The Fallacy of the Net Promoter Score: Customer Loyalty Predictive Model

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Agenda

Customer Loyalty Measurement

NPS Critiques

Research Framework

Analysis and Findings

Contribution

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Customer Loyalty Measurement

Single-question customer metrics have become very popular as tools to measure customer loyalty

1. Customer Satisfaction (CSAT)

Key Question

Overall, how satisfied are you with this brand / product / service?

Rationale

"CSAT is adaptable, it can be applied with a range of scales to measure specific parts of the experience."

Overall Satisfaction Measures of Customer Satisfaction
How satisfied were you with [BRAND]?

| Delighted | Pleased | Mostly Satisfied | Mixed | Mostly Dissatisfied | Unhappy | Terrible |

The following faces express various feelings. Please select the face that best shows your feeling about [BRAND].
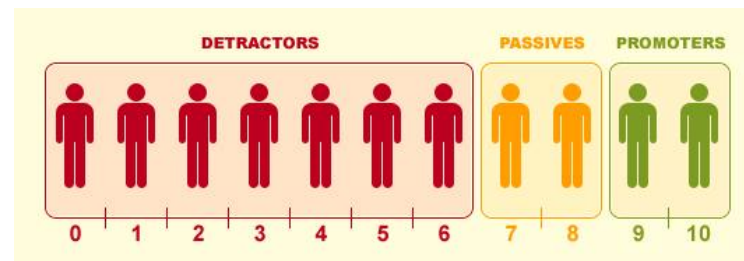
2. Net Promoter Score (NPS)

Key Question

How likely are you to recommend our company/ product/ service to your friends & colleagues?

Rationale

"Loyalty is more efficient than acquisition, therefore focus on those who promote you"

NPS = % Promoters - % Detractors

DETRACTORS   PASSIVES   PROMOTERS

0 1 2 3 4 5 6   7 8   9 10

Customer Loyalty Measurement

3. Customer Effort Score (CES)

Key Question

How much effort did you personally have to put forth to handle your request?

Scores range from 1 (low effort) to 5 (high effort)

