Brazilian E-Commerce Analysis Project

In this project, I explore the Brazilian e-commerce (Olist) dataset and conduct an in-depth Exploratory Data Analysis (EDA). The analysis focuses on customer behavior, delivery performance, and spending patterns across different cities and states. The insights gained aim to provide a better understanding of the Brazilian e-commerce market, highlight promising areas for investment, and identify regions where operational improvements could enhance customer satisfaction and business performance.

EDA Questions

I load the different tables provided in the Olist dataset, including customer information, order details, payment information, product metadata, and seller information.

In [47]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


orders = pd.read_csv("C:/Users/liadz/Downloads/Brazil_project/data/olist_orders_
customers = pd.read_csv('C:/Users/liadz/Downloads/Brazil_project/data/olist_cust
payments = pd.read_csv('C:/Users/liadz/Downloads/Brazil_project/data/olist_order
order_items = pd.read_csv("C:/Users/liadz/Downloads/Brazil_project/data/olist_or
products = pd.read_csv("C:/Users/liadz/Downloads/Brazil_project/data/olist_produ
category_translation = pd.read_csv("C:/Users/liadz/Downloads/Brazil_project/data
sellers = pd.read_csv('C:/Users/liadz/Downloads/Brazil_project/data/olist_seller


orders.head()
```

Out[47]:

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

In [48]:
```
orders['order_status'].value_counts()
```

Out[48]:
```
order_status
delivered      96478
shipped         1107
canceled         625
unavailable      609
invoiced         314
processing       301
created            5
approved           2
Name: count, dtype: int64
```

In [49]:
```
orders.isnull().sum()
```

Out[49]:
```
order_id                            0
customer_id                         0
order_status                        0
order_purchase_timestamp            0
order_approved_at                 160
order_delivered_carrier_date     1783
order_delivered_customer_date    2965
order_estimated_delivery_date       0
dtype: int64
```

convert the relevant columns to datetime format to enable time-based analysis of order patterns and delivery performance.

In [50]:
```
date_columns = [
    'order_purchase_timestamp',
    'order_approved_at',
    'order_delivered_carrier_date',
    'order_delivered_customer_date',
    'order_estimated_delivery_date'
]

# pd.to_datetime to each date column
for col in date_columns:
    orders[col] = pd.to_datetime(orders[col])

orders.dtypes
```

Out[50]:
```
order_id                                 object
customer_id                              object
order_status                             object
order_purchase_timestamp         datetime64[ns]
order_approved_at                datetime64[ns]
order_delivered_carrier_date     datetime64[ns]
order_delivered_customer_date    datetime64[ns]
order_estimated_delivery_date    datetime64[ns]
dtype: object
```

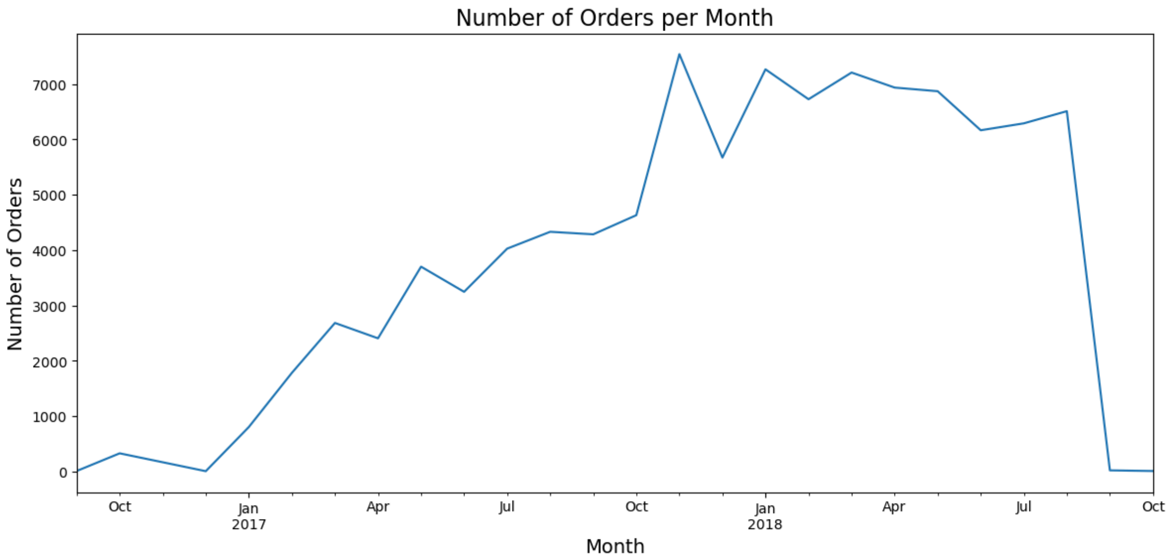
In this section, I create a new feature to extract the purchase month and year for each order. Then I group the orders by month to visualize the trend of order volume over time. This helps identify seasonality patterns, growth trends, and peak shopping periods.

In [51]:
```
# Create a year-month column
orders['purchase_year_month'] = orders['order_purchase_timestamp'].dt.to_period(

orders[['order_purchase_timestamp', 'purchase_year_month']].head()
```

Out[51]:

	order_purchase_timestamp	purchase_year_month
0	2017-10-02 10:56:33	2017-10
1	2018-07-24 20:41:37	2018-07
2	2018-08-08 08:38:49	2018-08
3	2017-11-18 19:28:06	2017-11
4	2018-02-13 21:18:39	2018-02

In [52]:
```
# Group orders by purchase year-month and count them
monthly_orders = orders.groupby('purchase_year_month').size()

plt.figure(figsize=(14,6))
monthly_orders.plot()

plt.title('Number of Orders per Month', fontsize=16)
plt.xlabel('Month', fontsize=14)
plt.ylabel('Number of Orders', fontsize=14)
plt.show()
```



How Long Does It Take to Deliver an Order?

In this section, I calculate the actual delivery time in days for each order by subtracting the purchase date from the delivery date. Then I visualize the distribution of delivery times to understand typical delivery performance and identify common delivery durations.

In [53]:
```
# Calculate actual delivery time in days for each order
orders['actual_delivery_days'] = (orders['order_delivered_customer_date'] - orde
```

```
orders[['order_purchase_timestamp', 'order_delivered_customer_date', 'actual_del
```

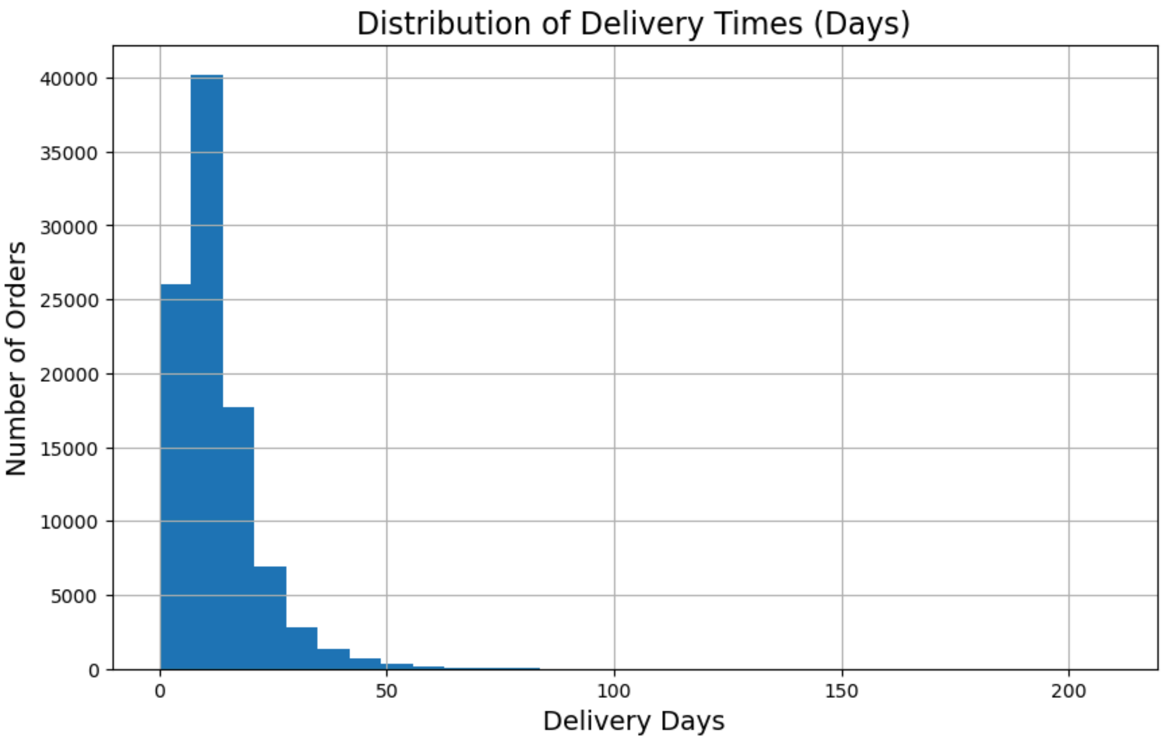
Out[53]:

	order_purchase_timestamp	order_delivered_customer_date	actual_delivery_days
0	2017-10-02 10:56:33	2017-10-10 21:25:13	8.0
1	2018-07-24 20:41:37	2018-08-07 15:27:45	13.0
2	2018-08-08 08:38:49	2018-08-17 18:06:29	9.0
3	2017-11-18 19:28:06	2017-12-02 00:28:42	13.0
4	2018-02-13 21:18:39	2018-02-16 18:17:02	2.0
5	2017-07-09 21:57:05	2017-07-26 10:57:55	16.0
6	2017-04-11 12:22:08	NaT	NaN
7	2017-05-16 13:10:30	2017-05-26 12:55:51	9.0
8	2017-01-23 18:29:09	2017-02-02 14:08:10	9.0
9	2017-07-29 11:55:02	2017-08-16 17:14:30	18.0

Distribution of Delivery Times

In [54]:

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10,6))
orders['actual_delivery_days'].hist(bins=30)

plt.title('Distribution of Delivery Times (Days)', fontsize=16)
plt.xlabel('Delivery Days', fontsize=14)
plt.ylabel('Number of Orders', fontsize=14)
plt.show()
```



