UNLOCKING THE SECRETS OF CUSTOMER LOYALTY

WHITEPAPER

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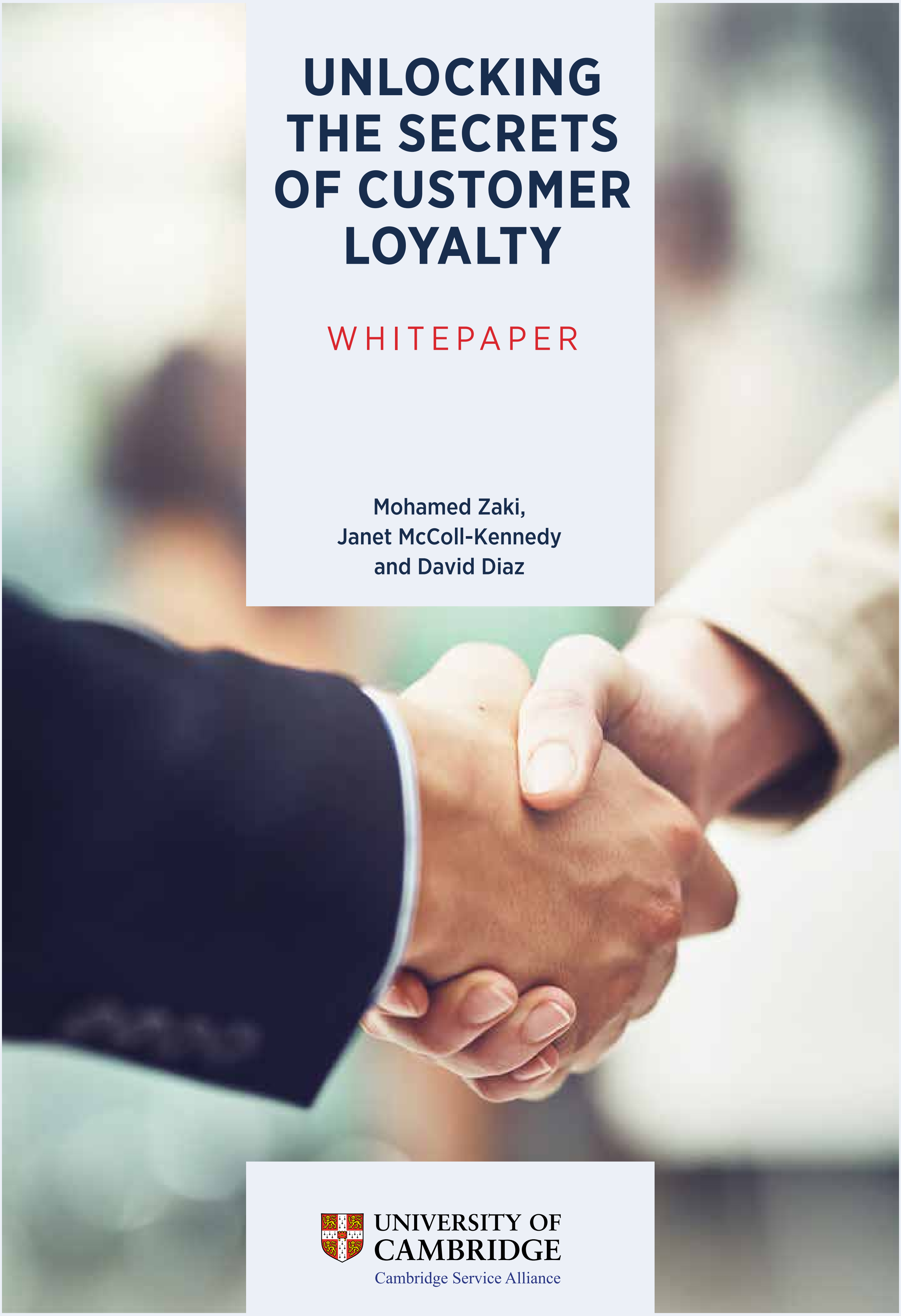

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Cambridge Service Alliance

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EXECUTIVE SUMMARY

Customer retention plays in a critical role in a firm's long-term sustainability. Until recently, however, firms have tended to rely on one-dimensional survey techniques to measure their customers' loyalty. We know from previous research that this is problematic, masking underlying dissatisfaction with a company's products and services and that a significant proportion of its customers are at risk of churn. With better insights, these customers could be prevented from seeking alternative providers.

