

CUSTOMER AND ORDER MANAGEMENT ANALYSIS

BY
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1. List all customers.

```
SELECT * FROM customers;
```

Result Table



	customer_id	customer_name	city	signup_date
▶	1	Alice Brown	New York	12-01-23
	2	David Smith	Chicago	05-02-23
	3	Maria Lopez	Houston	20-02-23
	4	John Carter	Miami	15-03-23
	5	Sarah Miller	New York	01-04-23
	6	Michael Green	Seattle	10-04-23
	7	Emma Wilson	Boston	01-05-23
	8	Oliver Jones	Chicago	12-05-23
	9	Sophia Davis	Miami	02-06-23
	10	James Taylor	Houston	15-06-23
	11	Isabella Martin	Seattle	01-07-23
	12	Lucas Lee	New York	10-07-23
	13	Mia Harris	Boston	01-08-23
	14	Ethan Clark	Houston	11-08-23
	15	Ava Lewis	Chicago	20-08-23
	16	Noah Walker	Miami	01-09-23
	17	Liam Hall	Seattle	12-09-23
	18	Charlotte King	New York	01-10-23
	19	Amelia Scott	Boston	12-10-23
	20	Benjamin Young	Houston	25-10-23

- The customer table shows a well-distributed signup pattern across months.
- Multiple customers joined within short intervals, showing steady onboarding.
- Customer diversity supports balanced analytics across the dataset.

2. List all orders.

```
SELECT * FROM orders;
```

Result Table

	order_id	customer_id	order_date	amount
▶	101	1	01-03-23	120.5
	102	1	15-04-23	89.99
	103	2	22-03-23	45
	104	3	01-04-23	150
	105	4	05-04-23	200
	106	5	12-05-23	99.99
	107	6	22-05-23	130.75
	108	7	01-06-23	67.4
	109	8	15-06-23	89
	110	9	02-07-23	210
	111	10	10-07-23	180.5
	112	11	22-07-23	75.99
	113	12	05-08-23	155.2
	114	13	15-08-23	54.9
	115	14	25-08-23	95
	116	15	01-09-23	102.75
	117	16	10-09-23	220
	118	17	22-09-23	80.25
	119	18	02-10-23	140.4
	120	19	14-10-23	60.6
	121	20	29-10-23	175
	122	10	02-11-23	90
	123	5	28-10-23	115
	124	3	11-11-23	210.25
	125	14	12-11-23	99.99

- Orders vary significantly in amount, indicating mixed spending behaviors.
- Order dates span across different months, showing repeated business activity.
- Some customers contribute multiple orders, while others contribute only one.

3. Find customers from New York.

```
SELECT * FROM customers WHERE city='New York';
```

Result
Table



	customer_id	customer_name	city	signup_date
▶	1	Alice Brown	New York	12-01-23
	5	Sarah Miller	New York	01-04-23
	12	Lucas Lee	New York	10-07-23
	18	Charlotte King	New York	01-10-23

- It shows whether those customers actively made purchases or not.
- Comparing with the orders table reveals their spending contribution.

4. Count customers per city.

```
SELECT city, count(customer_id) AS count_cust FROM customers GROUP BY city;
```

Result Table

	city	count_cust
▶	New York	4
	Chicago	3
	Houston	4
	Miami	3
	Seattle	3
	Boston	3

- Higher customer count often correlates with higher total orders.
- This distribution helps understand how customer base affects revenue patterns.

5. Total revenue generated.

```
SELECT sum(amount) AS Tot_rev FROM orders;
```

Result Table



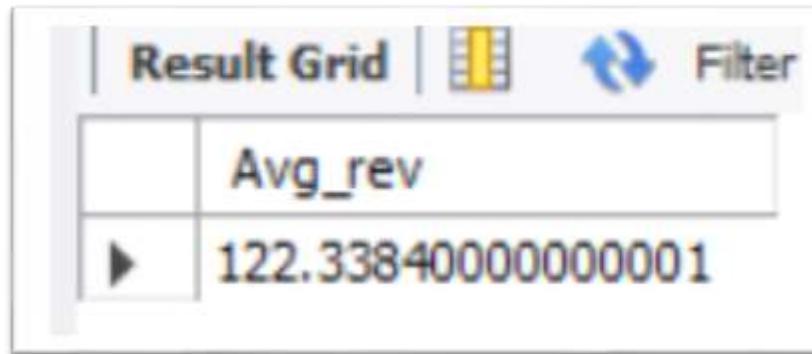
Tot_rev
3058.46

- High-value orders significantly boost overall revenue.
- The mix of small and large orders creates a balanced revenue curve.

6. Average order value.

```
SELECT AVG(amount) AS Avg_rev FROM orders;
```

Result Table



A screenshot of a database result grid titled "Result Grid". The grid has one column labeled "Avg_rev" and one row containing the value "122.33840000000001". There are navigation arrows at the bottom left of the grid.

Avg_rev
122.33840000000001

- Average order value reflects both frequent small purchases and occasional large ones.
- Helps compare customer behavior between light spenders and premium spenders.

7. Total spending per customer.

```
SELECT  
    customer_id,  
    sum(amount) AS Tot_amnt  
FROM orders  
GROUP BY customer_id;
```

- This comparison clearly separates high-value and low-value customer groups with repeated orders and high contribution ,less order and least contribution to the revenue.

