

E-Commerce Sales Analysis Dashboard: Real-Time Analytics for Business Growth

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Abstract— Developing a real-time analytics dashboard that enables e-commerce businesses to track and optimize sales, customer behaviour, and marketing strategies for data-driven decision-making. The dashboard includes sales tracking (total revenue, orders, conversion rates), customer insights (new vs. returning customers, lifetime value), product performance (best-selling items, inventory levels), marketing analysis (traffic sources, ad performance), and operational efficiency metrics (order processing, returns, shipping). The system leverages real-time APIs and data streaming technologies to provide live updates on key performance indicators (KPIs), enabling businesses to adjust their strategies quickly. Data visualization tools like Power BI enhance usability and decision-making.

By offering real-time sales analytics, customer segmentation, and marketing ROI tracking, the dashboard helps businesses identify growth opportunities, reduce inefficiencies, and improve overall customer engagement, leading to increased profitability. The product performance module helps businesses understand what products are the best sellers, how much inventory they have left, and what the return rates look like, ensuring they understand product life cycle and stock management. The dashboard is combined with marketing analytics, allowing for insights on click-through rates and other variables based on traffic source (organic, paid, social, referral). It determines response and key performance indicators for campaigns and ads, including return on ad spend (ROAS) and cost per acquisition (CPA), to support marketing teams in better spending and high performance. The information in the dashboard extends across operational efficiency metrics, including order processing times, shipping times, return rates, and fulfillment accuracy, and KPIs, providing operational teams with critical bottleneck information, and providing insight on logistics workflows and customer service.

Index Terms—Machine learning, K-means clustering, E-commerce, RFM model, Customer Segmentation, Customer Behaviour analysis, Data-driven decision making, Sales performance tracking, Marketing ROI.

I. INTRODUCTION

Global e-commerce industry has experienced exponential growth, leading to increased competition among businesses. To remain competitive, companies must leverage real-time data analytics to monitor performance, understand customer preferences, and optimize sales strategies. Many businesses rely on static reports, manual data analysis, or outdated business intelligence tools, which lead to delayed insights and slow decision-making. These inefficiencies can result in lost revenue opportunities, poor customer retention, and ineffective marketing campaigns. The E-commerce Sales Analysis Dashboard is designed to provide businesses with real-time visibility into their sales metrics, customer behavior, product performance, and operational efficiency. Metrics are useful for spotting sales trends, tracking progress toward targets, and quickly reacting to revenue changes. Customer insights provide you with more data to analyze "new vs. returning customers," CLV (Customer Lifetime Value), geographic purchasing patterns, among others. Customer insights enable you to better understand customer segmentation and personalization opportunities, and to enhance retention activities.

Real-Time Sales Tracking: Monitors revenue, order volume, conversion rates, and average order value.
Customer Insights: Analyze new vs. returning customers, customer lifetime value (CLV), and geographical trends. The E-commerce Sales Analysis Dashboard addresses this challenge by providing real-time insights into key business areas, including sales performance, customer behavior, marketing effectiveness, product demand, and operational efficiency. By integrating with multiple data sources such as payment gateways, web analytics tools, e-commerce platforms, and CRM/ERP systems, the dashboard enables businesses to track and optimize their sales strategies. Businesses can monitor revenue

fluctuations, identify best-selling products, and analyze customer segments based on purchasing behavior. Additionally, the dashboard provides insights into marketing campaign performance by evaluating traffic sources, conversion rates, and customer acquisition costs, ensuring efficient budget allocation. The E-commerce Sales Analysis Dashboard is a game-changer for businesses looking to enhance operational efficiency and drive growth. Analyzing product performance with the dashboard provides e-commerce businesses with insights into their best-sellers, current inventory levels, and product rate of returns that enables them to plan inventory and make merchandising decisions with greater confidence. Additionally, the marketing analytics portion assess the performance of campaign activity from several resource origins, conversion rate, cost-per-customer acquisition, etc. so that marketers can fine-tune campaign activity and budget allocation. The operational metrics that measure shipping time, order processing time, or return frequency, can identify bottleneck challenges in the fulfillment processes and optimize logistics.

