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EXAMINING THE ROLE OF PARTICIPANTS' PERSONALITY TRAITS ON DATA QUALITY IN ONLINE PANEL SURVEYS

In the era of extensive digital transformation, all business areas are experiencing disruptive changes, and the marketing research industry is no exception. With research agencies increasingly depending on online panellists from commercial research panels, it is crucial to understand the characteristics of panel participants and their potential impact on the quality of collected data. The present study explores the role of participants' personality traits on the quality of data collected via online consumer panels. A quantitative study examined Big Five personality characteristics and social desirability of the responses in the context of online panel participation. The study results indicate that self-selected panel participants tend to be more extroverted and have lower conscientiousness scores than non-participants. Participants with higher openness and lower conscientiousness scores also tend to provide more socially desirable responses. The findings implicate that participants with specific personality traits might be overrepresented in commercial online panels and are more likely to provide socially desirable responses, impacting data quality and reliability.

Keywords: *internet surveys, marketing research, personality traits, data quality*

1. Introduction

The widespread use of information technologies and social media with direct interaction and synchronous communications in real-time changed how we interact and communicate in both personal and business spheres. At the same time, both qualitative and quantitative research methods and techniques are now applied in online and mobile environments, with research participants taking a more active role in the research process (Brosnan et al., 2019). The trend is noticeable in all research areas: academic, governmental, and commercial institutions increasingly rely on the Internet as a source of research participants.

For some time now, marketing research agencies have been refocusing from traditional computer-assisted telephone surveys (CATI) to online and mobile research as the more efficient way of data collection. In addition, during the COVID-19 pandemic, face-to-face surveys became impossible due to the social distancing rules, and digital research became necessary with

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the insights industry rapidly shifting online (ESOMAR, 2020). According to Statista (2022), online data collection is currently the predominant way of data collection, with 89% of the companies utilizing online panel research and 60% regularly using mobile research for their research projects.

Online data collection is mainly conducted through consumer panels where pre-registered participants are invited to participate in surveys based on specific eligibility criteria. A significant increase in the utilization of online participant panels for data collection raises the importance of ensuring the validity and reliability of collected panel data and calls for a better understanding of various characteristics of survey respondents.

2. Online consumer panels

The first simple forms for online data collection were created in the early 1990s (Babin & Zikmund, 2015; Buchanan & Hvizdak, 2009; Groves, 2011). Over the following 20 years, these simple forms evolved into advanced online data collection and analysis software with an interactive and user-friendly interface and a range of functions that enable the implementation of complex surveys over the Internet. Since the 1990s, in parallel with the development of information technologies, other factors, such as the reduction in the number of respondents willing to participate in traditional survey research, have influenced the growing application of online survey research (McDaniel & Gates, 2018). As a result, survey panel research became one of the most popular ways of data collection in various disciplines, including management research, marketing, HR, and public opinion research (Ljepava & Selakovic, 2017; Porter et al., 2019).

Further technological development and the widespread use of smartphones opened new research opportunities. Research conducted with a sample of marketing research agencies in 2012 (Fine & Menictas, 2012) anticipated the increasing degree of smartphone use for commercial online surveys, noting that at that moment, 38% of the interviewed agencies had clear strategies or policies for smartphone-based survey research. With more than 60% of marketing research agencies using mobile research nowadays (Statista, 2022), these anticipations showed to be correct. Gartner Annual CMO Survey (McIntyre & Virzi, 2020) places marketing analytics, digital commerce and research into the top five vital strategic capabilities, even in the light of COVID-19 challenges and budget cuts that marketing departments have been facing worldwide. ESOMAR's report (2022) also shows that within the past five years, there has been a continuous increase in investments in online research, especially in online research panels.

Additionally, according to Gartner Marketing Technology Survey (Bloom et al., 2022), marketing technology investment steadily increased globally in all marketing areas before the COVID-19 pandemic. However, although the increase in martech investments has been expected in response to COVID-19, the opposite happened, and survey respondents reported lower utilization of their marketing technologies in 2022 compared to 2020. The only area showing a steady increase in the utilization of technologies is marketing research.