Average and Standard Deviation of Delivery Time

In [55]:
```
# Filter only delivered orders
delivered_orders = orders[orders['actual_delivery_days'].notnull()]

# Calculate average delivery time
average_delivery_days = delivered_orders['actual_delivery_days'].mean()

# Calculate standard deviation of delivery time
std_delivery_days = delivered_orders['actual_delivery_days'].std()

print(f"Average Delivery Time: {average_delivery_days:.2f} days")
print(f"Standard Deviation of Delivery Time: {std_delivery_days:.2f} days")
```

```
Average Delivery Time: 12.09 days
Standard Deviation of Delivery Time: 9.55 days
```

Check If the Company Met Its Promised Delivery Dates

In [56]:
```
delivered_orders = delivered_orders.copy()

# Create a new column to check if the delivery was late
delivered_orders['late_delivery'] = delivered_orders['order_delivered_customer_d

# Count how many late vs on-time deliveries
late_delivery_counts = delivered_orders['late_delivery'].value_counts()

# Calculate percentage of late deliveries
late_delivery_percentage = (late_delivery_counts[True] / late_delivery_counts.su

print("Late Deliveries Count:")
print(late_delivery_counts)
print(f"\nPercentage of Late Deliveries: {late_delivery_percentage:.2f}%")
```

```
Late Deliveries Count:
late_delivery
False    88649
True      7827
Name: count, dtype: int64

Percentage of Late Deliveries: 8.11%
```

In most cases (91.89%), deliveries arrive on time, although this is a high percentage, there is room for improvement in delivery times.

How Does Average Delivery Time Vary Across Cities?

In this section, I merge customer location information into the orders dataset to analyze delivery times across different cities. Then I calculate the average and standard deviation of delivery times for each city and and filters out cities with less than 10 deliveries to ensure statistical reliability. This allows me to identify the cities with the fastest and slowest average delivery times, providing insights into regional logistics performance.

In [57]:
```
# Merge customer information into delivered_orders
delivered_orders = delivered_orders.merge(customers[['customer_id', 'customer_ci

delivered_orders[['customer_id', 'customer_city', 'customer_state']].head()
```

Out[57]:

	customer_id	customer_city	customer_state
0	9ef432eb6251297304e76186b10a928d	sao paulo	SP
1	b0830fb4747a6c6d20dea0b8c802d7ef	barreiras	BA
2	41ce2a54c0b03bf3443c3d931a367089	vianopolis	GO
3	f88197465ea7920adcdbec7375364d82	sao goncalo do amarante	RN
4	8ab97904e6daea8866dbdbc4fb7aad2c	santo andre	SP

In [58]:
```
# Group by customer city and calculate mean and standard deviation of delivery t
# Add a count of orders per city
city_delivery_stats = delivered_orders.groupby('customer_city')['actual_delivery

city_delivery_stats.columns = ['customer_city', 'avg_delivery_days', 'std_delive

city_delivery_stats.head(n=10)
```

Out[58]:

	customer_city	avg_delivery_days	std_delivery_days	num_orders
0	abadia dos dourados	11.333333	8.504901	3
1	abadiania	29.000000	NaN	1
2	abaete	9.916667	4.999242	12
3	abaetetuba	26.545455	14.590159	11
4	abaiara	35.000000	14.142136	2
5	abaira	14.500000	0.707107	2
6	abare	17.000000	2.828427	2
7	abatia	18.666667	5.507571	3
8	abdon batista	14.000000	NaN	1
9	abelardo luz	18.666667	13.793718	6

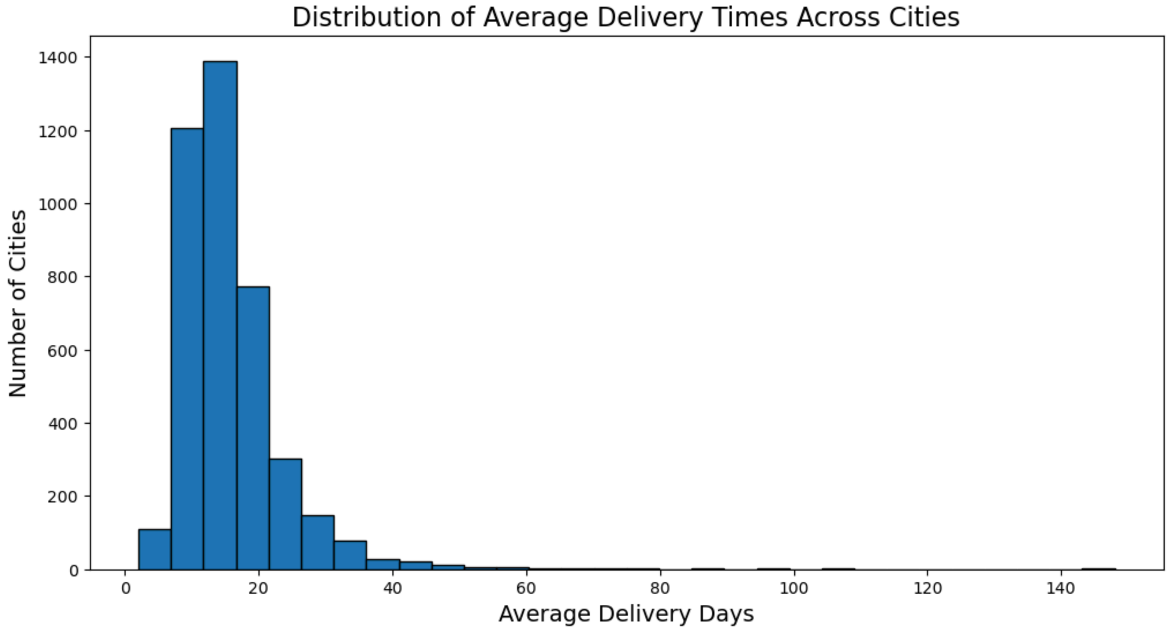
In [59]:
```
# Keep only cities with at least 10 delivered orders
filtered_city_delivery_stats = city_delivery_stats[city_delivery_stats['num_orde

# Top 10 fastest cities (with at least 10 orders)
fastest_cities = filtered_city_delivery_stats.sort_values('avg_delivery_days', a

# Top 10 slowest cities (with at least 10 orders)
slowest_cities = filtered_city_delivery_stats.sort_values('avg_delivery_days', a

print("Top 10 Fastest Cities (with ≥10 orders):")
```

```
print(fastest_cities)

print("\nTop 10 Slowest Cities (with ≥10 orders):")
print(slowest_cities)
```

```
Top 10 Fastest Cities (with ≥10 orders):
                customer_city  avg_delivery_days  std_delivery_days  num_orders
473             biritiba-mirim           5.400000           1.505545          10
2887                       poa           6.105882           4.611124          85
314                      aruja           6.132353           3.573971          68
2856    pirapora do bom jesus           6.312500           2.821790          16
3741          taboao da serra           6.443662           4.910542         284
3981   vargem grande paulista           6.651163           3.859951          43
3527    sao lourenco da serra           6.666667           4.292347          12
1084                     cotia           6.714876           4.485720         242
3321      santana de parnaiba           6.735955           4.814403         178
1221                  duartina           6.800000           4.442222          10

Top 10 Slowest Cities (with ≥10 orders):
             customer_city  avg_delivery_days  std_delivery_days  num_orders
2018               lagarto          35.636364          53.134307          11
3339              santarem          32.627907          13.113104          43
2982      presidente dutra          31.142857          31.257878          14
2339              montanha          30.400000          62.828161          10
482              boa vista          29.250000          28.092110          40
567            brejo santo          28.600000          20.331694          10
3496   sao jose de ribamar          28.142857          16.533682          14
102               altamira          27.520000          11.288342          25
2125                macapa          27.283019          23.285335          53
3                abaetetuba          26.545455          14.590159          11
```

