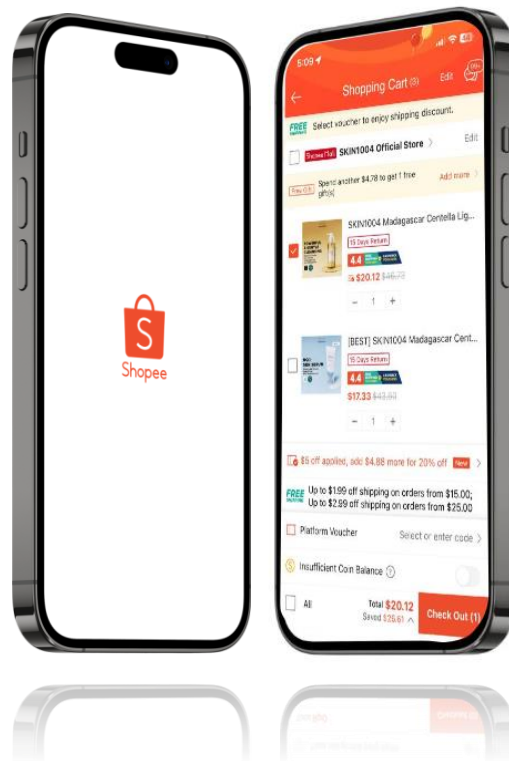


From Enigma to Engagement: Optimising Customer Retention Strategies for Shopee Thailand

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BC2407 Analytics II Presentation



Our Agenda

1 Business Understanding

2 Proposed Solution

3 Data Preparation

4 Data Understanding

5 Data Modelling

6 Deployment of Solution

7 Evaluation of Solution

Business Understanding



1

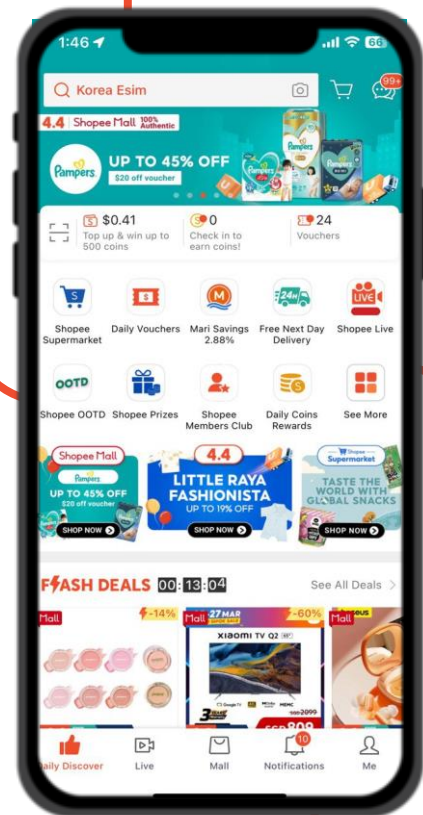
Shopee Background

- First launched in 2015
- Today, Shopee is one of the prominent players in the e-commerce industry

2

Southeast Asia (SEA) E-commerce Landscape

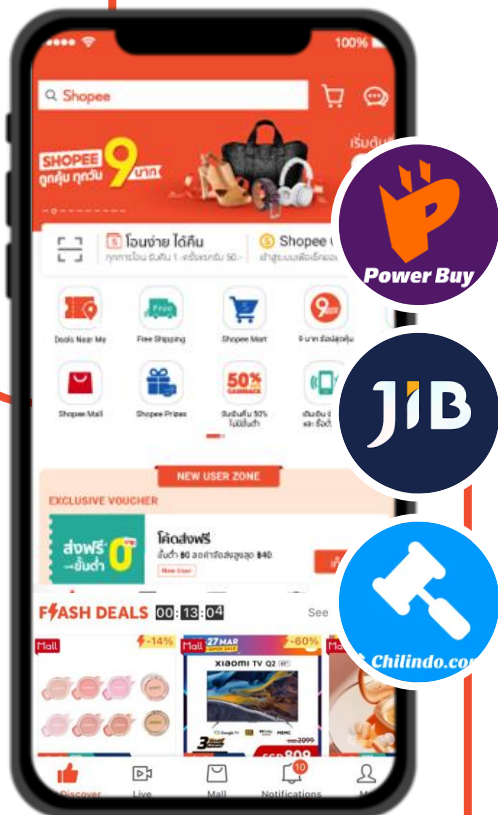
- Southeast Asia's e-commerce market boasts a population exceeding 600 million and a combined GDP of 3 trillion USD (Jaouadi & Chuidian, 2023)