This research applied a more nuanced approach to understanding customer loyalty, looking at what customers think, feel and do in order to arrive at a more accurate prediction of their future behaviour. By combining this framework with advanced machine learning techniques and applying them to attitudinal, emotional and transactional customer datasets in a B2B context, we have developed an approach which was 93% reliable in its prediction of churn.

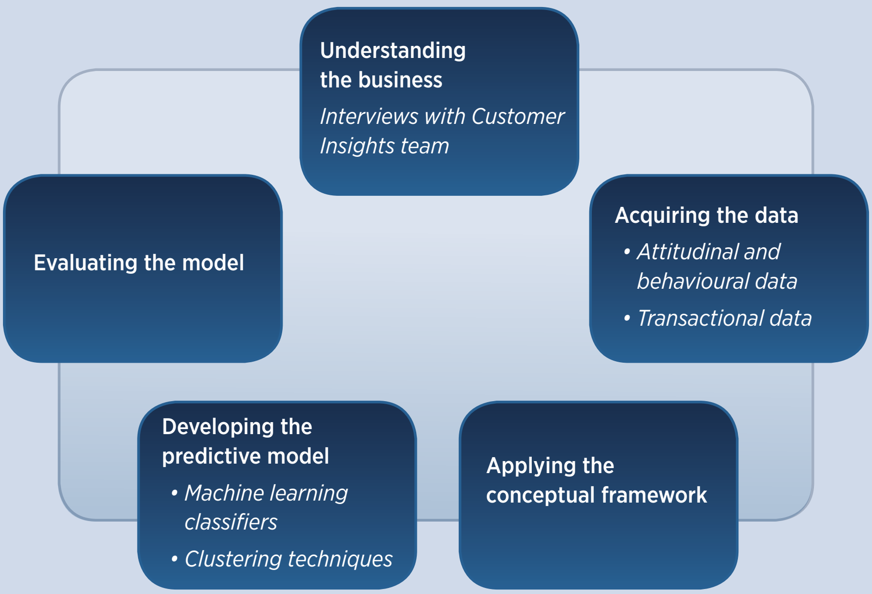
RESEARCH QUESTION

By combining advanced machine learning techniques with a multi-faceted conceptualisation of customer loyalty, can we understand what customers are really thinking, feeling and doing? And can those insights reliably predict customer churn?

METHODOLGY

Building on customer loyalty management theory, the Cambridge Service Alliance suggests a new conceptual framework that integrates prior research to unpack three dimensions of loyalty: attitudinal, emotional and behavioural.

The approach was tested with a global product and service provider in the construction sector. Initially, 15 interviews were carried out with members of the firm's customer insights team to get a good business understanding of the problem. Appropriate datasets were then identified that would reveal the three dimensions of the customer experience. Using the conceptual framework, predictive variables were selected and the machine learning model was deployed, tested and evaluated.



01 INTRODUCTION:

WHY IS CUSTOMER LOYALTY IMPORTANT?

67% of **customers mention bad experiences** as a reason for churn. *Salesforce*

65% of **companies measure NPS** compared with **44%** that measure CSAT and **14%** that measure CES. *Lumoa*

Increases **customer retention rates** by **5%** and profits by **25% to 95%**. *Harvard Business Review*

Churn can increase by up to **15%** if businesses fail to respond to customers over social media. *Gartner*

87% of **organisations** agree traditional experiences **no longer satisfy customers.** *Accenture*

67% of **customer churn** is preventable if firms resolve issues the first time they occur. *Ameyo*

Attracting a new customer is **6 to 7** times **more expensive** than retaining a current one. *Salesforce*

Among **B2B** decision makers, lack of speed in interactions with their suppliers is the number one pain point, mentioned twice as often as price. *Qualtrics*

Customer loyalty has a direct and measurable impact on a firm's performance. According to a 2018 analysis by PwC, customers are now so used to great customer experience that 32% say that they will walk away from a brand after just one bad experience. If attracting a new customer costs six to seven times more than keeping an old one, customer loyalty needs to be firmly on companies' radars.

