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Segmenting Australian online panellists based on volunteering motivations

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Abstract

Purpose – The purpose of this paper is to seek to assess whether online commercial panel volunteering can be segmented based on their motivations, using the volunteer functions inventor. The authors also investigate whether segments exist which differ in demographic characteristics.

Design/methodology/approach – The authors survey 484 Australian online panel volunteers using an adapted version of the 30 item of the volunteer function inventory (VFI) scale developed by Clary et al. (1998). Data were analysed using confirmatory factor analysis (CFA) and cluster analysis, as well as ANOVA and $\chi^2$ test comparisons of demographics between clusters.

Findings – CFA verifies that the VFI scale is suitable instrument to gauge online participants’ motivations. Cluster analysis produced a five-cluster solution, where respondents with low motivations overall comprised the largest grouping. Segments are interpreted by assessing the difference between the total sample average and the segment profile. The examination also identifies that the only demographic factor that varies across the five clusters is “respondents” employment status”.

Research limitations/implications – Future research could explore if differences in segments result in differences in online participation. The high number or respondents with low motivations may explain the relatively high levels of churn that take place within online panels and as a result panel operators would need to continually attract new members. Further research could also investigate whether the levels of motivation change over time and if so what effect such variation would produce on respondents’ retention.

Originality/value – Research on online panel respondents’ motivation is still limited and investigating online panellists’ motivation as volunteers is very important as it unveils, as in the study herein reported, that alternative types of respondents may be driven by different factors when joining an online panel (or completing a given survey). Recruitment strategies could, therefore, be shaped to suit the motivation of the different segments. By refining the matching between volunteers’ profiles and their motivation, managers could improve how volunteers are recruited, managed and retained.

Keywords Volunteering, Respondents’ motivations, Online panels

Paper type Research paper
Introduction

In most primary marketing research there is a reliance on people’s opinions or reactions (as consumers, potential consumers, managers and respondents at large) to provide the necessary information to examine the phenomenon under investigation. In general, it is assumed that those agreeing to participate in research do so voluntarily and consent to help researchers with limited, if any, individual benefit (Loosveldt and Carton, 2002). As such, research participants can be considered to be volunteers (Vocino and Polonsky, 2011). Online survey participants also meet the more general definitional criteria of volunteers, as identified in a cross-section of the volunteering literature (Cnaan et al., 1996): they have free will to join, benefit others (and possibly themselves) and can receive some compensation.

Given that billions of dollars are being spent on marketing research (Honomichl, 2008), not to mention the vast sums spent on other types of research using voluntary participants, it is surprising that there is limited understanding why respondents consent to participate in research (Han et al., 2009) and the participants’ views of the surveys they complete (Loosveldt and Storms, 2008). People’s underlying motivations are important and may determine whether they participate in research or not (Dillman, 1991). For example, Loosveldt and Carton (2002) suggest that research participants who score highly on utilitarian individualism (i.e. those who strive for personal gain and do not focus on others) are less likely to respond to surveys. Others, such as Han et al. (2009), find that survey participation is motivated by a multitude of reasons, some of which were intrinsic and others which were extrinsic. Larson and Sachau (2009) find that individual personality factors influence how people respond to specific types of surveys as well as affecting attitudes and intention to buy particular products.