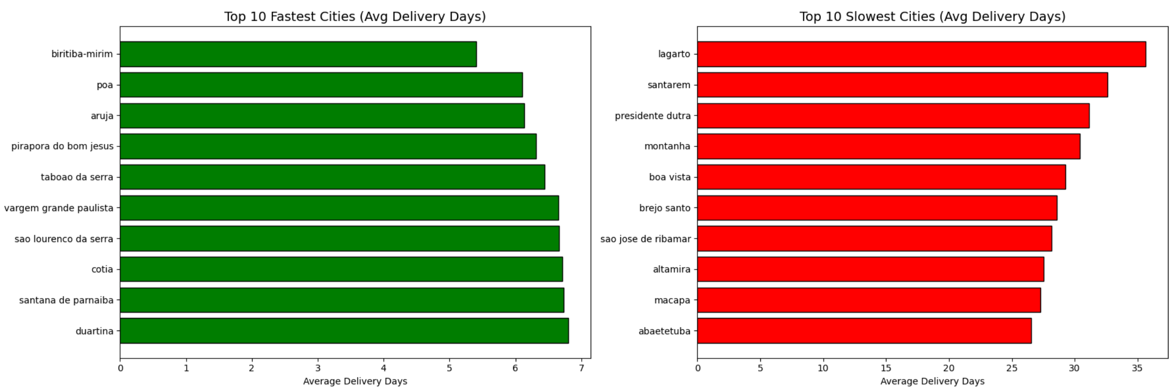
In [60]:

```
import matplotlib.pyplot as plt

plt.figure(figsize=(12,6))

plt.hist(city_delivery_stats['avg_delivery_days'], bins=30, edgecolor='black')

plt.title('Distribution of Average Delivery Times Across Cities', fontsize=16)
plt.xlabel('Average Delivery Days', fontsize=14)
plt.ylabel('Number of Cities', fontsize=14)
plt.show()
```



Top 10 fastest and slowest cities

In [61]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(18,6))

plt.subplot(1, 2, 1)  # 1 row, 2 columns, plot 1
plt.barh(fastest_cities['customer_city'], fastest_cities['avg_delivery_days'], c
plt.title('Top 10 Fastest Cities (Avg Delivery Days)', fontsize=14)
plt.xlabel('Average Delivery Days')
plt.gca().invert_yaxis()  # Fastest on top

plt.subplot(1, 2, 2)  # 1 row, 2 columns, plot 2
plt.barh(slowest_cities['customer_city'], slowest_cities['avg_delivery_days'], c
plt.title('Top 10 Slowest Cities (Avg Delivery Days)', fontsize=14)
plt.xlabel('Average Delivery Days')
plt.gca().invert_yaxis()  # Slowest on top

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



How Do Shipping Times Vary Between States?

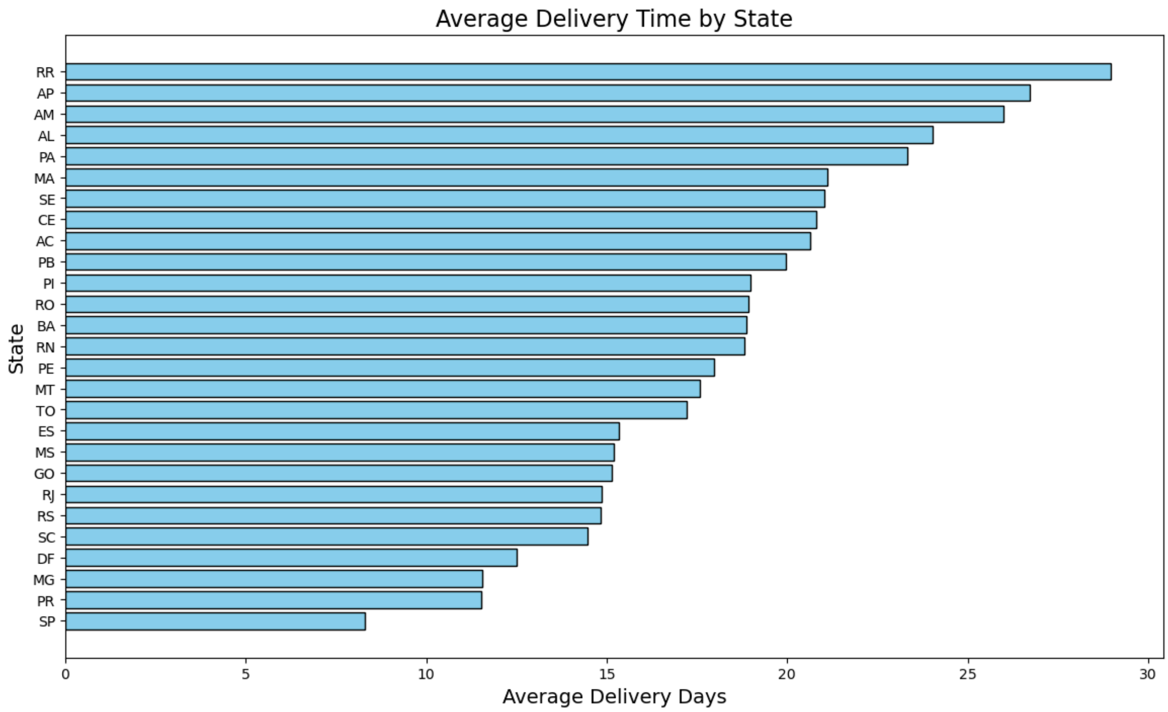
In this section, I analyze how delivery times vary between Brazilian states. I calculate the average and standard deviation of delivery times per state, then visualize the results with a bar chart. This helps identify regional differences in logistics performance and highlights states with faster or slower deliveries.

In [62]:
```
# Group by customer state and calculate mean and standard deviation of delivery
state_delivery_stats = delivered_orders.groupby('customer_state')['actual_delive

state_delivery_stats.columns = ['customer_state', 'avg_delivery_days', 'std_deli

state_delivery_stats.head()
```

Out[62]:

	customer_state	avg_delivery_days	std_delivery_days	num_orders
0	AC	20.637500	10.777665	80
1	AL	24.040302	11.480919	397
2	AM	25.986207	13.852891	145
3	AP	26.731343	21.413379	67
4	BA	18.866400	11.695508	3256

In [63]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(14,8))

