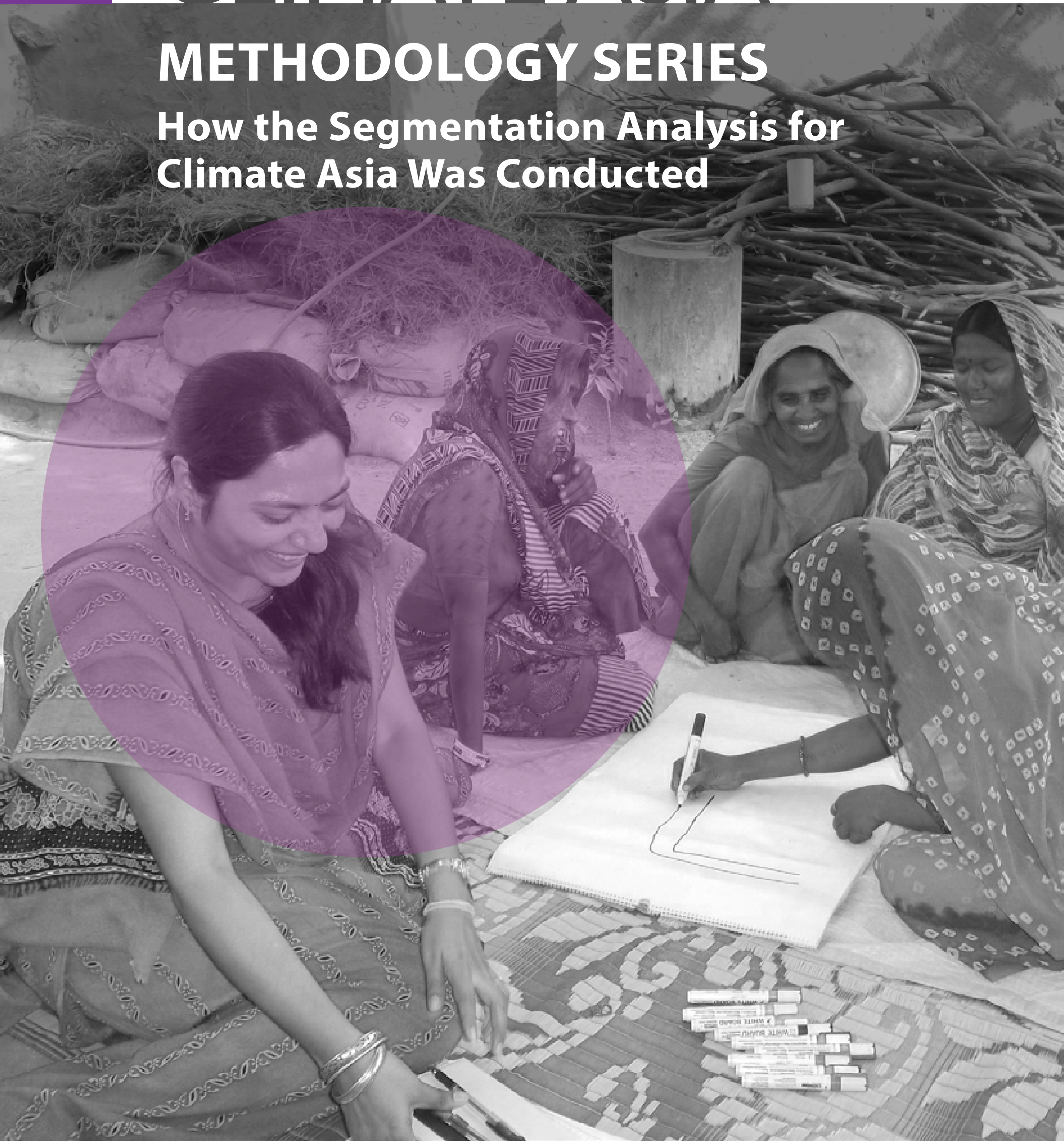
CLIMATE ASIA

METHODOLOGY SERIES

How the Segmentation Analysis for Climate Asia Was Conducted



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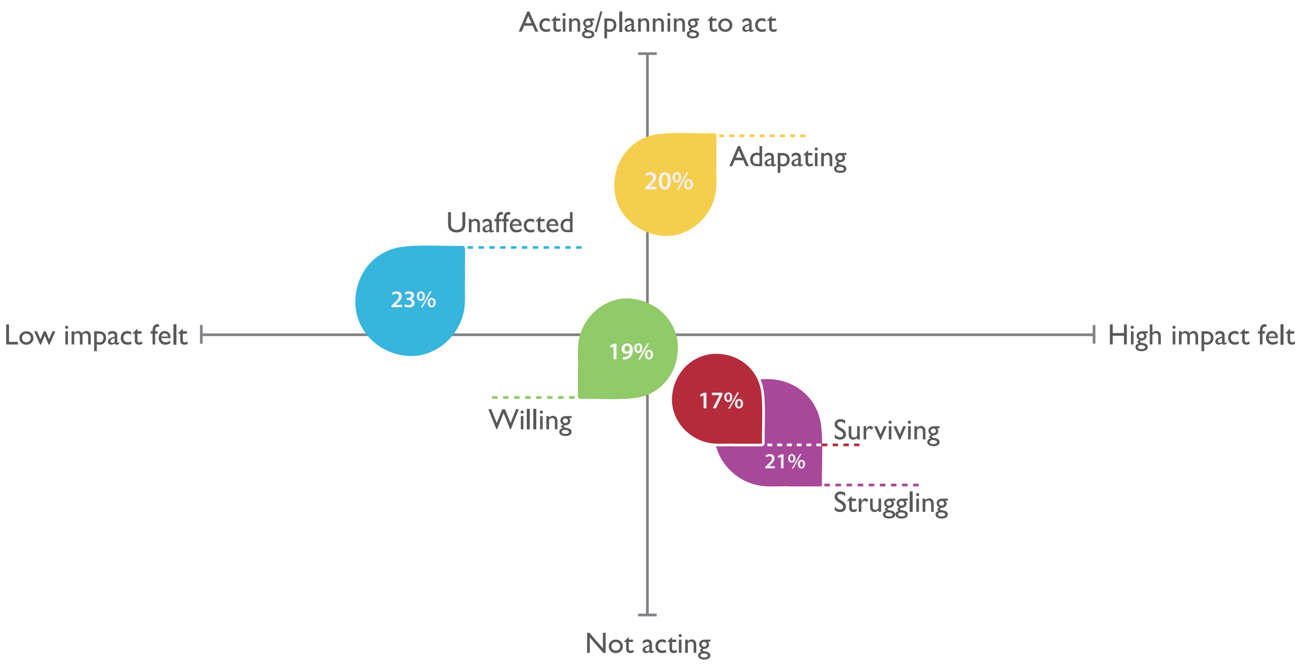
CLIMATE ASIA

METHODOLOGY: HOW THE SEGMENTATION ANALYSIS FOR CLIMATE ASIA WAS CONDUCTED

This report outlines how the regional audience segmentation for Climate Asia was carried out. The audience segmentation for each country is explored in each country report.

In order to understand people's needs and identify opportunities to communicate with them effectively, Climate Asia has analysed survey data from across the region and placed people into five discrete segments, using a process called cluster analysis. Each segment varies in the factors that enable and prevent response. As such, each has different communication needs and can be supported in different ways. We have called these segments surviving, struggling, adapting, willing and unaffected.

The proportions of these segments within a country represent the extent to which people in the country perceive impacts and are taking action to respond to them.



- Surviving: "Finding it too hard to take action"
- Struggling: "Trying to take action but finding it very difficult"
- Adapting: "Acting and wanting to do more"
- Willing: "Worrying about tomorrow"
- Unaffected: "Believe there is no need to do anything"

This document gives an overview of the analysis carried out to achieve these segments:

1. Setting the hypotheses
2. Scoring and validation of scales
3. Identifying characteristics to segment participants
4. Cluster definition
5. Validation of the final cluster solution
6. Increasing the number of observations clustered

SECTION 1:

Prior qualitative investigation and a review of existing literature on climate change adaptation meant the research team had theories on how items from several question sets should relate to each other.

The literature review included existing models on climate change adaptation such as Practical Action's framework "From Vulnerability to Resilience"[1] or the Livelihood Vulnerability Index by M. Hahn et al (2009)[2] among many others.

The initial qualitative investigation included focus group discussions with people from various socio-economic backgrounds in some of the seven countries researched by Climate Asia. It also included an initial round of workshops with experts and opinion formers from these countries.