The extensive research on survey response rates often implicitly assumes that different respondents’ motivations drive response behaviour (Dillman, 2011), although this factor is not generally considered when designing survey questionnaires. For example, the literature exploring the role of incentives in increasing response rates (Göritz, 2008) implies that an extrinsic (i.e. financial) motivation is required for respondents to complete surveys. Yet, few studies measure extrinsic motivations to evaluate the effectiveness of incentives. Limited research has tried to explicitly consider links between respondent motivations and response behaviour, showing, for example, that response rates increase when the survey topic is of interest to participants (Shropshire et al., 2009), suggesting that involvement affects response rates. Loosveldt and Carton (2002) find that a higher level of utilitarian individualism reduces the degree to which people volunteer to participate in research. While a range of theories have been proposed for investigating response behaviour (Han et al., 2009), research generally does not seek to measure how the associated motivational characteristics of participants influence survey participation or responses. For example, Poon et al. (2003) have manipulated the motivational appeals used in survey invitations to assess how these influence survey response, but did not assess consumers’ disposition to the underlying factors (i.e. involvement). As such they did not test whether variation in response occurred based on respondents’ level of involvement. Rather they inferred involvement matters due to differences in response rates to alternative appeals. There are a few exceptions where researchers have sought to assess how individuals level of a given motivations influences survey response behaviour. Daugherty et al. (2005) found that an array of motivational factors, drawn from the volunteering literature, influenced people’s attitudes towards online panels, although they did not look at how motivations then related to behaviours. Kaufmann et al. (2011) studied motivations of survey participants who undertook “work” in Mechanical Turk and found that these online volunteers responded to both intrinsic and extrinsic motivations and that individual motivations influence behaviour.
More recently, Vocino and Polonsky (2011) examined online panellists’ motivations using the volunteer function inventory (VFI) scale originally developed by Clary et al. (1998). This multi-dimensional scale comprises six types of motivations (values, social, career, understanding, enhancement and protective) which have been found to influence a variety of volunteering behaviours. Daugherty et al. (2005) also used VFI dimensions to examine participation in online research panels and, although they found these broad dimensions held, they did not test the full dimensionality of the VFI scale when assessing participant motivations.

The research proposed herein investigates the associations between volunteering as an online survey respondents and motivations. Specifically, the research seeks to understand:

1. which motivation-based segments of online panellists can be identified; and
2. whether segments identified differ in demographic characteristics.

Panel managers’ knowledge of online panellists’ motivation as volunteers is an important research area, as it may unveil what kinds of respondents might be most involved in particular types of behaviours, then recruitment strategies could be shaped to suit the motivation of the different segments. By refining the matching between volunteers’ profiles and their motivation, online panel managers could improve volunteer recruitment, management and retention. Segmentation-based approaches to engaging volunteers are not new. They have been investigated in other research contexts, such as retirees (Callow, 2004), corporate workers (Wymer, 2003), university students (Garver et al., 2009) and environmentalists (Dolnicar and Randle, 2007). When undertaking sampling for clients, commercial panels draw on the pool of respondents who have registered with the given provider. Panel operators are therefore limited in their ability to draw representative samples from within the wider panel pool. It has been suggested (see, e.g. Baker et al., 2010) that some demographic segments are either over or under represented in online panels or that respondent demographics may impact on response behaviour within online survey contexts (Holbrook et al., 2006). As such it is important to identify if the motivational segments of volunteers differ in demographic characteristics. If differences exist, then, we posit that having a “skewed” demographic sample, may introduce additional sampling bias skewing the sample based on respondent motivations. Some evidence suggests that there are differences in response behaviour based on demographics. For example, some researchers have found that older respondents are slower in cognitive processing and thus take more time in responding to surveys (Yan and Tourangeau, 2008), which may infer they respond to surveys differently than other demographics (Malhotra, 2008). Antin and Shaw (2012) have found differences in motivations of online volunteers exist between Mechanical Turk respondents in India and the USA. However, none of these works examine how respondent motivations explain response behaviours, which is the groundwork to target alternative segments of respondents.

This paper is organised as follows. We provide a brief overview of research panels and volunteering/participating in research. This is followed by a discussion of motivations to volunteer, the VFI scale and the limited work on motivations to participate in research. The discussion of the research methodology is then presented, which is followed by the study results and the implications resulting from the findings.
Online panels

While there are many different ways to volunteer for research, within this paper, we focus on only one type, that is, voluntary opt-in commercial online panels. We focus on this area because these panels are increasingly being used in research (e.g. Couper, 2000; Couper and Miller, 2008; Göritz, 2004, 2008; Larson and Sachau, 2009; Vocino and Polonsky, 2011). The use of online panels is particularly important as the proportion of the population participating in traditional types of research has decreased (Namiranian et al., 2006).

