fontweight='bold')
```

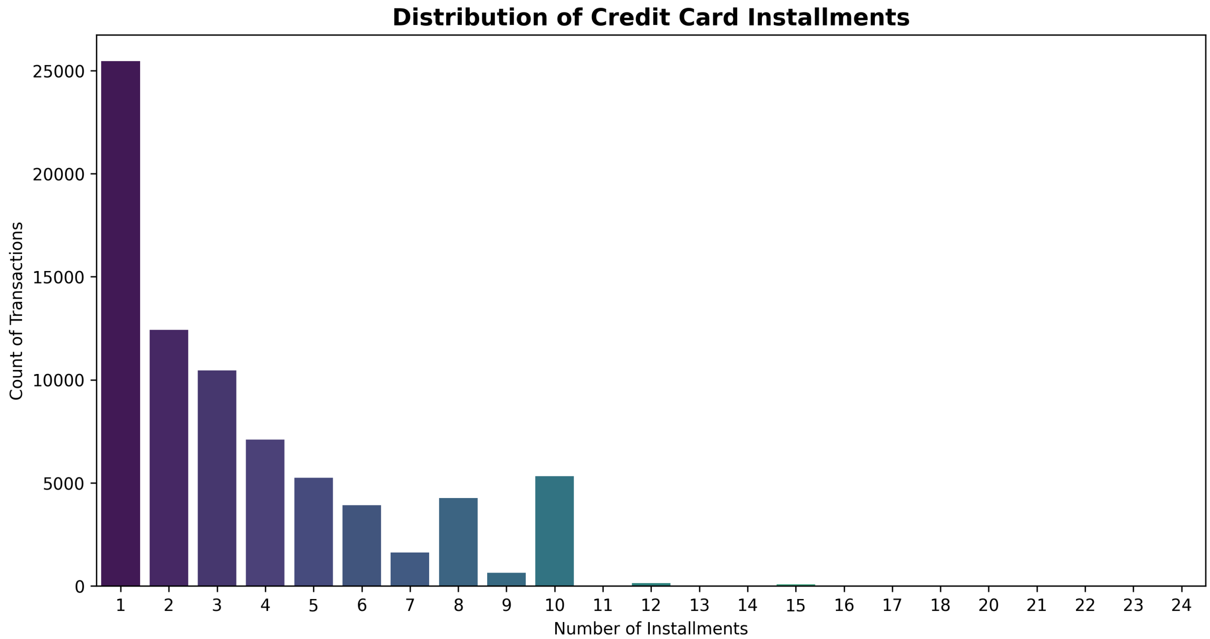
```
plt.ylim(0, installment_aov['price'].max() + 20)
plt.show()
```



Analysis of Installment Distribution

Since installments are strictly associated with **Credit Card** payments, we will filter the dataset to focus solely on credit card transactions. This allows us to understand the preferred installment plans of customers.

In [21]:
```
credit_card_data = payments_df[payments_df['payment_type'] == 'credit_card']
credit_card_data=credit_card_data[credit_card_data['payment_installments']>0]
plt.figure(figsize=(12, 6), dpi=300)
sns.countplot(x='payment_installments', data=credit_card_data, palette='viridis')

plt.title('Distribution of Credit Card Installments', fontweight='bold', fontsize=1
plt.xlabel('Number of Installments')
plt.ylabel('Count of Transactions')
plt.show()

