What's Important?

Identifying Drivers of Satisfaction with Public Service Organisations in New Zealand:

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What is this paper about?

Satisfaction research undertaken by many organisations aims to measure how well organisations are performing on service elements thought to be important in the delivery of quality services. Most of these studies aim to identify which aspects of service are most important. The idea is that as not all service elements are equally important; improving performance with some elements of service will have a bigger impact on overall customer satisfaction than others.

This paper outlines a *method* for identifying which aspects of service are most important in producing customer satisfaction. This method, factor analysis regression, results in a more robust understanding of drivers of satisfaction than the traditionally used stand-alone regression analysis.

The Common Measurements Tool (CMT)

The CMT is a customer satisfaction tool designed specifically for public services. In this respect, the CMT is a solid approach with evidence supporting it, with the added benefit of access to benchmarking information.

Nexus Planning & Research has used factor analysis regression in conjunction with the CMT to identify drivers of satisfaction. It has proven to be a very good approach for understanding drivers of satisfaction with a public sector organisation.

Identifying Drivers via Regression Analysis

Regression analysis is the method used most widely by market research companies to identify service elements that are 'important'. Regression analysis builds a model that discriminates between satisfied and dissatisfied customers. In other words, which aspects of service, when present, generally result in satisfied customers, and when absent, generally result in dissatisfied customers. It is these elements of service that have the largest potential to improve customer satisfaction.

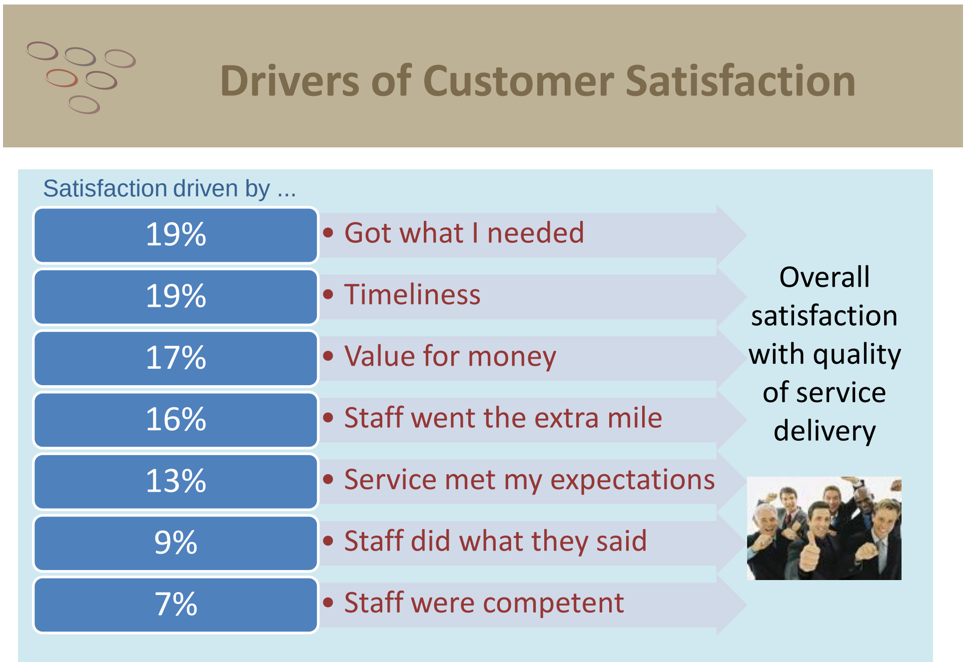
The Problem

One of the challenges of conducting a regression analysis is dealing with correlations between the explanatory variables i.e. the service elements. So for example, ratings of aspects of service such as 'staff are polite and friendly' are related to other attributes such as 'staff are good listeners.' This is, not surprisingly, a common occurrence in survey data. It is called multi-collinearity and is a big problem for regression analysis:

1) Multi-collinearity can (and does) produce unstable models. For example, multi-collinearity can produce non-sensical results such as negative relationships where we would expect positive ones e.g. 'polite and friendly staff' contribute to dissatisfied customers (this makes no sense). It can produce unstable models e.g. a small change in the model such as the removal of a non significant attributes results in big changes in the model (this shouldn't happen).
2) It can lead to erroneous interpretation as it does not show the 'full picture'. For example, you may have a result which does not include any mention of staff being 'good listeners'. Naturally our interpretation is that 'listening' is not important in driving customer satisfaction, *but this is not necessarily true*. The attributes that are not included in the model may have been excluded because they are correlated with attributes in the model, NOT because they have no bearing on customer satisfaction. Their exclusion can lead to a narrow focus on a specific service element that needs to be addressed, rather than a more holistic programme that addresses the underlying dimension that is causing the problem.

The following demonstration shows just how vulnerable interpretation from regression analysis is, in the face of multi-collinearity. This analysis is from a real study where the CMT was used with a public sector organisation in New Zealand.

The first step was to identify a model that identifies the best predictors[1] of customer satisfaction based on a set of 18 explanatory variables included in the survey.

