Why decision driven analytics is key to driving customer engagement in fuel retail

Peter Baudains, Head of Solutions and Analytics Innovation at The ai Corporation (ai), writes about the importance of using data analytics to improve customer engagement.

The pandemic and resulting national lockdowns have created a challenging operating environment for fuel retailers, with less people travelling and sales decreasing. As a result, many retailers are turning to data analytics and associated technology to reduce costs and improve customer service.

Some of the most interesting - and potentially more beneficial - projects focus on using data analytics to improve customer engagement. Helping to retain and understand existing and new customers better. Identifying individual customer's needs, and then adapting service levels to meet those needs and expectations. Indeed, it is becoming widely accepted that a data driven business can understand their customers better and tailor their services in a much more systematic way.

For example, by analysing the data which a retailer holds on an individual's purchases - the types of product an individual buys, the extras they might add to their basket, the regularity of fill-ups or the location of their favoured store or forecourt - retailers can personalise their marketing efforts, which may involve not sending a customer a particular type of email or loyalty reward, because they understand what an individual is likely to buy, when and where. They can time and tailor their approach. They can send customers useful information or have one of their team call a customer, who might be thinking of buying from a competitor.

In the fuel card world, this might involve identifying novel and flexible pricing and rebate structures, which are based around the operational needs of the customer and derived from analysis on customer usage patterns. Another analysis might investigate the routes typically taken by a fleet and to provide incentives to fill up at locations which fit those patterns. This type of approach benefits all the involved parties: the driver, because it is convenient; the fleet manager, because it is cheaper; and the retailer, because it locks customer usage into their network.

Insights are only as good as the questions you ask

Despite the benefits, the continued existence of the data-value gap tells us that many data analytics projects are still destined to fail. And while many organisations continue to improve two important competencies which remain central to successful data and analytics projects (data governance and analytics skills), a third element to this trifecta is often overlooked.

No matter how advanced your data analysis function is, your data will not provide you with a ready-made solution unless you ask it the right questions. Many businesses forget that any analysis needs to be decision driven. In a recent article, experts explain how some approaches that are data-driven can focus on using available data to answer the wrong question.

A much better approach is to start with the question that needs answering; find the data that enables the question to be answered and then design an analytics approach that is directed at evaluating the available alternatives. To explore this idea a bit further, it is helpful understand a commonly used classification of analytics projects, which states that data and analytics projects typically fall into one of three types

- Descriptive analytics, which aim to describe what has happened. These types of projects are concerned with sourcing relevant, timely and accurate data, followed by cleaning, enriching, and visualising the data to provide an intuitive explanation of an event that has occurred or a historical perspective of an ongoing process. A common use of descriptive analytics is in the development of business dashboards which aim to summarise business performance through KPIs.

- Predictive analytics, which consider future events and attempt to answer the question of what is likely to happen. Projects of this type will involve a predictive model, often constructed by training a machine learning or statistical forecasting algorithm with a historical dataset. By learning and extrapolating correlations in the data, these models attempt to capture the essence of a behaviour or causal link which results in beneficial predictions. Examples include forecasting customer demand or classifying a transaction as fraud or genuine (the future event being predicted here is not the transaction itself but the revealing of the true nature of the transaction).

- Prescriptive analytics, which tackles the question of what should be done. The goal of this type of project is to understand what intervention can be made to a system to proactively achieve some desired outcome. This type of project typically includes elements of both descriptive analytics (to understand the as-is) and predictive analytics (to provide the to-be).

However, the biggest challenge with prescriptive analytics is to understand which interventions work and which might have unintended consequences. There needs to be an investigation using causal analysis to examine the link between the intervention proposed and the outcome that is sought. This can be obtained via simulation, various statistical or optimisation techniques and/or by performing a randomized experiment.

Fraud prevention is an excellent use case here. A descriptive analysis will tell you all about your fraud problem (when/ where/how much). A predictive model can provide an indication of which transactions might be risky. While a prescriptive analysis will consider which interventions will lead to the best business outcomes.

For example, by detailing which transactions should be declined in real-time, which should lead to the automatic blocking of a card before the next transaction is made, before it is reviewed by a human analyst. In this case, prescriptive analysis can be performed automatically to optimise profit, accounting for the cost of fraud loss, operational costs of manually reviewing transactions, as well as declining the payment at the point of sale, which, in the case of retail fuel, may lead to vehicles blocking the forecourt.

If a project is going to be decision-driven, it must have some form of prescriptive element to it. This prescriptive element investigates the interventions that can be made through the decision (the alternatives) and links the underlying data, and any models developed along the way, to that decision.

So, how does this help fuel retailers?

Let’s take a fuel card issuer, who is seeking to reduce customer churn. Descriptive analytics will inform the decision-maker of the extent of the problem and can also identify characteristics of those customers that have churned. Predictive analytics can provide a ranking of current customers based on their propensity to become ‘churners’. A predictive model will likely have been built based on characteristics of those historical churners. But this only gets the decision-maker so far. The final step, and arguably the most critical, as provided by prescriptive analytics, will determine what actions can and should be taken by the business to maximise customer retention. This may involve performing an experiment exploring the impact of a possible intervention.

The decision-driven framework proposes that the possible interventions should be determined at the outset of the project and direct both the data collection and modelling phases of the project. Placing interventions and alternatives at the front and centre of the analytics project is critical. Successful data analytics projects in retail fuel need to be structured, focused, and even fixated, on understanding the interventions available to improve customer experience and engagement.

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