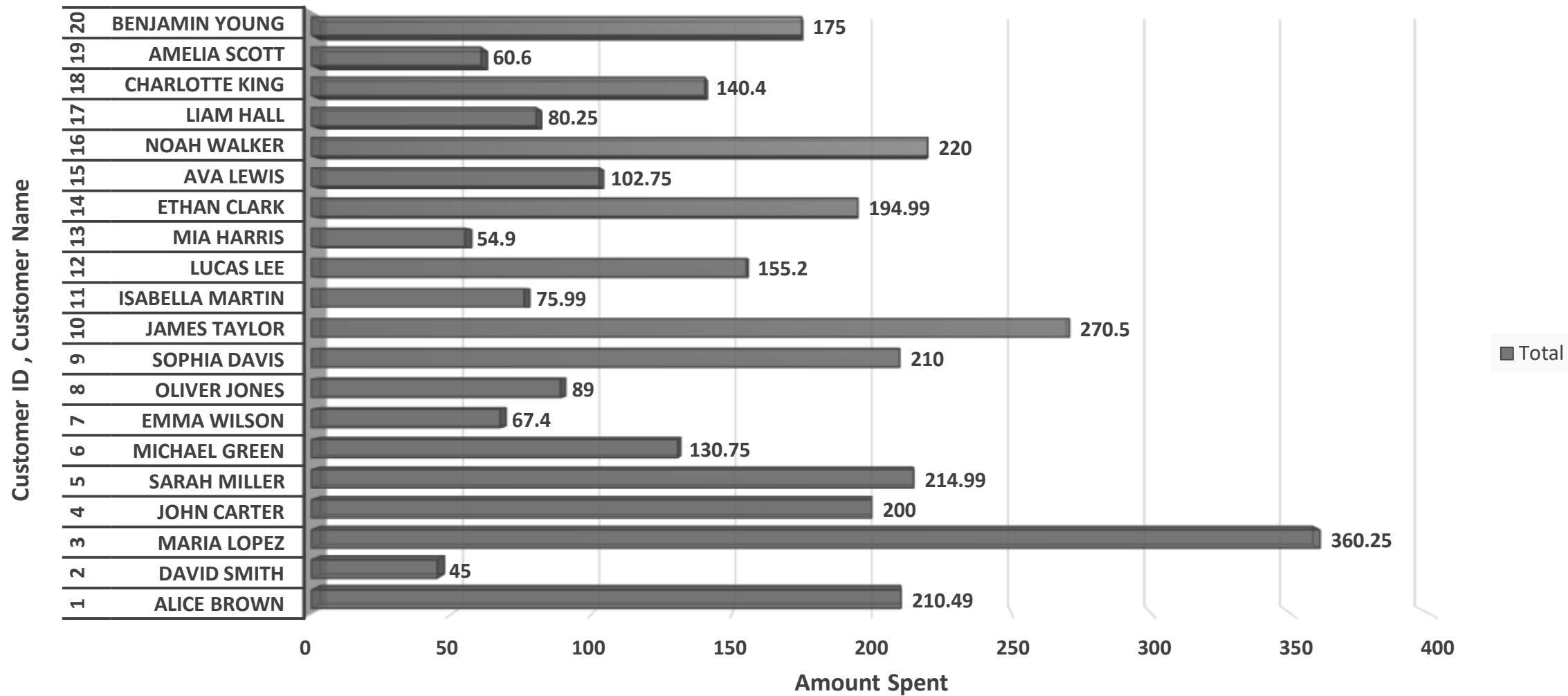
Result Table

Result Grid | Filter Row

	customer_id	Tot_amnt
▶	1	210.49
	2	45
	3	360.25
	4	200
	5	214.99
	6	130.75
	7	67.4
	8	89
	9	210
	10	270.5
	11	75.99
	12	155.2
	13	54.9
	14	194.99
	15	102.75
	16	220
	17	80.25
	18	140.4
	19	60.6
	20	175

Graphical Representation

Total Spent By Each Customer

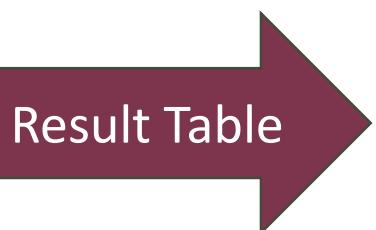


8. Customers with no orders.

SELECT

```
c.customer_id,  
c.customer_name,  
o.customer_id,  
o.order_id FROM customers c  
LEFT JOIN orders o  
ON c.customer_id=o.customer_id  
WHERE o.customer_id IS NULL;
```

Result Table



	customer_id	customer_name	customer_id	order_id

- These customers signed up but never made a purchase.
- Their inactivity highlights missed revenue opportunities.

9. Orders made in October.

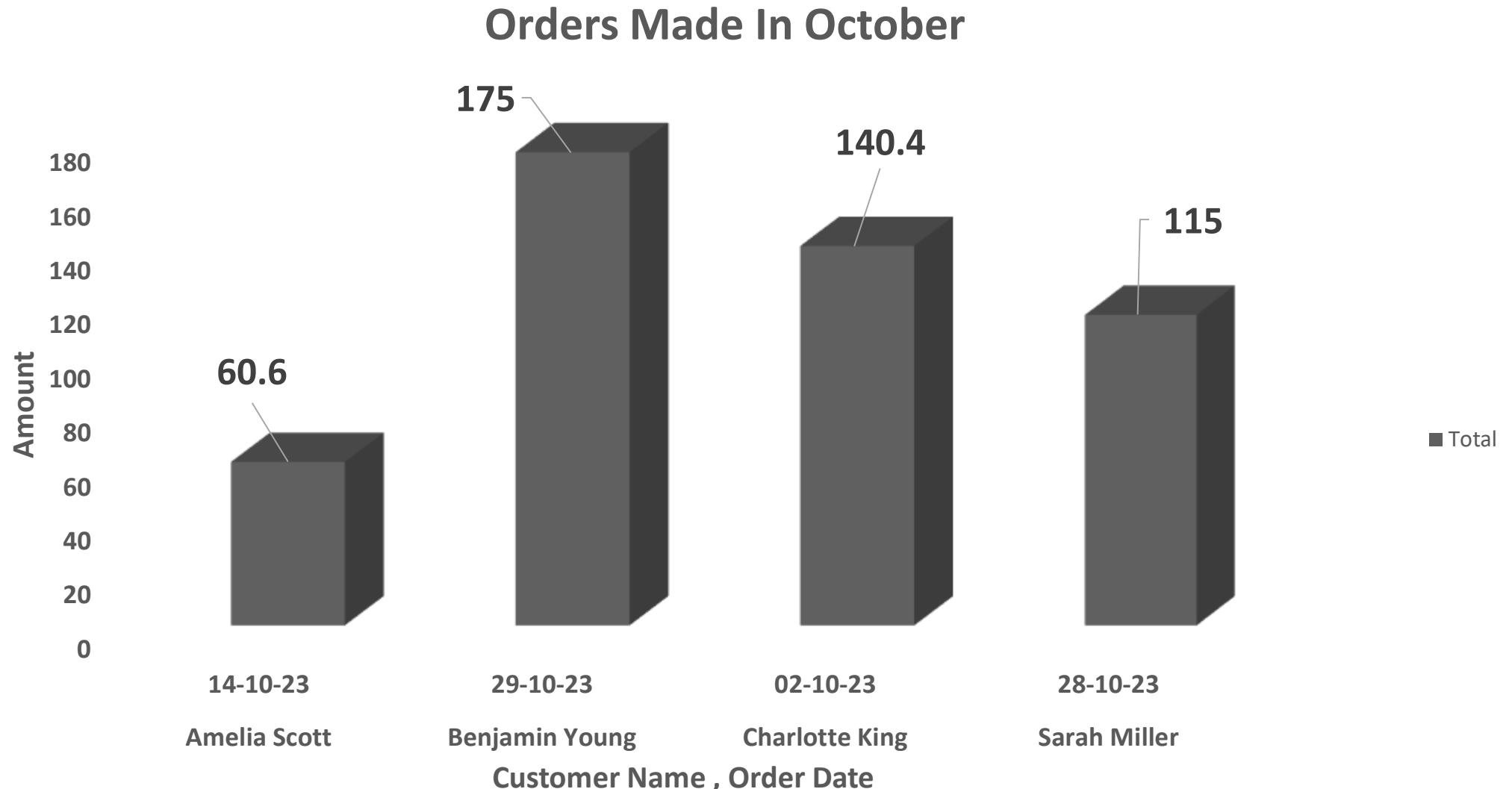
```
SELECT *  
FROM orders  
WHERE MONTH(order_date)='10';
```