And, to be fair, for many of them it is. Recognising its importance, they have put in place mechanisms that measure customer satisfaction, typically Net Promoter Scores (NPS). The conventional wisdom that emerged in the 2000s was that NPS was such a reliable indicator of customer loyalty (Reichheld, 2003) that it could be used on its own. However, more recent research has shown that it is not only problematic to rely on a single measure of customer loyalty, these scores can be seriously misleading. High overall satisfaction scores do not mean that your customers are happy with you (Zaki, 2019). We found that while a large percentage of customers gave scores of 8.5 out of 10 or more, 90 per cent of them had used the comments section to voice significant complaints. But these complaints were not being addressed because the high scores were lulling the firm into a false sense of security. Further analysis revealed that this lack of response resulted in lost sales. For instance, one customer designated as "satisfied" had reduced their purchases from over $200,000 to less than $2000.

Customer loyalty is complicated and it can be fragile – and surveys are a blunt instrument. Not only do they measure just one aspect of customer satisfaction, there are significant challenges in deploying them. Only a small subset of customers ever complete them – and this subset gets ever smaller as survey fatigue becomes endemic. One CSA partner reported only one to two per cent response rates – not enough to generate robust results. Even if all of those customers were saying the same thing, it is easy for senior management to ignore them, on the basis that the sample size is not statistically significant.

To get a better understanding of the problem and come up with an actionable solution, the Cambridge Service Alliance has been unpicking what is meant by customer loyalty in order to develop a more nuanced approach to measuring it. It has combined these insights with the power of machine learning and big data to get inside customers' hearts and minds. The approach it has developed was 93% accurate in its predictions of which customers are going to stay loyal (Zaki et al, 2020).

02 UNDERSTANDING CUSTOMER LOYALTY?

Customer loyalty is, in some ways, easy to describe. It's a buyer's attachment or commitment to a product, service, brand or organisation (Lam et al., 2004; Briggs et al., 2007). This attachment stems from the customer's experience. But what is it about that experience that influences attachment? Is it simply the quality of the product or the service? If it is, surely we would all be loyal to the same brands? But human beings are more complex than that, and different customers have a different response to the same experience.

Acknowledging that human behaviour is complicated means that we need to be more sophisticated in how we analyse it and measure it. Based on previous research (Oliver, 1999), we have developed a multifaceted understanding of customer loyalty which has three key dimensions: what people think (their attitudinal behaviours), what people feel (their emotional behaviours) and what people do (the actions they take).

UNDERSTANDING WHAT CUSTOMERS THINK

Measuring customers' attitudinal responses to a product or service can be broken down into two elements: its performance and its desirability (Oliver, 1999). In other words, does the product perform well? Was the service delivered seamlessly? How satisfied were we with our cumulative interactions with the brand? Do we want to buy more from this provider? This attitudinal response has been linked to customer loyalty (eg Oliver, 1980 McDougall and Levesque, 2000) and it is what gets measured using simple survey techniques.

UNDERSTANDING WHAT CUSTOMERS FEEL

However, we also know that there is a strong emotional component to customer loyalty (Verhoef et al., 2009). Customers who 'love' or 'adore' a product or service exhibit a high level of loyalty (Oliver, 1999, Barnes et al., 2016). Equally, customers who have a negative experience during the customer journey may 'attitudinally' rate their experience as positive when surveyed, masking the fact that they are unhappy with aspects of their experience. To understand what they are really feeling, we need to analyse their free text or verbatim comments in which they express their true emotional response.

THINK

How do you rate the quality of our product or service?

What do you think of your experience?

DATA typically from scores from satisfaction surveys

FEEL

Do you love our brand?

Or have we done something to annoy you?

DATA typically in a verbatim format such as free-text survey questions, emails, phone calls, social media

ACT

Will you buy again?

How much will you spend?

Will you tell your friends?

DATA typically from finance systems showing recency, frequency and monetary value of purchases.