The voluntary opt-in commercial online research process is different to a traditional request to participate in an online survey. Panel members are recruited through various forums and are invited to join an online panel, where they agree to receive invitations to participate in research (Couper, 2000). As part of the registration process, panel members are asked to complete a profile survey that describes their demographic characteristics as well as some behavioural characteristics (Callegaro and DiSogra, 2008). Panel members are then periodically sent invitations to participate in research for clients of the panel owner, based on the client’s specification of sample characteristics as defined by respondents’ in pre-existing profiles. These invitations vary in terms of their information and, in some instances, simply alert participants that a survey is available for completion. Researchers have identified that varying the content of information letters can be used to better appeal to potential respondents underlying motivations, thereby increasing participation (Evangelista et al., 2012). Unfortunately, panel operators do not know the underlying motivations of individual respondents a priori, because these motivations are not directly observable and would require additional “questioning” to be identified.

The panel members then make an informed decision about whether to participate and selected respondents then have the option to complete or not complete the survey. Thus, individuals have to further voluntarily agree (i.e. opt-in) to complete each individual survey.

Panellists as volunteers

People can volunteer for research purposes through random, one-off solicitations (such as phone interviews, e-mail solicitations, mall intercepts or focus groups). Others may respond to an appeal (i.e. some form of advertising or communication) to participate in given research projects, as frequently occurs in health contexts when researchers seek participants having a particular condition so that they can be used in either an experimental or control group.

Others may choose to join research panels where they agree to regularly receive invitations to participate in research panels, by phone, post or by becoming members of online research panels (Göritz, 2009; Hansen and Pedersen, 2012). In many cases respondents receive some “compensation” or financial incentive. Although such compensations are typically very low, some researchers have disputed whether such payments are appropriate (Russell et al., 2000). Thus, some researchers argue that compensation changes the relationship between participants and research, where respondents become employees rather than volunteers (Larson and Sachau, 2009). Despite receiving a small financial compensation, online panellists, however, do meet the definitions of volunteers proposed in much of the volunteering literature. For example, the United Nations (1999, pp. 26-34) definition of volunteering states that a volunteering activity should:

1. “Not be undertaken primarily for financial reward, although the reimbursement of expenses and some token payment may be allowed”.

2. “The activity should be undertaken voluntarily, according to an individual’s own free-will”.
“(3) “Be of benefit to someone other than the volunteer, or to society at large, although it is recognised that volunteering brings significant benefit to the volunteer as well”.

These criteria are consistent with Cnaan et al.’s (1996) review of definitions of volunteering. They found that in the 12 definitions examined, seven included people who have expenses paid by the organisation and five included people who received a stipend or were paid to “volunteer”. Thus, the small incentives that online panellists receive in form of money, rewards points or entry into a prize competition (Göritz, 2008) are in accordance with most volunteering definitions. Limited payments are also acceptable under most ethical guidelines as long as the payment is not “disproportionate to the time involved, or any other inducement that is likely to encourage participants to take risks, is ethically unacceptable” (National Health and Medical Research Council (NHMRC), 2007, p. 20).

While some researchers argue that research participants volunteer because of incentives, others suggest that participants volunteer for altruistic reasons (Tishler and Bartholomae, 2003). For example, Cnaan et al. (1996) find that all volunteering definitions were based on an assumption that others (or strangers) would benefit from the volunteering activity, although four of the definitions also included the ability of volunteers to benefit themselves. Similarly, Loosveldt and Carton (2002) find that people who choose not to participate in survey research are less altruistic (i.e. higher levels of utilitarian individualism). Han et al. (2009) find that individual rewards, either monetary or expressed as some other personal benefit, positively influence response rates to surveys and thus are important to some survey volunteers. On the other hand, Kaufmann et al. (2011) conclude that extrinsic motivations have a significant effect on the time spent on the Mechanical Turk research platform. However, even intrinsic motivations appear important especially when they relate to factors such as “task autonomy” and “skill variety” (Kaufmann et al., 2011).