The dashboard utilizes 'hot' live data sources stream through outage-proof technologies like Apache Kafka or Amazon Kinesis that auto-update and continuously stream data structures that build operational and marketing analytics in real-time. This way, an e-commerce business can measure, monitor and share 'live insights' that supports faster and wiser decision-making based on live data sources. The dashboard, augmented with powerful visual analytics tools like Power BI or Tableau, produce complex data in an intuitive and interactive way. As such, it ensures all stakeholders in the process - from marketing teams to executive management - have access to the information they need, allowing them to contextualize metrics to take action without hindrance. In summary, the E-Commerce Sales Analysis Dashboard is a transformative framework for the modern e-commerce business. It keeps them competitive by providing a holistic view of their e-commerce operations while enabling real-time data-driven, decision-making activity. If they leverage the technology effectively, e-commerce business will attain an approximate increased level of visibility.

II. LITERATURE SURVEY

Sari JN, Nugroho LE, Ferdiana R, Santosa PI^[1] highlights the importance of behavioral

segmentation, which is the classification of consumers based on their interactions with the brand, including purchase and historical research. However, these methods are still limited due to their static nature and cannot be transferred to real data.

Rajput, L., and Singh,^[2] demonstrated the Effectiveness of clustering algorithms such as K-word and Hierarchical cluster formation in identification specific customers based on complex data. Additionally, collaborating methods show promise in improving segmentation accuracy by combining predictions from multiple models.

Vamsee, Ch Sai, D. Rakesh, I. Prathyusha, B. Dinesh, and Ch Bharathi.^[3] points out, recent. advances in data analytics highlight the importance of real-time data integration, including the Internet of Things and social media. This change constantly shifts the customer base, allowing businesses to respond quickly to changing customer behaviours.

Zhang, J. and Li, J^[4] illustrates the connection between advanced segmentation techniques and improved customer experience.

Alves Gomes, Miguel, and Tobias Meisen ^[5], Traditional mass marketing in this sector is becoming less and less relevant as customer-specific targeting becomes feasible due to the introduction of one-customer strategies, particularly in e-commerce. Developing a fundamental understanding of each customer's interests and motivations is crucial when using this strategy. Kumar, Amit.^[6] Standard Recency, Frequency, and Financial (RFM) analysis is contrasted with Deep LimeSeg. Based on its mathematical modelling, the RFM evaluation divides up its clientele according to the frequency, monetary value, and recency of their purchases.