UNDERSTANDING WHAT CUSTOMERS DO

Past behaviour is a good predictor of future behaviour. And how people behave is relatively easy to track. Do they buy – and buy again? How much do they spend and are they willing to pay premium prices? In the world of direct marketing, these metrics are commonly referred to as recency, frequency and monetary value of purchase and have been found to be good predictors of a customer's future behaviour (Ballings et el, 2012; Bardauskite, 2014; Tamaddoni et al 2015). Customers also demonstrate their loyalty to a brand by recommending it. It was this impulse that led to NPS becoming such a dominant force in loyalty measurement. If someone loves what you do, they will want to tell their friends

A NEW APPROACH

To understand customer loyalty, we need to understand and measure all of these things. Advances in machine learning mean that we are now in a position to do exactly that by extracting insights from different data sources at scale. Until now, machine learning methods have either looked at quantitative results (such as NPS scores) or qualitative results (such as analysis of free text responses) but not both.

UNDERSTANDING ITS CUSTOMERS: NETFLIX

The new 'digital first', platform-based disruptors understand the power of data in customer retention. In the creative industries, there used to be a widely held belief that it was impossible to predict an audience's response to a new film, book or play.

"Nobody, nobody – not now, not ever – knows the least goddam thing about what is or isn't going to work at the box office." Hollywood screenwriter, William Goldman.

Netflix has well and truly proved them all wrong. How? By using data to understand its customers. In 2009, it gave away $1 million in prize money to the group who came up with the best algorithm for predicting how its customers would respond to a movie based on previous ratings. This has proved to be money well spent. The algorithm is said to save Netflix $1 billion a year through customer retention. The algorithm has a huge amount of data to work on. Netflix knows what you've searched for, what you've watched and when and where you watched it, what rating you gave it, whether you skipped bits or watched bits again. And it uses all this data to show you the content that it thinks you will most enjoy. Not only that, but the data also helps it decide which new shows to commission.

WHEN IT COMES TO CUSTOMER LOYALTY, AMAZON IS STILL KING

According to marketing analysis website, Marketing Charts, in 2019 Amazon was US brand loyalty leader for the third year in a row. 82% of American households are estimated to be Prime members with a 93% retention rate after the first year and 98% after two years. Not only that, but on average, Amazon Prime members spent $1,400 each year as opposed to non-Prime members who only spent $600 annually (Statista).

Like Netflix, Amazon is using what it knows about its customers – what they've bought (and what they've considered but not bought), how they rate their purchases and what other people are buying – to create personal recommendations combined with a seamless service offering. The results speak for themselves.

03 CUSTOMER LOYALTY IN A B2B WORLD

Research into customer loyalty has tended to focus on consumer products and services. Arguably, the more complicated, relationship-based nature of B2B services makes a strong case for more focus on this area. With multiple decision-makers involved, word of mouth plays a particularly important part.

FIVE STEPS TO CUSTOMER LOYALTY: PUTTING THE MODEL INTO PRACTICE

The Cambridge Service Alliance has been working with a firm which provides products and services to the construction sector. Together we have developed a multifaceted, machine learning approach to analysing customer loyalty. Our methods follow the Cross-Industry Process for Data Mining (CRISP-DM) (Chapman et al., 2009), a structured process which is considered the "de facto standard for developing data mining and knowledge discovery projects." (Marbán et al., 2009)

1. UNDERSTANDING THE BUSINESS

We interviewed 15 employees from the firm's customer insight team to understand their current loyalty practices and identify strengths and weaknesses. We asked about their customers' pain points, how they measure customer loyalty and how are they using the insights they acquire. We learnt that the firm's aim is to make its customers feel appreciated, give them a sense of security and a frictionless customer experience. To help make this happen, the firm had developed a customer experience roadmap to highlight which areas are working well, which need improving and the reasons for each.

Five pillars of customer experience

1. **Engagement** – so everyone across the business is focused on the customer experience
2. **Standards** – so the customer experience is delivered consistently
3. **Tracking** – so projects are properly evaluated
4. **Measurement** – so the voice of the customer is captured through telephone surveys
5. **Continuous improvement** – based on the insights gleaned from 4.