display((credit_card_data['payment_installments'].value_counts().sort_index().to_fr
        .style.background_gradient(cmap='Blues', axis=1).format("{:,}"))
```



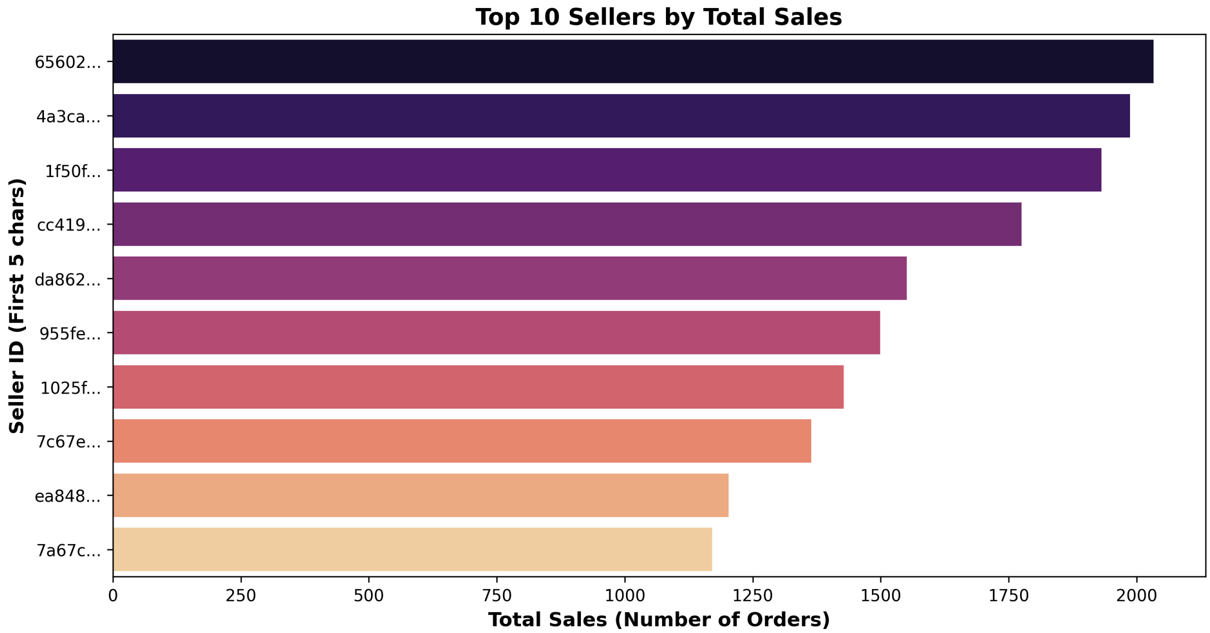
payment_installments	1	2	3	4	5	6	7	8	9	10	1
Transaction Count	25,455	12,413	10,461	7,098	5,239	3,920	1,626	4,268	644	5,328	2

8. Seller Analysis

Identifying key sellers who drive the most revenue. This helps in managing supplier relationships and identifying potential partnerships.

Top Seller Analysis

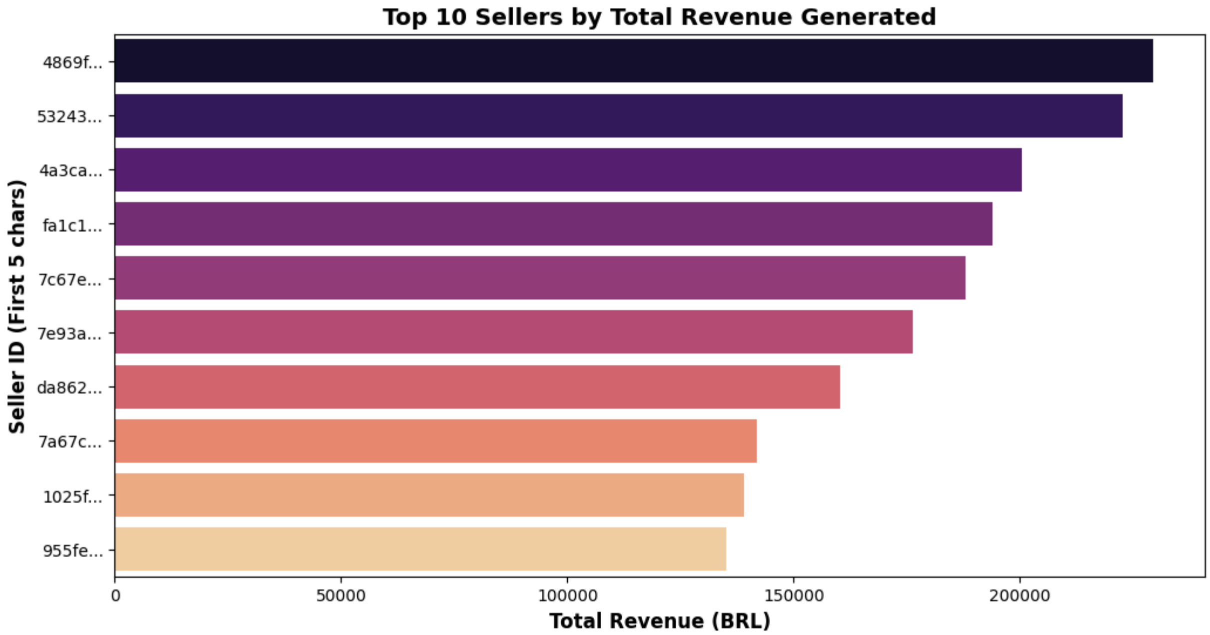
In [22]:
```
# Total Sales per seller
sell_count = items_df.groupby('seller_id')['order_id'].count().reset_index()
top_sellers = sell_count.sort_values('order_id', ascending=False).head(10)
top_sellers['short_id'] = top_sellers['seller_id'].str[:5] + '...'

# Visualizing ---
plt.figure(figsize=(12, 6), dpi=300)
sns.barplot(x='order_id', y='short_id', data=top_sellers, palette='magma')

plt.title('Top 10 Sellers by Total Sales', fontsize=14, fontweight='bold')
plt.xlabel('Total Sales (Number of Orders)', fontsize=12, fontweight='bold')
plt.ylabel('Seller ID (First 5 chars)', fontsize=12, fontweight='bold')
plt.show()

# Checking the exact revenue numbers
print("Top 5 Sellers Sales:")
display(top_sellers[['seller_id', 'order_id']].head(5))
```



Top 5 Sellers Sales:

	seller_id	order_id
1235	6560211a19b47992c3666cc44a7e94c0	2033
881	4a3ca9315b744ce9f8e9374361493884	1987
368	1f50f920176fa81dab994f9023523100	1931
2481	cc419e0650a3c5ba77189a1882b7556a	1775
2643	da8622b14eb17ae2831f4ac5b9dab84a	1551

In [23]:
```
# Calculating Revenue per Seller
seller_performance = items_df.groupby('seller_id')['price'].sum().reset_index()
top_sellers = seller_performance.sort_values('price', ascending=False).head(10)
top_sellers['short_id'] = top_sellers['seller_id'].str[:5] + '...'