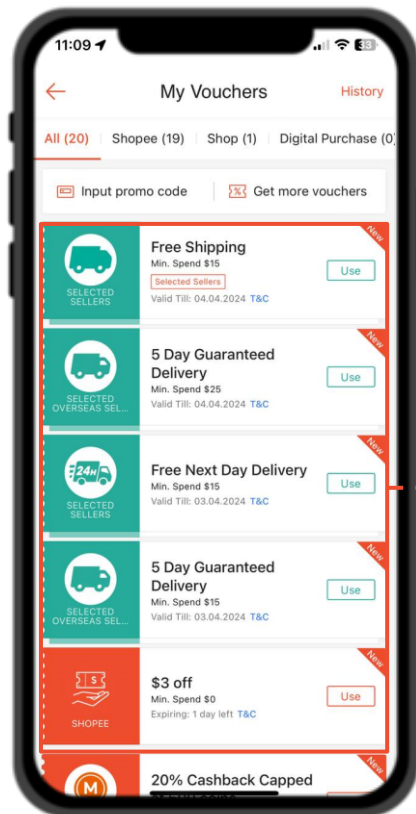


3

Business Problem

- Shopee's customer retention in Thailand: low point of 37%
- Emergence of local e-commerce platforms offering niche Thai products dilutes Shopee's market share
- 5% increase in customer retention can lead to a remarkable 95% boost in profits
- Shopee is paying 5-7 times more – in acquiring new customers compared to retaining existing ones
- Reduced customer lifetime value = negative impact on revenue and market competitiveness





4

Current Strategies & Opportunity

- Broad, **one-size-fits-all** incentives strategy
- **Dilutes marketing efforts and financial resources** as rewards given to users who would have made purchases without incentives
- Lack of targeted incentives wastes resources and misses retention opportunities

Opportunity: To **address and retain the segment truly at risk of disengagement and churn** to foster long-term retention

