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Internet Panels, Professional Respondents, and Data Quality

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Abstract

Most web surveys collect data through nonprobability or opt-in online panels, which are characterized by self-selection. A concern in online research is the emergence of professional respondents, who frequently participate in surveys and are mainly doing so for the incentives. This study investigates if professional respondents can be distinguished in online panels and if they provide lower quality data than nonprofessionals. We analysed a data set of the NOPVO (Netherlands Online Panel Comparison) study that includes 19 panels, which together capture 90% of the respondents in online market research in the Netherlands. Latent class analysis showed that four types of respondents can be distinguished, ranging from the professional respondent to the altruistic respondent. A profile of professional respondents is depicted. Professional respondents appear not to be a great threat to data quality.

Keywords: online panels, professional respondents, respondent profile, response styles, speeding, straight-lining

Internet coverage in Europe is increasing rapidly; according to Eurostat (2014) a boundary was crossed in 2007 when a majority of households had Internet access; this grew to 79% in 2013. Furthermore, the difference between persons with and without Internet access, the digital divide (Couper, 2000), in Europe is diminishing (Mohorko, De Leeuw, & Hox, 2011, 2013). The Netherlands, together with the Scandinavian countries, has one of the highest Internet penetrations in Europe. Also, in the Netherlands, the percentage of

households with an Internet connection is far above the percentage households listed for a fixed-line telephone connection (Bethlehem, Cobben, & Schouten, 2011).

As a result, Internet surveys have become more prevailing for data collection (Lozar-Manfreda & Vehovar, 2008). Online research has many advantages: it is fast with relatively low costs, complex questionnaires and audio-visual stimuli can be implemented. Due to the absence of interviewers, web surveys result in answers with less social desirability, especially when sensitive questions are asked (De Leeuw, 2012; Tourangeau, Conrad, & Couper, 2013). A major problem with Internet surveys is the sample selection, as general population sampling frames of Internet users are not available (Bethlehem & Biffigandi, 2012; De Leeuw, 2012). A potential solution is creating online panels; either by using other data collection methods to build probability-based Internet-panels, or by using volunteer panels of willing Internet-users (Couper & Miller, 2008; Callegaro et al, 2014).

The majority of online research is based on nonprobability panels (AAPOR Standards Committee, 2010). Only a few panels (Knowledge Networks in the USA, LISS and CentERdata in the Netherlands, and the GESIS panel in Germany) recruit panel members with probability-based methods. Most online panels use a broad range of recruitment methods, which are based on self-selection of respondents, who 'opt-in' as panel members. Furthermore, panel agencies commonly use incentives to engage respondents, using either money or bonus points that can be cashed in later (Göritz, 2006).

The combination of self-selection, material incentives, and the increased use of nonprobability panels leads to a growing concern for professional respondents and what they might do to data quality. Comley (2005) first mentioned the possibility of professional respondents; he defined them as respondents who participate in many online surveys and only participate when an incentive is offered. More ad hoc definitions followed in which professional respondents are described as respondents who participate in many surveys (Coen, Lorch & Piekarski, 2005; Conrad, Tourangeau, Couper, & Zhang, 2010), and/or are members of multiple panels (Fulgoni, 2005; Ericksen, 2009; Gittelman & Trimarchi, 2009).

The concern about professional respondents is based on the assumption that they are not motivated by intrinsic interest, but are extrinsically motivated by incentives (Conrad et al, 2010; Whitsett, 2013). As a result they might rush through the questionnaire, using shortcuts and heuristics to complete the questionnaire with minimal effort. This response behaviour is called 'satisficing' (Krosnick & Alwin, 1987; Krosnick, 1991) and may lead to less accurate answers and poor data quality (Tourangeau, Rips, & Rasinski, 2000).

However, studies on professional respondents and their influence on survey data are scarce and are mainly dispersed through white papers and conference proceedings (Hillygus, Jackson, & Young, 2014). Furthermore, these studies use ad-hoc definitions (member of multiple panels and frequent survey participation) and there is no consensus on how many surveys or how many panels is too many; for a review see Whitsett (2013). In this study, we use a model-based Latent Class Analysis to identify professional respondents in online panels. We investigate their influence on survey quality, using a rich and unique data set from the Netherlands Online Panel Comparison (NOPVO) study. This study includes 19 panels, which captured 90% of the respondents in online market research in the Netherlands in 2006. We address three interrelated research questions:

-*Can different types of respondents be empirically distinguished in Internet panels?*

-Do professional respondents differ in demographic and psychographic characteristics compared to other types of respondents?
-Do professional respondents provide data of lower quality than nonprofessionals?