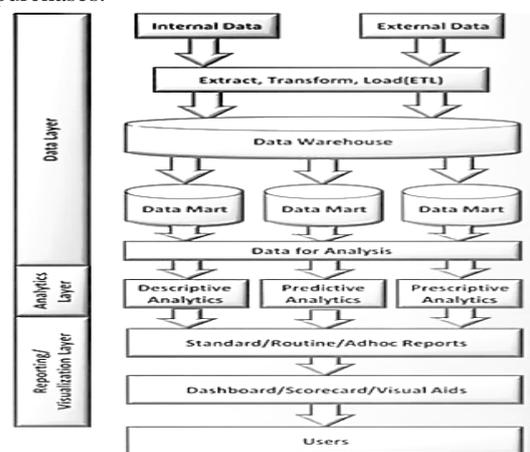


Fig.1. Architecture Workflow

III. METHODOLOGY

The E-Commerce Sales Analysis Dashboard is designed with a rigorous methodology that supports the provision of continuous, real-time, data-driven insights to segment customers and grow business. The methodology starts with data cleaning and collection, which involves pulling the critical customer data (e.g., purchase history, demographics, and engagement metrics) from the e-commerce website. Exploratory data analysis (EDA) is carried out, within the dashboard to find patterns, trends, and market or customer behavior that can be used to develop business or market strategy after the raw data has been validated, cleaned, transformed, and loaded to ensure data consistency and quality. In order to segment customers and predict their future behavior, the methodology uses machine learning techniques like segmentation clustering algorithms (e.g., K-Means, DBSCAN) and classification techniques (e.g., decision tree, SVM). Highlighting data and feature engineering techniques are also used to enhance the data set with valuable features to improve the models performance. Model evaluation includes using metrics for clustering (silhouette score) and for classification (accuracy, precision and recall). The insights available on the dashboard can be visualized in the dashboard that enables real-time, live monitoring and analysis of customer segments. The dashboard can also facilitate A/B testing of personalized marketing campaigns to investigate the impact on customer engagement and conversion of targeted marketing campaigns. By integrating predictive models, the system will enable marketing strategies that nurture customers by predicting customer behaviours such as purchase and churn risk. The outputs produced by these models are easily integrated into the dashboard, where users can monitor customer segments, observe behavioral shifts, and analyze purchase patterns through real-time visualizations. The data can be used to observe customer clusters with each segment's performance over time, or how segments respond to various marketing strategies. A particularly advanced and useful feature of dashboards is it allows for A/B testing of personalized marketing campaigns.

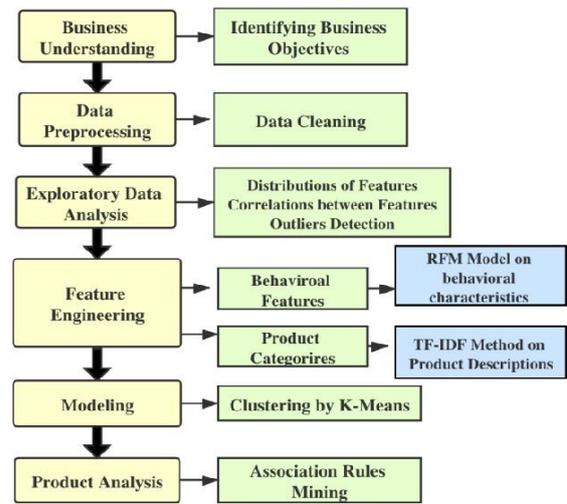


Fig.2.Build and Deployment

```

df1.head()
  country  id week_year  revenue  units
0      KR  702234    03.2019    808.08    1
1      KR  702234    06.2019   1606.80    2
2      KR  3618438   08.2019    803.40    1
3      KR  3618438   09.2019    803.40    1
4      KR  3618438   09.2019    803.40    1

df1.tail()
  country  id week_year  revenue  units
235569  CN  2452476    27.2020   41160.0    200
235570  CN  2452476    27.2020   50856.0    400
235571  CN  2452476    27.2020   79920.0   1200
235572  CN  4553904    27.2020    4788.0    100
235573  CN  4553904    27.2020    4188.0    100
  
```

Fig.3: Data-Set

Users can create different campaigns and launch them across different customer segments, capturing immediate impact on engagement, conversion rates, and revenue. This presents the opportunity to adapt effectively and continuously optimize marketing based on actual customer behaviour. When predictive analytics into the dashboard is included, it can be more than a reporting tool - it can become a business assistant. Dashboards can provide predictions of customer churn likelihood, identify upselling and cross-selling prospects, and even predict the likelihood of purchase in a given time frame. This enables marketing and sales teams to be proactive with immediate and targeted actions to influence customer retention, conversion rates, and sustainable business growth.

IV. IMPLEMENTATION

An Indian e-commerce website provides the e-commerce sales dataset that we are using. We obtained it from Kaggle. We are primarily using two significant data sets that we are considering: Order list.