# Sort states by average delivery days
state_delivery_stats_sorted = state_delivery_stats.sort_values('avg_delivery_day

plt.barh(state_delivery_stats_sorted['customer_state'], state_delivery_stats_sor

plt.title('Average Delivery Time by State', fontsize=16)
plt.xlabel('Average Delivery Days', fontsize=14)
plt.ylabel('State', fontsize=14)
plt.show()
```

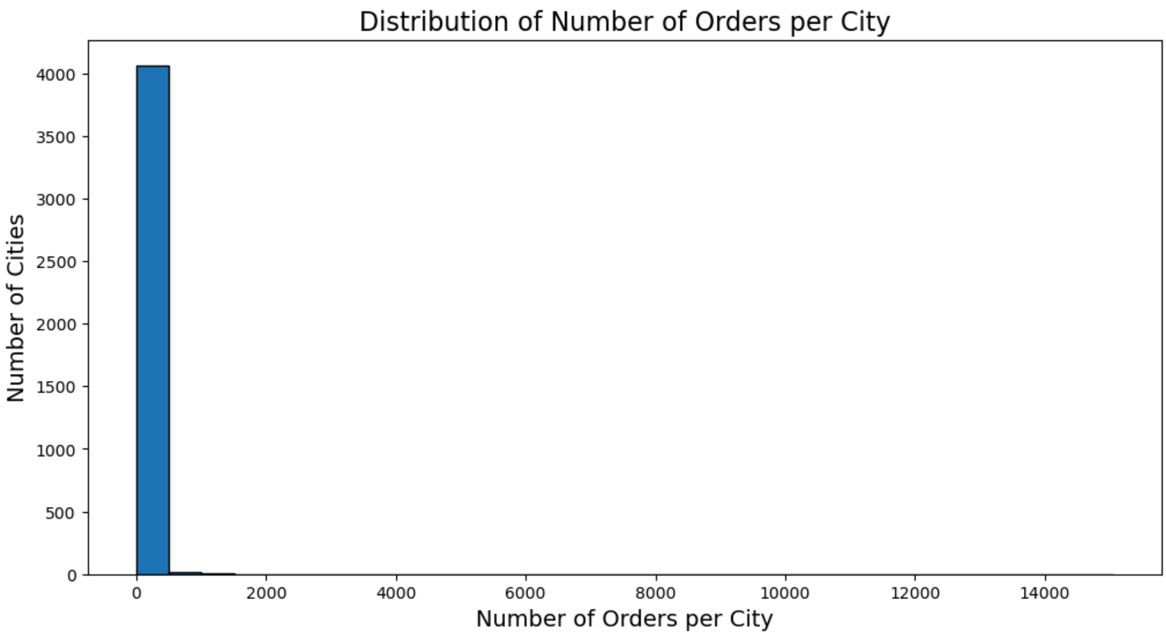


Conclusion:

- The states of São Paulo (SP), Paraná (PR), and Minas Gerais (MG) have the fastest delivery times, with averages around 10–12 days.
- The states of Roraima (RR), Amapá (AP), and Amazonas (AM) have the slowest delivery times, averaging over 25 days.
- This indicates strong regional delivery performance differences, likely driven by infrastructure availability, distance from distribution centers, and geographic challenges.
- Future logistics optimization could focus on improving delivery speeds to northern states.

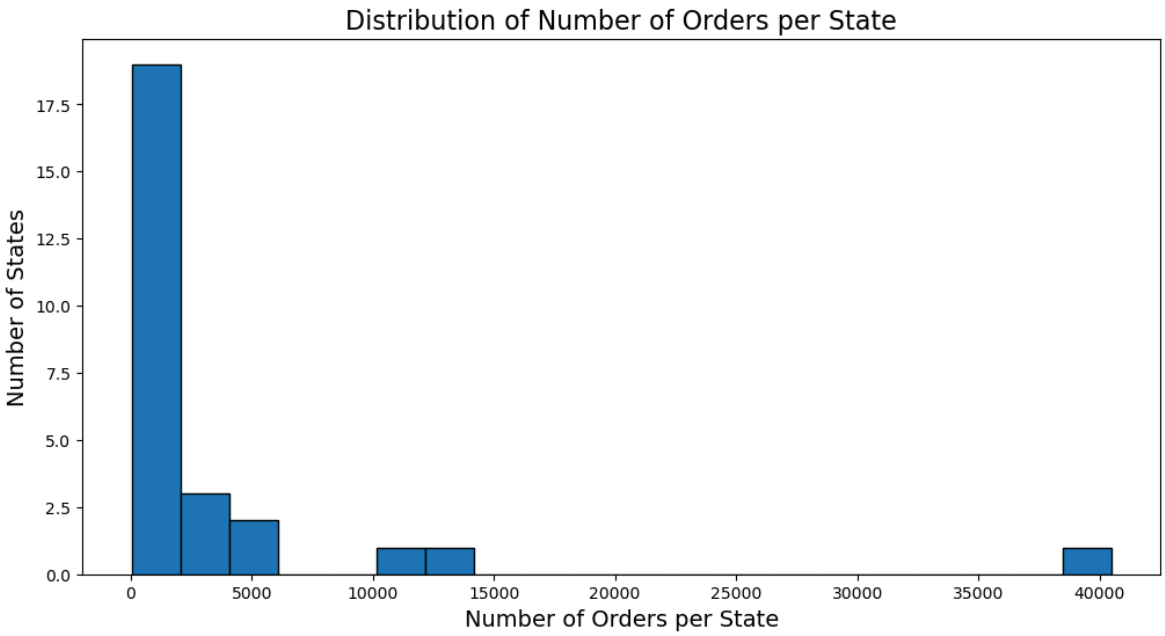
Distribution of Number of Orders per City and per State

In [64]:
```
import matplotlib.pyplot as plt

# Distribution of number of orders per city
city_order_counts = delivered_orders['customer_city'].value_counts()

plt.figure(figsize=(12,6))
plt.hist(city_order_counts, bins=30, edgecolor='black')
plt.title('Distribution of Number of Orders per City', fontsize=16)
plt.xlabel('Number of Orders per City', fontsize=14)
plt.ylabel('Number of Cities', fontsize=14)
plt.show()
```



The e-commerce market is extremely concentrated in big cities.

In [65]:
```
# Distribution of number of orders per state
state_order_counts = delivered_orders['customer_state'].value_counts()

plt.figure(figsize=(12,6))
plt.hist(state_order_counts, bins=20, edgecolor='black')
plt.title('Distribution of Number of Orders per State', fontsize=16)
plt.xlabel('Number of Orders per State', fontsize=14)
plt.ylabel('Number of States', fontsize=14)
plt.show()
```



Distribution of Orders per State:

- Most Brazilian states have a relatively small number of orders.

- A few states dominate order volume — especially São Paulo (SP), which heavily skews the distribution.

Distribution of Orders per City:

- The distribution across cities is even more extreme:
- Very few cities have high order volumes, while most cities have very few orders.
- Demand is highly concentrated in a few regions.

The company relies heavily on a few states for most of its revenue

Where Do Customers Spend More or Less (Cities and States)?

In this section, I analyze where customers spend more or less across different Brazilian states and cities. I aggregate total payments per order, then calculate the average and standard deviation of spending for each state and each city. I visualize the distribution of average payment values to identify regions with higher purchasing power and uncover spending patterns across the country.

In [66]:

```
total_payments = payments.groupby('order_id')['payment_value'].sum().reset_index

delivered_orders_payments = pd.merge(
    delivered_orders,
    total_payments,
    on='order_id',
    how='left'
)

delivered_orders_payments.head()
```

Out[66]:

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

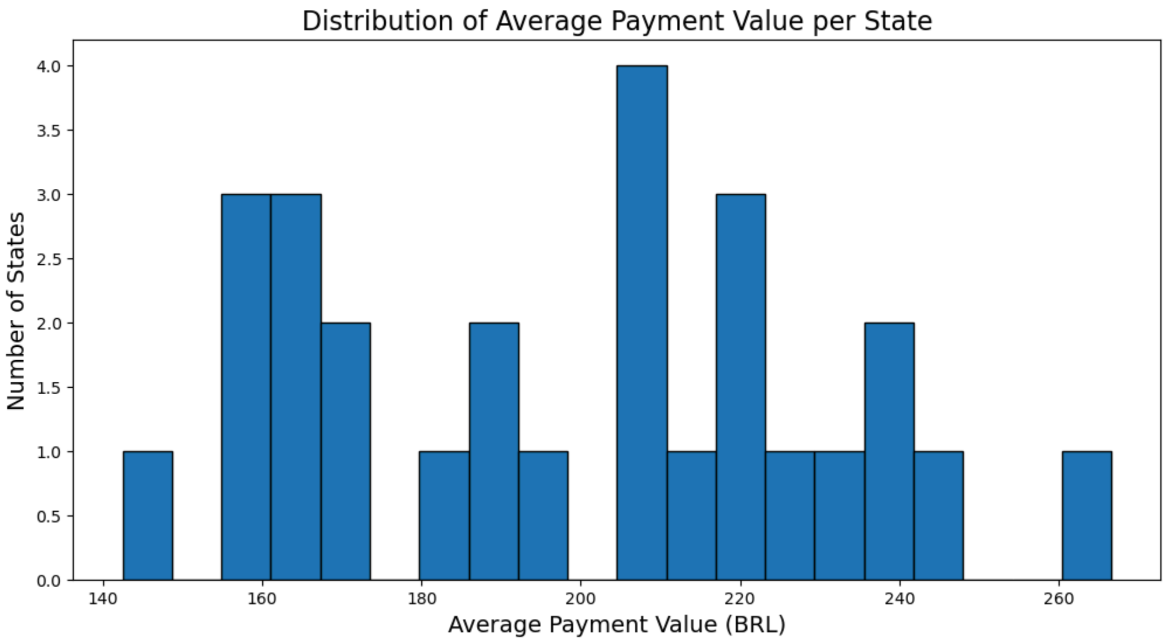
1. Average Payment Value by State

In [67]:
```
# Group by customer_state and calculate average and standard deviation of paymen
state_spending = delivered_orders_payments.groupby('customer_state')['payment_va