2. GETTING THE DATA

This phase involved collecting and integrating data from different sources and classifying it into attitudinal (thinking), emotional (feeling) and behavioural (doing).

The attitudinal data came from the firm's monthly telephone survey and it includes both structured and unstructured responses to questions about the customer's overall satisfaction, the likelihood of them making further purchases or recommending the firm to others and their perceptions of stock availability, staff responsiveness, communication, timeliness and accuracy. The emotional data came from an open-ended question: "Do you have any other comments or suggestions as to how we could improve this service?" We collected just over 5,000 records spanning a three-year period, between 2013 and 2015. The behavioural data came from the firm's financial system and consisted of more than a million individual transactions over the same three years.

3. APPLYING THE CONCEPTUAL FRAMEWORK

We used machine learning and natural language processing (NLP) techniques to work out what variables we would need to measure customer loyalty. To analyse attitudinal responses we used established scales: quality scores (Parasuraman et al 1988), overall satisfaction (Fonell, 1992) and repurchase intention (Bolton & Drew, 1991; Parasuraman, 2006). To analyse emotional responses we used a text mining model on the free text data set, using emotion analysis, a field of NLP which analyses people's opinions, sentiments, evaluations and emotions via the computational treatment of subjectivity in text (McColl Kennedy et al, 2019; Zaki, 2019, Zaki and Neely, 2019). To analyse behaviour, we used the product support data, looking at the recency, frequency and monetary value of their customers' transactions.

Our definition of a churning customer for this firm was someone who had not had a transaction for more than 90 days. This was based on the fact that the average time between transactions for all of its customers was 22.5 days.

4. BUILDING THE ALGORITHM ON A TRAINING DATASET

We established a target variable. We used transactional data from 2013 to find groups with similar patterns of behaviour and created a segment which had the highest risk of churn. We then used data from 2012 to try to predict which of those customers were most likely to belong to our 'at risk of churn' segment. And we split the data into two sets: one for training and one for testing.

5. TESTING THE MODEL.

To make sure it was working properly we also tested the model on a different dataset, using 2014 data as the target variable and 2013 data to generate our predictor variables. This further step allowed us to fine-tune and validate our model.

WHAT DID WE FIND?

Our prediction model correctly classified 93% of customers.

- During the three years the firm had used only Net Promoter Score to measure loyalty, it had thought that 70% of its customers were promoters, 25% were passives and 5% detractors. In fact, however, our approach showed that that 41% were likely to churn.
- We identified five distinct customer segments and their responses show why it is so important to take this multifaceted approach.
- 'Platinum' customers scored highly in their attitudinal responses but their emotional responses (captured through analysis of free text comments) betrayed some significantly negative responses.
- Conversely, in the next category ('Gold'), there were some extremely loyal customers that conventional approaches miscategorised as 'at risk'. Their attitudinal scores were relatively low which would usually classify them as a detractor whereas they were scoring very highly for emotional responses and making repeat, high value purchases.
- These findings support our thinking that emotional and behavioural responses are better indicators of loyalty than attitudinal measures.

04

FIND OUT

WHAT YOUR CUSTOMERS ARE THINKING, FEELING AND DOING.

By using our five-step approach.

1. Analyse your business context in order to understand the ways in which your customers interact with you (whether physically, socially or digitally) and what their expectations and pain points are. What are the current strengths and weaknesses of your customer service practice, how are you measuring customer loyalty and using those insights?

2. Identify your datasets. You will need attitudinal data (for example, from customer surveys), emotional data (for example, from free text comments in emails or on social media) and behavioural data (for example, sales data).

3. Apply the conceptual framework. You will need to establish scales for attitudinal data, apply Natural Language Processing techniques on free text and develop profitability variables for your sales data. You will also need to create a customer churn predictive variable based on the average time between customer transactions.

4. Build the predictive model and apply it to a training data set.

5. The last step is to validate the model and fine tune it by testing it on a different dataset.

1	2	3	4	5
Understand the business issues	Find the right data sources	Apply the conceptual framework	Build the predictive model	Evaluate the model by testing it on a different data set

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