# Visualizing ---
plt.figure(figsize=(12, 6))
sns.barplot(x='price', y='short_id', data=top_sellers, palette='magma')

plt.title('Top 10 Sellers by Total Revenue Generated', fontsize=14, fontweight='bol
plt.xlabel('Total Revenue (BRL)', fontsize=12, fontweight='bold')
plt.ylabel('Seller ID (First 5 chars)', fontsize=12, fontweight='bold')
plt.show()

# Checking the exact revenue numbers
print("Top 5 Sellers Revenue:")
display(top_sellers[['seller_id', 'price']].head())
```




```
Top 5 Sellers Revenue:
```

	seller_id	price
857	4869f7a5dfa277a7dca6462dcf3b52b2	229472.630
1013	53243585a1d6dc2643021fd1853d8905	222776.050
881	4a3ca9315b744ce9f8e9374361493884	200472.920
3024	fa1c13f2614d7b5c4749cbc52fecda94	194042.030
1535	7c67e1448b00f6e969d365cea6b010ab	187923.890

Seller Concentration Analysis

In [24]:

```python
# Calculte 80% of total revenue come from how many sellers
total_revenue = items_df['price'].sum()
seller_revenue = items_df.groupby('seller_id')['price'].sum().reset_index()
seller_revenue = seller_revenue.sort_values('price', ascending=False).reset_index(d
seller_revenue['cumulative_revenue'] = seller_revenue['price'].cumsum()
seller_revenue['cumulative_percentage'] = (seller_revenue['cumulative_revenue'] / t
sellers_80_percent = seller_revenue[seller_revenue['cumulative_percentage'] <= 80]
print(f"Total Revenue: {total_revenue:.2f} BRL")
print(f"Number of Sellers contributing to 80% of Revenue: {len(sellers_80_percent)}
```