Result Table

	order_id	customer_id	order_date	amount
▶	119	18	02-10-23	140.4
	120	19	14-10-23	60.6
	121	20	29-10-23	175
	123	5	28-10-23	115

- Monthly filtering highlights customer activity during that period.
- It shows whether the month had high or low business.

Graphical Representation

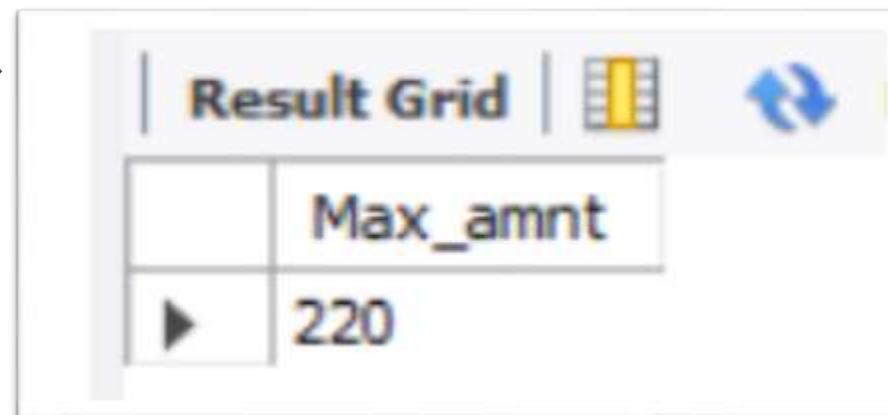


10. Highest order amount.

SELECT

```
MAX(amount) AS Max_amnt  
FROM orders ;
```

Result Table



The screenshot shows a software interface for viewing database results. At the top, it says "Result Grid". Below that is a small toolbar with icons for copy, paste, and refresh. The main area displays a single row in a grid. The first column is empty, and the second column contains the value "220". The column header is "Max_amnt".

	Max_amnt
▶	220

- The largest order stands out clearly compared to the rest.
- It significantly influences total revenue and average order value

11. Customers who spent more than 200 total.

SELECT

```
c.customer_id,  
c.customer_name,  
SUM(o.amount) AS tot_spent  
FROM customers c  
LEFT JOIN orders o  
ON c.customer_id=o.customer_id  
GROUP BY c.customer_id,c.customer_name  
HAVING SUM(o.amount)>200;
```

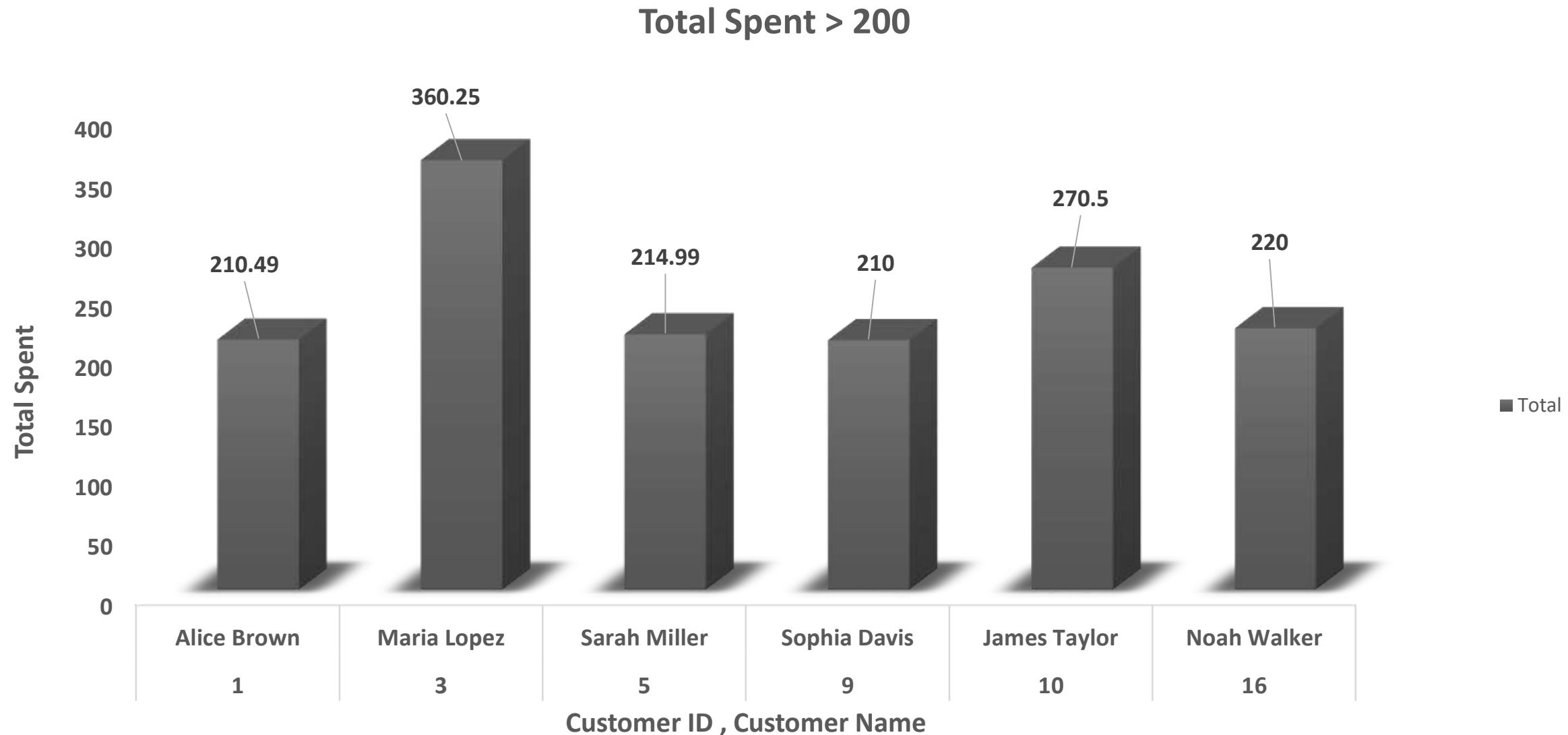
- These customers form the premium spending group.
- Their contributions make up a major percentage of total revenue