Rationale

Harvard Business Review
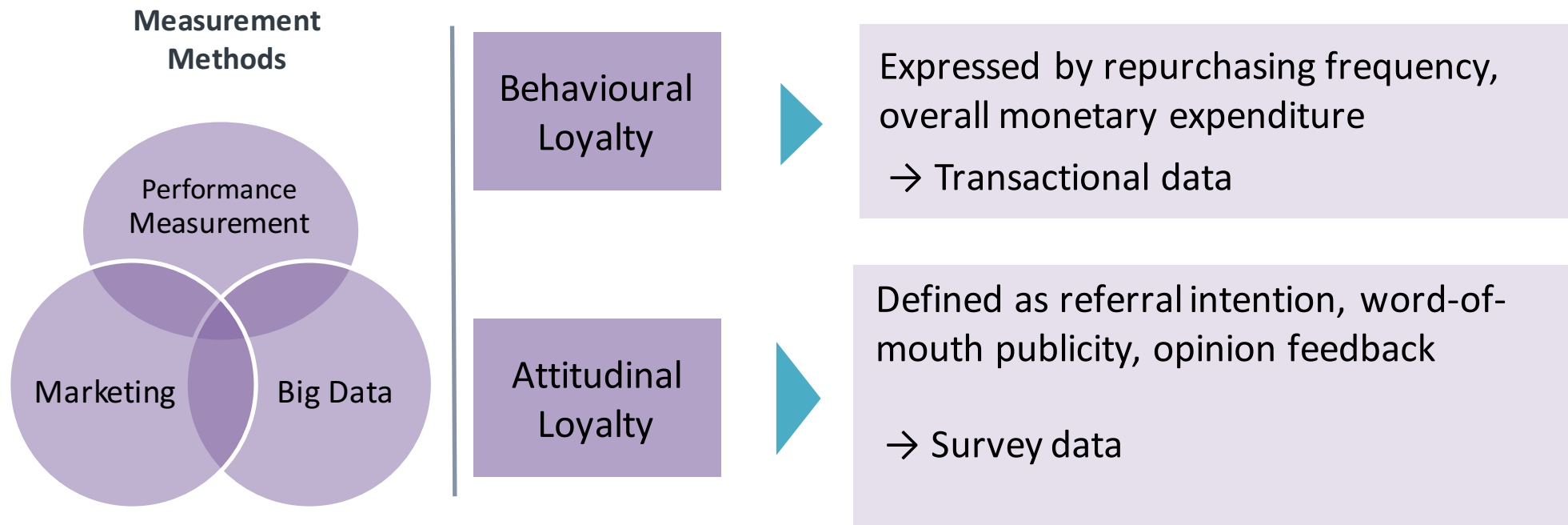www.hbr.org

To really win their loyalty, forget the bells and whistles and just solve their problems.

Stop Trying to Delight Your Customers

by Matthew Dixon, Karen Freeman, and Nicholas Toman

"Just make it **easy** for me"

Each claims to be the one metric that managers need to measure, monitor, and act on

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Literature Review: Customer Loyalty
Considered to powerfully impact a firm's performance and competitive advantage

Definition