Data

The data include 19 large Internet panels, which together capture 90% of the respondents to online market research in the Netherlands (Vonk, Van Ossenbruggen, & Willems, 2006)[1]. Each panel sampled 1000 participants between 18 and 65 years old. The entire sample of all panels was checked and un-doubled to avoid that respondents who are members of multiple panels would be invited more than once.

The same questionnaire was used for all panels. A broad variety of topics was included, in addition, questions about background data and panel membership were asked. Data collection was done by an independent party. The selected panel members received the invitation all on the same day, whereupon the questionnaire remained available online for seven days.

The final sample contains 9461 respondents. The participating agencies enriched the dataset with background information on sample and panel management. Unfortunately, for some panels this information was only partially available.

Professional Respondents in Internet Panels

To investigate the existence of professional respondents we used a Latent Class Analysis on five theoretically based indicator variables: the number of panel memberships, the number of completed questionnaires in the past four weeks, frequency of checking email accounts (Comley, 2005; Conrad et al., 2010; Ericksen, 2009; Fulgoni, 2005; Gittelman & Trimarchi, 2009), and whether intrinsic motivation (fun) and/or extrinsic motivation (incentive) are important for participation (Coen et al, 2005, Comley, 2005; Conrad et al, 2010).

Latent Class Analysis classifies respondents on one underlying latent categorical variable, using respondents' answer patterns on indicator variables (McCutcheon, 1987; Vermunt & Magidson, 2004). We employed a latent profile model using Mplus (Muthén and Muthén, 1998-2010). Model selection was based on the AIC, the BIC and the Bootstrapped Likelihood Ratio test (Nylund, Asparouhov & Muthén, 2007). These criteria selected the independence latent profile model with four classes, which had the lowest AIC, BIC and lowest chi-square. The entropy for this model is 0.99 indicating a very high classification (Murphy, Shevlin & Adamson, 2007). For a substantive interpretation, we inspect the means and thresholds of the indicator variables in Table 1. A low threshold indicates that relatively many respondents choose this answer.

Table 1. Independency model with four classes: means and thresholds of the four latent classes of respondents. LC's are indicating degree of being a professional respondent from LC.A an altruistic nonprofessional respondent to LC.D as a prototype professional respondent

		LC.A	LC.B	LC.C	LC.D
Means	Number of panels	2.71	3.92	4.86	5.86
	Number of questionnaires	1.00	2.47	4.00	5.00
Thresholds	Incentive	1.05	0.69	0.47	0.04
	Fun	0.56	0.26	0.11	-0.30
	Daily email checks	-4.44	-6.30	-6.28	-15.0
% Respondents		38%	28%	17%	17%

The four classes differ clearly in degree of being a professional respondent. The last class (LC.D) can be classified as the prototype of the *professional* survey respondent. They are far more often members of multiple panels and participate more frequently in surveys. The low thresholds indicate that they are motivated by both incentives and fun, and check their email more frequently.

Sharply contrasting these professional respondents at the other end is the first respondent type (LC.A). They have the smallest number of panel memberships and have completed the fewest questionnaires in the past four weeks. The high thresholds indicate that they check their email less often, and that both incentives and fun are far less important. This group can be classified as the *altruistic, nonprofessional* respondent.

The respondent type LC.B and LC.C in between show lesser degrees of professional respondent characteristics and classify as respectively semi-altruistic and semi-professional. The four respondent classes indicate an ordinal scale ranging from altruistic to professional. Since the classification quality is high, we use the empirical class assignments as indicator of degree of professional respondent in the subsequent analyses.

Profile of the Professional Respondent Types

A first step in getting to know prototype professional respondents, is investigating what type of persons they are. Therefore, an ordered logistic regression analysis was performed to investigate which variables characterize professional respondents. Both demographic and psychographic variables were available as predictors. Demographic variables are age, gender, education, household size, nationality, having paid work, and religion (raised in a religion & belongs to a religious denomination). Psychographic variables are sense of involvement, voting intention and behaviour, and life and health information. The participating panel agencies provided data on the demographic variables gender, educational level, and household size. Data on all other variables were collected through the online NOPVO questionnaire. The results of the analyses are summarized in Table 2.