Result Table

Result Grid | Filter Rows: _____

	customer_id	customer_name	tot_spent
▶	1	Alice Brown	210.49
	3	Maria Lopez	360.25
	5	Sarah Miller	214.99
	9	Sophia Davis	210
	10	James Taylor	270.5
	16	Noah Walker	220

Graphical Representation



12. Number of orders per customer.

SELECT

```
c.customer_id,  
c.customer_name,  
count(o.order_id) AS orders_count  
FROM customers c  
LEFT JOIN orders o  
ON c.customer_id=o.customer_id  
GROUP BY c.customer_id,c.customer_name;
```

- This analysis helps categorize customers into frequent and infrequent buyers.
- Some customers place multiple orders, Others place only one order.

Result Table

Result Grid | Filter Rows:

	customer_id	customer_name	orders_count
▶	1	Alice Brown	2
	2	David Smith	1
	3	Maria Lopez	2
	4	John Carter	1
	5	Sarah Miller	2
	6	Michael Green	1
	7	Emma Wilson	1
	8	Oliver Jones	1
	9	Sophia Davis	1
	10	James Taylor	2
	11	Isabella Martin	1
	12	Lucas Lee	1
	13	Mia Harris	1
	14	Ethan Clark	2
	15	Ava Lewis	1
	16	Noah Walker	1
	17	Liam Hall	1
	18	Charlotte King	1
	19	Amelia Scott	1
	20	Benjamin Young	1

13. Orders over \$150.

```
SELECT order_id ,amount FROM orders WHERE amount > 150;
```

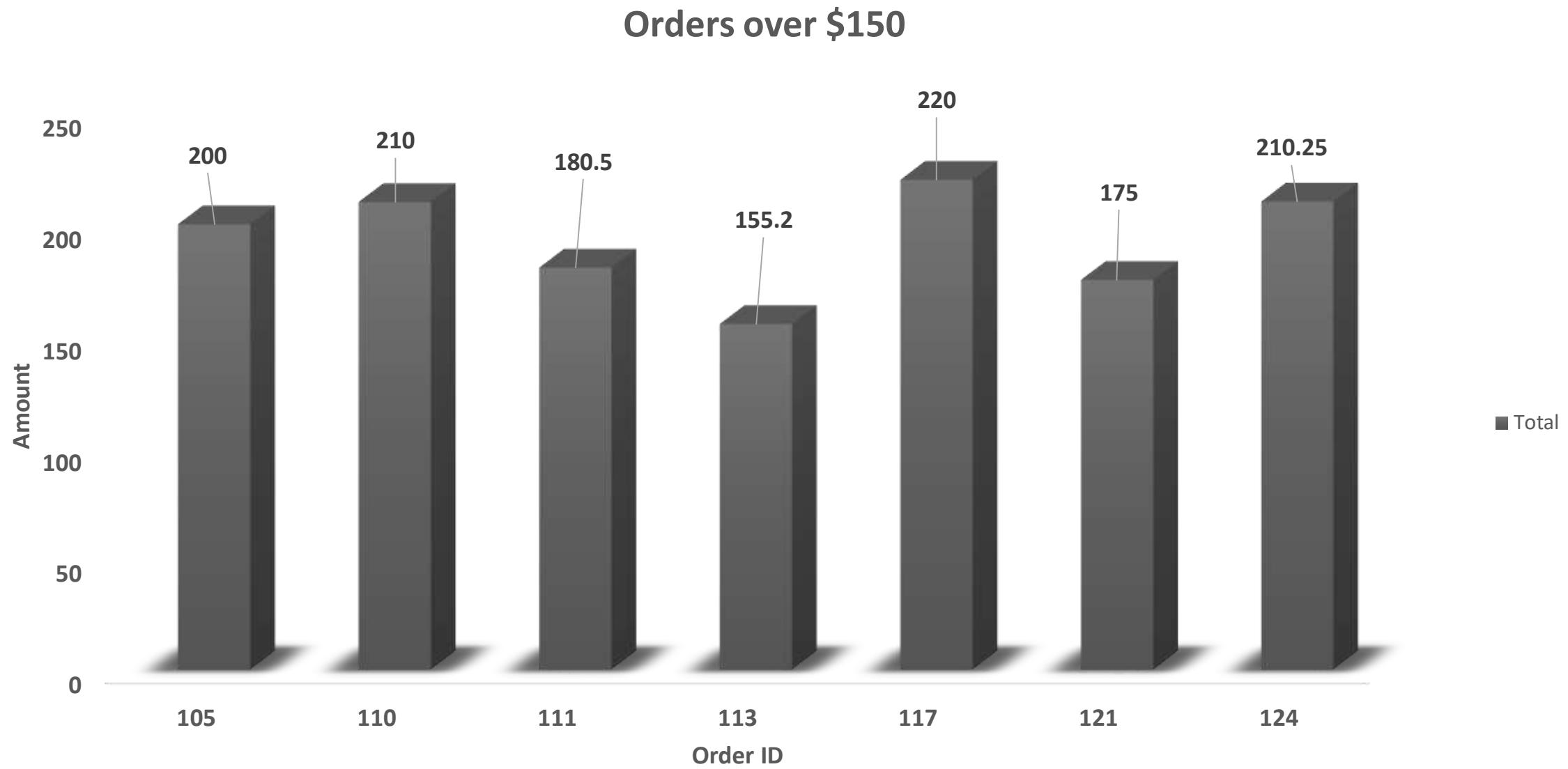
Result Table



	order_id	amount
▶	105	200
	110	210
	111	180.5
	113	155.2
	117	220
	121	175
	124	210.25

- High-value orders contribute disproportionately to total revenue.
- Comparing both tables shows which customers are high-value buyers.