"A buyer's overall attachment or deep commitment to a product, service, brand, or organization" (*Lam et al 2004*)

Measurement Methods

Performance Measurement

Marketing

Big Data

Behavioural Loyalty → Expressed by repurchasing frequency, overall monetary expenditure

→ Transactional data

Attitudinal Loyalty → Defined as referral intention, word-of-mouth publicity, opinion feedback

→ Survey data

Customer satisfaction and loyalty are one of central key focus of *marketing theory and practice*. **Loyalty** is a *complex psychological construct* (Pollack and Alexandrov 2013)
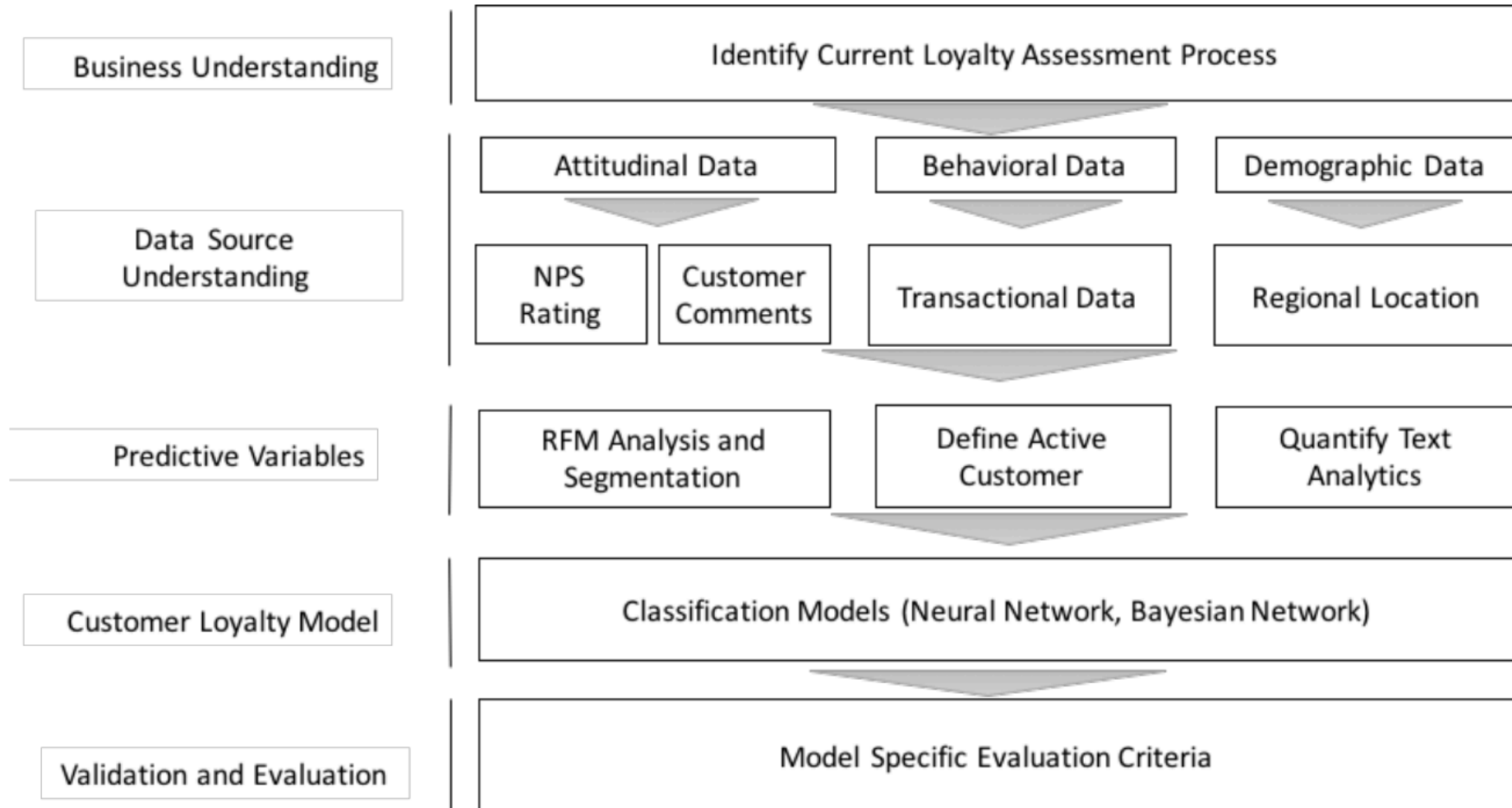
The Net-promoter Score Critiques