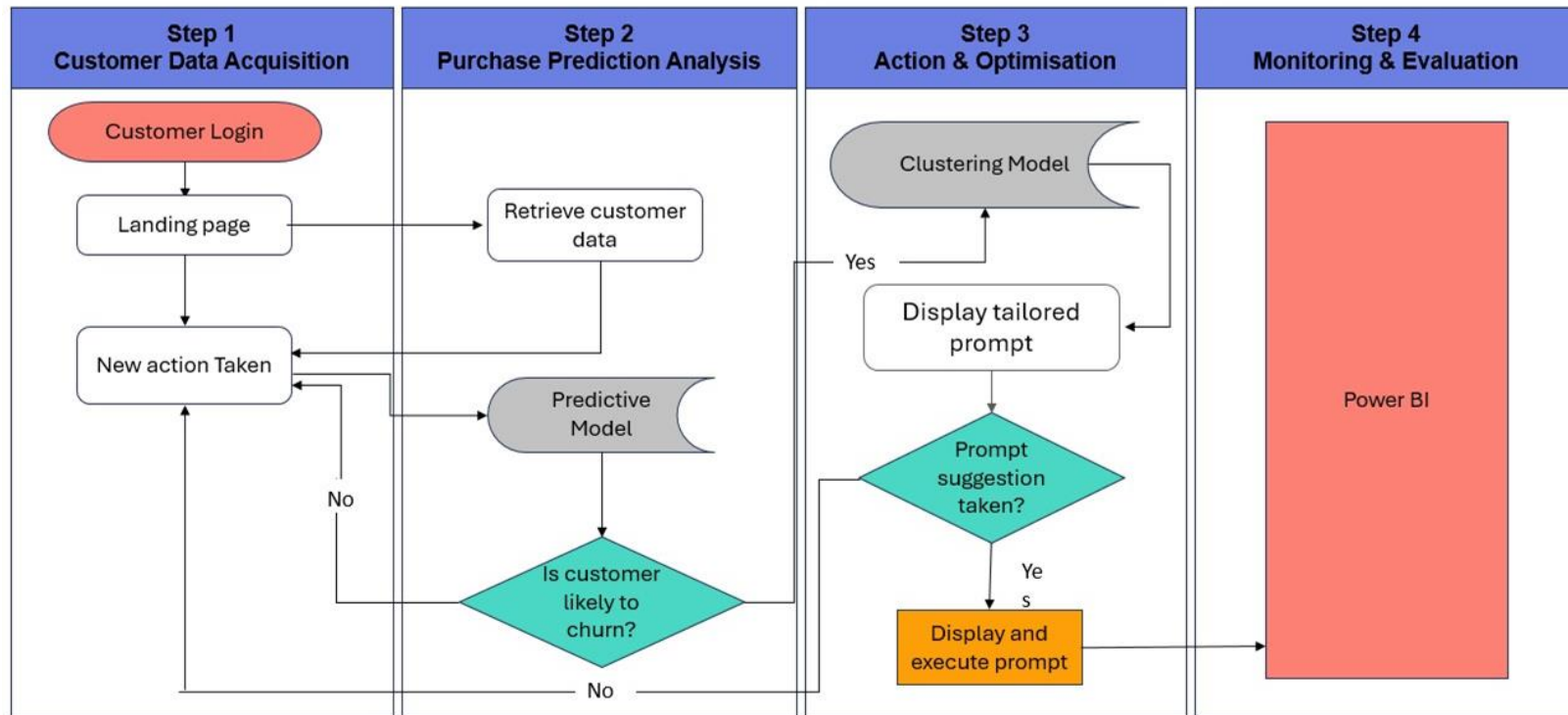
Problem Statement

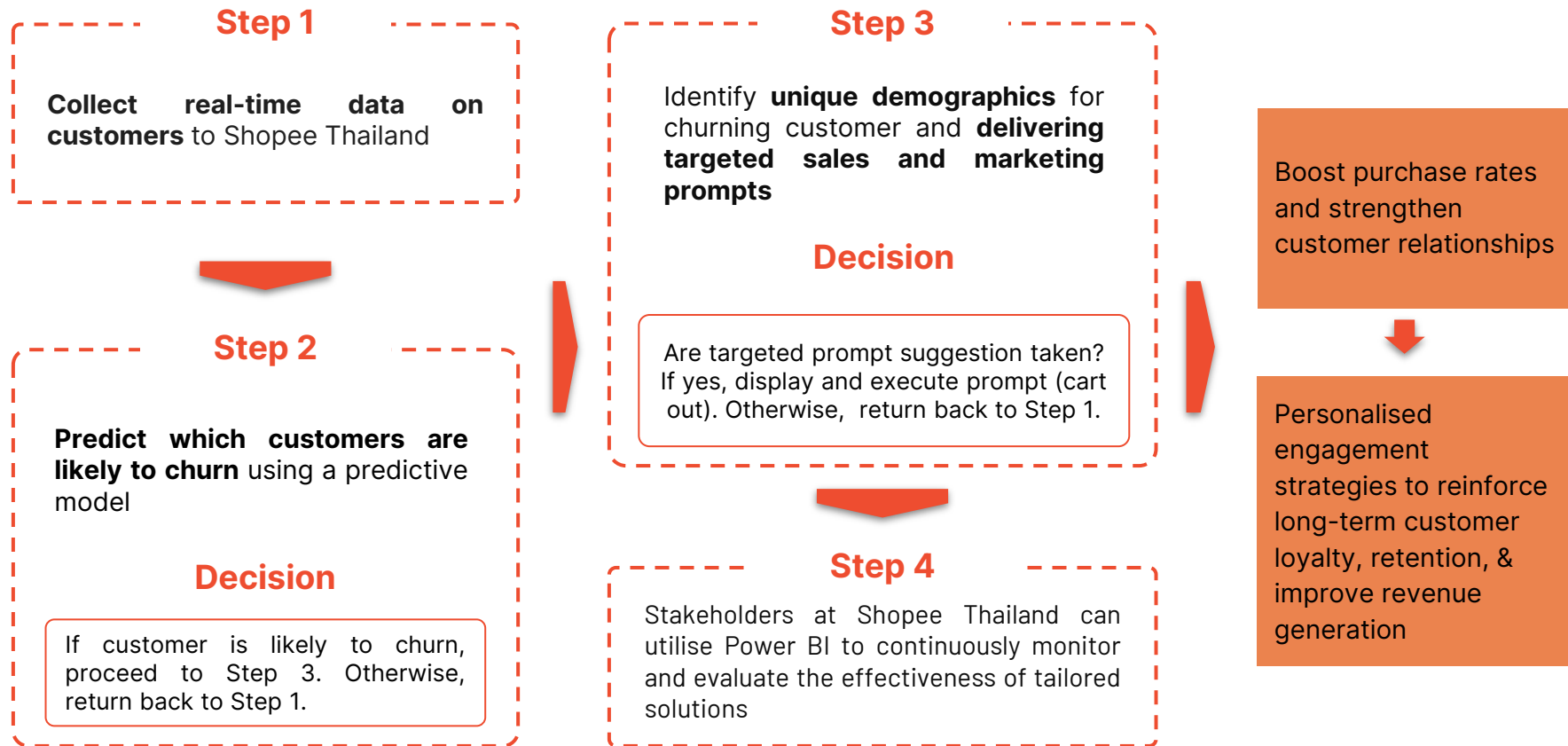
“ How can we leverage predictive analytics and machine learning to optimise customer retention strategies for Shopee Thailand to improve customer retention and improve revenue? ”