The team developed a set of hypotheses on the links between factors that influenced the perception of impact and the level of response, such as access to resources, access to information, willingness to respond, level of community co-operation or confidence in government. Both the initial qualitative data and the literature review allowed Climate Asia to develop a provisional framework for adaptive capacity to climate change which represented the potential links between such factors.

SECTION 2: SCORING AND VALIDATION OF SCALES

The next step was to assess which scales or constructs to develop to use in audience segmentation. Climate Asia's unique focus on people living with climate change meant many elements of the quantitative survey did not come from pre-existing tested and evaluated measures, but were informed by qualitative work and adapted from existing measures. (For more details see the full Climate Asia methodology paper.)

Therefore, scales were scored, and retrospectively tested for their appropriateness, both within and across the seven project countries in Asia. The following section details this testing through five parts:

1. Factor analysis
2. Identifying characteristics to segment participants
3. Cluster definition
4. Validation of the final cluster solution
5. Increasing the number of observations clustered

1 Pasteur, K (2011) From Vulnerability to Resilience. *A Framework for Analysis and Action to build Community Resilience.* Rugby: Practical Action Publishing. [online] Available from: http://practicalaction.org/media/view/9654 [5-9-2013] [Accessed 5 September 2013]

2 Hahn, M. et al (2009) "The Livelihood Vulnerability Index: A pragmatic approach to assessing risks from climate variability and change—A case study in Mozambique" Global Environmental Change, 19 (74-88)

1. Factor analysis:

Evidence that questions could be scored together to form meaningful measures was sought retrospectively. Factor analysis, specifically principal axis factoring (PAF), was used to assess this possibility, and subsequently to provide evidence of criterion validity.

Key scales and concepts based on Climate Asia's hypotheses were selected to support scale construction. Factor Analysis was also used for items that collectively measured latent (not directly observable) constructs.

Factor analysis method: The factor analysis used a PAF extraction approach, which is applicable to ordinal level data, as it uses a correlation rather than a covariance matrix. The approach is most suited when researchers have theoretical ideas about the relationship between variables[1] , as in Climate Asia's case. Rotations were permitted to maximise the loadings of items on factors in order to make results more interpretable. Specifically, promax rotation was employed since it is able to compute a large number of observations and is a non-orthogonal approach. This meant it allowed factors identified to correlate, as it would be unfair to assume independence of factors among the scales assessed.

Cultural comparability: PAF is only a dimension reduction technique and for all scales the extent to which items load onto a factor will differ between countries. In some cases the number of factors produced from the same items also differed. These differences in association were further compounded by how distinct cultures responded to items and if respondents were used to Likert scales. To test for expected differences, PAF was repeated in two different countries and in those cases where no agreement between results was found, researchers carried out additional analysis.

When the results from two countries agreed poorly, researchers attempted to find a solution that performed adequately in both. One common approach is to develop the scale using one data set and then assess the accuracy of this "measurement model" using other data. This was deemed not to be optimal, as confirmatory factor analysis also assesses parity in item loadings. Even when agreement was found between items feeding into a factor, individual item loadings were quite different between countries.

Scale scoring accounted for this by computing scales in which each item would contribute an equal weight (equivalent to a loading of 1). However, using confirmatory factor analysis would have incorporated the loadings. This would mean that confirmatory factor analysis would not be testing the fit of the scales scored, but the fit of a weighted scale. Because of the differences in loadings mentioned above the fit would have been poor.

Therefore when results agreed poorly, researchers attempted to identify any consistent factor structure. If one was not found, the performance of the differing factor structures were tested in each country through inter-item reliability analysis. The factor structures that produced the best reliability statistics and inter-item correlations over several countries were used.

Reliability testing: As outlined above, Cronbach's alpha was used to decide between differing factor structures produced by countries. However, reliability analysis was also run on all measures scored in this way. Furthermore, outputs not only produced an overall internal reliability score but also indicated if removing items would have further improved the reliability coefficient. Only scales with a reliability coefficient of 0.5 or greater were scored.

Scoring the measures: Most derived variables came from an average across several items, evidenced through factor analysis. Some other computed variables were derived from a count of responses, or through simple recoding. All scoring accounted missing values.