Order List: The purchase data is contained in this data set. It contains data like ID, purchase date, and

customer information. Order Information: Since clustering will be done using the K-Prototypes algorithm and the dataset will contain a mix of data types, including objects and categorical data, this data set includes the following information for order ID: order price, quantity, profit, and product category. a new data frame called "df_merged" that is produced by joining the columns of the two datasets and removing a few columns. There are ten columns and 1500 rows. Additional implementation code eliminates a few of those superfluous columns and removes the ones that are required.

Since K-Prototype cannot handle missing values or duplicate rows, data exploration entails importing the data set, importing the required libraries, and looking for missing values and duplicate rows. Next, look for distinct data distributions in the dataset to gain a thorough understanding before using various algorithms for clustering. Upon examining the e-commerce dataset, it was able to analyze various customer trends. The investigations are shown in the form of histograms and count plots below. After that, the data is changed to give each customer a score based on the purchases he has made. Prior to that, we will develop the new features "frequency" and "recency," while maintaining the previously developed "monetary" feature.

```
df1.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 235574 entries, 0 to 235573
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ---
 0   country    235574 non-null object
 1   id         235574 non-null int64
 2   week_year  235574 non-null object
 3   revenue    235574 non-null float64
 4   units      235574 non-null int64
dtypes: float64(1), int64(2), object(2)
memory usage: 9.0+ MB

[ ] # Splitting 'week_year' column on '.' and creating 'week' and 'year' columns
df1['week'] = df1['week_year'].astype(str).str.split('.')[0]
df1['year'] = df1['week_year'].astype(str).str.split('.')[1]
```

Fig.4: Data-Exploration

For each customer, recency will be the bare minimum of "days_since_last_purchase". The total number of orders placed by each customer during the period will be the frequency. Monetary will be the sum of each customer's purchases during that time. Since the most recent date, we will focus on sales over the previous 365 days. TIP: Customers from different countries may have the same "id." The monetary values become inaccurate as a result. To achieve this, we will implement a new feature: a distinct 'id+' identifier that combines the customer's country code.

```
segment_map = {
    r'^22$': 'hibernating',
    r'^1[-2][1-2]$': 'lost',
    r'^15$': 'can't lose',
    r'^1[-2][3-5]$': 'at risk',
    r'^3[1-2]$': 'about to sleep',
    r'^33$': 'need attention',
    r'^55$': 'champions',
    r'^3[-5][4-5]$': 'loyal customers',
    r'^41$': 'promising',
    r'^51$': 'new customers',
    r'^4[-5][2-3]$': 'potential loyalists'
}

rfm['segment'] = rfm['r'].map(str) + rfm['f'].map(str)
rfm['segment'] = rfm['segment'].replace(segment_map, regex=True)
rfm.head()
```

Fig.5: Data-Transformation

The optimal number of 'K', where K is the number of clusters, is found using the Elbow method. The K-Prototype Algorithm offers a 'Cost' function that incorporates the computation of mixed variables, in contrast to the K-Means and certain other clustering algorithms that compute WSSE (Within Sum-of-Squares Errors) using Euclidean distance. We plot the results of the elbow method.

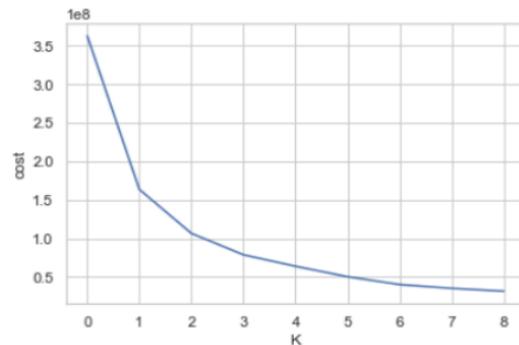


Fig.6: Elbow Method

In K-Prototypes, as done in K-Means, the goal is to find the point on the cost curve where further K is not resulting in an improvement in clustering performance. This inflection point represent the optimum K to help make certain trade-offs between interpretability versus data granularity when describing customer segments. By defining the optimum value of K using the Elbow Method in combination with K-Prototypes, we can construct customer segments that represent purchasing behaviour, demographics, and preferences in a coherent way, and use those segments for targeted marketing, personalized recommendations.