state_spending.columns = ['customer_state', 'avg_payment_value', 'std_payment_va

# Sort by highest average spending
state_spending_sorted = state_spending.sort_values('avg_payment_value', ascendin

state_spending_sorted.head(10)
```

Out[67]:

	customer_state	avg_payment_value	std_payment_value	num_orders
14	PB	266.604739	399.156363	517
0	AC	244.828125	231.906400	80
3	AP	240.922537	279.352729	67
1	AL	237.268992	280.911445	397
20	RO	234.467901	299.600200	243
13	PA	224.130603	282.812701	946
16	PI	221.160021	250.086633	476
21	RR	220.476098	213.899272	41
26	TO	219.005000	287.341179	274
19	RN	212.506962	242.091617	474

In [68]:
```
plt.figure(figsize=(12,6))
plt.hist(state_spending_sorted['avg_payment_value'], bins=20, edgecolor='black')
plt.title('Distribution of Average Payment Value per State', fontsize=16)
plt.xlabel('Average Payment Value (BRL)', fontsize=14)
plt.ylabel('Number of States', fontsize=14)
plt.show()
```



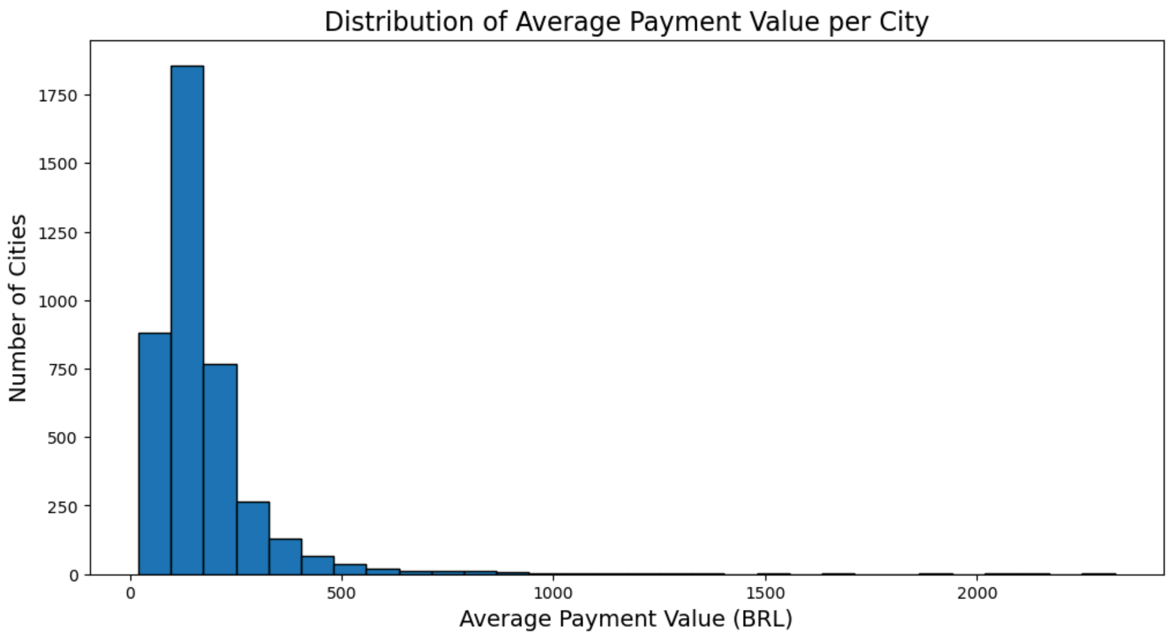
2. Average Payment Value by City

In [69]:
```
# Group by customer_city and calculate average and standard deviation of payment
city_spending = delivered_orders_payments.groupby('customer_city')['payment_valu

city_spending.columns = ['customer_city', 'avg_payment_value', 'std_payment_valu

# Sort by highest average spending
city_spending_sorted = city_spending.sort_values('avg_payment_value', ascending=

city_spending_sorted.head(10)
```

Out[69]:

	customer_city	avg_payment_value	std_payment_value	num_orders
2794	pianco	2324.99	NaN	1
2473	nova esperanca do piria	2252.66	NaN	1
1247	engenheiro navarro	2106.55	NaN	1
32	agrestina	2066.34	NaN	1
2216	mariental	1867.85	NaN	1
2097	loreto	1643.64	NaN	1
1593	ibitita	1534.58	NaN	1
2870	pirpirituba	1372.25	NaN	1
376	barao ataliba nogueira	1351.51	NaN	1
408	barra longa	1341.55	NaN	1

In [70]:
```
plt.figure(figsize=(12,6))
plt.hist(city_spending_sorted['avg_payment_value'], bins=30, edgecolor='black')
plt.title('Distribution of Average Payment Value per City', fontsize=16)
plt.xlabel('Average Payment Value (BRL)', fontsize=14)
plt.ylabel('Number of Cities', fontsize=14)
plt.show()
```

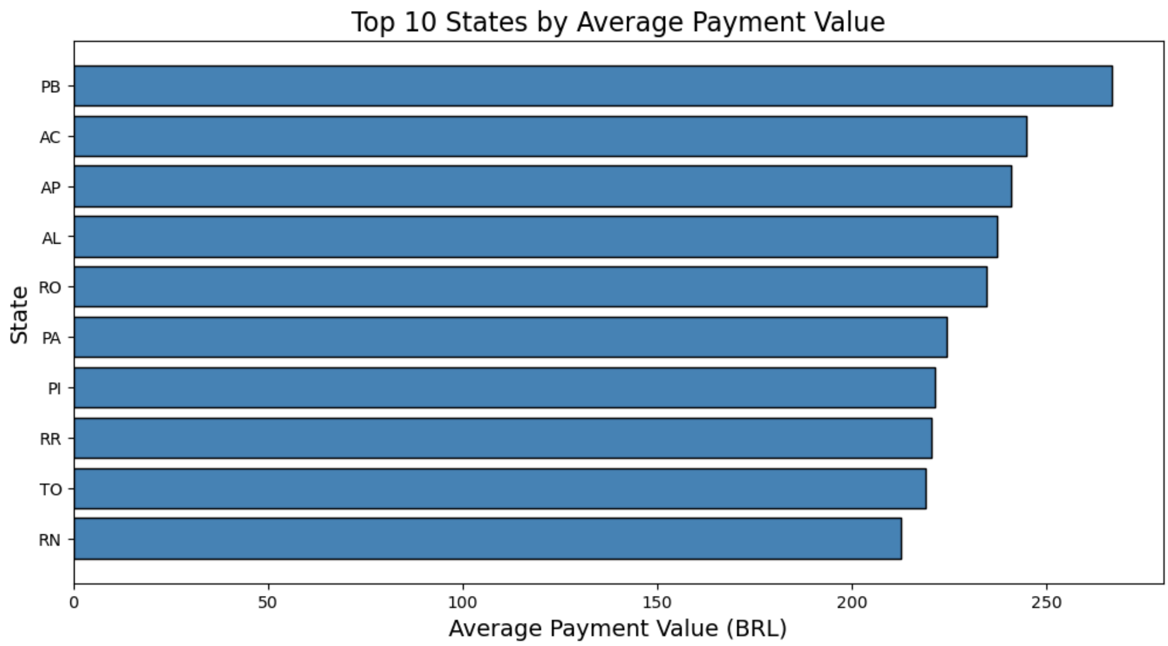


Insights:

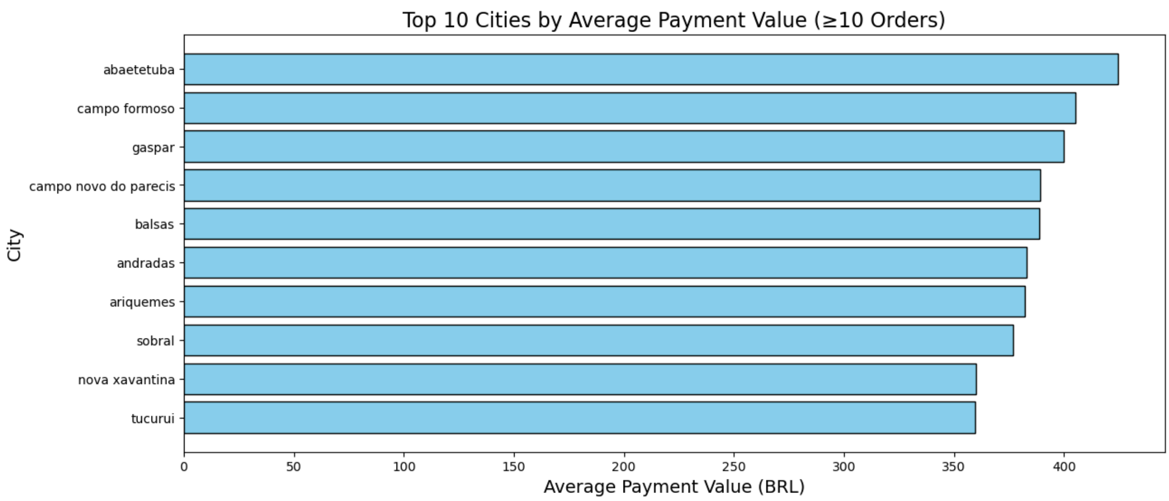
- Customer spending across cities is highly skewed, with a few cities showing extremely high average order values. However, most cities fall under 300 BRL per order.
- State-level spending shows moderate dispersion, with most states clustering between 150 and 250 BRL, but the distribution is not uniform or normal; it displays multiple local peaks and irregularities.
- Proper modeling of state-level spending variations could require non-linear methods (e.g., polynomial or spline regressions) to capture the real behavior.
- Special targeting efforts could be designed for niche high-value cities to maximize revenue from premium customers.

Top 10 States by Average Payment Value

In [71]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(12,6))
plt.barh(state_spending_sorted['customer_state'].head(10), state_spending_sorted
plt.title('Top 10 States by Average Payment Value', fontsize=16)
plt.xlabel('Average Payment Value (BRL)', fontsize=14)
plt.ylabel('State', fontsize=14)
plt.gca().invert_yaxis()
plt.show()
```