Proposed Solution

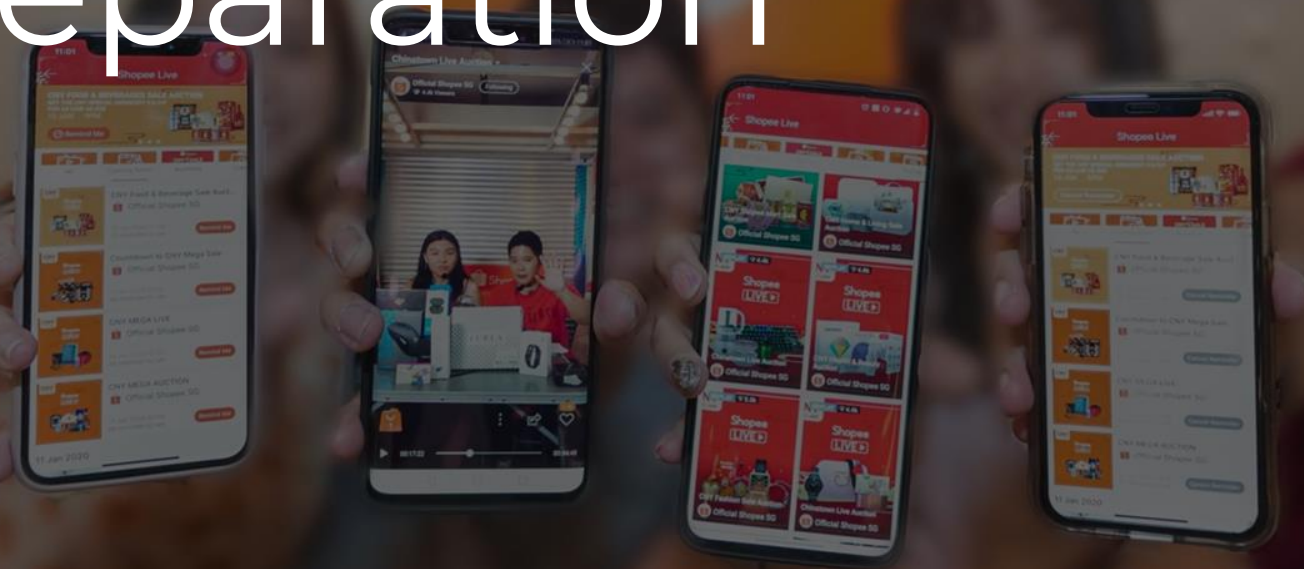


Our Proposed Solution





Data Preparation



Datasets Description

- Two datasets, "Ecommerce Customer Churn" and "Online Shoppers Purchasing Intention": 37 variables, categorised into categorical and continuous types
- Ecommerce Customer Churn": Approx. 1800 missing values exclusively within continuous variables
- Missing data primarily relate to customer demographic information
- Occurrence seems random, with many notable outliers

Imputation of Data through rflmpute

- rflmpute → rough fix median imputation and the Random Forest algorithm
- Preference for Median imputation due to skewed distributions and outliers in continuous variables (Shiksha, 2023)
- Ensures quality, integrity, and reliability of modeling and analysis

Data Standardisation

- Abbreviations like "CC" substituted with full counterparts like "Credit Card" for uniformity
- Ensures **consistency** and **comparability** across the dataset

Merging Dataset

- Revenue = 0 merged with Churn = 1, indicating churn
- Excluded '*CustomerID*' → lack of predictive value
- Excluded '*Visitor_Type*' → concentrate on returning visitors, given their direct relevance to churn analysis
- Enables **simultaneous utilisation** of user behavior and demographic variables

Data Understanding

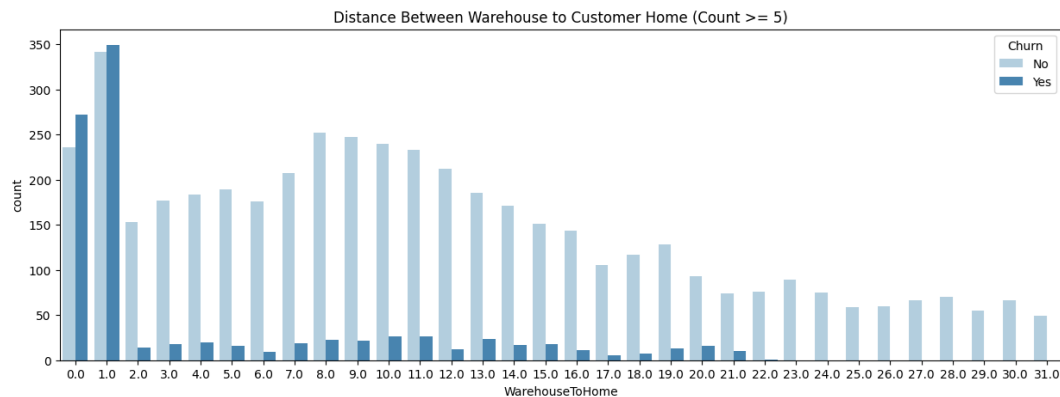
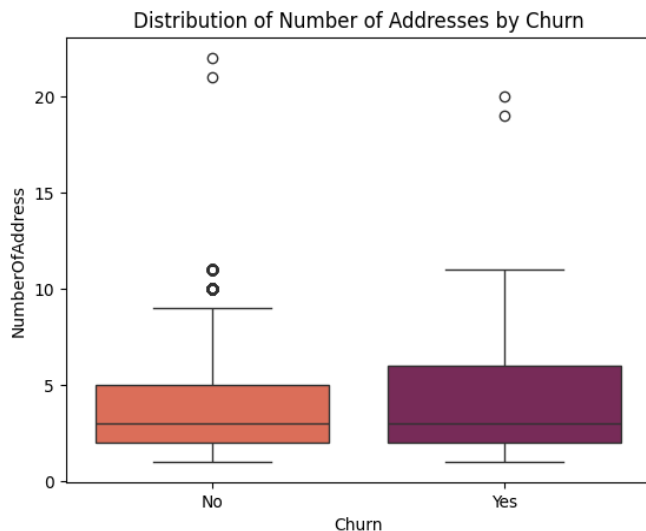
The background image shows a person's hands holding a smartphone. The phone's screen displays the Shopee app icon, which is a red shopping bag with a white 'S' and the word 'Shopee' below it. In the background, a computer monitor is visible, displaying a website with various product listings and promotional banners. The overall scene is slightly blurred, focusing attention on the phone and the text overlay.