Table 2. Demographic and psychographic profile of the respondent types. Regression coefficients and standard errors of the ordered logistic regression with dependent variable degree of professional respondent (N=7381).

	Regression coefficient	**Standard error**
Demographics, reported by panel agencies		
Gender (woman)	0.19**	0.050
Size of household (large)	-0.02	0.017
Educational level (high)	-0.03	0.014
Demographics, reported by respondents		
Birth year	-0.00	0.002
Raised in a religious belief (yes)	-0.03	0.047
Considers self to be part of a religious denomination or philosophical group (yes)	-0.07	0.054
Dutch nationality (yes)	-0.05	0.288
Paid job for at least 15 hours per week (yes)	-0.11*	0.047
Psychographics, reported by respondents		
Social psychological		
Involved, likes to work together with other people (yes)	-0.13**	0.043
Consider self to be a thinker (yes)	0.12**	0.046
Political		
Voted in 2003 (yes)	-0.07	0.094
Considers self politically “left” (very)	-0.04	0.024
Interested in politics (very)	0.05*	0.024
Voting intention (yes)	-0.04	0.040
Life and health		
Satisfied with life at the moment (very)	-0.07**	0.024
Good health (very)	-0.18**	0.031
Drinks (often)	-0.03**	0.011
Nagelkerke R^2	0.03	

* $p<0.05$, ** $p<0.01$

Compared to “altruistic nonprofessional” respondents, “professional” respondents are more often female and have less often a paid job. Similar results were reported by Whitsett (2013), who summarized nine studies on demographics of frequent respondents in online panels in the USA.

Professional respondents also differ on social-psychological variables; they prefer to finish a task on their own instead of working together and see themselves more as thinkers than doers. Furthermore, they describe themselves as being more interested in politics, but there is *no* difference in political orientation or voting behaviour. The latter was also reported by Fulgoni (2005). Finally, professionals are less satisfied with their lives and describe their health as poorer. The differences are small, but not negligible. For example, the regression coefficient 0.19 of gender indicates that in the prototype professional respondent class 59.5% is female, while in the altruistic respondent class this is only 48.4%. There is no difference in age, education, nationality, and religious orientation.

Especially in market research, it is debated whether speeding may be a characteristic of professional respondents (Greszki, Meyer, & Schoen, 2014; Hillygus et al, 2014). In our data, the Spearman correlation between the time to complete the questionnaire in minutes and the ordinal latent class indicator is -0.15 ($p<.001$). The altruistic nonprofessional respondents (class LC.A) averaged 13.5 minutes, while the prototype professional respondents (class LC.D) averaged 11.8 minutes. The overall mean completion time was 12.9 minutes.

Professional Respondents and Measurement Error

The interest in professional respondents is mainly driven by the concern that they are bad respondents, who undermine the quality of online panel data through satisficing and falling back on response styles (AAPOR Standards Committee, 2010). Below we describe four important response styles that are used to investigate whether the data of the more extensively motivated professional respondents differ in quality from the data of the more intrinsically motivated altruistic respondents. Subsequently, we check whether differences found are explained by socio-demographic characteristics.

Response Styles

Several response styles can be distinguished (Baumgartner & Steenkamp, 2001; Billiet & Davidov, 2008; Greenleaf, 1992): acquiescence, extremeness, middle of scale-answers, and straight-lining. *Acquiescence* (ARS) is the tendency to agree with statements regardless of their content; this is also called ‘yeah-saying’ (Baumgartner & Steenkamp, 2001; Billiet & Davidov, 2008; Holbrook, 2008). *Extreme responding* (ERS) is the tendency to endorse the most extreme answers (positive or negative) regardless of content (Baumgartner & Steenkamp, 2001; Greenleaf, 1992). The tendency to choose the neutral *middle* category (MPR) is distinguished as a clear response style (Baumgartner & Steenkamp, 2001). With nondifferentiation or *straight-lining*, the same answer on the Likert scale is given for different questions (Krosnick, 1991; Krosnick & Alwin, 1988; McCarty & Shrum, 2000); the middle-scale response style is one form of straightlining, but there are many forms of straightlining (e.g., always choosing the second category). Straight-lining or nondifferentiation is considered a good indicator for low data quality in online questionnaires (Fricker, Galesic, Tourengeau, & Yan, 2005).