V. RESULTS AND DISCUSSIONS

The outcomes of the aforementioned implementation are presented and discussed. First, the outcomes of the first module's customer segmentation of the E-

Commerce Dataset using the K-Prototypes algorithm. Second, there are other clustering algorithms that use the same data set but simply rename it differently depending on the situation.

Increase customer engagement:

One of the immediate and obvious benefits of using advanced segmentation is improved customer experience.

RFM Segmentation Analysis:

RFM Score Calculation: The RFM model scores customers on three key dimensions based on their purchasing behavior: The measure is when the buyer last made a purchase.

Increased ROI for your business:

The main benefit of high-end consumer products is significantly improving your business's ROI. Traditional mass marketing often wastes resources by targeting the wrong audience with irrelevant content.

Conversion rate and bigger sales:

Using machine learning models for segmentation is directly correlated to conversion rate. Businesses can improve business performance by providing personalized recommendations and suggestions to customers.

Inventory and Supply Chain Optimization:

High-level segmentation allows businesses to improve their inventory and products by providing better insights into purchasing patterns.

Efficiency of the Proposed System:

The proposed system is highly efficient in optimizing e-commerce customer segmentation through data analytics and machine learning. It processes large volumes of customer data quickly, thanks to scalable cloud infrastructure and well-optimized machine learning algorithms. By employing advanced clustering techniques and predictive models, the system accurately segments customers based on behavior and preferences, leading to highly targeted and relevant marketing efforts.

Data Exploration

For greater visibility in the plots we convert the dates to monthly periods:

```
df2c = df2b.to_period("M")
```

```
df2c.head()
```

	country	id	monetary	units
date				
2019-01	KR	702234	808.08	1
2019-02	KR	702234	1606.80	2
2019-02	KR	3618438	803.40	1
2019-03	KR	3618438	803.40	1
2019-03	KR	3618438	803.40	1

We aggregate the units and revenue of the same period.

Fig.7: Aggregated Data

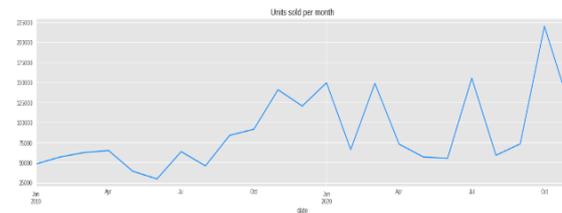


Fig.8: Unit Chart

The scores given by RFM classify the customers into different groups and help in understanding their behavior. Then, according to those scores, marketing strategies are designed. Champions are the customers with the highest Recency, Frequency, and Finance scores. It shows that they shop very frequently, spend a lot of money, and have bought recently. Such customers can be rewarded for their participation through loyalty programs or special discounts. The frequency and even recent shopping behavior of loyal customers with the average money score accounting for consistency and even recent shopping habits. It further strengthens their confidence by personal motivation. On the other hand, "risky customers" have high values but have not made any recent purchases. These customers will require an integrated strategy including special offers or discounts to bring them back into the cycle of purchasing. Each section has details regarding strategic planning and insurance. Using machine learning models in segmentation directly relates to conversion rate. Businesses enhance their business performance through personal recommendations and suggestions made to the customers. For example, e-commerce sites that make tailored recommendations by search patterns, purchase history, and customer demographics would show more engagement and products bought.

	id	country	recency	frequency	monetary	r	f	m	rfm_score	fm
0	600018	CN	29	7	21402.78	4	4	5	445	4
1	600060	CN	155	1	1201.14	2	1	2	212	1
2	600462	CN	211	2	2033.64	2	2	2	222	2
3	600888	CN	8	3	2335.80	5	3	3	533	3
4	601014	CN	225	1	230.52	2	1	1	211	1