Regarded as an attitudinal measure for assessing customer loyalty

#1 No empirical evidence that attitudinal loyalty metrics significantly correlate with the relative change in revenue within the respective industry

#2 Single metric alone can not predict customer loyalty and unlikely to deliver insights to managers for actions

#3 NPS is not a sufficient approach to the customer loyalty measurement and because recommendations alone are not enough to drive business success

#4 Customers could give high NPS scores (promoters), while a firm could lose a percentage of their customers' base.

#5 These metrics misinform managers and divert them away from marketing actions

#6 NPS does not provide such a prescription for firms to diagnose the underlying causal factors of their customers.

(Grisaffe 2004; Keiningham et al. 2007; Kristensen and Eskildsenn 2011; Morgan and Rego 2006; Pollack and Alexandrov 2013; Pingitore et al. 2007)
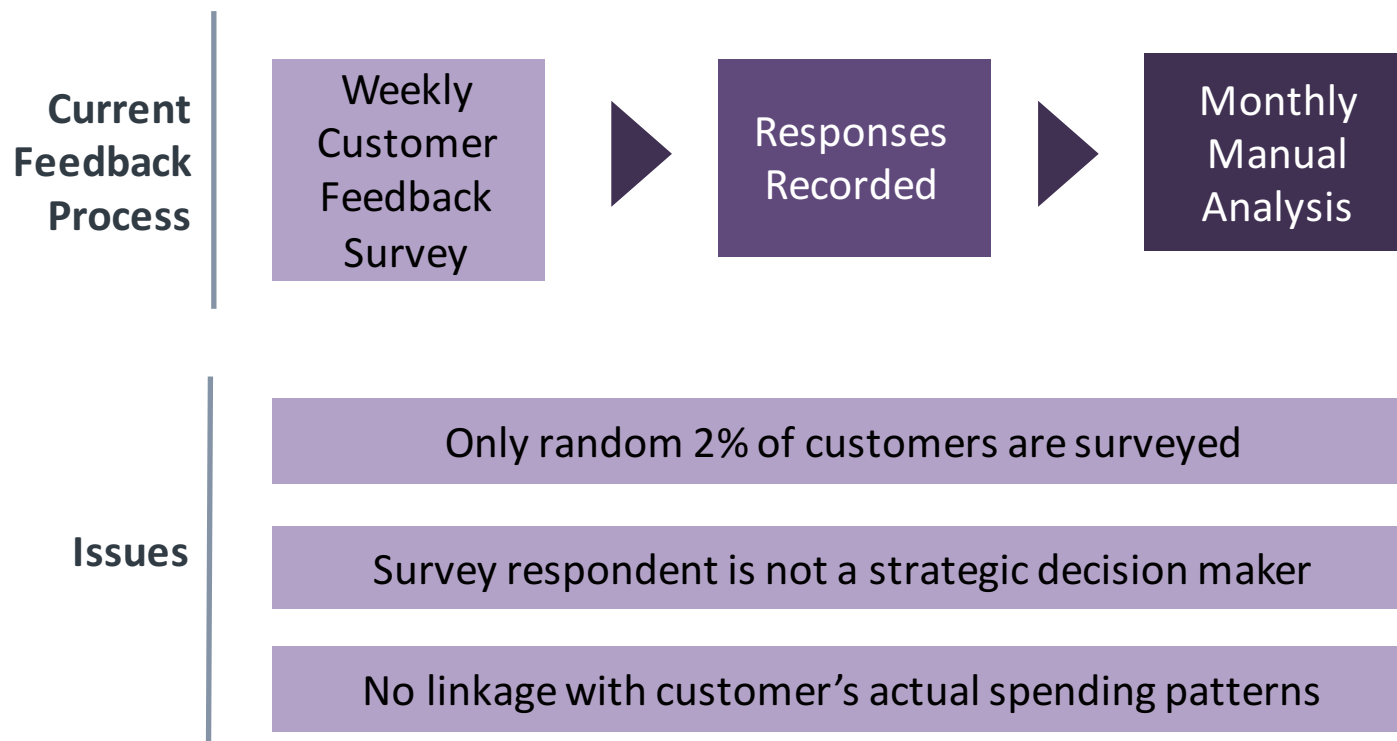
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Research Framework and Methodology

Adapted from Cross-Industry-Standard-Process for Data Mining (Chapman et al. 2000; Villarroel Ordenes et al. 2014)

Business Understanding- Finning Case Study
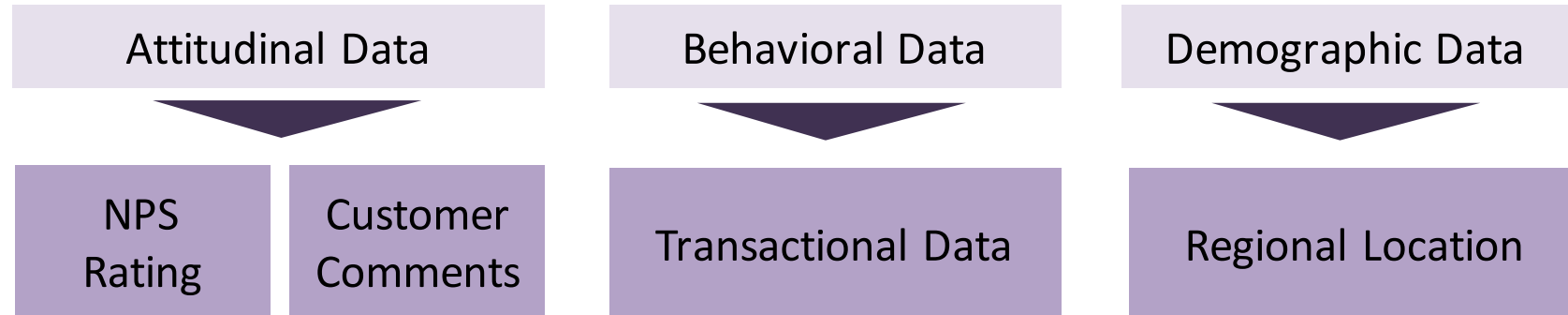*Company interviews were conducted to grasp current loyalty assessment process*