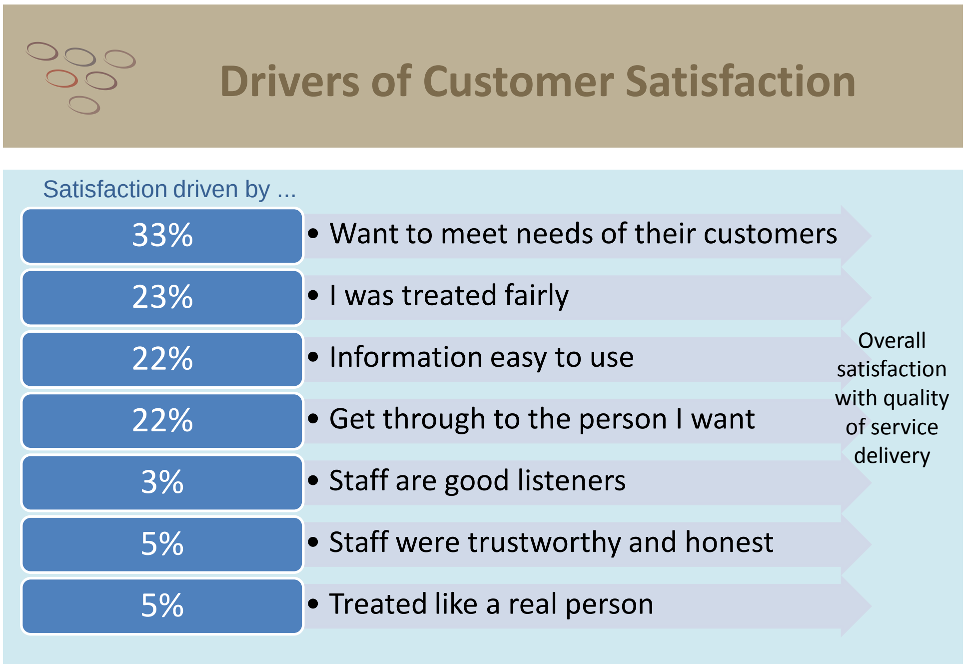


R^2_a=89%

This model accounts for 89% of satisfaction with the service received by the customer. It appears to makes sense – nothing seems strange. We know that there is correlation between the predictor variables (because we have looked at the paired correlations) but so what?

Well look at this next analysis. We next removed all the above service elements from the set of predictor variables, and re-ran the analysis without them. We used the same process to identify the best predictors in the remaining set of service elements. The following model was emerged:

[1] Using backwards regression identified all significant service elements. Only non significant attributes are excluded.



R^2_a=81%

Again, there is nothing strange here. The coefficients are in the expected direction (nothing is negative when it should be positive) and the model accounts for most of the variance in overall satisfaction, *but it is a completely different model*. Why were these service elements not included in the first model they are important? The answer is of course because of multi-collinearity.

Implemented in a public service organisation, these two models would lead to different decisions on what aspects of service should be improved. The first would lead to focus on outcomes, value and timeliness, the second to people-skills when dealing with customers, when in fact both are important.

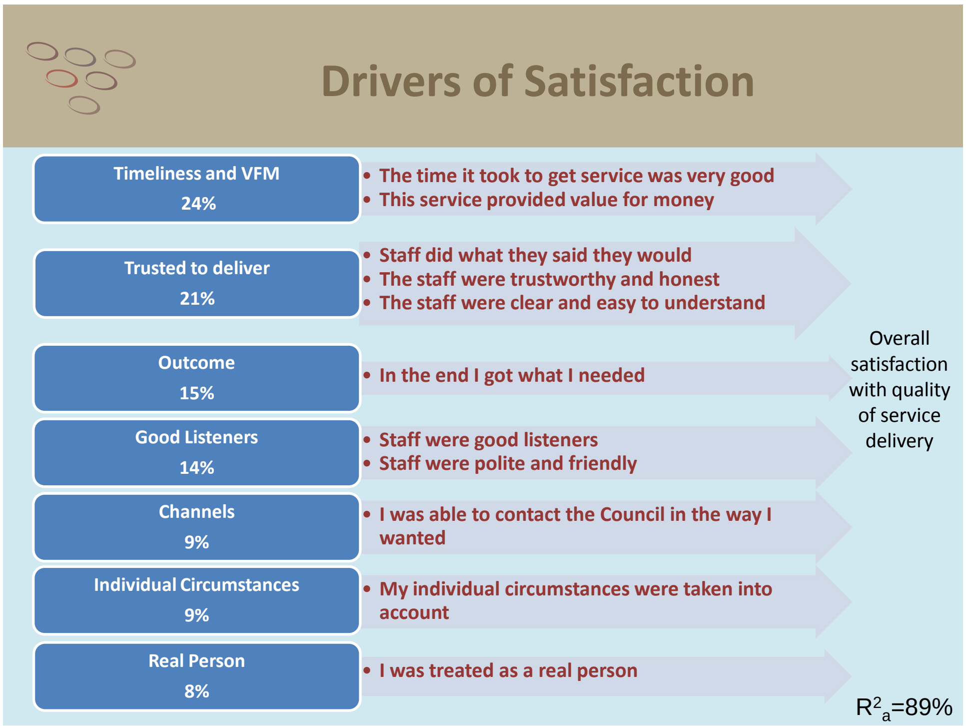
Our Approach – Factor Analysis Regression

Our approach to dealing with this is to recognise that there is useful information in the relationships between the explanatory variables. These relationships tell us about under-lying dimensions. What we need is a technique that can take the service elements we have in our survey and identify the dimensions or factors underlying them. For example, do, 'staff are good listeners', 'staff are polite and friendly', and 'staff are easy to understand', identify an underlying dimension which we could call staff communication?

If we can identify the 'under-lying' dimensions so that they are independent from one another, then we can use regression to work out which of these dimensions is most important without fear of the mis-interpretation that can result from multi-collinearity.

The approach we recommend is factor analysis regression. Factor analysis looks for relationships between the explanatory variables to identify the factors or dimensions under-pinning the data. Having identified these under-lying dimensions, we then look at which are most important in driving satisfaction.

The following example is from the same study as the earlier two models. It provides more holistic understanding of what drives satisfaction by identifying the dimensions underlying customer satisfaction.



In summary, this approach has two key advantages over stand alone regression:

- It produces models that are not plagued by multi-collinearity.
- Its allows for a more holistic interpretation that takes into account the dimensions under-pinning the service elements included in the survey.