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1 BrownJ. D. (2009) "Principal components analysis and exploratory factor analysis – Definitions, differences and choices.". Shiken: JALT Testing & Evaluation SIG Newsletter.

Validity testing: While factor analysis provides evidence of criterion validity, in order to further validity testing, and to develop scales not derived from factor analysis, researchers developed correlation matrices to examine associations between key variables. The expected correlations were taken as evidence of predictive validity. Separate correlation matrices were produced for six of the seven countries (data from China was excluded because of timing issues) and both Spearman's rho and Pearsons Correlation coefficients were used to examine the associations. In general the correlation matrices provided further evidence of the derived variables' validity along with other measures in the scale.

Checks for collinearity: Collinearity is a situation in which a high proportion of variance in a scale item is explained by other items. It means the item is partly redundant, as it only contributes a small amount of unique information to a computed scale. High levels of collinearity are not just indicative of redundant items: when a scale is scored from a small number of items, then medium to high levels of collinearity between items can result in a non-normal distribution.

This is caused by derived scale values calculated from the same item units (for instance all 1 or all 2) having a much higher frequency of respondents. This is because collinearity is reflective of participants selecting the same responses. Therefore, collinearity was assessed between items used in key scored scales for each country, and then across all seven countries.

To assess collinearity of items in a scale, the research team used principle components analysis (PCA) to create a component score from items used and then saved this to the data set. The items contributing to the score were then regressed against the PCA scores, enabling access to collinearity checks through the condition index. A condition index of 15 to 29 is indicative of moderate collinearity, and condition index of 30 or greater indicates significant collinearly. When a condition index had a score close to or greater than 15, individual items were investigated further by looking for a high proportion of mutual variance explained between two items. Offending items were either removed or the scale was not scored in the respective countries.

2. Identifying characteristics to segment participants

Cluster analysis does not perform well when a large number of variables are used to segment populations. Because participants could only be segmented through a limited number of characteristics, the usefulness of the variables measuring them needed to be assessed. Usefulness was assessed in several ways, such as reviewing Climate Asia's logic model. In addition, two statistical approaches were used, regression and collinearity tests. These are reviewed below, along with prior steps taken to ensure the analysis was robust, in four parts:

- Checking the distribution of variables
- Checking for collinearity between scored scales
- Running regression
- Identification of segmentation variables

Checking the distribution of variables: For a range of reasons outlined below, the team used both ordinal and multi-nominal logistic regression to identify key variables for segmentation. One particular problem with both these regression approaches is perfect prediction, and small cell counts. Both affect goodness of fit statistics, but perfect prediction makes the odds of outcome membership misleading.

Therefore ahead of analysis, the distributions for each potential segmentation variable were examined by country and, where appropriate, scores were re-classified to ensure a large number of cases at each value in a variable. Typically this involved re-classifying interval level data into ordinal level. Furthermore, it was deemed that moving from distance based measures to ranked based measures would work to reduce variance, some of which came from artificial sources such as differences in sampling between the countries and culturally mediated differences in responding.

Checking for collinearity between scored scales: In regression, collinearity between the variables entered into a model can make odds unreliable. At this stage of the analysis collinearity was assessed for scales, rather than individual items contributing to scales. Furthermore, for cluster analysis to work at its best, the variables used to segment a sample require good discriminatory power. Medium to high levels of collinearity between variables are indicative of high agreement between scales and thus low discriminate ability. Therefore collinearity was assessed between variables included in the regression models for each country and overall. This was done using the condition index, and results indicating moderate to high levels of collinearity were used to inform decisions on what variables to segment by.

Running regressions: Clustering techniques separate cases through distance across several variables. This distance therefore depends on the association between variables in addition to their scores. For region-wide segmentation to represent meaningful and distinct climate response groups, variables used would need to have consistent associations across countries. So regression was used to evaluate the strength and stability of associations between variables and thus their usefulness in distinguishing between groups of respondents.

Both ordinal and multi-nominal regressions were conducted to examine the relationships between variables deemed potentially useful for segmentation and variables that were thought key to segmentation. Key variables were "response action", "impact perceived" and "overall likelihood to change". Additionally, the relationship between these key variables was also examined through regression. Researchers used probability based regression because likelihoods of group inclusion were deemed most useful when attempting to identify associations of variables key to group inclusion.