Categorisation of Variables

Category	Description
Demographic	These features represent basic characteristics of customers that might influence their loyalty and satisfaction.
Transactional	Transactional features relate to the customer's purchasing behaviour and preferences, which can signal their satisfaction and likelihood to continue using the service.
Engagement	These features are indicative of how engaged the customers are with the ecommerce platform, which can be critical for understanding churn.
Session	These features offer context about the session that might correlate with customer behaviour and preferences

1

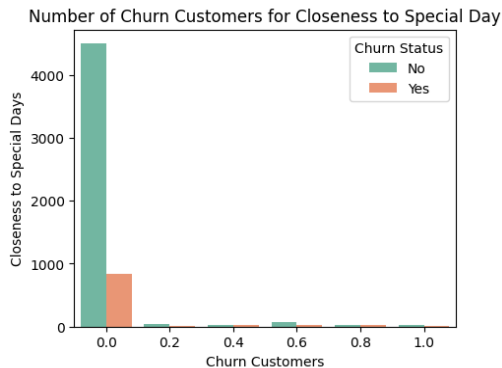
Multivariate Analysis - Demographic Variables



Distance of home from warehouse & Number of addresses not a significant predictor of churn

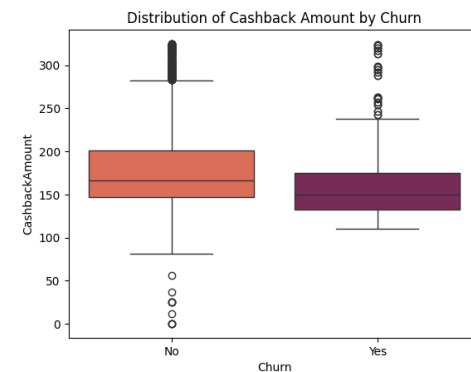
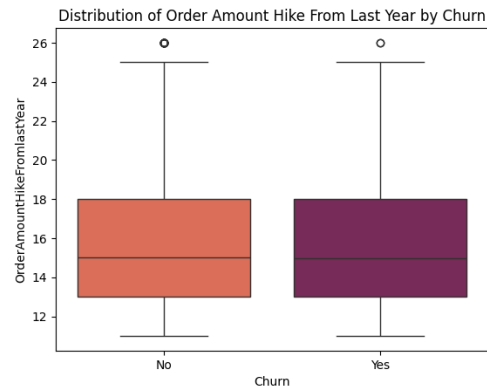
2 Multivariate Analysis - Transactional Variables

'*OrderAmountHikeFromLastYear*' does not significantly differ between churned and retained customers



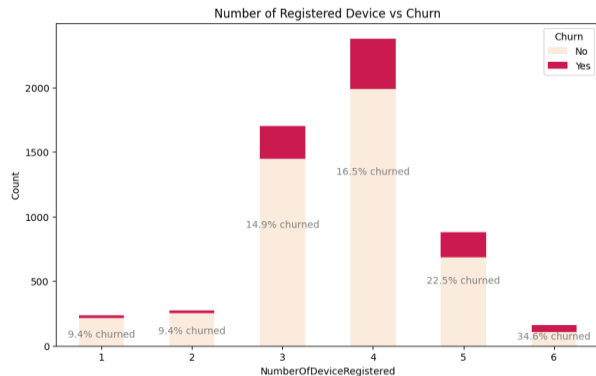
Lowest churn rates are observed during periods not closely aligned with special days

'*CashbackAmount*' distributions show a wider interquartile range for non-churned customers



3

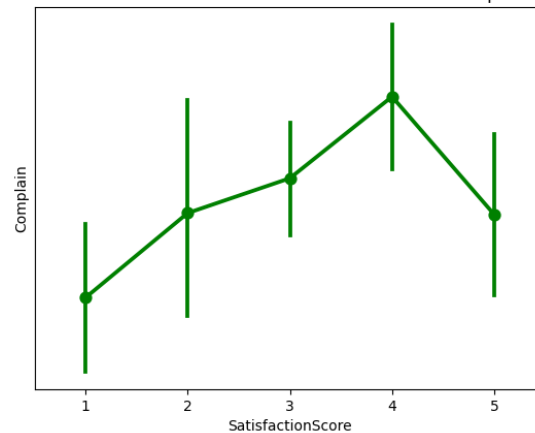
Multivariate Analysis - Engagement Variables



Churn rate increases with *'NumberOfRegisteredDevice'*

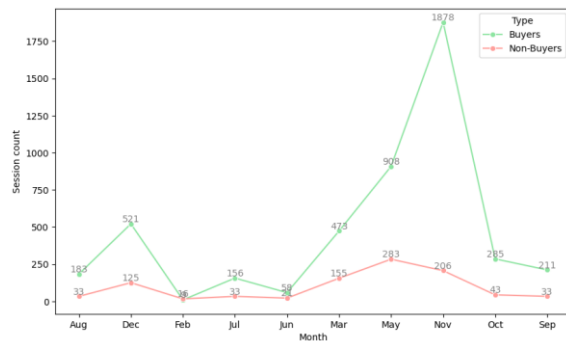
- Weak inverse relationship between *'SatisfactionScore'* and *'Complain'*
- High satisfaction scores show a correlation with increased churn rates
- Indicates a complex relationship

Correlation Plot between Satisfaction Score and Complaints

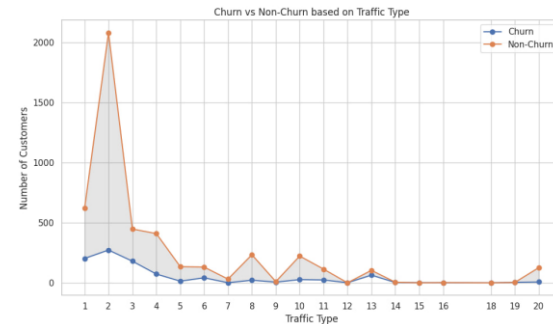
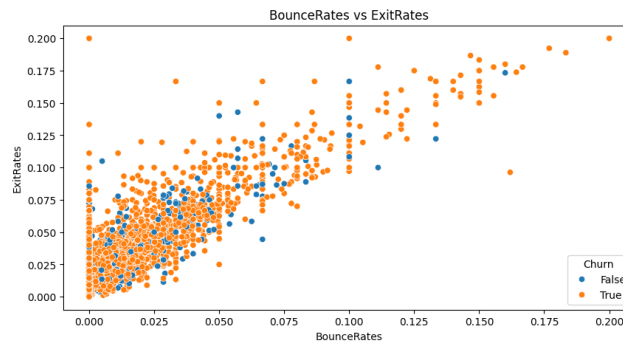