Customer loyalty is assessed on the NPS as a stand-alone metric

Current Feedback Process

Weekly Customer Feedback Survey ▶ Responses Recorded ▶ Monthly Manual Analysis

Issues

Only random 2% of customers are surveyed

Survey respondent is not a strategic decision maker

No linkage with customer's actual spending patterns

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Data Understanding – Data Sources
Data from multiple sources were gathered for the purpose of this study

Attitudinal Data	Behavioral Data	Demographic Data

NPS Rating	Customer Comments	Transactional Data	Regional Location

- Data Timeframe – limited to about 3 years (2012, 2013, 2014, 2015 Q1)

- Data Size – over **1 million** records (1,044,512) on transactional level

- Transactional Data– Sales, Product Support (PS), Customer Service Agreement (CSA)

- Sales – New, Used or Lease transaction types

- PS and CSA – Parts and Service transaction types

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Data Preparation – RFM Analysis
Customers were scored based on their actual spending behavioural patterns

Technique	Data Employed	Purpose
RFM Analysis	PS Transactions	Assessing Customer Profitability
Clustering using K-means	RFM Scores	Grouping customers with similar profitability together

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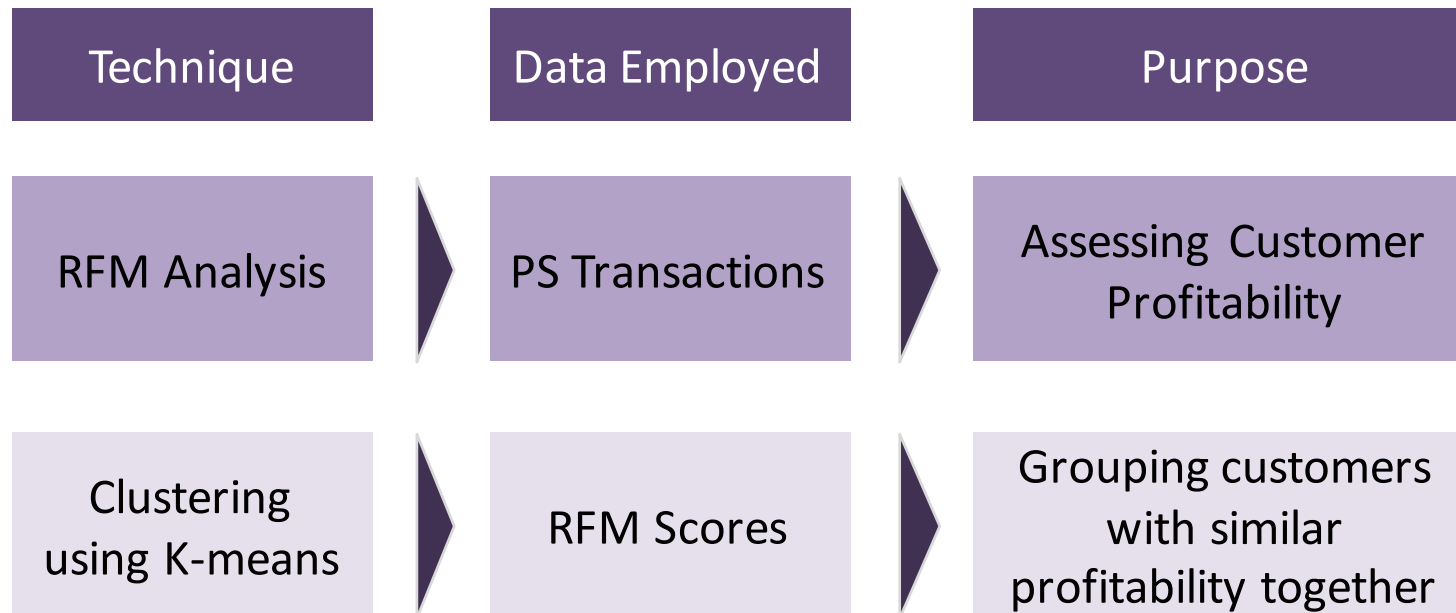
RFM Analysis – Results