Whether one agrees with incentives or not, these are used in many volunteering contexts, including survey research. The volunteering literature suggests that different volunteers may be participating in the associated behaviours for different motivations or reasons (Clary et al., 1998), with incentives or personal benefits representing only one possible driving force.

Recruiting online panellists

Prior to developing a plan to recruit online panellists, it is important to identify the particular motivations for participating and then define specific strategies intended to appeal the specific need-based segments recruiters wish to pursue (Göritz, 2004; Hansen and Pedersen, 2012). Understanding the value sought by people when volunteering in general is helpful to developing suitable plans to address recruitment of these same volunteers in online research contexts.

Wilson and Musick (1999) argue that “people can be attached to the volunteer labour force in the same way people can be attached to the conventional labour force [italic added]” (p. 245). Following human capital theory, people who possess more developed capabilities such as education, income and occupation have a competitive advantage in the volunteer market as they are supplied with more advanced knowledge, organisational skills and discretionary time (Wilson and Musick, 1999). Social capital is an additional resource volunteers possess (Wilson and Musick, 1999) and it identifies resources, such as information, trust and cooperative labour, gained and organised through social links which may assist in people deciding to volunteer.

Further literature has identified other motivations for volunteering, which is used in the customised design of recruiting strategies. Peterson (2004), for instance, proposed promoting information
Regarding volunteering opportunities and suggested that the needs of the community should be used to attract volunteers with a strong altruistic motivation. Organising volunteering teams was a recommended strategy for attracting volunteers with a social relations motivation. Promoting public recognition programmes may be helpful for attracting volunteers with a status reward motivation, and promoting of how community service can help advance a volunteer’s career was recommended for attracting those with a material reward motivations. As such, more research is needed to identify preference-based segments of potential volunteers.

As previously stated, Clary et al. (1998) developed the VFI, which comprises six dimensions - values, understanding, social, career, protect, and enhancement - which are similar to the volunteering motivations proposed by Peterson (2004). One benefit of using the VFI scale and dimensions is that it has been used in different volunteering contexts globally, with at least 171 papers using or referring to this scale (according to Google Scholar, on 10 January 2013), thus allowing comparative conclusions to be drawn. Additionally, factors of the VFI have also been in the online volunteering context (Daugherty et al., 2005) and the scale's six motivational dimensions have been found to be valid when applied to online panellists (see, e.g. Vocino and Polonsky, 2011).

Methodology

Data collection

The sample for the study was recruited from one Australian-based online panel. 484 respondents were used, reflecting the population of “online panellists”. Respondents were recruited by the commercial provider to reflect the Australian population. The survey topic focused on respondents experiences of participating in panels.

The online panel operator complies with industry standards for managing the panel, as well as the European Society for Opinion and Marketing Research (ESOMAR hereafter) guidelines relating to online panels (ESOMAR, 2009). The survey included the 30 items of the VFI proposed by Clary et al. (1998) adapted for an online context by Vocino and Polonsky (2011), which are reported in Table I. Within the scale there are six dimensions (each assessed by five items) which are designed to capture the “domain” of volunteering. This includes:

- value motivations, which represents people’s personal values including a strong desire to assist others (i.e. more altruistic motivations);
- understanding motivations, which represents a desire to learn;
- enhancement motivations, which focuses on egotistic issues such as making the volunteer feel valued and that they make a difference;
- career motivation, which is focused on extrinsic motivations, where participation assists the individual getting a job or with their current job;
- social motivations, which relate to a desire for panellists to be connected to other people; and
- protective motivations, which relate to using panel participation to overcome negative emotions, such as “escaping from my troubles,” “overcoming guilt” and “feeling less lonely.”