In [72]:
```
# Filter big cities (at least 10 orders)
big_cities = city_spending_sorted[city_spending_sorted['num_orders'] >= 10]

# Sort by average payment
big_cities_sorted = big_cities.sort_values('avg_payment_value', ascending=False)

# Plot Top 10 big cities
plt.figure(figsize=(14,6))
plt.barh(big_cities_sorted['customer_city'].head(10),
         big_cities_sorted['avg_payment_value'].head(10),
         color='skyblue', edgecolor='black')

plt.title('Top 10 Cities by Average Payment Value (≥10 Orders)', fontsize=16)
plt.xlabel('Average Payment Value (BRL)', fontsize=14)
plt.ylabel('City', fontsize=14)
plt.gca().invert_yaxis()
plt.show()
```



Best-Selling Product Categories Overall

In [73]:
```
order_items.head(), products.head(), category_translation.head()
```

Out[73]:
```
(                           order_id  order_item_id  \
 0  00010242fe8c5a6d1ba2dd792cb16214              1   
 1  00018f77f2f0320c557190d7a144bdd3              1   
 2  000229ec398224ef6ca0657da4fc703e              1   
 3  00024acbcdf0a6daa1e931b038114c75              1   
 4  00042b26cf59d7ce69dfabb4e55b4fd9              1   
 
                          product_id                         seller_id  \
 0  4244733e06e7ecb4970a6e2683c13e61  48436dade18ac8b2bce089ec2a041202   
 1  e5f2d52b802189ee658865ca93d83a8f  dd7ddc04e1b6c2c614352b383efe2d36   
 2  c777355d18b72b67abbeef9df44fd0fd  5b51032eddd242adc84c38acab88f23d   
 3  7634da152a4610f1595efa32f14722fc  9d7a1d34a5052409006425275ba1c2b4   
 4  ac6c3623068f30de03045865e4e10089  df560393f3a51e74553ab94004ba5c87   
 
    shipping_limit_date   price  freight_value  
 0  2017-09-19 09:45:35   58.90          13.29  
 1  2017-05-03 11:05:13  239.90          19.93  
 2  2018-01-18 14:48:30  199.00          17.87  
 3  2018-08-15 10:10:18   12.99          12.79  
 4  2017-02-13 13:57:51  199.90          18.14  ,
                          product_id  product_category_name  \
 0  1e9e8ef04dbcff4541ed26657ea517e5             perfumaria   
 1  3aa071139cb16b67ca9e5dea641aaa2f                  artes   
 2  96bd76ec8810374ed1b65e291975717f          esporte_lazer   
 3  cef67bcfe19066a932b7673e239eb23d                  bebes   
 4  9dc1a7de274444849c219cff195d0b71  utilidades_domesticas   
 
    product_name_lenght  product_description_lenght  product_photos_qty  \
 0                 40.0                       287.0                 1.0   
 1                 44.0                       276.0                 1.0   
 2                 46.0                       250.0                 1.0   
 3                 27.0                       261.0                 1.0   
 4                 37.0                       402.0                 4.0   
 
    product_weight_g  product_length_cm  product_height_cm  product_width_cm  
 0             225.0               16.0               10.0              14.0  
 1            1000.0               30.0               18.0              20.0  
 2             154.0               18.0                9.0              15.0  
 3             371.0               26.0                4.0              26.0  
 4             625.0               20.0               17.0              13.0  ,
     product_category_name product_category_name_english
 0            beleza_saude                 health_beauty
 1  informatica_acessorios         computers_accessories
 2              automotivo                          auto
 3         cama_mesa_banho                bed_bath_table
 4        moveis_decoracao               furniture_decor)
```

In [74]:
```
# Merge order items with product info
order_items_products = order_items.merge(products, on='product_id', how='left')

# Merge with category translation
order_items_products = order_items_products.merge(category_translation, on='prod

order_items_products[['order_id', 'product_id', 'product_category_name_english']
```

Out[74]:

	order_id	product_id	product_cate
0	00010242fe8c5a6d1ba2dd792cb16214	4244733e06e7ecb4970a6e2683c13e61	
1	00018f77f2f0320c557190d7a144bdd3	e5f2d52b802189ee658865ca93d83a8f	
2	000229ec398224ef6ca0657da4fc703e	c777355d18b72b67abbeef9df44fd0fd	
3	00024acbcdf0a6daa1e931b038114c75	7634da152a4610f1595efa32f14722fc	
4	00042b26cf59d7ce69dfabb4e55b4fd9	ac6c3623068f30de03045865e4e10089	

In [75]:

```
# Merge with delivered orders to get city and state
order_items_full = order_items_products.merge(delivered_orders[['order_id', 'cus

order_items_full[['order_id', 'customer_city', 'customer_state', 'product_catego
```

Out[75]:

	order_id	customer_city	customer_state	product_category_
0	00010242fe8c5a6d1ba2dd792cb16214	campos dos goytacazes	RJ	
1	00018f77f2f0320c557190d7a144bdd3	santa fe do sul	SP	
2	000229ec398224ef6ca0657da4fc703e	para de minas	MG	f
3	00024acbcdf0a6daa1e931b038114c75	atibaia	SP	
4	00042b26cf59d7ce69dfabb4e55b4fd9	varzea paulista	SP	

Top 10 Best-Selling Categories Overall

In this section, I identify the top 10 best-selling product categories across the entire dataset. I use a bar chart to visualize the most popular categories based on the number of orders. This analysis highlights customer preferences and helps businesses understand which types of products drive the most sales.