Graphical Representation



14. First 5 customers by signup date.

SELECT

```
customer_id,  
customer_name,  
signup_date  
FROM customers  
ORDER BY signup_date LIMIT 5;
```

Result Table



	customer_id	customer_name	signup_date
▶	5	Sarah Miller	01-04-23
	7	Emma Wilson	01-05-23
	11	Isabella Martin	01-07-23
	13	Mia Harris	01-08-23
	16	Noah Walker	01-09-23

- Early customers often have stronger long-term engagement.
- Their purchasing pattern reveals how early adoption affects spending

15. Last order of each customer.

```
WITH OrderRank AS (
    SELECT customer_id,order_id,amount,
    ROW_NUMBER()
    OVER (PARTITION BY customer_id ORDER BY order_id) AS rn
    FROM Orders
)
SELECT * FROM OrderRank WHERE rn = 2;
```

Result Table



	customer_id	order_id	amount	rn
▶	1	102	89.99	2
	3	124	210.25	2
	5	123	115	2
	10	122	90	2
	14	125	99.99	2

- Recent orders indicate currently active customers.
- Older last-order dates suggest declining engagement

16. Join customer + order details.

```
SELECT
```

```
    c.customer_id,  
    c.customer_name,  
    c.city,  
    c.signup_date,  
    o.order_id,  
    o.customer_id,  
    o.order_date,  
    o.amount
```

```
FROM customers c
```

```
INNER JOIN orders o
```

```
ON c.customer_id = o.customer_id;
```

- Joining both tables shows complete customer activity in one view.
- It reveals which customers are contributing the most to revenue.

Result Table

Result Grid | Filter Rows: Export: Wrap Cell Content:

	customer_id	customer_name	city	signup_date	order_id	customer_id	order_date	amount
▶	1	Alice Brown	New York	12-01-23	101	1	01-03-23	120.5
	1	Alice Brown	New York	12-01-23	102	1	15-04-23	89.99
	2	David Smith	Chicago	05-02-23	103	2	22-03-23	45
	3	Maria Lopez	Houston	20-02-23	104	3	01-04-23	150
	4	John Carter	Miami	15-03-23	105	4	05-04-23	200
	5	Sarah Miller	New York	01-04-23	106	5	12-05-23	99.99
	6	Michael Green	Seattle	10-04-23	107	6	22-05-23	130.75
	7	Emma Wilson	Boston	01-05-23	108	7	01-06-23	67.4
	8	Oliver Jones	Chicago	12-05-23	109	8	15-06-23	89
	9	Sophia Davis	Miami	02-06-23	110	9	02-07-23	210
	10	James Taylor	Houston	15-06-23	111	10	10-07-23	180.5
	11	Isabella Martin	Seattle	01-07-23	112	11	22-07-23	75.99
	12	Lucas Lee	New York	10-07-23	113	12	05-08-23	155.2
	13	Mia Harris	Boston	01-08-23	114	13	15-08-23	54.9
	14	Ethan Clark	Houston	11-08-23	115	14	25-08-23	95
	15	Ava Lewis	Chicago	20-08-23	116	15	01-09-23	102.75
	16	Noah Walker	Miami	01-09-23	117	16	10-09-23	220
	17	Liam Hall	Seattle	12-09-23	118	17	22-09-23	80.25
	18	Charlotte King	New York	01-10-23	119	18	02-10-23	140.4
	19	Amelia Scott	Boston	12-10-23	120	19	14-10-23	60.6
	20	Benjamin Young	Houston	25-10-23	121	20	29-10-23	175
	10	James Taylor	Houston	15-06-23	122	10	02-11-23	90
	5	Sarah Miller	New York	01-04-23	123	5	28-10-23	115
	3	Maria Lopez	Houston	20-02-23	124	3	11-11-23	210.25
	14	Ethan Clark	Houston	11-08-23	125	14	12-11-23	99.99

17. Total revenue per city.

SELECT

```
c.city, SUM(o.amount) AS total_revenue FROM Customers c  
INNER JOIN Orders o  
ON c.customer_id = o.customer_id GROUP BY c.city;
```

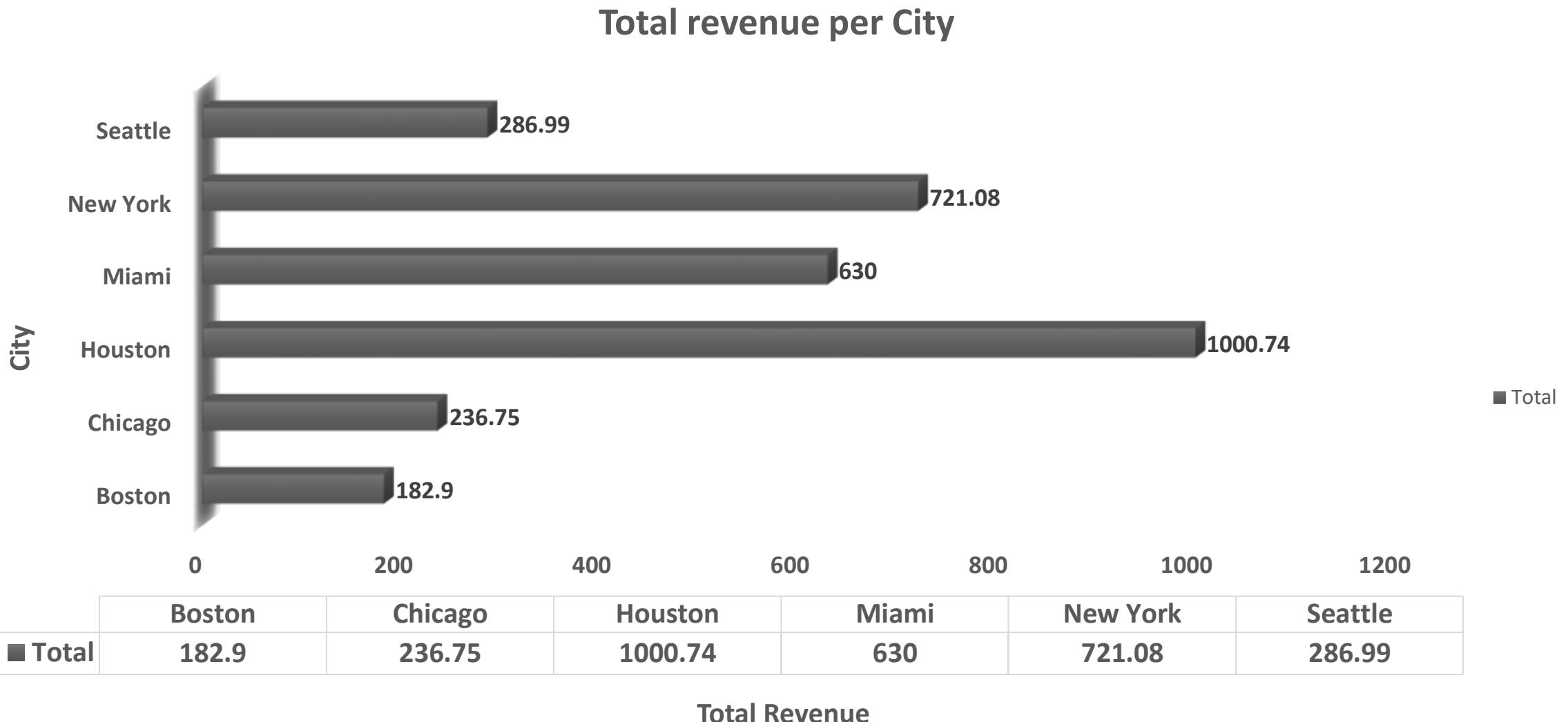
Result Table



city	total_revenue
New York	721.08
Chicago	236.75
Houston	1000.74
Miami	630
Seattle	286.99
Boston	182.9

- Revenue differs based on where more active customers are.
- Some locations have fewer customers but higher spending.