Fig. 9: RFM Score chart

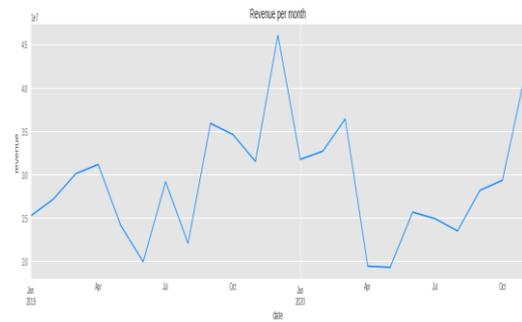
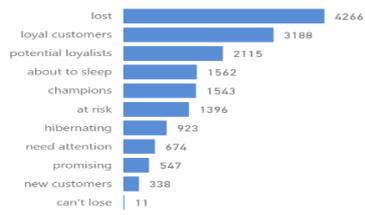


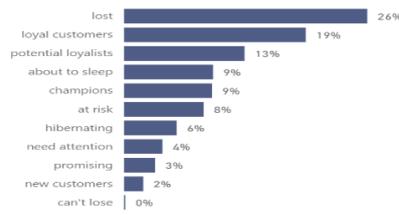
Fig.10: Revenue per month chart

Customer Segmentation

No. of customers per segment



Percentage of customers per segment



Revenue last 365 days per segment

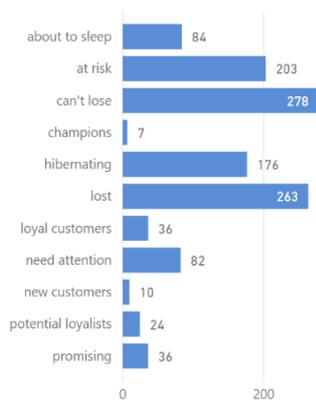


country	id	rfm_score	monetary
CN	638544	555	\$21,482,333
CN	4424580	555	\$16,912,322
TR	4341960	555	\$16,550,998
ID	3929094	555	\$8,748,885
JP	3520734	555	\$6,207,520
TR	4494150	555	\$4,874,668
KR	3618438	555	\$4,615,660
PH	4245048	555	\$4,358,516
IN	2111100	555	\$4,270,718
PH	3894492	555	\$4,106,366
PH	1145142	555	\$3,524,879
ID	3857664	555	\$3,027,574
JP	4540974	555	\$2,997,014
TR	3249114	555	\$2,731,448
VN	792522	555	\$2,677,779
JP	2115414	255	\$2,424,169
TR	4422780	355	\$2,315,341
ID	3721002	555	\$2,109,054
TR	4564152	555	\$2,105,041
TH	2195970	555	\$1,811,210
JP	4377870	555	\$1,616,119
ID	4052706	555	\$1,601,799
JP	2030526	455	\$1,519,340
JP	2182446	455	\$1,492,058
KR	3301296	555	\$1,309,154
JP	2022306	555	\$1,256,759
CN	622710	555	\$1,230,348
BD	2616906	555	\$1,222,554
IN	1802436	555	\$1,100,335
BD	2599086	555	\$989,857
IN	1803118	555	\$963,447
ID	3868038	555	\$930,220
CN	2452476	255	\$922,590
Total			\$358,381,027

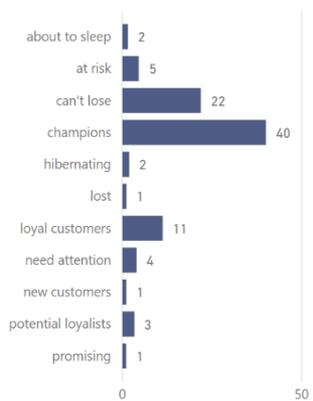
Fig.11: Visualization of the Data using PowerBi

RFM Analysis

Days since last purchase (average per customer)



No. orders last 365 days (average per customer)



Revenue last 365 days (average per customer)