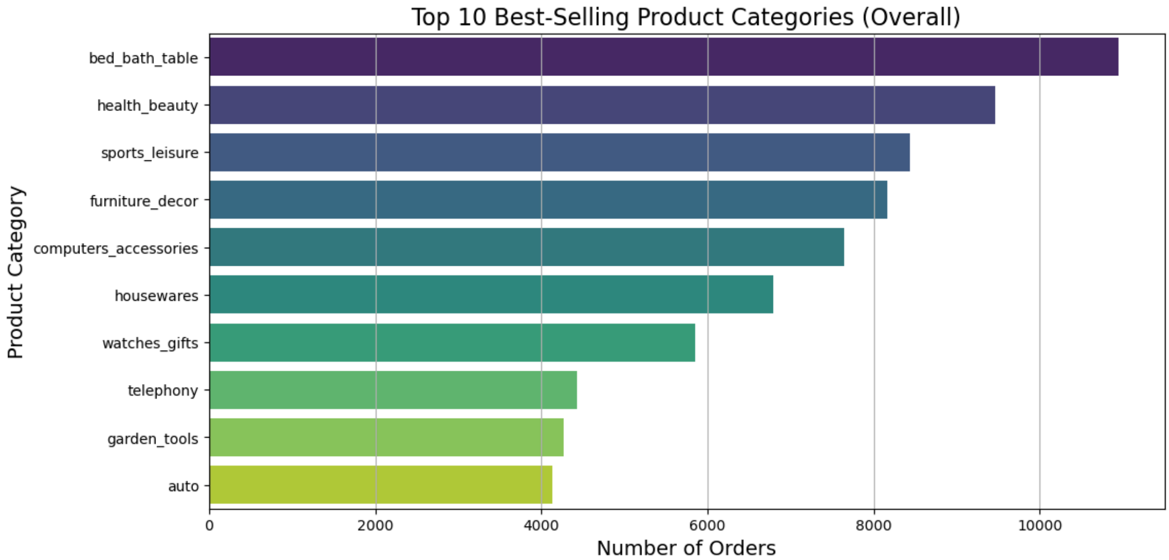
In [76]:

```
top_categories = order_items_full['product_category_name_english'].value_counts(

top_categories
```

Out[76]:

```
product_category_name_english
bed_bath_table           10953
health_beauty             9467
sports_leisure            8431
furniture_decor           8160
computers_accessories     7643
housewares                6795
watches_gifts             5857
telephony                 4430
garden_tools              4268
auto                      4139
Name: count, dtype: int64
```

In [77]:
```
# Prepare DataFrame
top_categories_overall_df = order_items_full['product_category_name_english'].va
top_categories_overall_df.columns = ['product_category', 'num_orders']

# Plot
plt.figure(figsize=(12,6))
sns.barplot(
    data=top_categories_overall_df,
    x='num_orders',
    y='product_category',
    hue='product_category',  # <-- ADD this
    palette='viridis',
    dodge=False,              # <-- IMPORTANT: to prevent separation
    legend=False              # <-- Hide redundant legend
)
plt.title('Top 10 Best-Selling Product Categories (Overall)', fontsize=16)
plt.xlabel('Number of Orders', fontsize=14)
plt.ylabel('Product Category', fontsize=14)
plt.grid(axis='x')
plt.show()
```



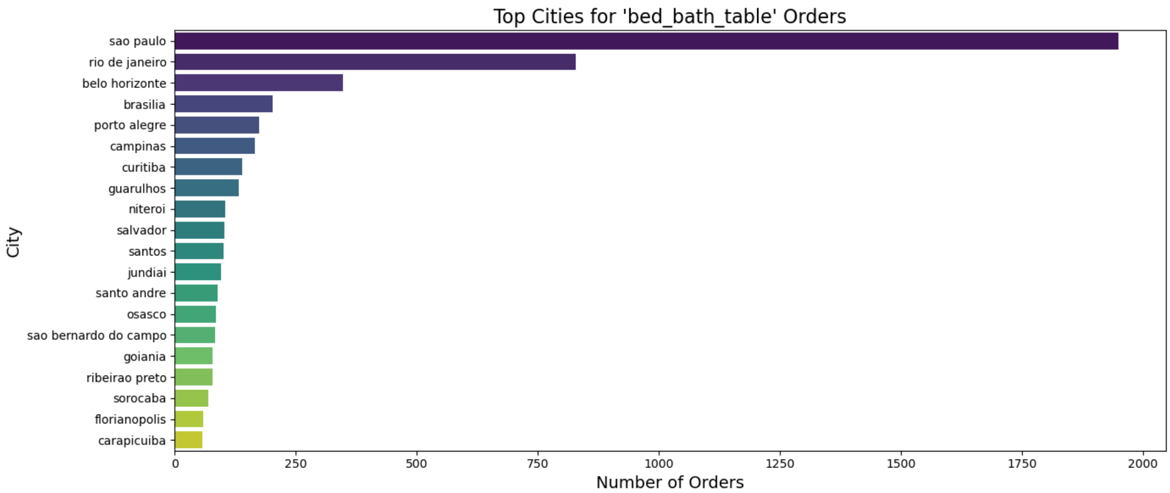
Conclusion: The most popular product categories overall are dominated by home-related products (bed, bath, decor, housewares) and personal care (health, beauty). Technology (computers, telephony) and sports products are also strong segments.

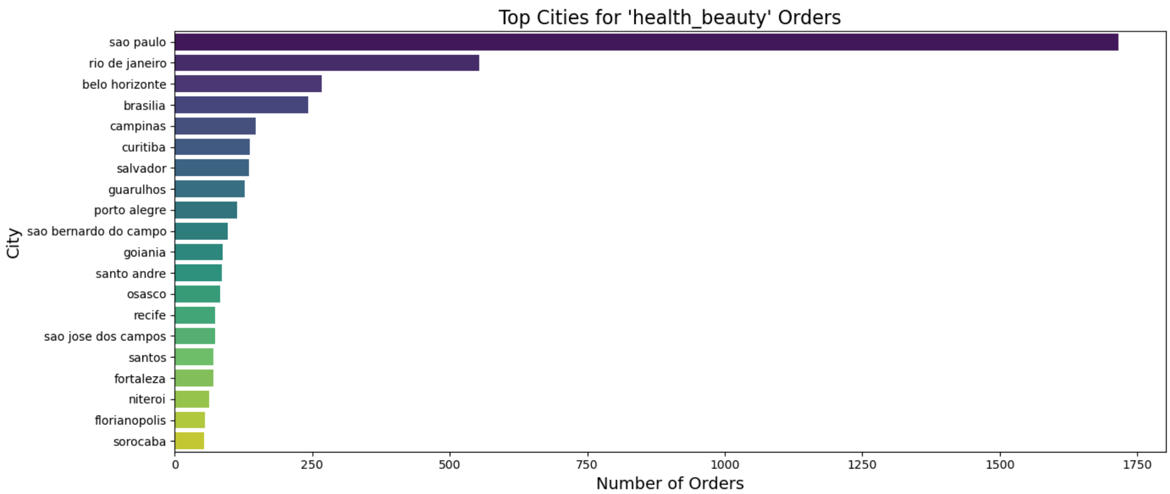
Two best-selling product categories

In this section, I focus only on the two best-selling product categories overall. I analyze how widely each of these categories is distributed across different cities.

In [78]:
```
import seaborn as sns
import matplotlib.pyplot as plt

for category in top_2_categories:
    plt.figure(figsize=(14,6))
    subset = category_city_counts[category_city_counts['product_category_name_en
    subset_sorted = subset.sort_values('order_count', ascending=False).head(20)
```

```
    sns.barplot(
        data=subset_sorted,
        x='order_count',
        y='customer_city',
        hue='customer_city',   # <-- this links hue and palette correctly
        palette='viridis',
        dodge=False,
        legend=False
    )
    plt.title(f"Top Cities for '{category}' Orders", fontsize=16)
    plt.xlabel('Number of Orders', fontsize=14)
    plt.ylabel('City', fontsize=14)
    plt.tight_layout()
    plt.show()
```



