SEGMENTING ONLINE PANELLISTS: A VOLUNTEERING PERSPECTIVE

Michael Jay Polanski
Sara Dolnicar

Andrea Vocino
Jason Buchanan

About Our Speakers
Andrea Vocino is Lecturer at the School of Management and Marketing at Deakin University, and PhD candidate in the Department of Marketing, at Monash University. His thesis is on the relationships between store names and product brand names as brand signals. His research interests also include marketing research methods and marketing science with particular emphasis to applications making use of covariance structure analysis. He has published in the Asia Pacific Journal of Marketing and Logistics, Marketing Intelligence & Planning and Journal of Database Marketing & Customer Strategy Management. He is a Highly Commended Award Winner at the Literati Network Awards for Excellence 2009. More information about the author can be found on his webpage http://andrea.vocino.name.

Jason Buchanan is the Managing Director of Research Now's Asia Pacific region, and was responsible for establishing Research Now in Australia in 2005. In his 5+ years with Research Now both in the UK and in Australia, Jason has worked across a wide range of online market research projects, across a diverse portfolio of clients. Overall, Jason possesses over fifteen years commercial experience, seven of which have been fostered within the market research, marketing and advertising based industries.
He holds a B.Bus (Marketing) from the Queensland University of Technology, is a full member of AMSRS and is on the AMSRS/AMSRO joint task force to develop guidelines to increase online research quality and standards in Australia.
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Introduction

The research into online panels has generally focused on issues of increasing response rates or recruitment (Bosnjak and Batinc 2002), potential bias (Deutskens, de Ruyter, Wetzel and Oosterveld 2004) and differences between online versus traditional research approaches (McDonald and Adam 2003). While this research realm is indeed important there has generally been less examination of the motivations of why respondents join online panels. Participants, in all forms, are the lifeblood of research across disciplines, as well as being critical for the operations of the market research industry. Thus, understanding the motivations for participating in online panels will continue to be pressing, especially as online panel become the norm in the research industry.

Online panellists are, which Couper (2000) defined voluntary-online panels as, individuals who make informed decisions to receive requests to respond to surveys. As such, panellists are volunteers, even though they may receive some compensation for their time and effort in the form of cash, ‘online money’, or the possibility to win a prize. It can be argued that if participants see participation as a form of employment, this may impact how they engage with research companies or complete surveys.

Given that at present we still consider these people as volunteers, we can use the literature on volunteering to better understand the motivations of online panel participants. There are a range of methods proposed in the literature for understanding why individuals volunteer in a range of contexts. Across volunteering situations and nations, one measure that has been widely used is Clary et al’s (1998) Volunteer Function Inventory (VFI), which has six dimensions (each comprising 5 items) constructs and they measure:

“Values (expressing deeply held beliefs about the importance of helping others)
Social (conforming to the norms of significant others)
Career (seeking ways to get started or advance in the world of work)
Understanding (engage in activities that promote learning)
Enhancement (enhancing one’s self sense of self worth) and
Protective (escaping negative feelings) (Okun, Barr and Herzog 1998 p. 609)”
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Objective

The purpose of this study was to segment online participants based on their motivations to participate and to profile the similarities and differences between segments according to the Clary et al's (1998) six VFI dimensions characteristics.

Methodology

The sample for the study was recruited from one Australian based online panel and comprised of three groups; ongoing panellists; those excluded from the panel for speeding and flat-lining (i.e. 3 strikers) and those withdrawing from online panels. The preliminary results presented within this paper are based on 314 usable respondents from within the sub-sample of ongoing panellists. The first stage of the analysis was to confirm the psychometric properties of the VFI within the online panel context; as if this was not applicable then it could not be used to develop segments of volunteers. Confirmatory factor analysis using Mplus 5.2 was undertaken to determine the reliability, convergent and discriminate validity of the VFI dimensions.

