Intelligent Analytic Interfaces

Changing User Behaviour: Nudge Along

MARKET NEED

Providing analytics-driven insight does not guarantee that people will take note of it and change their decision-making behaviours. For example, did a customer identified as a churn risk respond to the intervention recommended; or did loan officers in a bank actually base their lending decisions on the output of risk models?

Measuring the success of any analytics-driven project, therefore, requires looking beyond the insights that are produced to ways in which these insights are communicated and delivered to ensure that behavioural change takes place.

This research will benefit any company that wishes to make sure that the application of analytics results produces the required or expected outcome. For example, did a customer identified by a supermarket as a user of baby products take advantage of a promotion on nappies that was on offer that week? If not, can a message be *tailored* for that customer to encourage them to take advantage of such a promotion the next time? Using tailored messages, our research is working on encouraging the greatest level of change in a customer/user's behaviour .

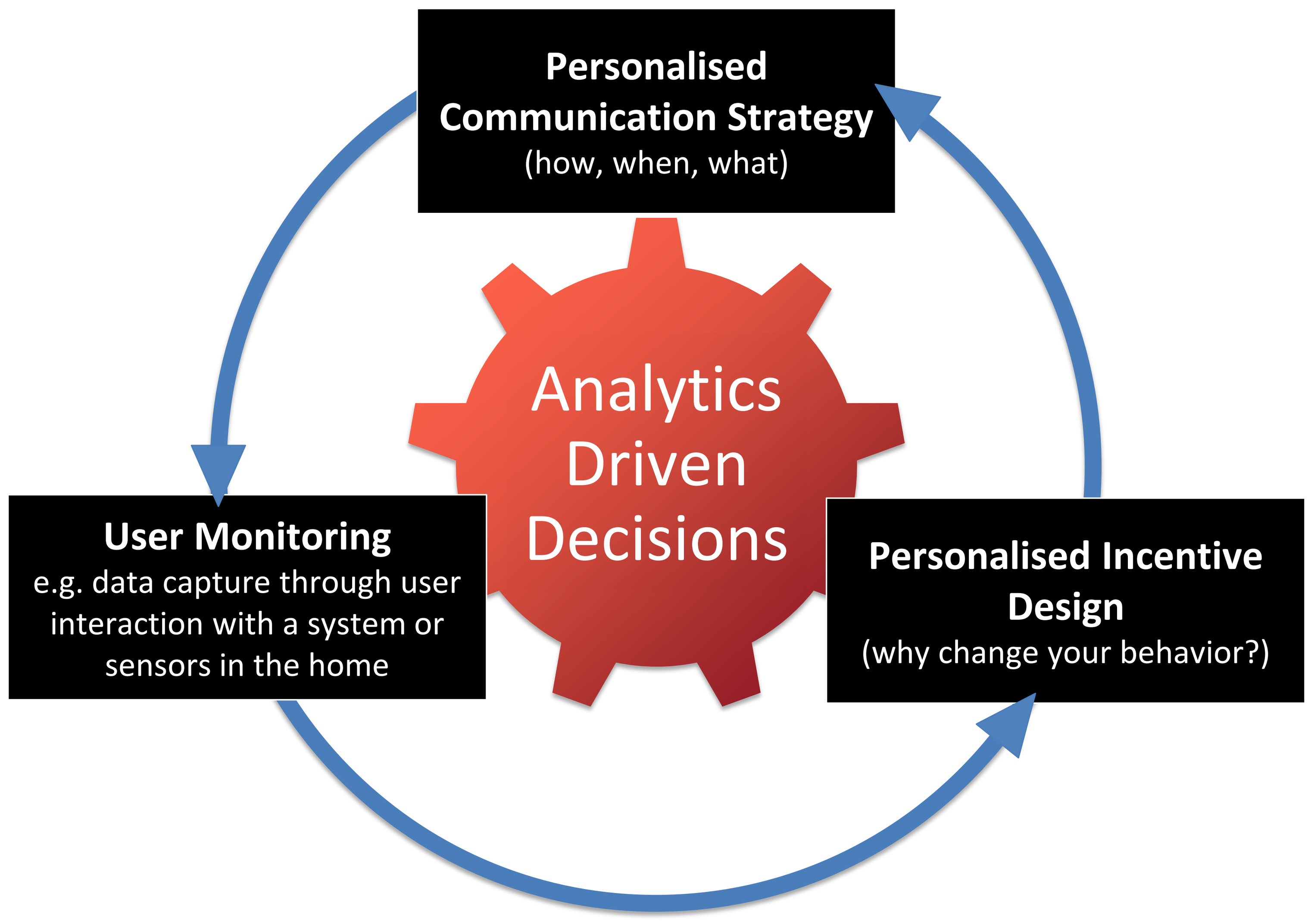

Figure 1: Ensuring maximum change in user behaviour based on analytics-driven insights requires a closed-loop process.

TECHNOLOGY SOLUTION

Figure 1 models the process that should surround analytics-driven decision making to ensure the greatest changes in behaviour occur. **User Monitoring** would come from a company's own customer data, and would include details on a customer's interaction with the company's systems, etc. A **Personalised Incentive Design** would require finding an incentive by which a customer may change their behaviour. There are a range of approaches that can be taken e.g., including details on money-saving methods, running promotions, etc. The next step is to communicate this incentive to the customer using a **Personalised Communication Strategy**. The communication strategy should take into account the medium used (e.g. text message, email, etc.), the content of the message itself, the communication frequency (how often recommendations are made to customers) and the communication variety (should the messages change from one communication to the next).