4 Multivariate Analysis - Session Variables

A time series plot of '*Month*' against session count shows a spike in retained customers in May and November



Sessions with increased exit and bounce rates are more inclined towards churning



'*TrafficType*' 13 stands out with an exceptionally high churn rate → significant risk factor and a potential predictor for customer attrition

Data Modelling

A person wearing an orange t-shirt with the Shopee logo is holding a brown cardboard box. The box also features the Shopee logo. The background is a blurred outdoor scene with greenery and a building.

Churn Prediction

Methodology

Objective

Accurately predict customers who are likely to churn

Approach

Employ supervised machine learning algorithms for classification.

Models Used

Random Forest

CART

Logistic Regression

Target Variable

Churn

1: Customer has churned
0: Customer retained

Features Selection

**Original
Feature Set**

35
Variables



**Engagement &
Session Feature
Set**

22
Variables

Features Selection

Excluded Features

Variables deemed less informative: 'HourSpendOnApp', 'OperatingSystems', 'Browser', 'Region', 'Weekend'.

Variables with marginal predictive value: 'NumberOfRegisteredDevice', 'SatisfactionScore'.

Variables with high correlation: 'OrderCount', 'Administrative', 'Informational', and 'ProductRelated' excluded in favour of 'DaySinceLastOrder', 'Administrative_Duration', 'Informational_Duration', 'ProductRelated_Duration'.

Final Features

Tenure, Complain, DaySinceLastOrder, Administrative_Duration, Informational_Duration, ProductRelated_Duration, BounceRates, ExitRates, PageValues, Month, TrafficType

Results of Predictive Models

Model	Accuracy	Precision	Recall	F1-Score
Random Forest Model	94.67%	82.27%	86.93%	84.54%
CART Model	92.36%	73.48%	85.16%	78.89%
Logistic Regression Model	89.69%	63.59%	87.28%	73.58%

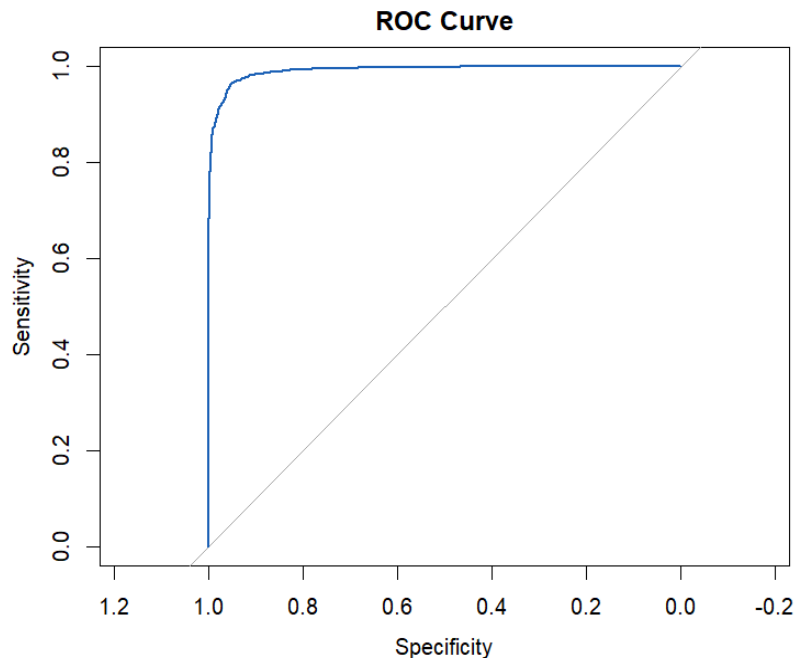
Selected Model Evaluation: Random Forest

Type of random forest: classification
Number of trees: 500
No. of variables tried at each split: 3

OOB estimate of error rate: 4.35%

Confusion matrix:

	1	0	class.error
1	2520	136	0.05120482
0	122	3155	0.03722917



Clustering Algorithm

Methodology

Objective

Segment the at-risk customers into meaningful groups for tailored marketing interventions

Approach

Employ unsupervised machine learning technique

Model Used

K-Prototypes Clustering

Rationale

Iterative optimisation approach with the ability to handle mixed data types effectively and clusters customers based on both numerical and categorical attributes

Features Selection

**Original
Feature Set**

35
Variables



**Demographic &
Transactional
Feature Set**

12
Variables

Feature Selection

Excluded Features

Variables deemed less informative:
'OrderAmountHikeFromLastYear', 'NumberOfAddress'.

Variables with marginal clustering value: 'Gender', 'SpecialDay'.