Graphical Representation



18. Customers who joined after July.

SELECT

```
customer_id,  
customer_name,  
city,  
signup_date  
FROM customers  
WHERE MONTH(signup_date)>7;
```

- These newer customers show how quickly new users convert into buyers.
- Comparing their orders reveals early engagement levels.

Result Table



	customer_id	customer_name	city	signup_date
▶	13	Mia Harris	Boston	01-08-23
	14	Ethan Clark	Houston	11-08-23
	15	Ava Lewis	Chicago	20-08-23
	16	Noah Walker	Miami	01-09-23
	17	Liam Hall	Seattle	12-09-23
	18	Charlotte King	New York	01-10-23
	19	Amelia Scott	Boston	12-10-23
	20	Benjamin Young	Houston	25-10-23

19. Monthly order revenue.

SELECT

```
MONTH(order_date) AS month_num,  
SUM(amount)  
FROM orders GROUP BY month_num ;
```

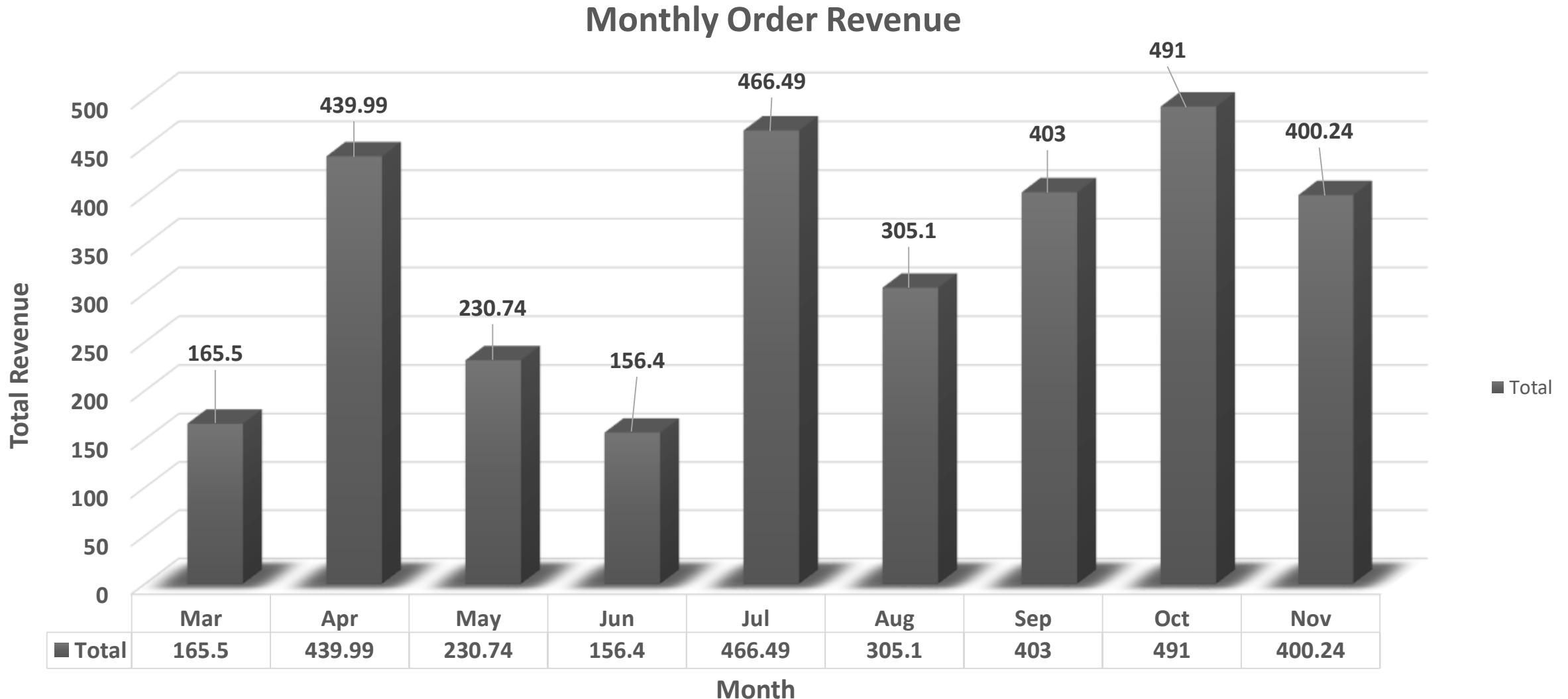
Result
Table



	month_num	SUM(amount)
▶	3	165.5
	4	439.99
	5	230.74
	6	156.4
	7	466.49
	8	305.1
	9	403
	10	491
	11	400.24

- Revenue varies month to month based on customer activity.
- Some months show clear spikes, driven by multiple high-value orders.
- Other months show fewer orders.

Graphical Representation

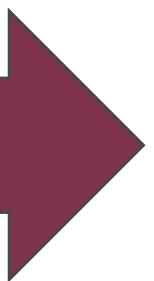


20. Find duplicate city names.

SELECT

```
city,  
count(*) AS Dup_city_names  
FROM customers  
GROUP BY city  
HAVING count(*)>1;
```

Result
Table



	city	Dup_city_names
▶	New York	4
	Chicago	3
	Houston	4
	Miami	3
	Seattle	3
	Boston	3

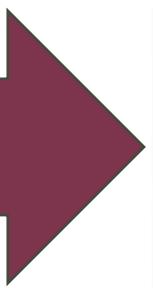
- The duplication highlights key areas of customer presence.
- This cluster often results in higher total order volume.