Since online data collection became more widespread in management and marketing research, the central question raised by researchers was related to the sample representativeness of online surveys. One of the prerequisites for conducting methodologically rigorous online research, which will yield high data quality, is access to a suitable sample that can be further subjected to socio-demographic segmentation based on the research requirements. For this purpose, during the mid-2000s, research agencies started developing online consumer panels to serve as databases of potential research participants (Börkan, 2010, Das et al., 2011). Panel participants are recruited in advance, and respondents are invited to complete the survey on demand. Companies, research institutions, and research agencies are turning to professional consumer panel providers to conduct the needed research online, using the potential for demographic segmentation offered by such panels (ESOMAR, 2022).

3. Data quality and online consumer panels

Data quality in survey research has been extensively studied over the years. High data quality is essential for obtaining valuable insights and establishing a reliable and valid foundation for data-driven decision-making. Data quality in survey research is a multidimensional construct that encompasses multiple dimensions and lacks an unified definition. In their study on factors affecting the data quality of online questionnaires, Jaeger and Cardello (2022) argued that data quality in survey research can be defined as a construct linked to accuracy, reliability, validity and completeness of responses with specific metrics, further defining these dimensions. Data quality in survey research encompasses various attributes, including reliability, validity, accuracy, and sample representativeness (Shmidt et al., 2003). With the advancement of online data collection platforms, maintaining survey data quality has become a challenge for all quantitative researchers.

To understand the challenges related to the quality of data collected through online panels, we need to distinguish between two types of online consumer panels: non-probability and probability. Probability consumer panels consist of a large number of participants randomly selected to participate in the research, are often based on government census data or similar lists, and are considered valid, reliable, and representative sources of survey participants. However, non-probability online panels, also called paid online panels, consist of a non-random sample of participants actively recruited by posting ads on websites or social media platforms to attract potential participants to register (Lehdonvirta et al., 2021). The ads are presented as an opportunity to earn additional income or awards, and the participants' pool is solely created based on the participants' self-selection. These panels are the most popular in business and consumer research and are often managed by marketing research agencies. These panels are non-representative, and unlike the probability panels, which can provide accurate and representative data, the non-probability online panels are based on self-selection and can attract a specific type of incentives-motivated panelists. (Zhang et al., 2020).

In many cases, the open recruitment strategy applied in non-probability panels can lead to the accumulation of the same panel members registered on many different panels that respond to many surveys. This phenomenon is known as professional survey respondents - individuals who fill in hundreds of surveys to get different types of incentives in return for research participation and has been widely discussed in the literature previously (Bethlehem, 2010; Lin et al., 2009; Hillygus et al. 2014; Matthijsse et al., 2015; Sandorf et al., 2020, Zhang et al., 2020). Another study also draws attention to selection bias in Internet research because specific socio-demographic categories might be represented to a lesser or greater extent, and different categories of respondents are more or less willing to participate (Bethlehem, 2010). An open, non-probability panel can assemble a large number of panel participants. These respondents register on the panel through web advertisements and seek opportunities to join online panels for a monetary reward (Brüggen et al., 2011, Sandorf et al., 2020, Zhang et al., 2020). Some studies show that less than 1% of the population fills up about 30% of online surveys (McDaniel & Gates, 2018). According to these findings, professional survey respondents fill in around 80 surveys in 90 days, often completing multiple surveys in one day. The potential professionalization of survey participation carries a series of dilemmas regarding obtaining potentially distorted and less reliable research results.

According to Brosnan et al. (2019), online survey panel participation drivers can be categorized into survey-based and participant-based factors. Survey-based factors impacting research participation, such as survey length, topics, design, invitations, and the number of reminders sent, have been researched fairly well (De Bruijne & Wijnant, 2014, Sánchez-Fernández et al., 2012, Sauermann & Roach, 2013). An additional body of research looked at participant-based factors such as the desire to help, curiosity, and interest in a topic (Brüggen et al., 2011, Keusch, 2013, Zillmann et al., 2014), while the studies on the impact of participant-based personality factors on panel participation are limited.