Each item was measured on a seven-point agree/disagree scale. Additional measures were also included on respondent demographics.
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<td>People I am close with place a high value on online panels’ collaborations</td>
<td>0.896</td>
<td>0.018</td>
<td>496.16</td>
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<td>Being a panel member is an important activity to the people I know best</td>
<td>0.865</td>
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<td>I can learn more about the cause for which I am working</td>
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<td>0.017</td>
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<td>Being a panel member allows me to gain a new perspective on things</td>
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<td>hands on experience</td>
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<td>I can learn how to deal with a variety of people</td>
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<td>I can explore my own strengths</td>
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<td>Q4B_54</td>
<td>Being a panel member makes me feel important</td>
<td>0.881</td>
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<td>Q4B_55</td>
<td>Being a panel member increases my self-esteem</td>
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<td>Being a panel member makes me feel needed</td>
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<td>75.191</td>
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<td>Q4B_57</td>
<td>Being a panel member makes me feel better about myself</td>
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<td>0.012</td>
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<td>Q4B_58</td>
<td>Being a panel member is a way to make new friends</td>
<td>0.755</td>
<td>0.021</td>
<td>35.910</td>
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**Note:** The items and scales were taken from Vacino and Polonsky (2011)
Confirmatory factor analysis (CFA)

The first stage of the analysis was to confirm the psychometric properties of the VFI within this sample. Using Mplus 7.11 (Muthén and Muthén, 2013), CFA was undertaken to determine convergent and discriminate validity of the VFI dimensions. As per Vocino and Polonsky (2011), we made use of the maximum likelihood mean-adjusted (MLM) estimator. Under MLM, mean and covariance structures, instead of the covariance structures, are analysed. The MLM provides maximum likelihood parameter estimates with robust standard errors and a mean-adjusted $\chi^2$ (Muthén and Muthén, 2013), which is also referred to as the Satorra-Bentler type of $\chi^2$ (Satorra and Bentler, 1994). A power analysis of the parameter estimates was conducted post hoc using the Monte Carlo simulation method (Muthén and Muthén, 2002; Wolf et al., 2013) to determine whether or not the sample size would create a bias in the parameter estimates, and overall solution propriety.

Cluster analysis

In the second stage of the research we used the six composite dimensions of the VFI - values, understanding, social, career, protect and enhancement – as the segmentation base. The aggregated scores for each dimension were binarised, meaning that a positive value (1 or above) was assigned a 1 and a neutral or negative value (0 or smaller) was assigned a 0. The sample size complies with minimum sample size requirements as recommended by Dolnicar et al. (2014), according to which the sample should be of the size of at least 70 times the number of variables in the segmentation base (in this case six variables times 70 = minimum of 420 respondents).

Selecting the correct number of segments in segmentation analysis is known to be one of the key challenges of segmentation analysis (Thorndike, 1953). We addressed this problem by using the benchmarking framework for the selection of numbers of clusters proposed by Dolnicar and Leisch (2010) which accounts for both sample and algorithm randomness. We drew 200 bootstrap samples from the data for alternative three- to ten-cluster solutions. We then computed the Rand Index across all replications and inspect the box plot (Figure 1) to assess which number of clusters leads to the most stable and reproducible solution.

Figure 1 illustrates the development of stability over repeated computations for three to ten segments. As expected, stability generally decreases with increasing number of clusters. The three segment solution is most reproducible, but has the disadvantage that two of the three segments are characterised by above and below average responses for all dimensions. The four and five segments solutions still reach high stability level, with just under 80 per cent agreement across multiple computations. As a consequence the five segment solution is chosen for profiling: it provides both high stability levels and enough segments to capture heterogeneity in the online panel respondent population. It does need to be noted that Clusters 2 and 5 may include people who have demonstrated response styles in their survey completing behaviour (i.e. consistently high or low responses), which may means the size of these segments could be exaggerated (Dolnicar and Lazarevski, 2009).