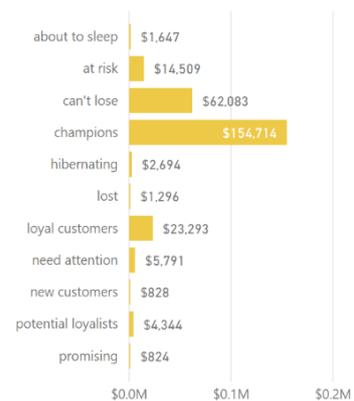
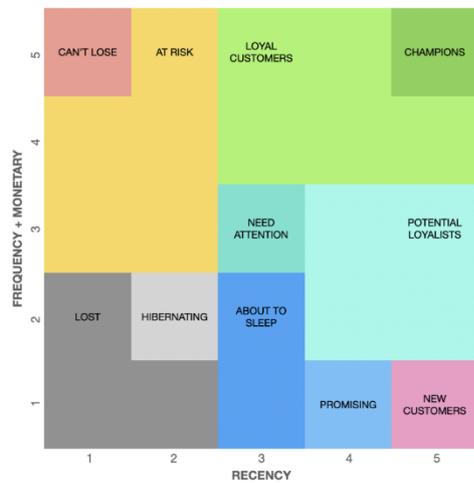


Fig.12: Visualization of RFM Data using PowerBi

Reference



Customer Segment	Activity	Actionable Tip
ABOUT TO SLEEP	Below average recency, frequency and monetary values. Will lose them if not reactivated.	Share valuable resources, recommend popular products / renewals at discount, reconnect with them.
AT RISK	Spent big money and purchased often. But long time ago. Need to bring them back!	Send personalized emails to reconnect, offer renewals, provide helpful resources.
CAN'T LOSE	Made biggest purchases, and often. But haven't returned for a long time.	Win them back via renewals or newer products, don't lose them to competition, talk to them.
CHAMPIONS	Bought recently, buy often and spend the most!	Reward them. Can be early adopters for new products. Will promote your brand.
HIBERNATING	Last purchase was long back, low spenders and low number of orders.	Offer other relevant products and special discounts. Recreate brand value.
LOST	Lowest recency, frequency and monetary scores.	Revive interest with reach out campaign, ignore otherwise.
LOYAL CUSTOMERS	Spend good money with us often. Responsive to promotions.	Upsell higher value products. Ask for reviews. Engage them.
NEED ATTENTION	Above average recency, frequency and monetary values. May not have bought very recently though.	Make limited time offers. Recommend based on past purchases. Reactivate them.
NEW CUSTOMERS	Bought most recently, but not often.	Provide on-boarding support, give them early success, start building relationship.
POTENTIAL LOYALISTS	Recent customers, but spent a good amount and bought more than once.	Offer membership / loyalty program, recommend other products.
PROMISING	Recent shoppers, but haven't spent much.	Create brand awareness, offer free trials.

Fig13: Segmentation of the data using Power BI

VI. CHALLENGES AND SOLUTIONS

Integrating deep learning to perform more detailed segmentation Although machine learning models are often used for segmentation, deep learning (especially excluding neural networks) can be more efficient and sophisticated segmentation models. Future work can explore the use of deep learning techniques such as convolutional neural networks (CNN) and recurrent neural networks (RNN) to capture nonlinear relationships across customers, resulting in accurate segmentation predictions. This will lead to greater personalization for customers, increasing conversion rates and customer satisfaction. Use streaming data for real-time segmentation behavior, and click time. Creating a real-time segmentation process using streaming data allows businesses to instantly respond to customer behaviors, such as transaction changes or product recommendation marketplace based on real-time data. Encourage impulse purchases and more engagement. 6. Improve customer privacy and ethical data use as application standards become more important.