Customers were scored based on their actual spending behavioural patterns

New_Cuno	Recency	Frequency	Monetary	Recency_Score	Frequency_Score	Monetary_Score	RFM_Score
FIN01425	92	13	170389.47	1	2	5	125
FIN01761	14	26	105758.16	3	3	5	335
FIN02543	11	14	9325.05	4	2	3	423
FIN01992	174	4	220.00	1	1	1	111
FIN01394	21	10	841.10	2	2	1	221
FIN03381	76	15	8906.77	1	2	3	123
FIN04250	14	38	71348.02	3	3	5	335
FIN00272	12	61	92463.13	3	4	5	345
FIN00804	40	4	31083.00	2	1	4	214
FIN02511	46	7	35254.93	1	1	4	114
FIN02874	11	18	21441.22	4	2	4	424
FIN02176	18	96	176817.70	3	4	5	345
FIN03391	13	75	86651.25	3	4	5	345
FIN04478	11	97	71948.82	4	4	5	445

K-means Clustering – Results

Customers were segmented into 11 groups to mimic the NPS scale

Cluster Sizes
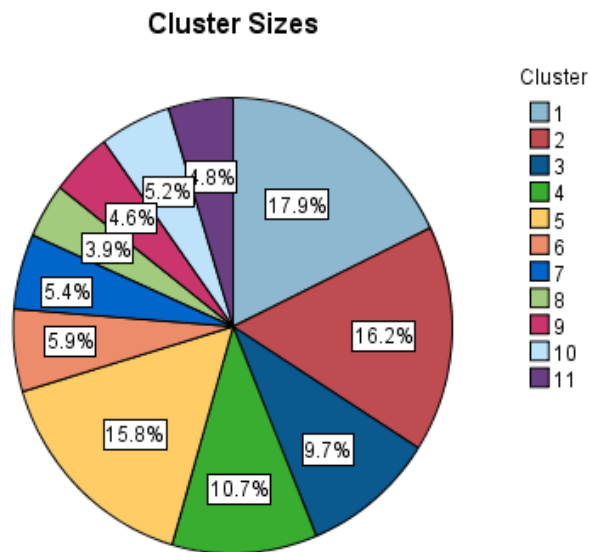
Cluster Number	Average RFM	Corresponding NPS Scale	NPS Category
5	111	0	
9	112	1	
8	221	2	
4	222	3	Detractor
10	223	4	
11	332	5	
3	333	6	
7	334	7	Passive
6	343	8	
2	344	9	
1	555	10	Promoter

RFM Clusters Vs. Survey NPS
Comparison between each NPS category and RFM equivalent was performed

Misclassified NPS	2012	2013	2014
Promoter → Detractor	291	522	524
Passive → Detractor	126	185	218
Promoter → Passive	135	147	104
Passive → Promoter	44	18	32
Detractor → Promoter	10	2	3
Detractor → Passive	9	8	10
% of customer misclassified	72%	85%	82%

Data Preparation – Defining Active Customer

"Active customer" was generated due to lack of formal definition

Define
Average number of days between two consecutive transactions for all customers

Calculate
Diff_Recency = Date of lastest transaction – Date of second latest transaction

Generate
If customer Recency < Avg. Diff_Recency → Loyal
Else → Churner

Result
If customers have not bought within **71 days** → **Churner**
Therefore, able to predict whether customers are likely to churn

