```
import pandas as pd

df = pd.read_csv('ecommerce_customer_data_custom_ratios.csv')
df.head()
```

	Customer ID	Purchase Date	Product Category	Product Price	Quantity	Total Purchase Amount	Payment Method	Customer Age	Returns	Customer Name	Age	Gender	Churn
0	46251	2020-09-08 09:38:32	Electronics	12	3	740	Credit Card	37	0.0	Christine Hernandez	37	Male	0
1	46251	2022-03-05 12:56:35	Home	468	4	2739	PayPal	37	0.0	Christine Hernandez	37	Male	0
2	46251	2022-05-23 18:18:01	Home	288	2	3196	PayPal	37	0.0	Christine Hernandez	37	Male	0
		2020-11-								Christine			

Customer Behavior Analysis – Alfido Tech

This project analyzes customer transaction data to identify purchasing patterns, customer segments, and churn risks. The goal is to provide actionable insights to improve customer engagement and retention.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250000 entries, 0 to 249999
Data columns (total 13 columns):
 #   Column                 Non-Null Count   Dtype  
---  ------                 --------------   -----  
 0   Customer ID            250000 non-null  int64  
 1   Purchase Date          250000 non-null  object 
 2   Product Category       250000 non-null  object 
 3   Product Price          250000 non-null  int64  
 4   Quantity               250000 non-null  int64  
 5   Total Purchase Amount  250000 non-null  int64  
 6   Payment Method         250000 non-null  object 
 7   Customer Age           250000 non-null  int64  
 8   Returns                202404 non-null  float64
 9   Customer Name          250000 non-null  object 
 10  Age                    250000 non-null  int64  
 11  Gender                 250000 non-null  object 
 12  Churn                  250000 non-null  int64  
dtypes: float64(1), int64(7), object(5)
memory usage: 24.8+ MB
```

```
df.describe()
```

	Customer ID	Product Price	Quantity	Total Purchase Amount	Customer Age	Returns	Age	Churn
count	250000.00000	250000.000000	250000.000000	250000.000000	250000.000000	202404.000000	250000.000000	250000.000000
mean	25004.03624	254.659512	2.998896	2725.370732	43.940528	0.497861	43.940528	0.199496
std	14428.27959	141.568577	1.414694	1442.933565	15.350246	0.499997	15.350246	0.399622
min	1.00000	10.000000	1.000000	100.000000	18.000000	0.000000	18.000000	0.000000
25%	12497.75000	132.000000	2.000000	1477.000000	31.000000	0.000000	31.000000	0.000000
50%	25018.00000	255.000000	3.000000	2724.000000	44.000000	0.000000	44.000000	0.000000
75%	37506.00000	377.000000	4.000000	3974.000000	57.000000	1.000000	57.000000	0.000000

```
df.columns = df.columns.str.lower().str.replace(" ", "_")
df.isnull().sum()
```

	0
customer_id	0
purchase_date	0
product_category	0
product_price	0
quantity	0
total_purchase_amount	0
payment_method	0
customer_age	0
returns	47596
customer_name	0
age	0
gender	0
churn	0

dtype: int64

```
df['purchase_date'] = pd.to_datetime(df['purchase_date'])
df['revenue'] = df['product_price'] * df['quantity']
df['month'] = df['purchase_date'].dt.month
```

```
import datetime as dt

snapshot_date = df['purchase_date'].max() + dt.timedelta(days=1)

rfm = df.groupby('customer_id').agg({
    'purchase_date': lambda x: (snapshot_date - x.max()).days,
    'customer_id': 'count',
    'revenue': 'sum'
})