```
Total Revenue: 13591643.70 BRL
Number of Sellers contributing to 80% of Revenue: 543 out of 3095 total sellers (17.
54%)
```

> **Alarming!** 80% of total revenue comes from a small group of sellers (~20%), indicating high dependence on a few top performers. This level of concentration is alarming and creates significant business risk if these sellers churn.

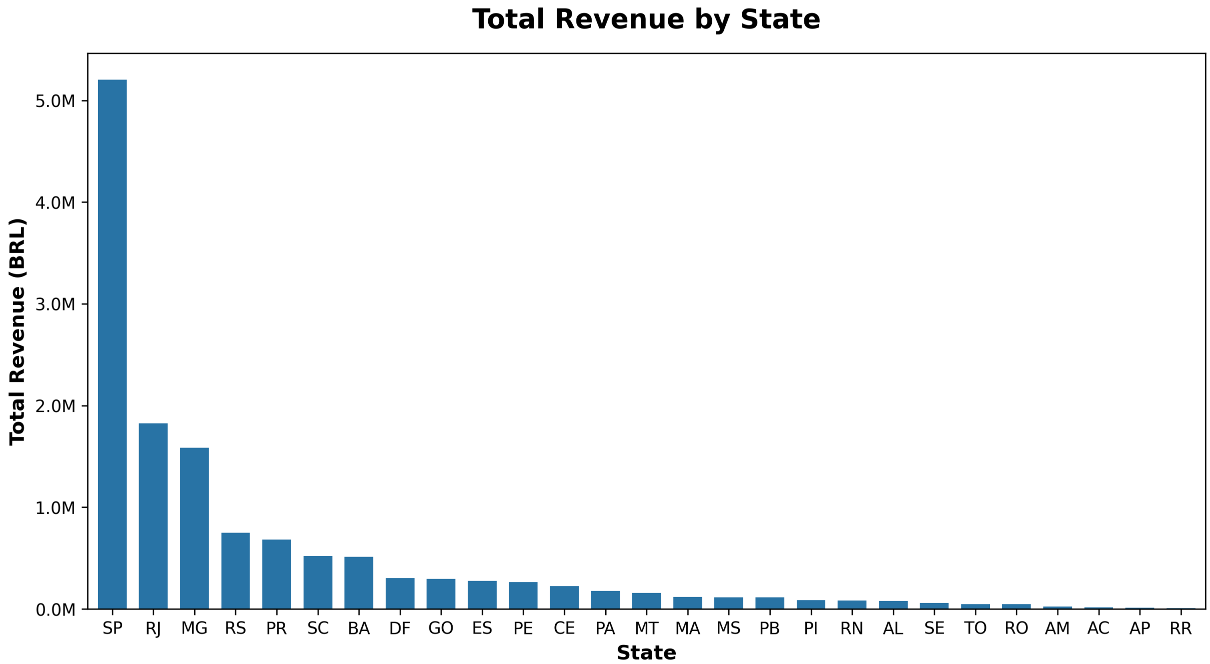
9. Regional Analysis: Revenue, Volume & Freight Costs

In this section, we analyze Olist's market performance across different Brazilian states. Instead of looking at a single metric, we break down the regional data into three key dimensions:

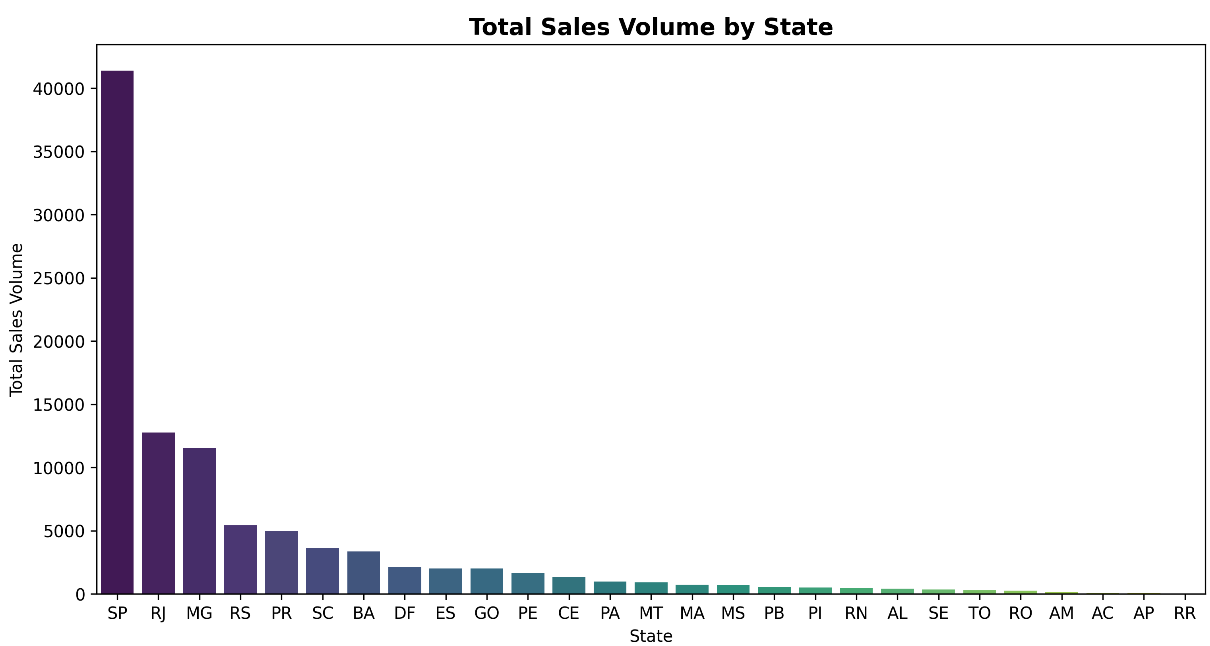
1. **Total Revenue by State:** To identify the most profitable regions and financial strongholds.
2. **Sales Volume by State:** To understand customer demand density and market penetration.
3. **Average Freight Cost:** To evaluate logistical efficiency and shipping affordability across states.
4. **Geographical Analysis** We visualize the geographical footprint of Olist's market. We use a **scatterplot** to map the density of customer locations across Brazil.
5. **Customer per Seller by State** To identify supply gaps across different states. This comparative analysis allows us to correlate financial success with physical demand and identify logistical challenges in specific regions.

In [25]:

```
# Prepare Data
revenue_data = orders_df.merge(items_df, on='order_id').merge(customers_df, on='cus
state_revenue = revenue_data.groupby('customer_state')['price'].sum().sort_values(a
state_sales = revenue_data.groupby('customer_state')['order_id'].nunique().sort_val

# Freight Cost by State
freight_data = orders_df.merge(items_df, on='order_id').merge(customers_df, on='cus
state_freight = freight_data.groupby('customer_state')['freight_value'].mean().sort
avg_freight = freight_data['freight_value'].mean()

# Visualization
fig, ax = plt.subplots(figsize=(12, 6), dpi=300)
state_revenue.plot(kind='bar', color='#2874A6', ax=ax, width=0.7)

