Contact Centre uses the latest in AI to improve customer outcomes, set KPIs & reduce volume

A contact centre handling 1000's of daily contacts adopted the latest AI text analytics to increase customer satisfaction and reduce contact volumes.

The situation

Good customer service is an opportunity to repair a bad customer experience. Indeed, bad experiences corrected through exceptional customer service have been shown to turn a dissatisfied customer into a brand advocate. However, understanding why outcomes vary between agents can prove difficult, requiring proper categorisation and real-time tracking of outcomes.

This case study shows how a contact centre provider, handling thousands of customer contacts on a daily basis, was able to use PrediCX to improve customer outcomes, set intelligent KPIs for their agents, and simultaneously reduce overall contact volume.

20% increase in customer satisfaction
5% reduction in contact volumes
25% efficiency increase in AHT
41% of contact shown to be avoidable

Approach

PrediCX is a Machine Learning platform that allows for rapid building of accurate Machine Learning models, able to be applied in real time for incoming customer data. This led to customer interactions being automatically classified, allowing for real-time early warning, actionable insight, and next-best-action to be derived. Furthermore, sentiment and sales intent models can be built to allow smart reassessment of existing agent KPIs, maximising their performance without the need for CSat surveys.

Fresh topics – Time saved and performance improved

PrediCX rapidly generated new topics and models that were demonstrably more accurate and relevant, with previous 'bucket' categories reduced by over 50%, and older categories having their accuracy and specificity increased. Newer, smaller issues (potential early indicators of problems) were identified that would previously have been overlooked, allowing agent effort to be directed towards solutions instead of categorising.

Agent performance optimised

Models were created for standard sentiment, and emotional cues or 'intents' such as: 'didn't understand', 'bad previous advice', 'previous agent disconnected', 'repeated problem', and highlighted issues such as other agents not performing, excessive customer effort, repeated issues, and likely to churn or unfulfilled sales.

> "…happens in REAL TIME, advising the agent what to do next if a customer expresses particular intent or behavior"

These issues were used to redesign elements of the customer journey as well as coach agents; one of the issues surfaced was a 50% disparity between best and worst performing agents. Capturing and measuring these parameters for the first time allowed the company to redesign its agent coaching plans and move to real time information and templates.

Additionally, cross referencing this output with the topic model, highlighted contact types and situations that were problematic and allowed the platform to advise on the next best action. This can happen in real time, advising the agent what to do next if a customer expresses particular intent in a certain situation as well as allowing for partial automation.

Conclusion

Immediate operational improvements included:

- 20% increase in customer satisfaction
- 5% reduced demand
- 5% saved from improved early warnings
- 25% increased efficiency in AHT
- 20% improvement in scripts and templates

The output from the models allowed them to make changes, immediately measure the impact and also underpin a business case for automation. Customer satisfaction with agents increased markedly, and coupled with the highlighted opportunities for operational improvement, the client was able to provide their customer with a far better service. 41% of their existing contact was shown as being avoidable or able to be fully automated, significantly reducing costs and increasing scalability for the client.