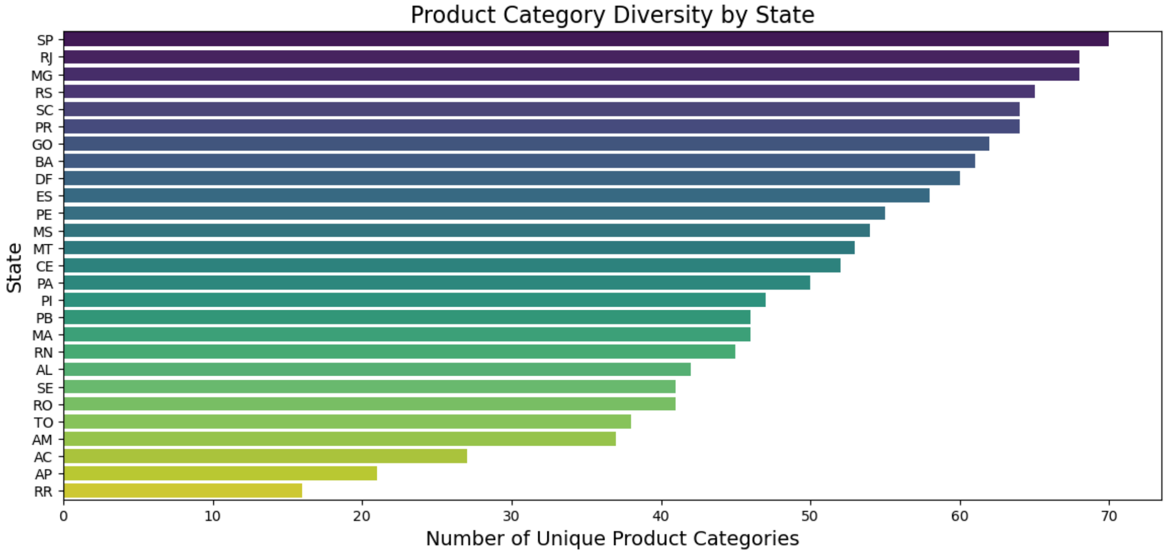


Demand is highly concentrated in major cities, particularly São Paulo and Rio de Janeiro, which account for a significant share of orders in both categories. This suggests that businesses targeting these categories should prioritize these cities when planning marketing strategies, inventory allocation, and logistics.

Product Category Diversity by State

I calculate the number of unique product categories ordered in each state. This helps understand whether customer demand is broad and varied (high diversity) or narrow and focused on specific needs (low diversity).

In [79]:
```
plt.figure(figsize=(14,6))
sns.barplot(
    data=state_category_diversity_sorted,
    x='product_category_name_english',
    y='customer_state',
    hue='customer_state',     # Fix added here
    palette='viridis',
    dodge=False,
    legend=False
)

plt.title('Product Category Diversity by State', fontsize=16)
plt.xlabel('Number of Unique Product Categories', fontsize=14)
plt.ylabel('State', fontsize=14)
plt.show()
```



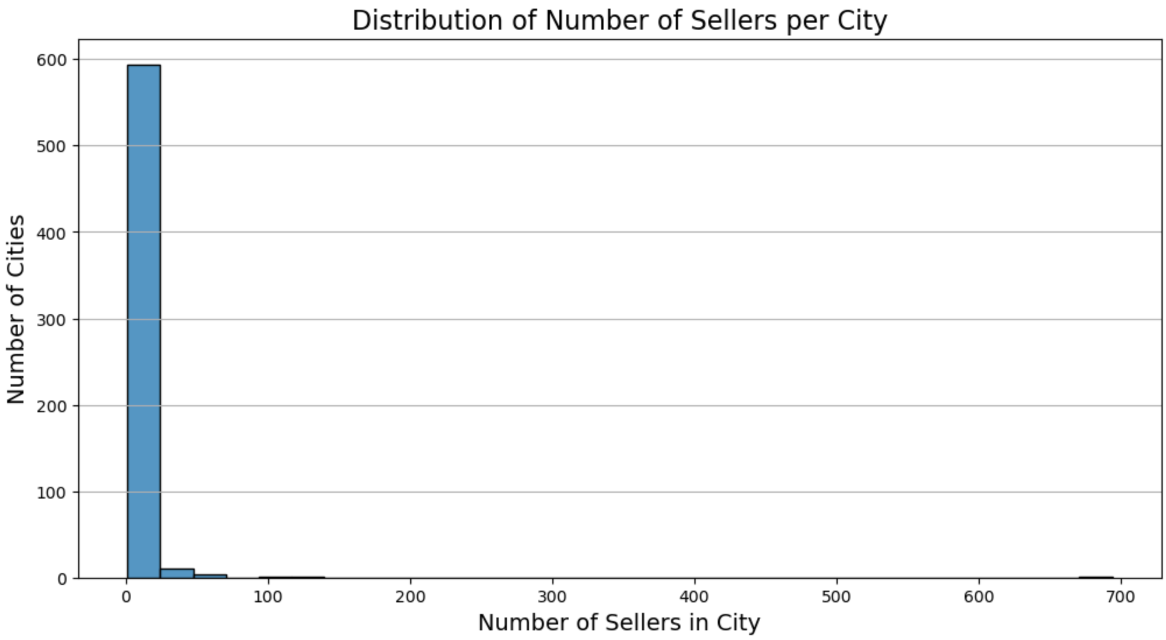
Conclusions:

- States like São Paulo (SP) and Rio de Janeiro (RJ) show the highest category diversity, suggesting mature, varied consumer demand.
- Smaller states tend to have lower diversity, possibly reflecting more focused market needs.

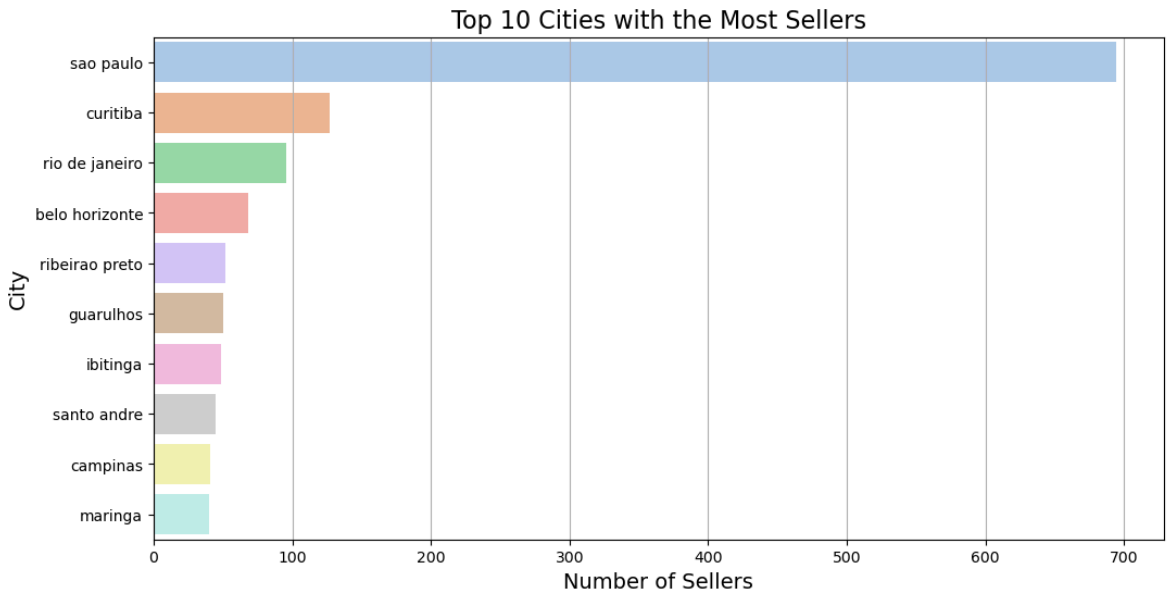
Seller Distribution Across Cities

In this section, I analyze how sellers are distributed across cities in Brazil. First I visualize the overall distribution of the number of sellers per city, then highlight the top 10 cities with the highest number of sellers. This analysis provides insight into the concentration of sellers and helps identify key commercial hubs within the country.

In [80]:
```
# Number of sellers per city
sellers_per_city = sellers['seller_city'].value_counts()

sellers_per_city.head()

import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12,6))
sns.histplot(sellers_per_city, bins=30, edgecolor='black')
plt.title('Distribution of Number of Sellers per City', fontsize=16)
plt.xlabel('Number of Sellers in City', fontsize=14)
plt.ylabel('Number of Cities', fontsize=14)
plt.grid(axis='y')
plt.show()
```



In [81]:
```
plt.figure(figsize=(12,6))
sns.barplot(
    x=top_10_seller_cities.values,
    y=top_10_seller_cities.index,
    hue=top_10_seller_cities.index,   # Fix: assign hue
    palette='pastel',
    dodge=False,
    legend=False
)

plt.title('Top 10 Cities with the Most Sellers', fontsize=16)
plt.xlabel('Number of Sellers', fontsize=14)
plt.ylabel('City', fontsize=14)
plt.grid(axis='x')
plt.show()
```


Top 10 Cities with the Most Sellers
sao paulo
curitiba
rio de janeiro
belo horizonte
ribeirao preto
guarulhos
ibitinga
santo andre
campinas
maringa
City
0
100
200
300
400
500
600
700
Number of Sellers