The second stage of the research then used the metric composite constructs to cluster the 314 respondents using topology representing networks (Martinetz and Schulten, 1994). Topology representing networks are self-organizing neural networks and have been chosen because they have been shown to be best able to reveal true data structure in a large-scale experiment with artificial data sets (Buchta et al., 1997). The third stage of the analysis then describes the characteristics of the clusters identified.

Results and Discussion

The CFA results identified that the six dimensions were found to hold across the sample of respondents. That is the assessed fit of the proposed congeneric measurement model provided satisfactory support of the model per se – $S$-BY$^2$ (df=390) = 850.81 ($p = 0.000$), root mean square error of approximation (RMSEA) = 0.061, comparative fit index (CFI) = 0.930, Tucker Lewis index (TLI) = 0.922, standardized root mean square residual (SRMR) = 0.068. Discriminate validity, was assessed by observing the square root of the AVE of the six factors which must be greater than the correlation coefficients between the model's factors (Fornell and Larker 1981) and was found to generally support the dimensions. The CFA suggests that six VFI dimensions are applicable within the online panel context and thus these six dimensions can be used to develop clusters of respondents.
To determine the optimal number of clusters we computed 50 cluster analyses for each number of clusters from two to ten and assessed the stability with which pairs of respondents are repeatedly grouped in the same cluster (Dolnicar et al., 1999). The five cluster solution led to the largest increase in stability across the full range of number of clusters.

Table 1 defines the characteristics of each cluster. The focus of cluster description in terms of defining characteristics is generally to look at the mean value of each group as compared to the overall variable mean. As such, clusters can be described as rating higher or lower on a given attribute compared to the overall sample.

Naming clusters is a bit of an art as it seeks to draw out meaning based on the dimensions. There are two clusters where all six motivations have mean scores lower than the overall sample mean. Cluster 1 (22% of the sample) has been called Low Motivation Participants, as they are low on all six of the motivations. However, Cluster 3 (10.2% of the sample), which we labeled Apathetic Participants are statistically even lower on all six dimensions, other than values where they were equal to Low Motivation Participants. Thus, overall 32.2% of panellists appeared to have low motivations for participating. It may be that the relative newness or novelty of panels has resulted in these individuals joining. However, given their low motivations these individuals may be those that most frequently leave panels, which may explain the sometimes high levels of churn within panels, which has been found to vary between providers and even vary across countries within one panel. However, low motivation and apathetic panel members could also be less likely to accept invitations to participate in research. They may also have lower levels of quality completions, i.e. be more likely to speed complete surveys or flat-line (i.e. answer the same way for multiple questions). This was not examined within this study and it could be explored by examining the other subsamples, i.e. excluded panel members and those withdrawing from the panel. It would be posited that these two sub-samples would have higher proportions of low motivated and apathetic participants.

On the opposite extreme is Cluster 5 (12.5% of the sample) the Engaged Participants, whose mean scores across all motivations were higher than the sample mean. As such they seem to be more highly motivated across the six dimensions. Given their generally high motivations, it might be anticipated that these participants would respond more positively to research invitations.

Cluster 2, Egoists, is the largest individual cluster (32.8% of the sample). This group has higher than average Social (conforming to norms), Career, Enhancement (enhancing one's self worth) and Protective (escaping negative feelings) motivations. Egoists are less concerned with Values (helping others) and also lower than average on Understanding (i.e. promoting self learning). This group may be more financially driven, possibly seeing panel participation as a job rather than a volunteering experience.
TABLE 1: Participation Clusters