rfm.columns = ['recency', 'frequency', 'monetary']
rfm.head()
```

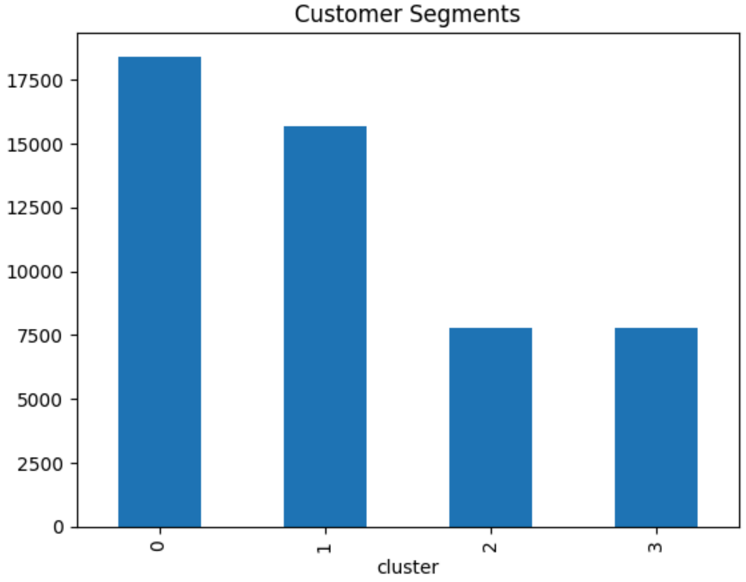
	recency	frequency	monetary
customer_id			
1	58	1	845
2	299	3	1070
3	89	8	5041
4	127	4	1433
5	171	8	7881

```
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

scaler = StandardScaler()
rfm_scaled = scaler.fit_transform(rfm)

kmeans = KMeans(n_clusters=4, random_state=42)
rfm['cluster'] = kmeans.fit_predict(rfm_scaled)

rfm.head()
```

	recency	frequency	monetary	cluster
customer_id				
1	58	1	845	1
2	299	3	1070	1
3	89	8	5041	2
4	127	4	1433	1
5	171	8	7881	2

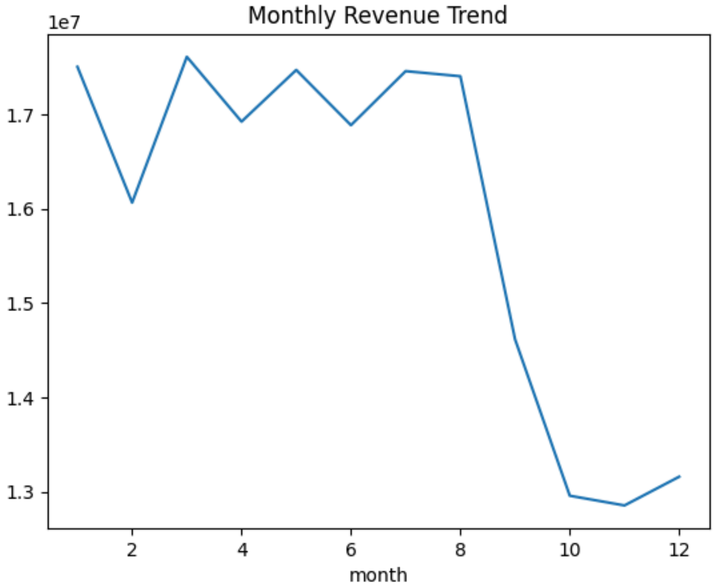
```
rfm['cluster'].value_counts().plot(kind='bar', title='Customer Segments')
```

```
<Axes: title={'center': 'Customer Segments'}, xlabel='cluster'>
```




```
df.groupby('month')['revenue'].sum().plot(title='Monthly Revenue Trend')
```

```
<Axes: title={'center': 'Monthly Revenue Trend'}, xlabel='month'>
```



Key Insights

- High-value customers contribute the most revenue.
- Certain clusters show churn risk due to low frequency and high recency.
- Monthly revenue shows seasonal purchasing trends.

Recommendations for Alfido Tech

1. Launch loyalty programs for high-value customers.
2. Re-engage at-risk customers with targeted offers.
3. Personalize marketing campaigns using customer segments.
4. Improve customer experience for repeat purchases.
5. Monitor churn indicators to retain customers early.

Conclusion

This analysis helped identify customer segments, purchasing patterns, and churn risks. These insights can help Alfido Tech improve customer retention, engagement, and overall business growth.

```
Start coding or generate with AI.
```