46% Churner
54% Loyal

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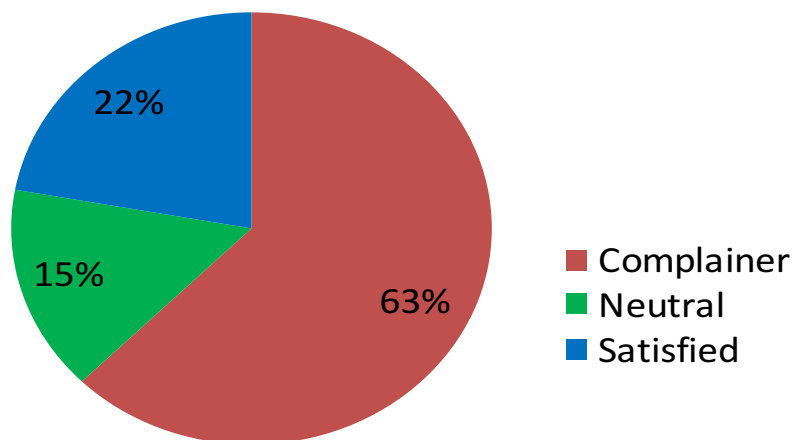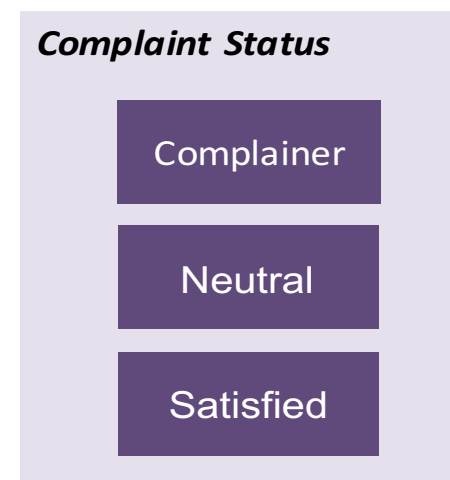Cambridge Service Alliance
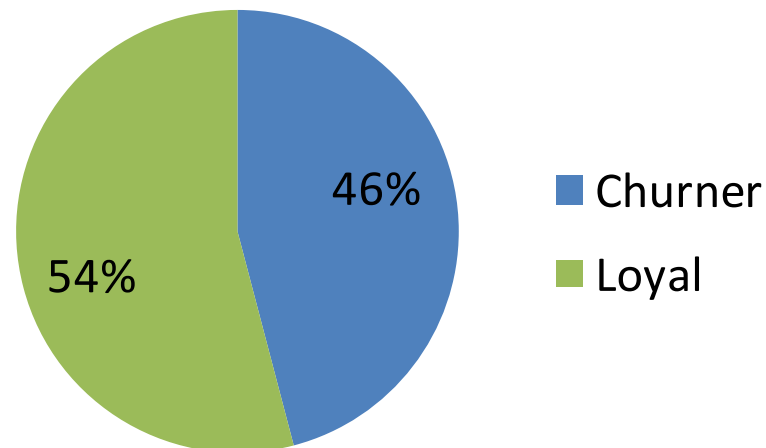
Data Preparation – Quantifying Text Analytics
Complaint status of survey comments were transferred into quantitative scores

Overall Satisfaction	Additional Comments
10	Part Service is the best part of XXXX and that one I will rate very high. However workshop costs a lot of money and is a waste of time. The problem is that [company] is only interested in doing business with big companies and doesn´t care about small one

1   **Comment Score** = Compliments − Complaints − Suggestions

2   **Calculate customer average across all survey entries**

3   *Bin scores into 3 satisfaction level categories*

Complaint Status

- Complainer
- Neutral
- Satisfied

Pie chart:
- 63% Complainer
- 15% Neutral
- 22% Satisfied

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Data Modelling and Prediction
Data was split into three sets to test the prediction accuracy of the loyalty model

Training Data (60%)

Results for output field ComputedLoyalty
Comparing $R-ComputedLoyalty with ComputedLoyalty

'Partition'	Training	
Correct	1,214	95.59%
Wrong	56	4.41%
Total	1,270	

Testing Data (30%)

Results for output field ComputedLoyalty
Comparing $R-ComputedLoyalty with ComputedLoyalty

'Partition'	Testing	
Correct	565	94.17%
Wrong	35	5.83%
Total	600	

Validation Data (10%)