Dilemmas related to professional survey participants include giving false or erroneous information, completing the questionnaire too fast to finalize the survey as soon as possible, or relying on straight-lining – filling in the same option for each item in a grid (Biddle & Sollis, 2021, Cornesse & Blom, 2020). In the case of fast completion of questionnaires, thanks to the quality control mechanisms included in the panel software, it is possible to eliminate entries that show an extremely short completion time during the survey quality check. Additionally, the challenges related to straight lining can be solved with the survey design; however, in the case of providing false or misleading information, the options for quality control are limited. The method used in traditional survey research of repeating the same set of questions in a different manner is also applied in online research; however, it can increase survey duration and lead to higher attrition rates (Babin & Zikmund, 2015). One standard procedure for correcting non-selective responses is the application of calibration (weighting) techniques. However, some studies indicate that weighting does not reduce selection bias in non-probability online panels Brüggen et al. (2016).

The effect of incentives on online panel participation represents the largest sub-area of survey participation studies Brosnan et al., 2019, and many studies indicate that incentives increase the level of response (Hillygus et al., 2014, Brüggen et al., 2011, Pedersen & Nielsen, 2016). Just like traditional survey research, incentives increase the response rate and reduce the rejection rate for web-based research (Brosnan et al., 2019, Hillygus et al., 2014, Pedersen & Nielsen, 2016); however, this is not without undue consequences. For example, the study on professional panel respondents (Sandorf et al., 2020) identified two types of professional respondents: the frequent survey respondents, "hyperactives" who have more stochastic decision process and participate more frequently in panel surveys, and "experienced" with a long history of panel participation and more deterministic decision process.

Some researchers (Mizes et al., 1984) argued that the incentives could lead to biased and skewed results, leading to decreased survey data quality. He claimed that incentives could cause participants to respond to the questionnaire in a socially desirable way that they believe would satisfy researchers. However, the findings from more recent studies examining online panel data quality are inconclusive. While, according to Chandler et al. (2019), online panels might yield low-quality data due to either the low interest of the panel participants or the lack of experience with the online panel systems, some researchers argued that the low-quality responses were mostly provided by the new panel members, not by professional panel members (Zhang et al., 2020). Similarly, another study indicated that professional respondents might not significantly impact data quality from online panels (Matthijsse et al., 2015).

Another study of data quality of platforms for online panel research (Eyal et al., 2021) concluded that the lowest data quality was from MTurk, specifically from professional respondents who reported MTurk as their main source of income. Similarly, a recent study strongly advised against collecting data from MTurk data without a previous quality screening of the participants (Goodman & Wright, 2022; Chmielewski & Kucker, 2020).

4. Participant-based personality factors in survey data collection

According to Eyal et al. (2021), the most critical aspects of data collection include attention, comprehension, honesty and reliability. When participants pay close attention to the survey questions, comprehend the questions well and provide honest and reliable responses, the resulting data is more likely to be high quality and provide the basis for gaining meaningful insights. While question comprehension can be ensured by carefully reviewing the questions and adjusting the questions to the targeted population, the level of control over attention, honesty, and reliability is limited, as it is mainly related to participant-based factors. Therefore, researchers need to understand who their participants are and the additional factors that might impact the quality and reliability of collected data (Anwyl-Irvine et al., 2021).

To understand the attention factor better, Gao et al. (2016) tested a validation question approach that asked respondents across six countries to select a particular answer within a survey to ensure they were paying close attention to the questions. Study results suggested that data quality is a common challenge in all countries included and that including validation questions in the survey might help detect less attentive participants in reading and answering survey questions.

In any research based on the self-report, the accuracy of the information obtained is related to the authenticity of the respondents' answers. The interest in research participation might come from extrinsic motivators such as incentives, and this topic has been thoroughly researched for both traditional and panel survey participation, as discussed in the previous section. However, the interest in research participation can also stem from specific psychosocial characteristics – personality traits and socio-demographic characteristics that might predict the preferences for participation in research (Brosnan et al., 2019, Brüggen et al., 2011, Larson & Sachau, 2009, Smith at al., 2012).