Strategic Inclusion

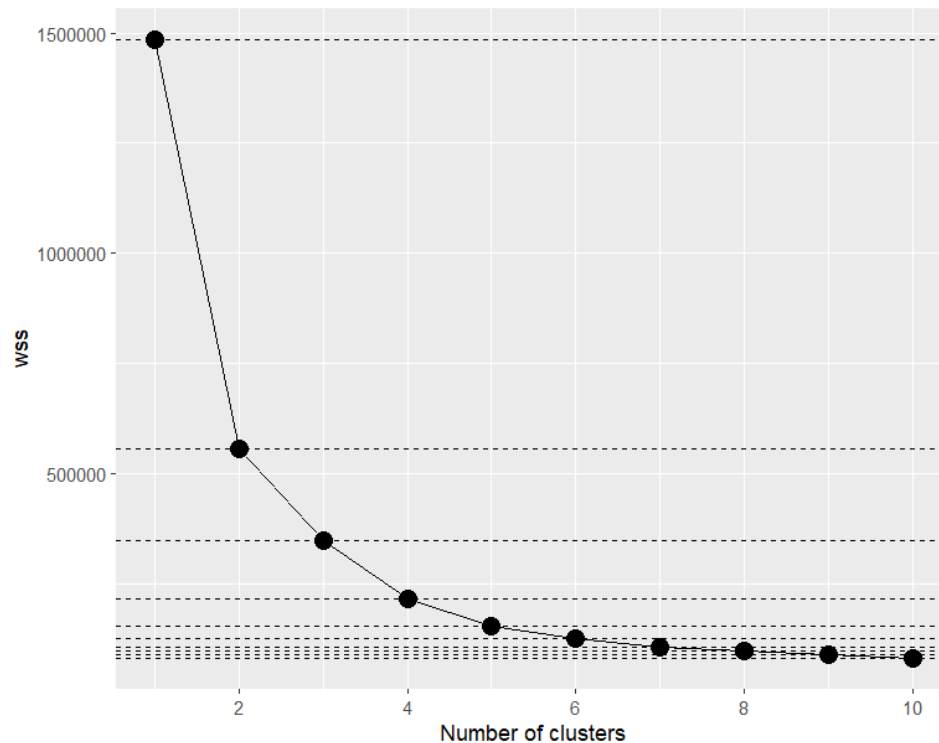
Although they are Engagement features, 'OrderCount' and 'DaySinceLastOrder' included for their strategic value.

Combined with 'CouponUsed', these features offer a comprehensive view of customer behavior.

Final Features

PreferredOrderCat,
PreferredLoginDevice,
PreferredPaymentMode,
CityTier, WarehouseToHome,
MaritalStatus,
CashbackAmount,
CouponUsed, OrderCount,
DaySinceLastOrder

Visualising the Elbow Method



Evaluation of Clusters

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> print(centers)
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	PreferredOrderCat	PreferredLoginDevice	CityTier	WarehouseToHome	PreferredPaymentMode	MaritalStatus
1	Fashion	Mobile Phone	3	19.14535	Debit Card	Married
2	Mobile Phone	Mobile Phone	1	17.54977	Debit Card	Single
3	Others	Mobile Phone	3	14.20000	Debit Card	Single
4	Mobile Phone	Mobile Phone	1	14.81579	Debit Card	Single

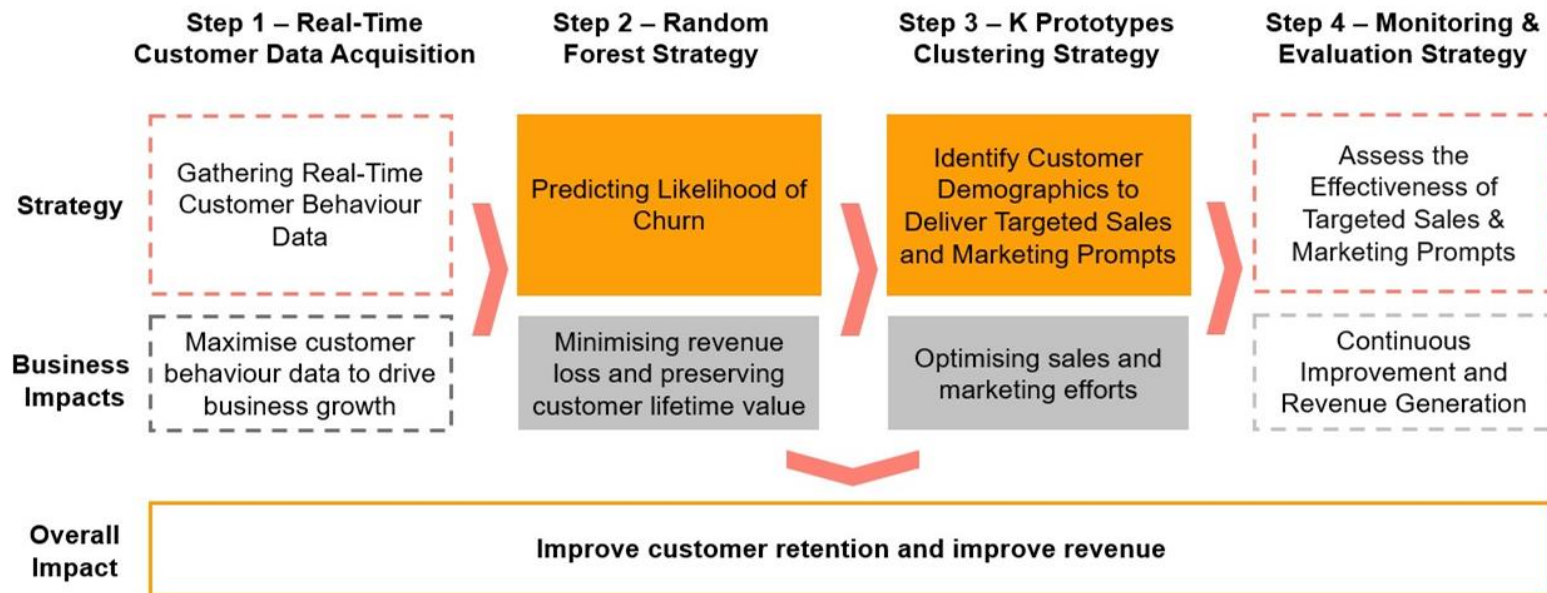
	CouponUsed	OrderCount	DaySinceLastOrder	CashbackAmount	Cluster
1	2.7732558	4.279070	4.587209	208.1279	1
2	1.7307692	2.705882	3.307692	156.3032	2
3	3.2000000	7.133333	8.600000	291.0667	3
4	0.9342105	1.697368	1.796053	126.3618	4

