A Better Understanding of Statisfaction Data through Constrained Analytics

THE PROBLEM
The information extracted from satisfaction surveys allows firms to improve their performance based on customer feedback, and maximize their service spending based on what customers care about most. On the surface, it may appear easy to analyze such survey data. However, Simon Blanchard and colleagues Sunghoon Kim, Wayne Desarbo, and Duncan Fong suggest analysis of such data is easier said than done as the results revealed by analytical tools such as regression are often provide misleading and inaccurate results.

Do you use the correct statistical tool to analyze your perceptions of service quality survey results?

Blanchard and colleagues analyzed service data from a midlevel insurance company that had distributed a service quality questionnaire to their customers. The survey measured 5 overarching dimensions of service quality (Reliability, Assurance, Tangibles, Empathy and Responsiveness) using 22 questions. Initial analysis shows that 98% of the possible correlations were significant and all 22 questions were predictive of overall service quality, indicating widespread multicollinearity, which is problematic for meaningful interpretations and recommending service quality improvements.

For instance, many of questions that significantly predicted overall service quality, did so negatively – interpretation of these results would suggest worsening performance on these service issues would improve perceptions of overall service quality. For example, the results suggested that if the firm were to improve the visual appeal of the materials it produces, customer overall satisfaction would actually decrease. These results are both non-sensical and un-actionable for managers.

THE SOLUTION: Implement managerial constraints directly into the analyses, while simultaneously performing variable selection and segmentation

To solve the problem, Blanchard and colleagues introduced 3 constrained models for the analysis of customer satisfaction data that avoid the pitfalls of previous tools while also accounting for heterogeneity in consumers’ perceptions of service quality. Incorporating segmentation directly into the model (as opposed to apriori or after the fact) is especially important as one segment may be especially concerned with reliability of the service provided, while another may have a greater need for an empathetic staff.

The common factors model: This model identifies the most important predictors of service quality for all respondents, but also indicates whether specific segments differ in their
emphasis of these issues. The model allows a firm to focus its effort on the service items that are most relevant to all consumers, while also providing insights into level of concern each segment has regarding each issue.

The distinctive factors model: This model identifies segments of consumers that value different aspects of their service experience. This allows a firm to maximize the efficiency of targeting. For example, while some items may be important to two segments, the model would reveal that one segment most heavily weights “National’s physical facilities are visually appealing” while the other is most concerned with, “National’s employees are neat appearing.”

The dimension constrained model: Many service quality surveys include multiple questions pertaining to the same service dimension (e.g., in SERVPERF, Reliability is measured via 5 items). Which of these items is most important? The dimensions constrained model identifies the specific service issues within each dimension (Reliability, Assurance, Tangibles, Empathy and Responsiveness) that are most important for each segment. This type of constrained model can be particularly important in the case that a firm has limited resources and wants to know how to most efficiently apply those resources.

To apply these models, firms can rely on a priori constraints, theories about their customers, or resource limitations. Together these considerations can help dictate which model should be applied. In the analysis the authors showed that the distinctive factors model best explained the data. This finding indicates that some National Insurance customers see service quality very differently than others, as shown via the analyses of the two identified segments. In one, overall service quality was best predicted by “When you have a problem, National shows a sincere interest in solving it” and “Employees of National understand your specific needs”. In the other segment, “National maintains error-free records”, “National treats you with care”, and “You feel safe in your transactions with National” were the best predictors of service. The results suggest one segment that primarily cares whether National understood and solved their needs and a second segment that was more concerned with the feeling that national treats them with care, provides a feeling of safety, and does not make mistakes.

IMPLICATIONS & CONCLUSIONS

By identifying the segments of consumers composing a business’s customer base, and their service priorities, firms are better positioned to address current needs while also marketing distinct but congruent solutions to potential prospects. Whereas having the right questions is important, an analyst must be careful in making sure that the analytical tools used provide correct insights. The models proposed by Blanchard and colleagues can now help those interested in the analysis of customer satisfaction data to obtain and implement real insights.


This Brief, based on the work of Simon Blanchard et al., was composed by Chris Hydock in collaboration with Simon Blanchard.