21. Top 5 highest spending customers.

SELECT

```
c.customer_id,  
c.customer_name,  
SUM(o.amount) AS total_spent  
FROM customers c  
INNER JOIN orders o  
ON c.customer_id=o.customer_id  
GROUP BY c.customer_id,c.customer_name  
ORDER BY total_spent DESC LIMIT 5;
```

Result
Table

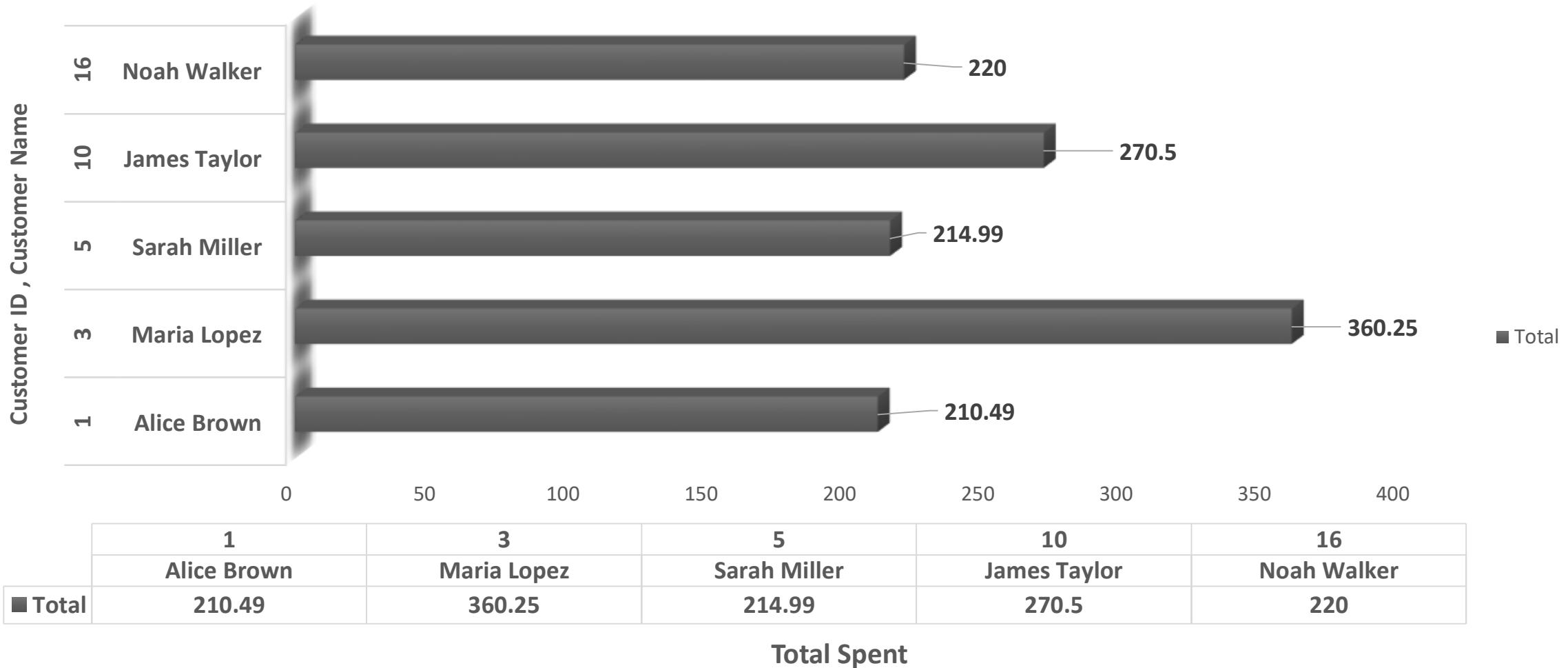


	customer_id	customer_name	total_spent
▶	3	Maria Lopez	360.25
	10	James Taylor	270.5
	16	Noah Walker	220
	5	Sarah Miller	214.99
	1	Alice Brown	210.49

- These customers contribute the majority of the total revenue.
- The ranking highlights clear differences in spending behavior.

Graphical Representation

Top 5 Highest Spent Customers



22. Orders sorted by amount (descending).

SELECT

```
c.customer_id,  
c.customer_name,  
o.order_id,  
o.amount  
FROM customers c  
INNER JOIN orders o  
ON c.customer_id=o.customer_id  
ORDER BY o.amount DESC;
```

- Sorting highlights the gap between low and high-value orders.
- Largest orders appear at the top, showing premium transactions.

Result Table

Result Grid | Filter Rows: | Export:

	customer_id	customer_name	order_id	amount
▶	16	Noah Walker	117	220
	3	Maria Lopez	124	210.25
	9	Sophia Davis	110	210
	4	John Carter	105	200
	10	James Taylor	111	180.5
	20	Benjamin Young	121	175
	12	Lucas Lee	113	155.2
	3	Maria Lopez	104	150
	18	Charlotte King	119	140.4
	6	Michael Green	107	130.75
	1	Alice Brown	101	120.5
	5	Sarah Miller	123	115
	15	Ava Lewis	116	102.75
	5	Sarah Miller	106	99.99
	14	Ethan Clark	125	99.99
	14	Ethan Clark	115	95
	10	James Taylor	122	90
	1	Alice Brown	102	89.99
	8	Oliver Jones	109	89
	17	Liam Hall	118	80.25
	11	Isabella Martin	112	75.99
	7	Emma Wilson	108	67.4
	19	Amelia Scott	120	60.6
	13	Mia Harris	114	54.9
	2	David Smith	103	45

23. Customers and their total number of orders (0 included).

SELECT

```
c.customer_id,  
c.customer_name,  
COUNT(o.order_id) AS tot_orders  
FROM customers c  
LEFT JOIN orders o  
ON c.customer_id=o.customer_id  
GROUP BY c.customer_id,c.customer_name;
```

- Combines data to show both active and inactive customers.
- Highlights customers who signed up but never purchased.