For all computations we use Topology Representing Networks (Martinetz and Schulten, 1994), a self-organising neural network algorithm similar to k-means, but adjusting not only the winning centroid, but also neighbouring centroids. We chose this algorithm because it has been shown in experiments with artificial data that Topology Representing Networks outperform most other clustering algorithms with respect to identifying the true cluster structure in the data (Dolnicar et al., 1998).
The assessments of differences in demographic characteristics between segments were tested using \( \chi^2 \) tests for nominal and ordinal variables and analyses of variance for metric variables. Computations were done using the open source statistical computing environment R (R Development Core Team, 2008) using extension packages flexmix (Leisch, 2004) and flexclust (Leisch, 2006).

**Results**

The CFA results identified that the six dimensions held across the sample of respondents. The assessed fit of the proposed congeneric measurement model provided satisfactory support of the model per se – S-By\( \chi^2(\text{df}=390)=1,071.001 \text { (p = 0.000)} \), root mean square error of approximation (RMSEA) = 0.060, comparative fit index (CFI) = 0.930, Tucker Lewis index (TLI) = 0.922, standardised root mean square residual (SRMR) = 0.058. Convergent validity was measured by observing: the strength in factor loadings and their associated significant t-values of each of the measures on the appropriate factor (factor loadings should be >0.7), and the average variance explained (AVE; questionable if <0.5) and composite reliability (CR; should be > 0.7). Table I shows how convergent validity was assessed.

Discriminant validity was assessed by observing the square root of the AVE of the six factors which ought to be greater than the correlation coefficients between the model’s factors (Fornell and Larcker, 1981) and was found to support the dimensions as displayed in Table II.

In order to assess whether the sample size was sufficiently large to run unbiased estimates, a power analysis at parameter level was undertaken through the Monte Carlo simulation method (Muthén and Muthén, 2002; Wolf et al., 2013). All the parameter estimates in the model had power \( W 0.8 \) except from the covariance between the factor Value and Professional had power 0.724 which was deemed acceptable.
The six VFI dimensions have been found to hold in the online panel context (Vocino and Polonsky, 2011). These were found to hold in the current study as well. The composite scores for the six VFI dimensions were then used to develop clusters of respondents. The profiles of the five segments of online panel members are provided in Figure 2, where the bars indicate the percentage of segment members who agree with any given dimension and the horizontal lines (with the dots) indicate the total sample average agreement.

<table>
<thead>
<tr>
<th>Table II.</th>
<th>ENH</th>
<th>PRO</th>
<th>VAL</th>
<th>CAR</th>
<th>SOC</th>
<th>UND</th>
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<tr>
<td>Latent construct correlations and squared average variance extracted (diagonal)</td>
<td>ENH 0.874</td>
<td>PRO 0.685</td>
<td>VAL 0.617</td>
<td>CAR 0.531</td>
<td>SOC 0.492</td>
<td>UND 0.691</td>
</tr>
</tbody>
</table>

Segments are interpreted by assessing the difference between the total sample average (expressed in the horizontal lines with the dots) and the segment profile (expressed in the bars). Cluster 5 “Curious Panellists” is the largest segment of the sample (138 respondents or 29 per cent of the sample). They appear to be low on all motivational categories (i.e. the dots are outside the bars) and thus might be participating in panels as a form of experience seeking, which if true, will have significant implications for panellists withdrawing once the novelty has gone from the panel experience. Cluster 2 we call “Engaged panellists” and is the second largest segment (i.e. 97
respondents or 20 per cent of the sample). They are highly motivated across all motivations, thus are participating for multiple reasons simultaneously. Cluster 3 we refer to as “Altruistic Panellists” and is the third largest segment (95 respondents or 20 per cent of the sample). These panellists focus on the motivations of Values (i.e. concern for others) and Understanding (i.e. learning) which are higher order intrinsic activities. Cluster 4 we call “Actualized Panellists” and are the second smallest segment of the sample (87 respondents or 18 per cent of the sample). This segment is also high on Values and Understanding, in addition to Protective, Social and Enhancement motivations, but low on Career (i.e. extrinsic) motivations. As such, they seem to be more internally focused on intrinsic drivers. Finally, there is Cluster 1 which we call “Extrinsic Panellists” and is the smallest segment (67 respondents, 14 per cent of the sample). While this group is high on values and understanding in a similar way to the Altruistic Panellists (Cluster 3), Extrinsic Panellists are also relatively high on Career motivations and as such may be using the Values and Understanding to benefit themselves (i.e. extrinsically), rather than simply focusing on intrinsic motivations.