Regression was run on the overall data set, and for each individual country. Key segmentation variables (listed above) were treated as dependent, and other variables deemed potentially useful from segmentation were regressed against them. Independent variables which assessed the areas of "perception of change in weather and environment", "barriers to responding", "trust in institutions", "community co-operation and "political cynicism" were examined in the same multivariate regressions. This established the optimum measure for representing each area alongside deciding if the area itself was useful for segmentation. Regression was later used on variables shortlisted for segmentation to examine their mutual influence on each other. Ordinal and multi-nominal regression were run with a logit link function, however, in situations where higher ranked outcomes were more probable, regressions were re-run with a complementary log-log link function.

Identification of segmentation variables: Odds ratios, collinearity and other variable performance information were then condensed into a single overview document for those variables deemed best performing. Researchers examined odds ratios for stability across countries alongside strength of association. From this work, five variables in total were identified for cluster analysis; all three key segmentation variables were included: "response action", "overall likelihood to change", "impact perceived", "information and resources barrier" and "community co-operation".

3. Cluster definition

Cluster definition covers statistical approaches used to identify cluster membership. Section three of this overview breaks down into six parts:

- Selecting a clustering method
- Assessing cluster stability
- Identifying an optimal range of clusters
- Standardisation of variables
- Identifying the final number of clusters
- Developing the final cluster solution

Selecting clustering method: research team could not use hierarchical clustering (HC) in SPSS as it failed to run. Instead the project used the K-means algorithm in SPSS, an alternative clustering method that is much more efficient, and therefore able to cluster a higher number of observations. However, the approach has several drawbacks, which the research team was able to take into account.
Initially K-means requires the number of clusters to be set prior to analysis, and therefore provides no straightforward data-driven way of identifying an optimal number of clusters. Secondly, the final cluster solutions provided by K-means depend on selection of initial centroids, and the default algorithm for initial centroid selection in SPSS in turn depends very much on how data has been ordered. The sections below outline how these issues were addressed at the point of analysis. The final drawback of the K-means clustering is that it is limited to quantitative data (variables at the interval or ratio level of measurement). While the data selected for segmentation was all at this level of measurement, K-means precluded redefining these variables at the ordinal level as one possible way to limit artificial variance which may have distorted results.

Cluster stability: As outlined above, any cluster solution produced by K-means depends on initial centroid selection. Unfortunately the algorithm for selecting the initial cluster centres depends on how data has been ordered in SPSS. To account for this weakness, the influence of different initial cluster centroids was tested by creating a dataset with 150 initial centroids, which were calculated from randomly selected observations. Random selection used 1%, 0.5% and 0.1%, per cent of all observations and each percentage was repeated 50 times over.

As the number of clusters to be identified needs to be stipulated before running K-means, the team ran 3, 4, 5, 6, 7, 8 and 9 cluster solutions. In addition to selecting the observations used randomly to create initial cluster centres, the initial cluster centres themselves were randomly selected from the centroid data file. Furthermore, the cluster analysis for 3, 4, 5, 6, 7, 8 and 9 cluster solutions were repeated twenty times to check stability of results, which meant that, at this stage, 140 separate cluster analyses were run. Even with a range of different starting points, it was deemed that cluster results for the twenty different runs would converge, if there were substantive groups of audiences. This was further ensured by enabling SPSS to run up to 200 iterations of centroids (re-definition of clusters) before the algorithm stopped, though in all cases a stable cluster solution was identified before this. The variation in sum of distances and stability in proportion to cases attributed to each cluster was used to assess cluster stability of the final solutions.

Identifying an optimal range of clusters: As mentioned above, in K-means the number of clusters needs to be set, which is a drawback. When the research team set the number of clusters at 3, 4, 5, 6, 7, 8 and 9, it examined the sum of distances produced by each solution. The sum of distances provides the distance of observations from the respective cluster centres, meaning that as the number of clusters increase, observations' distance from centres will decrease. This was reviewed to identify what cluster solutions provided the largest decreases in this statistic, rather than the smallest value.
This information was also reviewed alongside the need for observing which of the cluster solutions (3, 4, 5, 6, 7, 8 or 9) provided the most stable sum of distance statistic. This was decided by taking the range of sum of distances over the twenty runs for each of the different solutions. In order to identify the best range of the number of clusters, differences in final centroid values were also examined. This analysis indicated that 3, 4 and 5 cluster solutions were optimal.