Results for output field ComputedLoyalty
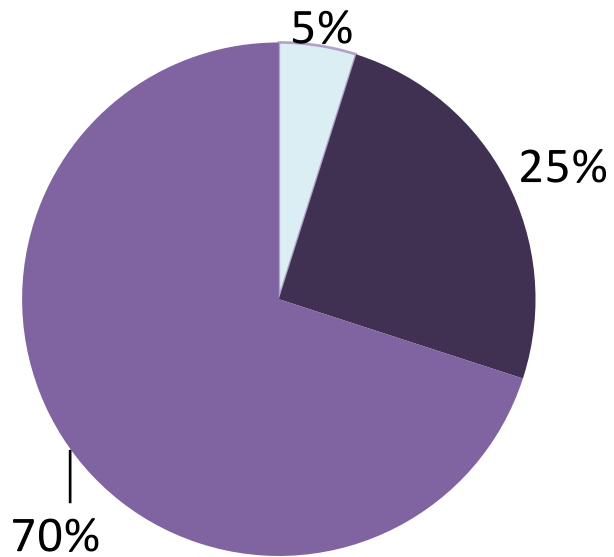Comparing $R-ComputedLoyalty with ComputedLoyalty

'Partition'	Validation	
Correct	178	94.18%
Wrong	11	5.82%
Total	189	

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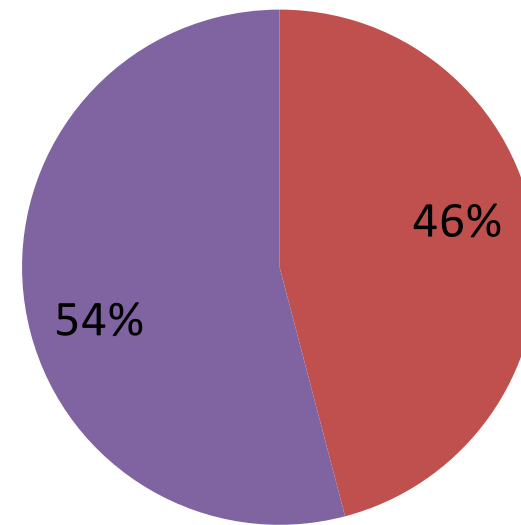
Insight Highlights
Customers' NPS score and purchasing pattern do not match across 3 years

Perceived NPS

5%

25%

70%

- Detractor
- Passive
- Promoter

Actual Behavior

46%

54%

- Churner
- Loyal

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Churners vs. Sales Volume
A root cause analysis of complaining customers was performed

Customer ID	Sales Volume (£)	Complaint Status	Comment	Resource
FIN0408720	1,333,736	Complainer	Generally, it's a long way with getting feedback and part order and delivery sometimes	Communication
			Drop the prices, Even from last year the prices seem too high	Price Value
FIN0053511	949,016	Complainer	Reduce the hourly rate a bit. I would like it to be towards 40 pounds per hour.	Price Value
			Make it cheaper	Price Value
FIN0343268	425,586	Complainer	Just keep us more informed. Not just leaving us here waiting, wondering if someone's coming or not.	Communication
FIN0391511	361,820	Complainer	They should improve on-site job training, improve quality control.	Process Adherence

Conclusion

- The study contributes towards proving the unreliability of the NPS as a single loyalty measures within B2B complex service organizations

- The framework integrates a multitude of demographic, behavioral, and attitudinal customer data when assessing customer loyalty

- The combination of multiple data when assessing customer loyalty supports criticism in the literature of using single loyalty metric

- The prediction model is developed using different big data techniques to predict customer loyalty and identify customers who have "churned"

- We extended the linguistic text mining approach to determine the complaint status and emotions and divides customers into groups of complainer, neutral or satisfied

Forthcoming Webinars

Date 14:30hr GMT	Topic	Invited speaker
December 12th	Feedback from the Frontline: Engaging Front-Line Employees in Service Contracts	Florian Urmetzer
2017		
January 9th	The Fallacy of the Net Promoter Score: Customer Loyalty Predictive Model	Mohamed Zaki
February 13th	**Classification of Noisy Data: An Approach Based on Genetic Algorithms and Voronoi Tessellation**	**Abdul Khan**
March 13th	The Ecosystem Value Framework: Supporting Managers to Understand Value Exchange between Core Businesses in Service Ecosystems	Florian Urmetzer

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