ax.set_title("Total Revenue by State", fontsize=16, fontweight='bold', pad=15)
ax.set_ylabel("Total Revenue (BRL)", fontsize=12, fontweight='bold')
ax.set_xlabel("State", fontsize=12, fontweight='bold')
# ax.grid(axis='y', linestyle='--', alpha=0.5)
ax.tick_params(axis='x', rotation=0)
ax.yaxis.set_major_formatter(plt.FuncFormatter(lambda x, loc: "{:.1f}M".format(x/1e
# sns.despine(top=True, right=True)
plt.show()
```

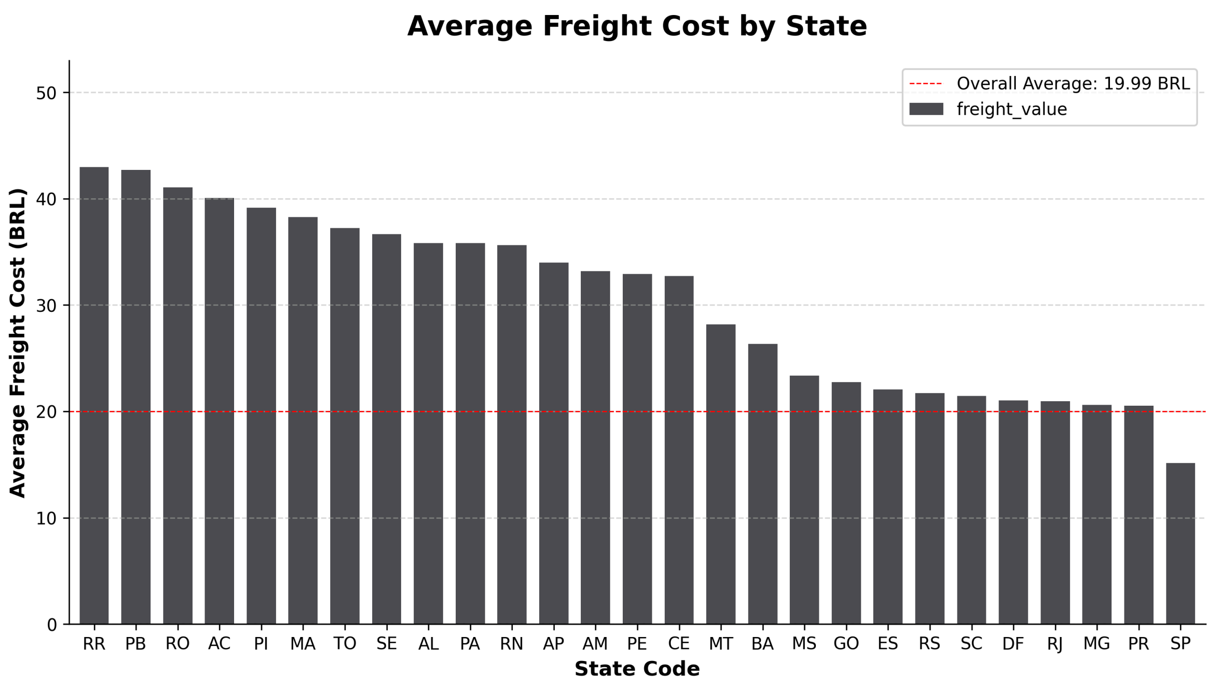


In [26]:
```
# Total Sales Volume by State
state_sales = revenue_data.groupby('customer_state')['order_id'].nunique().sort_val
# Visualization
plt.figure(figsize=(12, 6), dpi=300)
sns.barplot(x=state_sales.index, y=state_sales.values, palette='viridis')
plt.title('Total Sales Volume by State', fontsize=14, fontweight='bold')
plt.xlabel('State')
plt.ylabel('Total Sales Volume')
plt.show()
```



In [27]:
```
# Visualization for Average Freight Cost by State
fig, ax = plt.subplots(figsize=(12, 6), dpi=300)
state_freight.plot(kind='bar', color="#4C4E50", ax=ax, width=0.7)
ax.set_title("Average Freight Cost by State", fontsize=16, fontweight='bold', pad=1
ax.set_ylabel("Average Freight Cost (BRL)", fontsize=12, fontweight='bold')
```

```
ax.set_xlabel("State Code", fontsize=12, fontweight='bold')
ax.axhline(avg_freight, color='red', linestyle='--', linewidth=0.75, label=f'Overal
ax.set_ylim(0, state_freight.max() + 10)
ax.tick_params(axis='x', rotation=0)
ax.grid(axis='y', linestyle='--', alpha=0.5)
ax.legend()
sns.despine(top=True, right=True)
plt.show()
```



In [28]:

```
# Summary Table
summary_df = pd.concat([state_revenue, state_sales, state_freight], axis=1, keys=['