Survey nonresponse studies substantially impact understanding of the factors impacting research participation. Various nonresponse studies indicated that demographic characteristics such as gender, age, and education level could impact survey participation: females, younger people, and more educated people are more likely to participate in traditional survey research (Goyder et al., 2002, Moore & Tarnai, 2002). Personality characteristics can also play a crucial role in shaping data quality. Participants with certain traits may exhibit biased responses, acquiescence, or higher levels of social desirability, affecting the accuracy and representativeness of the data. However, not many studies have explored the direct impact of personality traits on the survey data quality. In a study of more than five hundred participants from an online market research pool (Larson & Sachau, 2009), researchers found that personality traits can be a moderating factor when lower incentives are offered. Specifically, Agreeableness, Conscientiousness, Openness and Extraversion were found to impact the product rating, and the participants with high scores on these personality traits provided more favourable product ratings even when offered low incentives. Another study by Falkenstern (2015) also looked into the relationship between Big Five personality traits and participation in the longitudinal study. The findings from his study indicated that different personality traits can predict attrition rates in longitudinal studies. The individuals with higher levels of Neuroticism were less likely to drop out, while Agreeableness and Conscientiousness had no impact on attrition in the longitudinal studies.

Some of the available studies have shown that certain personality traits are associated with higher levels of research participation. One of the first studies in this area (Rogelberg et al., 2006) indicated that participants with higher scores on Agreeableness and Conscientiousness were more likely to participate in the follow-up online survey. Nestler et al. (2015) argued that participants with higher scores in Openness, Conscientiousness, and Agreeableness were less likely to drop out while completing online surveys, while Extraversion and Neuroticism were not found to be predictors of survey dropout. In general, the majority of the studies looked at Big Five personality traits and Agreeableness and Conscientiousness are found to be significant predictors of research participation (Brüggen & Dholakia, 2010; Cheng et al., 2018; Nestler et al., 2015; Biddle & Sollis, 2021).

However, it needs to be noted that studies conducted on personality traits and online research participation either focused on longitudinal studies or were conducted on existing panel respondents. Few studies explored the personality traits of the cross-sectional survey respondents nor looked at the differences between nonprobability self-selected panel participants and non-participants.

5. Impact of social desirability response bias on survey data quality

The challenge of social desirability response bias has been present for a long time in quantitative research. Bergen and Labonte (2020) defined social desirability response bias as "a tendency to present reality to align with what is perceived as socially acceptable." Paulhus (1984) suggested two components impacting the social desirability bias. The first component is related to impression management, which involves intentionally presenting oneself in a manner that aligns with a particular situation or pleases an audience and that is not a realistic presentation of their behaviours or attitudes. The second component is self-deception, which can be unconscious and is driven by the desire to uphold a positive self-image. This bias can compromise the validity of the measured scores and cause a low survey data quality. Social desirability response bias can significantly change the results of the research studies, especially in survey studies, and can threaten the discriminant validity of the used scales (Larson, 2019).

Consequently, social desirability bias in survey responses can lead to inaccurate self-reports and invalid study conclusions (Latkin et al., 2017). Gittelman et al. (2015) noted that two sets of factors could impact social desirability bias in surveys. An individual's personality traits represent the first set of factors; they argued that individuals with certain personality traits are more likely to present themselves in a socially desirable manner when responding to survey questions. The second set of factors are survey-related factors such as the wording, order, and format of questionnaire items. These factors can increase social desirability bias in surveys, further impacting survey responses' validity and overall quality.

According to King and Bruner (2000), most research studies related to survey data quality discussed the challenges related to data reliability, and not many discussed the validity, including the potential impact of social desirability bias on survey results. They argued that providing socially desirable responses in self-report surveys may lead to spurious correlations between variables or the suppression or moderation effect of relationships between the constructs of interest, thus significantly impacting the overall data quality. Responding in a socially acceptable way can impact research results and produce biased data, leading to errors in data-driven decision-making and other planning strategies. Additionally, their study's results indicated that, in most cases, marketing researchers disregarded social desirability bias. Koivula et al. (2019) study concluded that online survey participants were more likely to provide socially desirable responses than mail survey respondents. This raises the question of whether online surveys yield more biased results than traditional mail surveys. The researchers argued that due to the low representation of specific population segments in online surveys and the increased probability of providing socially desirable responses mixed sampling approach with a balanced number of respondents from online and traditional surveys can yield the best results.