In the last step, segments were compared using additional information, information not used to group online panel members into segments. The results of these χ2 tests are provided in Table III. The examination identifies that the only demographic factor that differentiates between the five clusters is employment status. Analysis of standardised residuals was undertaken to determine which employment category contributed to the significance of the test. This identified that the only significant difference arose for those in home duties (z ≠ 2.2) who were under represented in Cluster 3 relative to the other clusters.

**Discussion**

In looking at the motivational segments, it is clear that there is generally a combination of factors acting simultaneously for online panellists. The Protective dimension where people use volunteering to overcome negative feelings is more salient for Engaged Panellists (Clusters 2) and Actualised Panellists (Cluster 4) whereas Altruistic values are high for all segments other than Curious Panellists (Cluster 5). The desire to enhance ones career is only high for Curious Panellists (Cluster 5) and Engaged Panellists (Cluster 2), with a desire for social engagement being a high motivation for Engaged Panellists (Clusters 2) and Actualized Panellists (Cluster 4). Learning new things (i.e. Understanding) is high across all panellist segments other than Curious Panellists (Cluster 5), with motivations around personal identity (i.e. Enhancement) being high for Engaged Panellists (Cluster 2) and Actualised Panellists (Cluster 4). Thus, while some motivations have differing importance within clusters, it would seem that each cluster is generally not driven to participate for one reason alone.

Given the importance of motivations in shaping behaviour, panel managers need to consider the size of each segment when managing respondents, that is, larger segments may be more important than smaller segments. Curious Panellists (Cluster 5) are the largest segment representing 29 per cent of the sample, however, they are relatively low across all six motivations. As such, it is unclear how to identify the extent of these respondents’ engagement with the online survey process. If motivations shape response behaviours, having curious, uncommitted panellists could be a problem and could potentially mean these respondents are less likely to complete surveys or more likely to drop out of the panel all together. Such a relationship would explain the relatively high levels of churn that take place within online panels (Baker et al., 2010) because large groups of panellists are not actively motivated to be involved and lose interest with the novelty of participating, challenging panel operators to continually seek new members.
Engaged Panellists (Cluster 2) are high on all motivations and are the second largest group of respondents (20 per cent). It may be that panel operators would find these participants easiest to engage because of the importance of all motivations, which could potentially mean they complete more surveys, although this needs to be empirically examined. Altruistic Panellists (Cluster 3) also represents 20 per cent of the sample, although they seem to be driven in a more focused way extrinsic factors relates to enhanced understanding and values to “help”. Thus, when promoting surveys to these Altruistic Panellists panel operators may use targeted appeals that focus on the altruist benefits of undertaking surveys, when inviting these panellists to participate. For example, something like: “Your participation will assist our customers in making better decisions and better serving their customers and their research”. Actualised Panellists (Cluster 4) is the second smallest (18 per cent) and seems to be similar to Engaged Panellists (Cluster 2), as Actualised participants were high on all motivations are other than Career. This suggests that they are highly motivated, but not by intrinsic factors. Thus survey invitation letters that highlight the personal benefits or monetary incentives may be less successful in regards to this group. Extrinsic panellists (Cluster 1) is the smallest group (14 per cent) and given their high motivational emphasis on personal benefits in regards to their career, they may be more focused on monetary incentives when considering participating. Additionally, panels could consider having different levels of participation, where panellist move up in the “career” by completing more surveys overtime. For example, “Completing this survey will provide you with X$ and will contribute X points to you becoming a premium panellist” (i.e. obtaining higher levels of rewards for completing surveys).