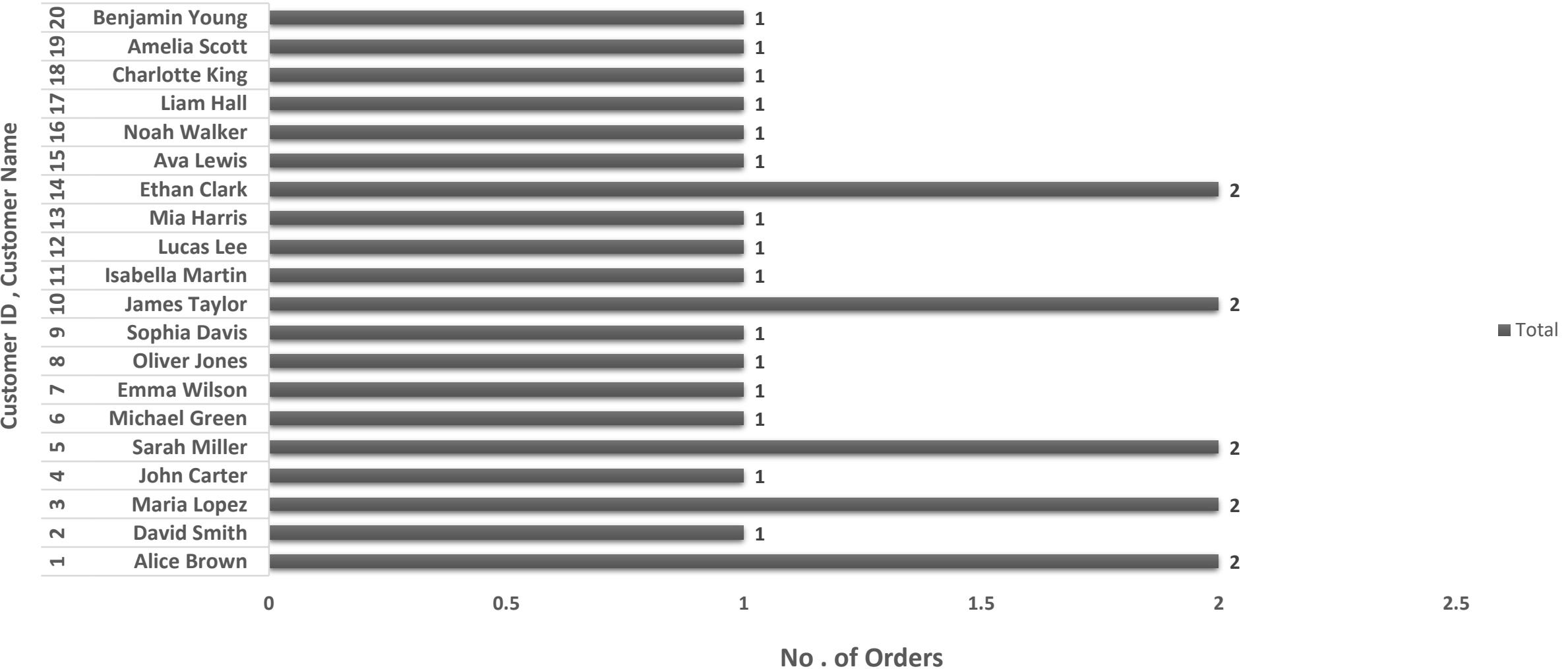
Result Table

Result Grid | Filter Rows: Export:

	customer_id	customer_name	tot_orders
▶	1	Alice Brown	2
	2	David Smith	1
	3	Maria Lopez	2
	4	John Carter	1
	5	Sarah Miller	2
	6	Michael Green	1
	7	Emma Wilson	1
	8	Oliver Jones	1
	9	Sophia Davis	1
	10	James Taylor	2
	11	Isabella Martin	1
	12	Lucas Lee	1
	13	Mia Harris	1
	14	Ethan Clark	2
	15	Ava Lewis	1
	16	Noah Walker	1
	17	Liam Hall	1
	18	Charlotte King	1
	19	Amelia Scott	1
	20	Benjamin Young	1

Graphical Representation

Number of Orders by Each Customer



24. Rank customers by spending (window function).

SELECT

```
c.customer_id,  
c.customer_name,  
SUM(o.amount) AS total_spent,  
DENSE_RANK() OVER (  
    ORDER BY SUM(o.amount) DESC  
) AS spend_rank  
FROM customers c  
JOIN orders o  
    ON c.customer_id = o.customer_id  
GROUP BY  
    c.customer_id,  
    c.customer_name  
ORDER BY total_spent DESC;
```



- Ranking showcases which customers contribute most to revenue.
- It highlights spending differences not visible in raw data.

Result Table

Result Grid | Filter Rows: Export: | Wrap

	customer_id	customer_name	total_spent	spend_rank
▶	3	Maria Lopez	360.25	1
	10	James Taylor	270.5	2
	16	Noah Walker	220	3
	5	Sarah Miller	214.99	4
	1	Alice Brown	210.49	5
	9	Sophia Davis	210	6
	4	John Carter	200	7
	14	Ethan Clark	194.99	8
	20	Benjamin Young	175	9
	12	Lucas Lee	155.2	10
	18	Charlotte King	140.4	11
	6	Michael Green	130.75	12
	15	Ava Lewis	102.75	13
	8	Oliver Jones	89	14
	17	Liam Hall	80.25	15
	11	Isabella Martin	75.99	16
	7	Emma Wilson	67.4	17
	19	Amelia Scott	60.6	18
	13	Mia Harris	54.9	19
	2	David Smith	45	20

25. Running total of order amounts (window function).

SELECT

```
c.customer_id,  
c.customer_name,  
o.order_id,  
o.amount,  
SUM(o.amount) OVER(  
    ORDER BY o.order_date  
) AS running_total
```

FROM customers c
JOIN orders o
ON c.customer_id = o.customer_id;

- Cumulative revenue shows how earnings build over time.
- This trend helps identify the most impactful transactions.

Result Table

Result Grid | Filter Rows: Export: Wrap

	customer_id	customer_name	order_id	amount	running_total
▶	1	Alice Brown	101	120.5	120.5
	3	Maria Lopez	104	150	270.5
	7	Emma Wilson	108	67.4	337.9
	15	Ava Lewis	116	102.75	440.65
	9	Sophia Davis	110	210	650.65
	18	Charlotte King	119	140.4	791.05
	10	James Taylor	122	90	881.05
	4	John Carter	105	200	1081.05
	12	Lucas Lee	113	155.2	1236.25
	10	James Taylor	111	180.5	1416.75
	16	Noah Walker	117	220	1636.75
	3	Maria Lopez	124	210.25	1847
	5	Sarah Miller	106	99.99	1946.99
	14	Ethan Clark	125	99.99	2046.98
	19	Amelia Scott	120	60.6	2107.58
	1	Alice Brown	102	89.99	2197.56999...
	8	Oliver Jones	109	89	2286.56999...
	13	Mia Harris	114	54.9	2341.47
	2	David Smith	103	45	2386.47
	6	Michael Green	107	130.75	2517.22
	11	Isabella Martin	112	75.99	2593.20999...
	17	Liam Hall	118	80.25	2673.45999...
	14	Ethan Clark	115	95	2768.45999...
	5	Sarah Miller	123	115	2883.45999...
	20	Benjamin Young	121	175	3058.45999...

*Thank
you*