The present study examines the impact of personality characteristics on participation in online consumer panels and how these personality characteristics further impact the quality of collected data. The study aims to provide answers to the following research question:

RQ1: Do individuals with different personality characteristics show different preferences for participation in paid online research panels?

RQ2: Is there a relationship between specific personality traits and providing socially desirable responses in surveys?

Based on the previous research findings, Big Five personality characteristics, social desirability response bias, and online panel participation have been explored. Considering the limited nature of the literature available in this area, the study took an exploratory approach since the theoretical framework for making specific hypotheses was not strong.

6. Methods

6.1. Procedures

A sampling method comparable to the recruitment process for online panel participants was employed. The recruitment process involved utilizing Internet advertisements on search engines and social media platforms to reach a similar population. Participants were invited to complete an online survey through search engine advertising, social media platforms, as well as messaging platforms such as Viber and WhatsApp.

6.2. Participants

The cross-sectional quantitative study was conducted with a sample of 567 Internet users. Following the data cleaning and elimination of the cases with missing data, the final study sample consisted of 454 participants. Of this number, 18.9% were 18-25 years old, 31.1% were 26-35 years old, and 36.3% were 36 to 44 years old, with the lowest number belonging to the oldest group, 45 years and more - 13.7%. A slightly higher number of females participated in the study (59.3%) than males (40.7%). The majority of participants reported holding a bachelor's degree (41.6%), followed by the participants with some graduate education (35%) and high school (22.9%). Additionally, more than one-third of the participants worked in the private sector (38.8%), with 23.1% working in the public sector and the third largest group being students (17%).

6.3. Measures

Demographics

Demographic variables were measured with nominal multiple-choice questions, including participants' age, gender, level of education, and working status.

Big Five Personality Characteristics

Participants' personality characteristics have been determined using the BFI-S (John & Srivastava, 1999). BFI-S is a 15-item personality inventory with five subscales, each measuring one of the Big Five personality characteristics. Cronbach alpha values were acceptable for all five subscales (Extraversion $\alpha = 0.914$; Agreeable-ness $\alpha = 0.852$; Openness $\alpha = 0.827$; Conscientiousness $\alpha = 0.810$; Neuroticism $\alpha = 0.848$), confirming the reliability of the scale used.

Social Desirability Bias

Social desirability bias has been measured with a modified short Marlowe-Crowne Social Desirability Scale (Reynolds, 1982). This is a dichotomous true/false 13-item scale with statements measuring personal attitudes and traits. A high score indicates a propensity to provide social desirability responses. Cronbach alpha was $\alpha = 0.730$, which is acceptable according to Reynolds (1982) due to the nature of the construct and measurement.

Online panel participation

Online panel participation was also measured with one categorical variable. Participants were asked if they were currently enrolled in an online participant panel and could respond "yes," "no, and I would not consider it in future," and "no, but I would consider it in future." For the present study, an extreme groups sampling design (EGA) has been applied with only cases from the extreme of the distribution further analyzed (Preacher et al., 2005). This sampling approach has been recommended in exploratory and pilot studies where the theoretical framework for making specific hypotheses is not strong.

7. Results

In order to assess whether individuals with different personality characteristics show different preferences for participation in paid online research panels, multiple analysis of variance (MANOVA) was conducted. The MANOVA was followed up by a discriminant functions analysis (DA) to determine the relationship between the dependent variables and their ability to differentiate the two groups of respondents.

Before conducting MANOVA, multivariate analysis assumptions were tested and satisfied. Box's test of equal covariance was non-significant [$F(21, 22391) = 1.136$, $p > .05$], indicating equality of the covariance matrices of the dependent variable across the tested groups. Levene's test of equality of the error variances was non-significant for all dependent variables ($p > .05$), indicating that error variance is equal across dependent groups. Multivariate normality was established by checking the residuals; Cook's distance and Leverage statistics did not identify relevant outliers.