With regard to demographic factors, these generally did not vary across segments. The only exception appears to be for employment status, with those in home duties under represented within
the Altruistic segment of panellists (Cluster 3). If this represents “mothers” it would make sense, as research has found that mothers have been found to be more altruistic in nature (Ong et al., 2013). Interestingly, students or retired persons were evenly distributed across segments, which is inconsistent with some thinking about these groups and volunteering. For example, it might have been expected that students would exhibit higher career motivations in their volunteering (Jones, 2011) and thus more likely to be within the Extrinsic segment of panellists or that retired panelists should be more altruistically motivated when volunteering (Einolf, 2009) and thus over-represented in the Altruistic panellist segment. This did not occur and as such, demographics and motivational segments appear to be mostly unrelated. Thus, when researchers and panel companies are selecting samples, there would only potentially be an issue associated with focused surveys on those undertaking home duties, as motivations may influence whether they respond to one alternative invitation type or another. This issue deserves further future investigations.

Implications and future research

Panel operators have a vested interest in increasing response rate from their online panellists/respondents. As such, they need to understand the motivations of panellists and being able to identify profile characteristics rather than asking researchers to assess this information in their surveys would be more beneficial for the validity of the research per se. This would allow the panel operator to better manage the survey invitation process, but also ensure that samples reflect groups across the motivational characteristics. Given that the first stage of building a panel is getting people to join the “sample pool” it is important to also undertake research examining the motivational aspects of joining an online panel. That is, understanding the motivational aspects of people’s decision to join or decline to join online panels is central, considering that there is a constant need to revitalise panels to address dropouts or simply to maintain panel health (Baker et al., 2010).

Panel operators and researchers can also use the motivational information to better understand whether alternative forms of “invitations” may be required to incentivise the uptake of demand response participation across different segments of the online panel population. Essentially existing research has sought to do this in an ad hoc way. To date most research in this realm has investigated how participants responded to different (manipulated) invitations. However, it is our contention that research ought to focus more on the aspects regarding the underlying motivational conditions of each participant and whether or not such volunteering motivations reflect some unobserved heterogeneity in the online panel population.

The fact that those who are low on all motivations (Curious Panellists, Cluster 5) is the largest cluster of respondents is possibly an area of concern for panel management and these respondents warrant further examination, especially in regards to ensuring that this segment is not the result of some type of response style behaviour (i.e. people only using part of the response scale).

As has been suggested earlier, if the Curious segment reflects respondents with low scores across the motivations, it may explain why there is high churn in panels. On the one hand this may be positive for researchers as panels are continually being revitalised. On the other, it places additional pressure on panel operators in sourcing additional respondents. Therefore, seeking to understand the Curious panellists and identifying whether they are in fact the most likely to drop out is important. This issue could possibly be managed by panel operators, if the motivations to participate in research were assessed as part of the profiling process of each respondent recruited and thus
some underlying evaluation could be undertaken of those who drop out or withdraw from the panel, as well as whether they undertake “inappropriate” behaviours, such as speeding, being inconsistent or invariant in their responses (e.g. flatlining).

Ensuring panels represent respondents from across volunteering segments will be important in enabling researchers, academics and industry, to undertake effective research (Baker et al., 2010). One of the criticisms of panels is that they may not represent the wider community and if this is indeed the case firms and researchers using the results of any panel-based research will be flawed. Measuring implicitly motivations will allow researchers and panel operators to assess the representativeness of samples on additional respondents’ characterises, allowing research to be more reflective of the community and its views.

Future research could also consider whether respondents’ motivations change over time. It may be that the survey experience evolves as people become more active survey participants. As was identified earlier, examining the motivations to join the panel is also something that could be examined. Additional including respondent motivation may allow unobserved heterogeneity in data to become observed and thus modelled, improving research using online panels more widely.

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