idx = pd.IndexSlice
summary_df.style.background_gradient(cmap='Blues', axis=1, subset=idx[['Total Reven
                .background_gradient(cmap='Blues', axis=1, subset=idx[['Total Sales
                .background_gradient(cmap='Reds', axis=1, subset=idx[['Average Frei
                .format("{:,.0f}")
```

Out[28]:

customer_state	SP	RJ	MG	RS	PR	SC	BA	DF
Total Revenue (BRL)	5,202,955	1,824,093	1,585,308	750,304	683,084	520,553	511,350	302,604
Total Sales Volume	41,375	12,762	11,544	5,432	4,998	3,612	3,358	2,125
Average Freight Cost (BRL)	15	21	21	22	21	21	26	21

Geospatial Analysis: Customer Density Map

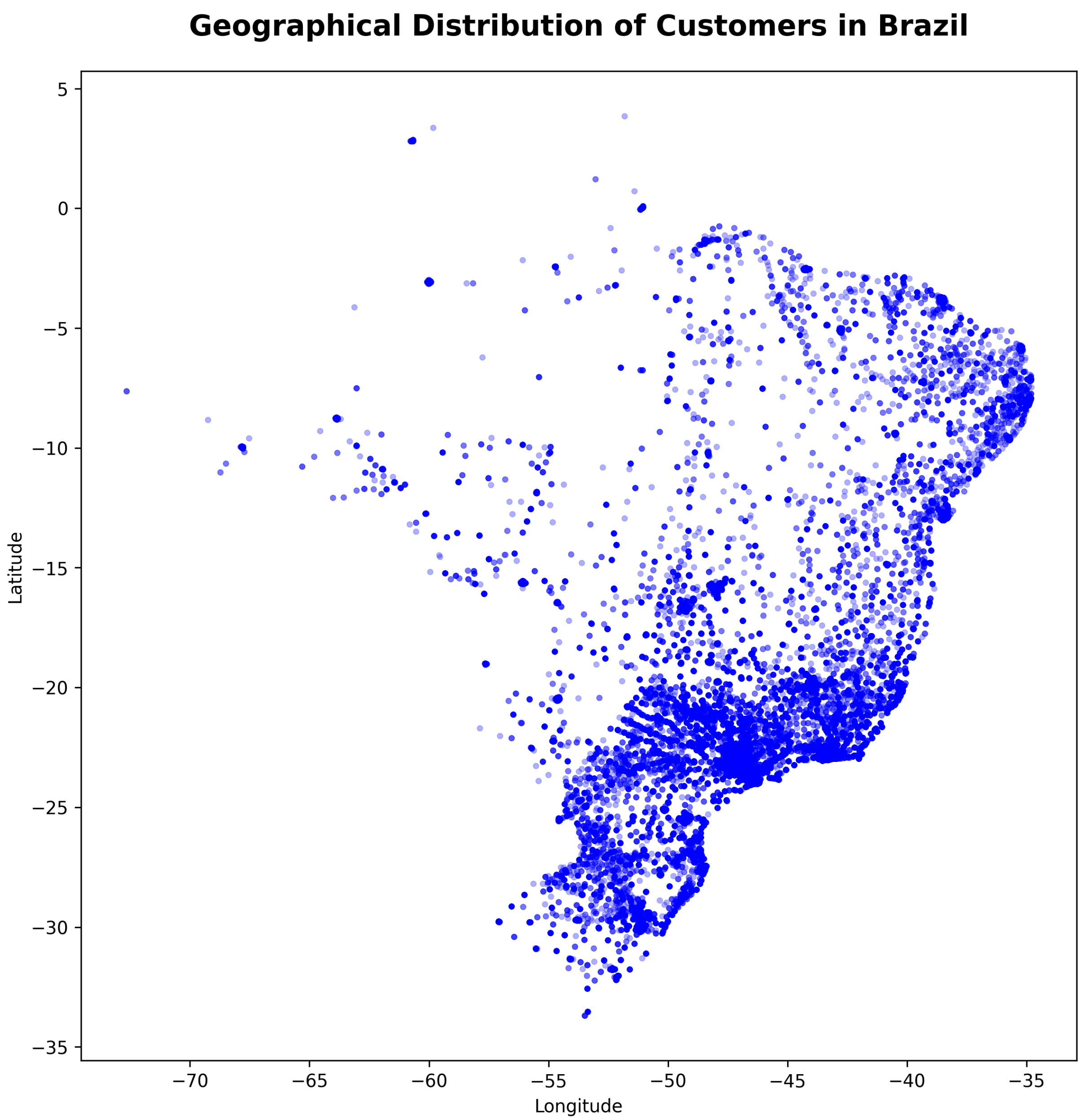
To understand the geographical reach of Olist, we visualize the distribution of customers across Brazil.

Key Steps:

1. **Coordinate Cleaning:** We applied a strict **Bounding Box** (Lat/Long limits) to filter out GPS errors that pointed to locations outside Brazil.
2. **Data Integration:** Merged customer records with unique geolocation data based on Zip Codes.
3. **Visualization:** The scatterplot below represents customer density, highlighting key market hubs.

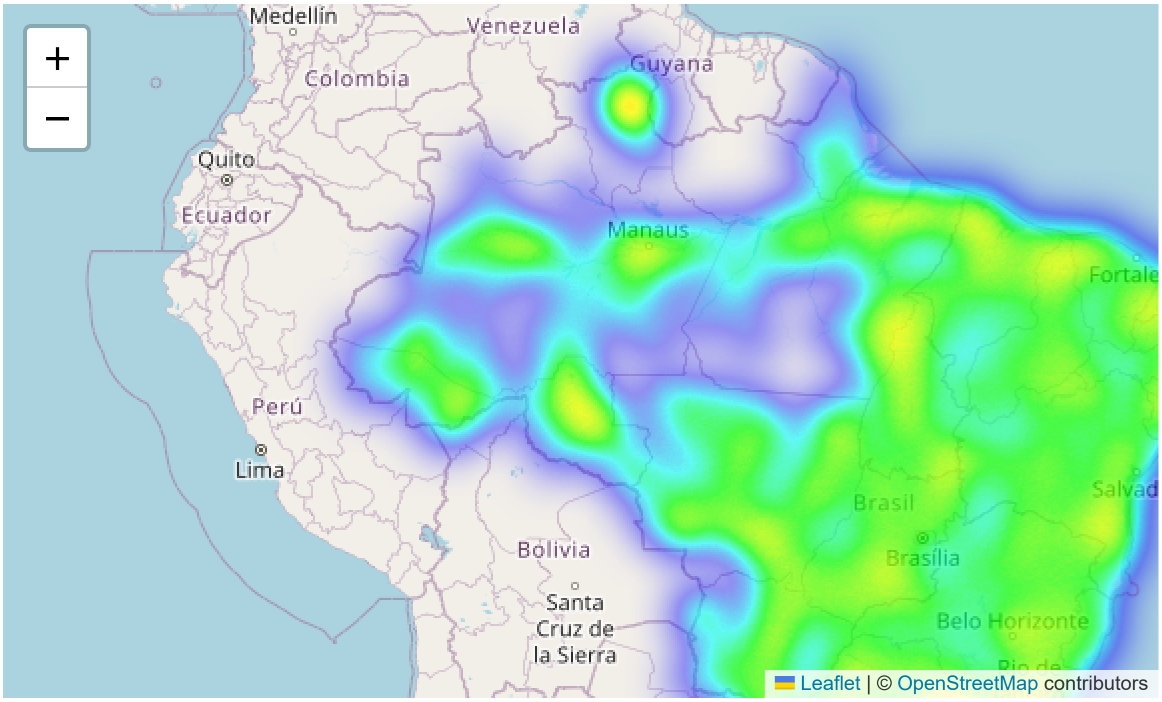
In [29]:
```
# --- Preparing Data ---
geo_data = geo_data[
    (geo_data.geolocation_lat <= 5.27438888) &
    (geo_data.geolocation_lat >= -33.75116944) &
    (geo_data.geolocation_lng >= -73.98283055) &
    (geo_data.geolocation_lng <= -34.79314722)
]
# Keeping only unique zip code prefixes
geo_unique = geo_data.drop_duplicates(subset=['geolocation_zip_code_prefix'])