A theoretical explanation for the occurrence of response styles is ‘satisficing’ (Krosnick & Alwin, 1987; Krosnick, 1991). Ideally, respondents optimize, they carefully go

through the question-answering process of: 1) understanding the question; 2) recalling relevant information; 3) evaluating that information; 4) selecting the answer (Tourangeau, 1984; Tourangeau et al., 2000). Satisficing respondents follow this process less thoroughly by using shortcuts and heuristics. Satisficing occurs in a weak or strong form. With weak satisficing, the respondent does go through the cognitive steps, but with cutbacks in effort; one or more steps of the question-answer process are gone through less carefully or attentively than is needed for optimizing. Extreme responding is an example of weak satisficing; the answers are based on the content of the question; however not the whole range of appropriate response categories is evaluated but the most extreme answer is chosen. Thus, in the last phase of the question-answer process, the selection of an answer, a shortcut is used. Strong satisficing occurs when the cognitive steps of the answering process are ignored completely and the respondent just chooses a plausible response that is believed to be acceptable to interviewer or researcher. This answer can be based on shortcuts, heuristics, or a random choice. Response styles associated with strong satisficing are acquiescence and straight-lining. Courtright, Brien and Stark (2009) mention that satisficing, and especially nondifferentiation, is prevalent under what they call “worst respondents” and contributes to a negative impact on data quality.

Professional respondents may differ in satisficing behaviour because they tend to be more extrinsically motivated and focused on incentives. To maximize their personal gain and receive as many incentives as possible, calculating respondents should aim to complete questionnaires with the least possible effort. Thus, professional respondents should be less motivated to optimize and professionals should have a higher likelihood to satisfice than the more intrinsically motivated altruistic respondents (Krosnick, 1991). Compared to the answers of the more intrinsically motivated altruistic respondents, the answers of professional respondents are expected to contain more straight-lining and more response style patterns, such as, acquiescence, extreme responding, and middle scale responding.

Demographic and psychographic variables also influence data quality (Groves, 1989) and differences in response styles have been found for demographic subgroups. Therefore, apparent differences in response styles between professionals and other groups of respondents could therefore also be caused by differences on demographic and psychographic variables between these groups.

To measure the above mentioned response styles, two series of questions are used that were offered in a matrix (‘grid’)-format. The NOPVO-questionnaire included two such grids. The first grid consisted of five opinion questions on politics, in which respondents gave their opinion about the former Dutch prime-minister Balkenende. The second grid contained five statements regarding the neighbourhood of the respondents concerning social cohesion and neighbourhood composition. The response categories formed a five-point Likert-scale: ‘totally agree’, ‘agree’, ‘neutral’, ‘disagree’, ‘totally disagree’.

Acquiescence was measured by counting the fraction 1 (‘totally agree’). Since both grids are only partially balanced, acquiescence was calculated using weighting. Extremeness was measured by counting the fraction 1 or 5 responses. Middle of scale answers were measured by counting the fraction of 3 (‘neutral’) responses. Nondifferentiation or

straightlining is indicated by its opposite, the index of differentiation or Pd (Probability of differentiation). This is given by $Pd = 1 - \sum_i P_i^2$,

where P_i is the proportion of responses in category i of a set of items (Krosnick & Alwin, 1988). If pure straightlining occurs, Pd=0, if uniform distribution, Pd is at maximum (often close to one).

Results Response Styles

A multivariate analysis of variance per grid was used to study differences in response styles between respondent types. The four response styles were used as dependent and respondent type as independent variable. This MANOVA showed that there is a significant difference in response styles between the four respondent types ($p<.001$). Follow-up analyses showed that only differentiation did not differ significantly on both grids (Table 3).

Table 3. MANOVA: Means (standard deviations) of the response style indicators for the four respondent classes, and effect sizes (Cohen's f) of the all differences.