Standardisation: Once 3, 4 and 5 cluster solutions were shortlisted, the above analysis was re-run using standardised variables (transformed into z-scores). Standardisation was deemed important because the five segmentation variables were measured on different scales, which meant that the K-means distance measure (Euclidean) would have given more weight to those scales with larger ranges.

When re-running the analysis in SPSS using standardised variables, the approach was much the same as outlined previously. SPSS was used to create initial cluster centres, using randomly selected 1%, 0.5%, 0.1% and an additional 0.01%, of the total sample. In this case random selection of observations and initial centroid creation took place 50 times over for each of the aforementioned percentages. Furthermore, the first 20 centroids were selected from the data file used above to assess cluster stability. These were entered into the data set as extreme values, as these initial centroids came from non-standardised variables and would therefore be outliers when compared to standardised variables with a mean of 0 and standard deviation of 1. This resulted in 240 initial centroids in the data file, which were randomly selected for 3, 4, and 5 cluster solutions. These cluster solutions were this time repeated five times, meaning that 15 different K-means analysis were run in total.

Selecting the final number of clusters: Once analysis was completed using standardised variables, the results were reviewed in order to identify a final number of clusters. The above criteria (largest reduction in sum of distances, most stability in sum of distance and the final centroid values for each of the three runs) were again reviewed. At this final stage the team also examined how observations moved from their original clusters to the new additional clusters. This was done by cross-tabulating new cluster membership against prior. For example over the three runs that were done, moving from a 3 to a 4 cluster solution resulted in the splitting of a single cluster into two. When cases were taken from across the three clusters, the latter would be indicative of an additional cluster having only a superficial benefit to classification.

Developing final cluster solutions: Once a five cluster solution was deemed optimal, another set of randomly selected initial centroids was created, using the same random proportions outlined above and resulting in a data file containing 440 initial centroids. From this dataset researchers selected five initial centroids at random, and the k-means procedure was run. This process was repeated 30 times, each using different randomly selected centroids, and the procedure enabled 300 iterations. The cluster solution that produced the lowest sum of distances was selected (this was run 26).

4. Validation of the final cluster solution

Validation took place using multinomial logistic regression, as cluster membership represented a nominal variable. Initially, a "full model" including all five segmentation variables was regressed against cluster membership. This was done initially to assess the chi-square statistic tested for difference in the logged likelihood (logged odds) of cluster membership between the full model and reduced models, which removed one of the segmentation variables. As expected, differences in likelihood between the reduced and full models were significant at ($P<0.000$) for all five segmentation variables, confirming all were important factors in segmentation. While all were significant, their contribution to cluster membership was not equal; the largest difference as outlined by chi-square statistics came from "response action", indicating this was the most important predictor of cluster membership. The smallest came from "overall willingness to change", meaning this was the least important predictor.

Secondly, the regression analysis enabled the research team to look at cluster membership prediction. As outlined above, multi-nominal regression provides a comparison of the likelihood of category membership between the full model and reduced models with each of the predictor variables removed in turn. Thus the regression computes each case's probability to be in one of the five cluster groups. A case therefore can be defined as belonging to the category associated with the highest probability. This means that predicted cluster membership can be contrasted against actual cluster membership in models with one of the five segmentation variables removed. The research team could then compare the actual effect of variable removal on cluster definition, through using crosstabs to look at the shift in membership between the actual clusters and predicted clusters.

When running a full regression model, the prediction, as expected, was 100% accurate, with each observation's predicted cluster matching the actual cluster. Removal of any the segmentation variables resulted in a drop in accuracy, for example removal of "overall willingness to change" (the least important segmentation variable) resulted in a drop of 13.5% in observations being predicted to fall into the correct clusters. Removal of the most important segmentation variable "response action" resulted in a drop of 26.3%. Cross tab analysis not only enabled evaluation of variables removal on overall accuracy but also, more importantly, showed how removal affected membership of specific clusters. For example while removal of "response action" resulted in approximately 26% of cases changing cluster membership, this shift was not equivalent in all clusters. "Response action" was particularly important for membership to cluster two, and its removal resulted in 64.1% of observations changing membership in this cluster. While this only resulted in an overall reduction in cluster size of 2.4%, the characteristics of this cluster would have dramatically altered.