Distinct patterns observed in these clusters can then direct us to **tailor specific marketing interventions**

Deployment of Solution



Our Proposed Framework



1

Real-Time Data Acquisition

Step 1 – Real-Time Customer Data Acquisition

Strategy

Gathering Real-Time Customer Behaviour Data

Business Impacts

Maximise customer behaviour data to drive business growth

- Leverages on the customer data to monitor and analyse customer behaviour data in real time
- Collect and analyse customer behaviour to gain insights to current consumer sentiments
- Leverage its sophisticated, existing real-time customer data acquisition system by harnessing its robust web scraping and data extraction capabilities (Shukla, 2023).

2

Predicting Likelihood of Churn

Step 2 – Random Forest Strategy

Strategy

Predicting Likelihood of Churn

Business Impacts

Minimising revenue loss and preserving customer lifetime value

- Analyze real-time customer data to identify churn probability
- Error Rate: 4.62%, indicating feasibility and relatively high accuracy
- Develop user-friendly API for seamless data input to the model
- Utilise in-house platform and Google Cloud Platform for reliability and scalability and automate responses to potential churn risks

3 Identify Customer Demographics for Targeted Prompts

- **Firstly**, run the K-Prototypes algorithm on Shopee Thailand's historical data to create clusters representing different customer profiles.
- Save these centroids
- **Secondly**, model measures the proximity between newly identified potential churn customer and established cluster centroids based on the customer's data and assigned to the nearest centroid
- **Lastly**, cluster will represent the customer profile that most closely matches the customer's current behaviour and characteristics → Implement the associated retention strategy linked to this specific cluster

Step 3 – K Prototypes Clustering Strategy

Strategy

Identify Customer Demographics to Deliver Targeted Sales and Marketing Prompts

Business Impacts

Optimising sales and marketing efforts

4 Monitoring & Evaluation of Tailored Initiatives

- Assess the impact of Phase 2 and 3 strategies on churn rates
- A real-time dashboard will be introduced to provide stakeholders immediate visibility into key performance metrics
- Empowers stakeholders to promptly identify and address gaps in customer satisfaction, enhancing retention efforts swiftly
- Proactive monitoring ensures continuous optimisation of targeted efforts, dynamically responding to customer feedback and behaviors

Step 4 – Monitoring & Evaluation Strategy

Strategy

Assess the Effectiveness of Targeted Sales & Marketing Prompts

Business Impacts

Continuous Improvement and Revenue Generation

Power BI

Real-Time Dashboard Demo

Evaluation of Proposed Solution



Benefits of Solution

Reducing Churn, Foster Better Relations

- Prediction of user's churn risk gives Shopee the opportunity to intervene
- Allow Shopee to tailor personalised engagement strategies, fostering stronger customer relations



Increase Retention Rate & Revenue Generation

- Satisfied customers are more likely to increase purchase frequency
- Loyal customers will decrease churn rates and improve profitability, improving competitiveness edge within the e-commerce landscape

Limitations

1

Reliance on Real-Time Customer Data

- Our proposed framework only involves one layer of algorithm to predict churn
- Any inaccuracies can lead to misguided predictions
→ wasting resources or missed opportunities

2

Complexities of Customer Behaviour

Essential to consider other factors in providing deeper and more accurate insights

Future Considerations

1

**Adapt to Evolving Customer
Behaviour & Market Dynamics**

2

**Incorporate New Data &
Adjusting Model Parameters**

3

**Incorporate New Features to
Improve Prediction of Churn**

Conclusion

1

Potential of Integrating Random Forest and K-Prototypes clustering for decreasing churn rates and enhancing customer retention

2

Strategic advantage of real-time monitoring of customer behavior for providing stakeholders with actionable insights

3

Personalisation of customer experience and optimization of marketing efforts to streamline cost and increase revenue

4

Utilization of sophisticated machine learning models and advanced analytics to align with the business objective of minimizing churn and increased customer loyalty



THANK YOU

Any Questions?

Shopee