The question remains as to how one chooses the optimum incentive and communication-type to achieve the desired behaviour change. At CeADAR the approach being taken to achieve the goal of maximum behavioural change is to use techniques from **case-based reasoning**. This forms the basis of the Recommendation Engine shown in Figure 2. The Recommendation Engine (**Nudge Along**) produces personalised communications, e.g. text or email messages, by taking in account customer usage profiles, relevant external data sources (e.g. typical weather conditions, etc), any past communications that customer has previously had with the system and the outcome of these prior communications. These personalised communications could be tips on how a customer can save energy by reducing their use of central heating or tips on how to save money by switching to a new tariff, etc. The Recommendation Engine monitors the outcome of the messages sent out to customers (were they successful?) and feeds this information back into its database so as to be able to improve its recommendations the next time around.

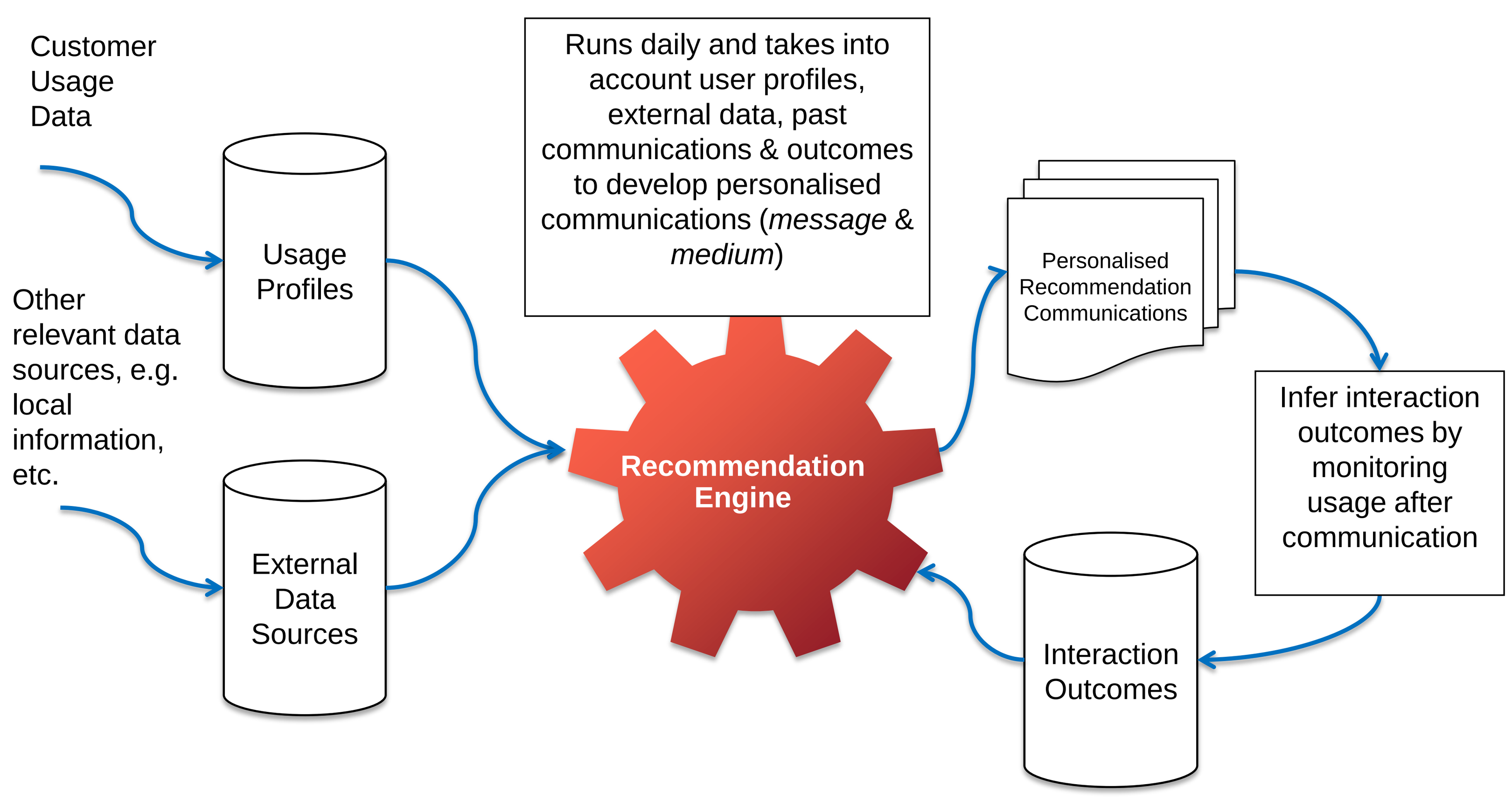

Figure 2: The Recommendation Engine cycle. The basis of Nudge Along

APPLICABILITY

This research will benefit any company which wishes to make sure that their communications with customers produce the required or expected outcome. For example, the ability to change user behaviour is of interest to any company that wishes to see the effects of a marketing campaign, or the effects of an attempt to get staff to save energy in their offices by switching off lights, etc. As a single example, studies have shown that by changing user's behaviour electricity use can be reduced by 2%. Such a reduction of energy use at peak demand time would be of great interest to utility companies who could save money by flattening the peak demand profile (that is, reducing the need to occasionally bring on-line less energy efficient oil-powered power stations, etc.).

RESEARCH TEAM

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