<table>
<thead>
<tr>
<th></th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Motivation</td>
<td>N=103 (32.8%)</td>
<td>N=69 (22.0%)</td>
<td>N=70 (22.3%)</td>
<td>N=40 (12.7%)</td>
<td></td>
</tr>
<tr>
<td>Values</td>
<td>Below Average</td>
<td>Below Average</td>
<td>Below Average</td>
<td>Above Average</td>
<td>Above Average</td>
<td>28.24 (4.16)</td>
</tr>
<tr>
<td>Social</td>
<td>Below Average</td>
<td>Above Average</td>
<td>Below Average</td>
<td>Below Average</td>
<td>Above Average</td>
<td>17.66 (5.79)</td>
</tr>
<tr>
<td>Career</td>
<td>Below Average</td>
<td>Above Average</td>
<td>Below Average</td>
<td>Above Average</td>
<td>Above Average</td>
<td>18.58 (5.75)</td>
</tr>
<tr>
<td>Understanding</td>
<td>Below Average</td>
<td>Below Average</td>
<td>Below Average</td>
<td>Above Average</td>
<td>Above Average</td>
<td>22.68 (5.50)</td>
</tr>
<tr>
<td>Enhancement</td>
<td>Below Average</td>
<td>Above Average</td>
<td>Below Average</td>
<td>Above Average</td>
<td>Above Average</td>
<td>19.90 (5.82)</td>
</tr>
<tr>
<td>Protective</td>
<td>Below Average</td>
<td>Above Average</td>
<td>Below Average</td>
<td>Above Average</td>
<td>Above Average</td>
<td>17.92 (5.87)</td>
</tr>
</tbody>
</table>

The final group we classified as Nonconformists. This group had higher than average means for four of the five motivations. The one motivation where they were lower than the overall mean was the social mean, reflecting a low motivation to comply with social norms. These individuals are thus somewhat similar to the Egoists, although they were also interested in learning. As such one might anticipate these people would be interested in participating in a wide cross section of studies and would possibly be more opinionated than egoists (i.e. less concerned with social norms).

The question of whether the panel is representative of the wider population is also an issue of interest. Unfortunately, all we can say is that we believe that the sample is representative of the people who agree to participate in online panels. We did undertake preliminary exploration of the
demographic characteristics between the panels and identified that there were in fact no statistically significant differences. This is indeed important, as it suggests that a representative demographic sample of participants will at least not be biased in terms of their motivations to join online panels.

Implications

Understanding online panellists' motivations for participating in research can assist panel providers and researchers more generally. Firstly it enables panel providers to develop strategies targeting different types of potential members, based on their motivations and thus ensures that panels continue to have a cross section of participants. This will be especially important in the Low Motivation and Apathetic segments, which possibly have higher churn levels because of segment members' low motivations to participate. This group may be increasingly difficult to attract, especially as the novelty of being an online panel member lessens. Thus, panel providers may need to spend more resources attracting the low motivation and apathetic participants, which might mean trying to make the experience more entertaining, or possibly more financially rewarding as it seems they may be less interested in long-term involvement. However work by Goritz (2004) has found that recruitment methods did not affect how long panellists remained members of panels, although she did not explore motivations of panellists or whether there were differences based on segments of panellists.

The results also can possibly be used to assist in managing panel profiles, as motivations may potentially be of interest to clients, especially those working in the non-profit or volunteering sectors. That is knowing why people participate in panels could potentially be used to attract volunteers to other activities. Targeting panellists may be a good place to start as one knows they have already volunteered for one type of activity. For example, in researching people who donate money to charities, panels may be a good source of participants, as they volunteer their time.

Thirdly, the understanding of different panel member segments, based on motivations, potentially provides additional opportunities to ensure that panels incorporate a cross-section of society. That is a panel that is populated solely with people who are motivated based on one of the dimensions; possibly will under-represent the wider community. As such, panels that actively promote financial incentives may attract fewer highly involved or nonconformist panel members, but be ideal for attracting low motivations and apathetic panel members.

Of course there are extensive opportunities to use this information in future research, for example, do different types of invitations have varying levels of take up by various segments? Are there other characteristics of these segments that might predict behavior, etc. Some of these other issues may have significant implications for panel providers. For example, if there are certain motivational characteristics of panellists who flat-line or speed complete, then panels could improve data quality.
by screening these people out or overcompensating in samples to ensure that sufficient quality responses from this segment are obtained. These other issues and their implications will be explored within the broader research project.

References