# Merging & Linking customers to their location
customer_loc_df = customers_df.merge(geo_unique, left_on='customer_zip_code_prefix'
# Checking the number of mapped customers
print(f"Mapped Customers: {customer_loc_df.shape[0]}")
# --- Visualizing the Map ---
plt.figure(figsize=(10, 10), dpi=300)
sns.scatterplot(
    x='geolocation_lng',
    y='geolocation_lat',
    data=customer_loc_df,
    alpha=0.3,
    s=10,
    color='blue',
    edgecolor=None
)
plt.title('Geographical Distribution of Customers in Brazil', fontsize=16, fontweig
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.axis('equal')
plt.show()
```

```
Mapped Customers: 99162
```



In [30]:
```
# ---  Interactive Heatmap ---
# Keeping only unique zip code prefixes
heat_data = geo_data.drop_duplicates(subset=['geolocation_zip_code_prefix'])[['geol

# Create Map centered on Brazil
map_brazil = folium.Map(location=[-14.2350, -51.9253], zoom_start=4)

# Add Heatmap Layer
HeatMap(heat_data, radius=15, blur=20).add_to(map_brazil)

#Show
map_brazil
```

Out[30]:



Market Opportunity: Supply vs. Demand

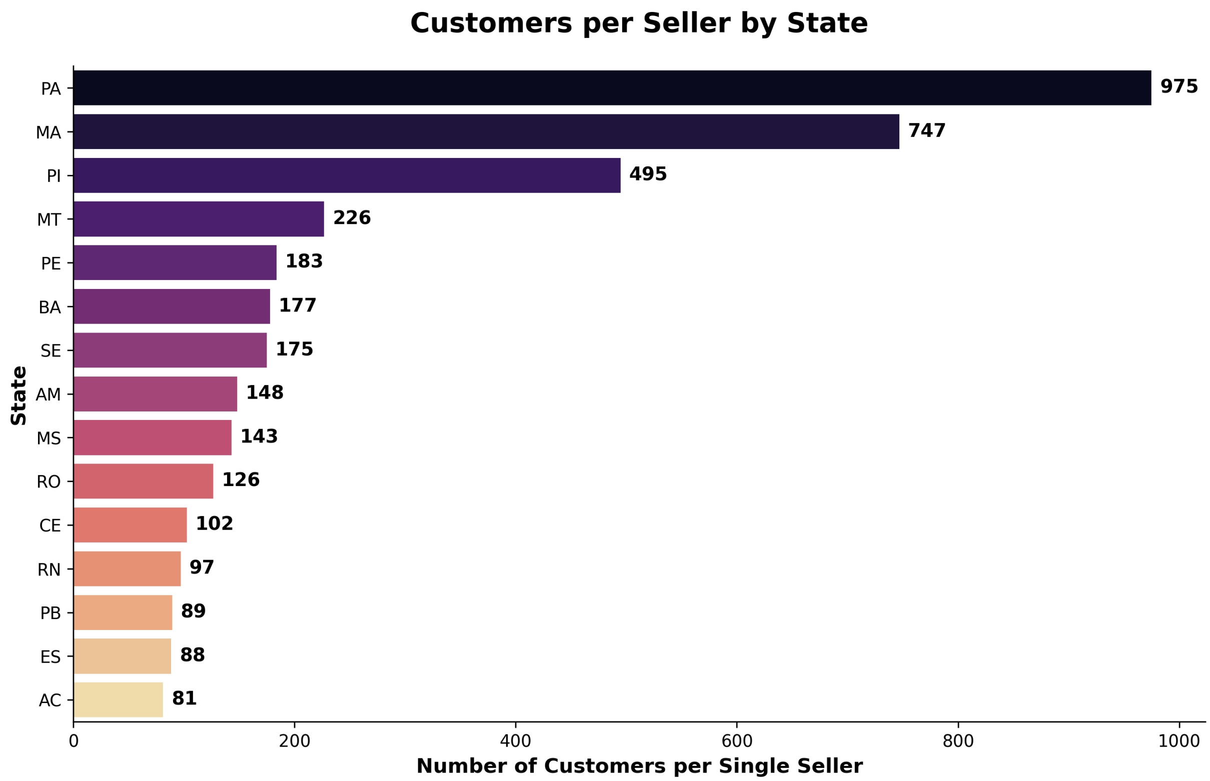
We calculate the **Customers-per-Seller ratio** to identify supply gaps across different states.

> **Insight:** States with a **high ratio** indicate high demand but low seller saturation, signaling a strategic opportunity for **new seller recruitment**.

In [31]:

```
# Prepare Data
cust_counts = customers_df['customer_state'].value_counts()
seller_counts = sellers_df['seller_state'].value_counts()

# Merge into one DataFrame & clean
market = pd.DataFrame({'Customers': cust_counts, 'Sellers': seller_counts})
market = market.dropna()

# Calculate Ratio
market['Customers_per_Seller'] = market['Customers'] / market['Sellers']
market = market.sort_values(by='Customers_per_Seller', ascending=False).head(15)

# Visualization
plt.figure(figsize=(12, 7), dpi=300)

ax = sns.barplot(
    x=market['Customers_per_Seller'],
    y=market.index,
    palette='magma'
)
plt.title('Customers per Seller by State', fontsize=16, fontweight='bold', pad=20)
plt.xlabel('Number of Customers per Single Seller', fontsize=12, fontweight='bold')
plt.ylabel('State', fontsize=12, fontweight='bold')

# Add Data Labels
```

```python
for p in ax.patches:
    width = p.get_width()
    ax.annotate(f'{int(width)}',
                (width, p.get_y() + p.get_height() / 2.),
                ha='left', va='center',
                fontsize=11, color='black', fontweight='bold',
                xytext=(5, 0), textcoords='offset points')
sns.despine()
plt.show()

# Insight Print
print(market[['Customers', 'Sellers', 'Customers_per_Seller']].head(5))
```




```
    Customers  Sellers  Customers_per_Seller
PA        975    1.000               975.000
MA        747    1.000               747.000
PI        495    1.000               495.000
MT        907    4.000               226.750
PE       1652    9.000               183.556
```

Final Executive Verdict

Elevator Pitch

Olist demonstrates strong market demand but is constrained by operational inefficiencies. Sustainable profitability will not come from further user acquisition alone, but from resolving logistics failures in remote regions and improving retention of high-value customers.

Strategic Action Plan: Three Pillars

1. Optimize Operational Resilience (Logistics & Quality)

Problem Data reveals that **regional logistic bottlenecks** and **quality failures in specific categories** are the primary drivers of customer attrition, actively eroding brand equity.

Action

- **Supplier Rationalization:** Enforce a strict **"Three-Strike Policy"** to immediately de-list sellers with high return rates or shipping delays.
- **Logistics Calibration:** Renegotiate SLAs in high-latency zones and restrict sales in regions where on-time delivery cannot be guaranteed.

---

2. Focus on High-Value Customers (RFM and Demand Trends)

Problem
Approximately 96% of customers make only a single purchase, indicating weak retention.

Action
Reallocate marketing spend from mass acquisition to retention, prioritizing high-RFM segments (Champions). Execute campaigns during [Peak Day/Hour identified from demand analysis] to maximize ROI.

---

3. Expand Selectively Based on Supply–Demand Gaps

Problem
Several regions show high customer demand but insufficient local seller supply, leading to higher delivery times and costs.

Action
Recruit local sellers in states with elevated Customers-per-Seller ratios to reduce logistics cost and improve delivery performance.

Conclusion

Long-term profitability depends on operational discipline rather than top-line growth alone. Address logistics failures, retain high-value customers, and expand only where supply and demand are structurally aligned.