Future work should focus on developing data anonymization and artificial intelligence techniques to protect users when providing personal information. Legal risk associated with privacy breaches. Emerging Market Segmentation - As e-commerce

expands into emerging markets, segmentation models must take into account diverse cultural, economic, and behavioral factors. It is important to develop a segmentation strategy that is appropriate for different regions and customers. Beyond compliance and addressing segmentation issues, research in this area will need to prioritize privacy-preserving machine learning. This includes developing new methods to provide differential privacy, federated learning, and other data anonymization techniques to protect personally identifiable information from consumers while enabling segmentation and predictive modelling. For example, there is a broader need to implement legislation like the GDPR, CCPA and other regulations on data protection and ethical AI usage that all contribute to consumer privacy, data security, and fairness in segmentation models. Establishing the protection of consumers not only reduces legal risk but also provides a level of confidence and transparency in the relationship between businesses and consumers. The second consideration in how future approaches segmentation would need to take in consideration is the growth of e-commerce into new or emerging markets where segmentation is more multidimensional and thus traditional models. These emerging markets can vary widely in economic conditions, cultural norms, internet penetration, and consumer behaviour, and will

require models that are sensitive to local context and adaptable as new variables emerge. Future segmentation models will require collection of local data based on regional specific information with specific local preferences, payment behaviours and language habits. This is the impetus for a geographic or regionally adaptive version of the segmentation framework that would allow e-commerce platforms to make choices or segmentations that were adaptive based on their market in terms of the contextual tailored level of appropriate segmentation that supports the scale of e-commerce businesses and allows for the context of the smaller market players to be included.

VII. CONCLUSION

The use of advanced technologies like machine learning and data analytics, as well as the development of an E-Commerce Sales Analysis Dashboard, is going to change the way companies will evaluate, analyze, and respond to customer behavior as it occurs.. The standard method of segmenting customers demographically, geographically, etc., is yielding to more dynamic methods which involve data, big data, real-time analytics and smart algorithms. The Dashboard integrates multiple data sources, including purchasing behavior, website browsing, behavioral data, and individual customer interactions, to create better segmentation based on deeper data insight. Machine learning algorithms are used to segment customers by signs tied to frequency of purchasing athletes, degree of engagement, and lifetime value of customers - all to affect targeted marketing campaigns, personalized product offers, and customer-specific pricing. As a result, brands benefit from improved customer engagement, increased sales conversion, and stronger brand loyalty - all through a live, evolving, and evolving solution iteratively guided by consumer behavior. In future updates, we can explore incorporating AI advancements, next-level automation, and intelligent logic to improve the quality and accuracy of customer segmentation. While objecting to traditional ML models provides valuable performance segmentation, applying deep learning models like CNNs or RNNs will allow the dashboard to discover complex, nonlinear customer behavior segmentation. Along with unstructured behavioral data from high-dimensionality, such as real-time search queries, session flow behavior, and time-series purchase

dynamics, this enables the segmentation of hyper-personalized customer segmentation and enhancements of customer intention prediction and customer lifetime value predictions.

The dashboard represents a new way to think about customer analytics. It connects a variety of data including: purchase history, website browsing behavior, behavioral data, transactional interactions, and engagement signals to create a connected view. Access to this breadth of interconnected data enables segmented analytics based on high-impact factors like; frequency of purchase, recency, average order value, engagement intensity, and customer lifetime value (CLV). Machine learning capabilities also provide the opportunity for the system to identify uniquely defined customer clusters that are informative of marketing responses, loyalty, and predicted future value. With the foundation of this richly detailed data set, companies may conduct precision-targeted marketing campaigns, personalized product recommendations, and potentially tailored and customized pricing structures specific to an individual customer and their behavioral predictions. Ultimately, the result is an observable increase in customer interactions, conversion, and brand loyalty. Critically, the dashboard functions as living adaptive ecosystem that continually evolves based on real-time feedback from customer interaction. The ongoing feedback loop guarantees that marketing programs stay aligned with customer behavior by increasing relevance and improving at all points in the customer journey. In the future, dashboards have the potential to advance even further with opportunities for artificial intelligence advances, intelligent automation, and deep learning.

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