		Altruistic nonprofessional	Semi-altruistic	Semi-professional	Professional respondent	Cohen's *f*
Political Grid	Acquiescence (ARS)	0.32 (0.25)	0.33 (0.25)	0.33 (0.25)	0.35 (0.25)	0.044
	Extreme responding (ERS)**	0.34 (0.30)	0.35 (0.31)	0.35 (0.31)	0.37 (0.32)	0.035
	Neutral Middle (MPR)**	0.27 (0.26)	0.27 (0.26)	0.23 (0.25)	0.23 (0.25)	0.078
	Differentiation	0.49 (0.19)	0.49 (0.19)	0.49 (0.19)	0.49 (0.19)	0.000
Neighbourhood Grid	Acquiescence (ARS)**	0.13 (0.19)	0.10 (0.18)	0.11 (0.18)	0.11 (0.19)	0.059
	Extremes (ERS)**	0.27 (0.31)	0.23 (0.30)	0.23 (0.30)	0.23 (0.31)	0.094
	Neutral Middle (MPR)*	0.24 (0.25)	0.26 (0.25)	0.24 (0.24)	0.26 (0.25)	0.040
	Differentiation	0.49 (0.17)	0.48 (0.16)	0.48 (0.16)	0.49 (0.16)	0.030

* $p<0.05$, ** $p<0.01$

The effects in the political grid are exactly the opposite of the effects found in the neighbourhood grid. With these opinion questions concerning the Dutch former prime-minister the professional respondents give more extreme and less neutral answers. Surprisingly, when asked about their neighbourhood professional respondents show less acquiescence and extreme responding and give more neutral answers. However, all the effect sizes are all very small. Cohen's *f* ranges from 0.035 to 0.094, while an *f* of 0.10 is considered a small effect (Cohen, 1988). The hypothesis that professional respondents show more satisficing behaviour when answering survey questions is not conclusively supported.

Small but inconsistent differences exist in data quality between altruistic, intrinsically motivated respondents and prototype professional respondents. However, the profiles of the respondents' types in Table 2 show that altruistic and professional respondents differ on a number of demographic and psychographic variables. When all significant variables in Table 2 are added as covariate, we find that except "involved" and "drinks" all covariates are highly significant, but the differences in response styles between the four classes, presented in Table 4, remain almost the same. We conclude that differences in demographic and psychographic respondent characteristics do not explain the differences in response styles.

Table 4. MANCOVA: Adjusted Means of the response style indicators, adjusting for all significant characteristics from Table 2, and effect sizes (Cohen's f) of the all differences.

		Altruistic nonprofessional	Semi-altruistic	Semi-professional	Professional respondent	Cohen's *f*
Political Grid	Acquiescence (ARS)	0.33	0.33	0.33	0.35	0.044
	Extreme responding (ERS)**	0.34	0.34	0.35	0.37	0.049
	Neutral Middle (MPR)**	0.27	0.27	0.23	0.23	0.078
	Differentiation	0.49	0.49	0.49	0.49	0.000
Neighbourhood Grid	Acquiescence (ARS)**	0.13	0.10	0.11	0.11	0.059
	Extremes (ERS)**	0.27	0.23	0.23	0.23	0.094
	Neutral Middle (MPR)	0.24	0.26	0.24	0.26	0.040
	Differentiation	0.49	0.48	0.48	0.49	0.030

* $p<0.05$, ** $p<0.01$

Conclusion and Discussion

Professional respondents do exist in online panels. A latent class model consisting of four classes had an excellent fit and clearly distinguished altruistic nonprofessional, semi-altruistic, semi-professional, and professional respondents. The empirical results confirm the assumptions of Comley (2005) and others (see Whitsett, 2013) that a professional respondent is a member of multiple panels, frequently participates in a large number of questionnaires, and is focused on incentives.

Furthermore, professionals check their email more often. This finding has not been mentioned in the literature before. A possible explanation could be that professional respondents are more curious and keener on invitations for new studies and therefore check their email more often. Professional respondents also use the Internet more frequently than the other groups and are, in general, more active on the web; checking emails is just one part of this more frequent Internet behaviour.

A more negative interpretation would be that the professionals check their email so often solely to maximize their personal gain; a fear present in the market research industry (Whitsett, 2013). Surprisingly, the results of this study showed that an incentive alone is not enough motivation for the professional respondent, since 'fun' also proved to be an important factor for participation. This is in line with both Dillman (1978), who already in 1978 advocated that researchers have to engage potential respondents and make the survey experience pleasant, and Puleston (2012a,b) who recently developed the theory of 'gamification,' which emphasizes the importance of ease, interest, and fun for questionnaire construction.