The effect of removing "overall willingness to change" was, however, not tied to a specific cluster, with the largest shift resulting in a shift of only 20.9% of cases in cluster 4. This meant that not only, was "overall willingness to change" the least important contributor to cluster membership but also its impact could be interpreted as fine tuning membership across the five clusters. For all other variables, their removal resulted in a large changes specific to one or two clusters. This said, a 13.5% drop in total accuracy was not negligible, and thus the inclusion of the "overall willingness to change" as a segmentation variable was still justified.

This process was then repeated with all possible combinations for removing two, three and four segmentation variables. Then key demographics were examined in the same way, for their utility to predict cluster membership (gender, age, type of area, geographic theme, occupation type, etc.) and other potential segmentation variables (food, energy and water concerns, trust in institutions, etc.). While many acted as significant predictors of cluster membership (therefore meaning clusters would have clear differences in relation to these variables) none provided a similar level of predictive validity as the five segmentation variables.

5. Increasing the number of observations clustered

The level of missing data was high across the segmentation variables for the regional data set (missing =10,763) meaning that when clustering took place using the five variables listed above 21,198 observations had complete data on all variables and were included in the analysis. While a large amount of missing data works to reduce the statistical efficiency of analysis; missing data is most problematic when it is predicted by characteristics. Analyses that have used non-random missing data are considered biased, as results are effectively ignoring or misrepresenting certain groups of participants. Any increase in the number of observations in this cluster analysis will therefore mitigate such biases and improve the robustness of results.

While the analysis outlined in section four of this note indicates that "overall willingness to change" is a significant and important predictor to cluster membership, its removal did not drastically change membership in any specific cluster. Furthermore, this variable had a high level of missing data; there were approximately 4,250 cases which had missing data only on "overall willingness to change" and none of the other four segmentation variables. This meant that cluster analysis with the "overall willingness to change" variable removed would increase the number of observations by the same amount. Furthermore, the missing data on "overall willingness to change" was not equally distributed by country, with Bangladesh, Indonesia and Vietnam having particularly high amounts of missing data and therefore being particularly underrepresented.

On considering the balance between keeping the original reliable and valid cluster profiles and reducing the high amount of missing data researchers decided to use multinomial regression to predict cluster membership without "overall willingness to change" for those observations with missing data on this variable. This resulted in an additional 4,250 observations being included in the analysis, increasing the generalizability of results and mitigating potential bias.

The observations using predicted cluster membership where then appended to the 21,198 cases from the original segmentation, widening the analysis to 25,445 cases. The effect of appending predicted cluster membership was subsequently examined. It was known that the removal of "overall willingness to change" for the appended observations would have changed the nature of clusters, but validation analysis also indicated that this change would be distributed in a relatively equal way between clusters. Examination of updated cluster membership confirmed this, with results showing changes in cluster characteristics were minor.

This was expected, as the rather small and consistent shift in cluster membership resulting in the removal of this variable only effected approximately 17% of observations, meaning that overall change in clusters was minor. To assess the benefit coming from appending additional observations, and the potential reduction in bias, the research team examined the association between missing data and characteristics which strongly related to cluster membership. Just under three quarters of the associations between missing data and these key characteristics were reduced when segments included the appended data. This reflected a decrease in how predictive characteristics were of the missing data, meaning appending the 4,250 cases lead to a reduction in potential bias and an increase in the generalizability of results.

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ABOUT CLIMATE ASIA

Climate Asia, a BBC Media Action project, is the largest-ever quantitative and qualitative research study into public understanding of climate change in Asia. Funded by the UK Department of International Development (DFID), Climate Asia interviewed over 33,500 people across seven countries – Bangladesh, China, India, Indonesia, Nepal, Pakistan and Vietnam. The resulting comprehensive data set paints a vivid picture of how people live with climate change now.

This report is one of many tools created from this unique data, all designed to help the planning and implementation of communication and other programmes to support people to adapt to the changes they face. They are available on the fully searchable and public Climate Asia data portal, www.bbc.co.uk/climateasia, including a climate communication guide, further information on Climate Asia's research methods and the tools used to conduct research, including the survey questionnaire. Since all of Climate Asia's data and tools are designed for the widest possible use, this report and data portal details are freely available to anyone who might be interested.

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