Based on demographic and psychographic variables, a profile of the professional respondent was constructed. Professional respondents are more often female and have less often a paid job. Their health is less good and they are slightly less satisfied about their lives; they also prefer working alone instead of together with others and consider themselves more as thinkers than as do-ers.

Despite these differences, the professional respondent is on many characteristics similar to the more altruistic nonprofessional respondent. No differences were found in important demographics like age, nationality, household size, educational level, and religion. Also no differences were detected in voting behaviour and political orientation, though professional respondents say that they are more interested in politics.

Professional respondents needed slightly less time to respond to the questionnaire. This is not necessarily an indication of satisficing. Professional respondents have more practice and experience, and this can positively influence performance (Chang & Krosnick, 2009). For example, Greszki et al. (2014) found that excluding speeders from the analysis made no difference on the results.

We could not find much empirical support for the common belief that professional respondents pose a threat to the quality of survey data. Looking into the occurrence of several undesirable response styles, we found only very small effects that also depended on the topic of the question. Professional respondents showed more response styles on one series of questions in grid format, but not on another grid. This result could not be explained by a learning or demotivating order effect, since the grid that showed increased response effects for the professional respondents was presented first in the questionnaire. The content of the questions themselves may have had an impact and it is possible that response styles are more associated with the topic of the questions than with respondent characteristics. An early study by De Leeuw and Hox (1998) indicated that aberrant or deviant response patterns are not so much a fixed respondent characteristic, but rather the result of an interaction between respondent and question characteristics. This view is supported by Van Meurs, Van Ossenbruggen and Nekkers (2009), who analysed data of multiple online surveys in a Dutch online panel and concluded that the presence of response styles was more dependent on the questionnaire itself than on respondent characteristics. Similar results were reported for Germany by Höckel (2012).

The grid, on which the professional respondents showed more satisficing behaviour as indicated by response styles, focussed on political questions and asked the respondents to rate the Dutch Prime Minister (Balkenende). At that point in time, there had been frequent elections following political crises involving several Balkenende governments. As each election is usually preceded by an abundance of election polls, it could be that frequent online respondents were becoming bored with another series of questions on the prime minister and reacted by showing more satisfying behaviour. This interpretation is in line with the earlier studies by De Leeuw and Hox (1998), Van Meurs et al (2009), and Höckel (2012) and underscores the importance of motivating respondents in online panels as advocated by Dillman (1978), Dillman, Smyth and Christian (2014) and Puleston (2012a,b).

This study focused on the internal validity of the data produced by professional respondents in online panels; we did not study the external validity. Our main conclusion is that professional respondents do indeed exist, but that there is not much empirical evidence

that their existence poses a serious threat to data quality. However, professional respondents do differ on a number of socio-demographic characteristics compared to other respondent types. When a panel consists of many professional respondents, this could pose a severe threat to the external validity and representativeness of the findings.

The effect sizes in our analyses are all small. In the logistic regression depicting the four respondent classes, the Nagelkerke pseudo R is very low, meaning that the predictor variables cannot predict respondent type very well. This also explains why these covariates do not diminish the effect of respondent type in the Mancova analyses. It could be that some important predictor is missing in the data. Another reason might be that the fraction of prototype professional respondents is not very high (17%) so their presence does not show up in differences in response style. Finally, the typology of altruistic to professional respondents, as indicated by the latent class analysis, also depends on the variables used to classify the respondents. Latent class analysis is an exploratory technique; it would be useful to replicate the analysis using a new data set.

Concerning the possibility of some important predictor being missing there is one striking result. If we add the panel research agency as categorical predictor variable (18 dummies) to the ordered logistic regression, the Nagelkerke R increases to 0.22, which we consider high. The interpretation is that the fraction of professional respondents varies strongly between the research agencies. We assume that much of this variation is the result of differences between the panel research agencies in recruitment practices and respondent incentive systems. For reasons of anonymity, we have no information on the identity of the panel agencies themselves, nor on their organizational practices, that can be connected to the respondents in our data. As a result we cannot further investigate the effects of organizational differences[1].

[1] The identity of all agencies is protected and unknown to the original NOPVO-researchers and to the authors.

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