The MANOVA indicated a significant multivariate effect for group membership, $F(8.8, 445) = 894$, $p < .001$, η_p^2 = .106. Univariate tests revealed that the effect was significant for both Extraversion, $F(1, 450) = 21.45$, $p < .001$, η_p^2 =.045, and Conscientiousness, $F(1, 450) = 26.03$, $p < .001$, η_p^2 = .055. These results suggest significant differences between the groups on Extraversion and Conscientiousness, and the effect size for group membership is moderate to large.

The results of the MANOVA are presented in Table 1. The results indicate that Extraversion and Conscientiousness significantly differentiated between panel participants and non-participants. On the other hand, Neuroticism, Openness, Agreeableness, and Level of Trust were not significantly different for the tested groups.

A discriminant analysis was conducted following the MANOVA to assess the propensity of the dependent variable to predict participation in non-probability consumer panels. Predictor variables were Neuroticism, Openness, Agreeableness, Extraversion, Conscientiousness and Level of Trust. The discriminant analysis revealed one significant discriminant function. The Wilks' Lambda statistic was significant at p =.000, indicating that the model was a significant predictor of group membership. Furthermore, this discriminant function significantly differentiated between the two groups – panel participants and non-participants. However, a closer examination of the structure matrix revealed only two significant predictors, Extraversion (r = .751) and Conscientiousness (r = .-675). The cross-validated classification showed that 64.6% of the original cases were correctly classified with this function. In addition, non-participants were classified with slightly better accuracy (64.3%) than panel participants (63.4%).

Table 1. Manova results

Dependent variable	df	F	Partial η ²	M (non-participants)	M (participants)
Trust	1	.629	.001	19.96	19.53
Neuroticism	1	.818	.002	8.46	8.72
Extraversion	1	26.0*	.55	8.16	9.27
Openness	1	1.666	.004	10.02	10.38
Agreeableness	1	.015	.000	8.28	8.31
Conscientiousness	1	21.5*	.45	9.93	8.76

In order to test if there is a relationship between specific personality traits and providing socially desirable responses in surveys, a multiple regression was conducted, with scores on different Big Five personality traits as predictors and scores on Marlowe-Crowne Social Desirability Scale as the dependent variable. Before conducting the regression analysis, the assumptions of multiple regression were tested. All variables of interest were measured on a continuous scale, a linearity check was confirmed by creating scatterplots, and no relevant outliers were identified. The correlation matrix did not indicate high correlation factors for predictor variables. Additionally, the multicollinearity test did not identify any multicollinearity in independent variables, as the Variance inflation factor (VIF) values were slightly above 1 for all tested variables. Following the assumption testing, the regression analysis was conducted (table 2). The results showed that the predictive model was significant, F(5,306) = 17.79, R2 = .19, p< .000. Conscientiousness and Openness personality traits were found to be significant negative predictors of social desirability bias (β=.-43, t= 9.2, p< .000, and β=-.11, t= 2.3, p= .0, respectively). The results showed that Neuroticism, Extraversion and Agreeableness were not significant predictors of participants` social desirability bias. Based on the R square value, predictors explain 19% of the overall variance. The results suggest that individuals with lower scores on Conscientiousness and Openness are more likely to provide socially desirable responses, thus possibly impacting the validity of the data collected.

Table 2. Regression analysis results

Predictor Variable	B	SE	Beta (β)	t	p
Constant	21.150	.749		28.234	.000
Neuroticism	.013	.036	.017	.351	.726
Extraversion	.033	.047	.033	.700	.484
Openness	-.082	.036	-.108	-2.300	.022
Agreeableness	-.024	.037	-.031	-.660	.510
Conscientiousness	-.357	.039	-.430	-9.213	.000

8. Discussion

The present study aimed to investigate the impact of personality traits on preferences for participation in paid online research panels, and potential relationships between personality traits and providing socially desirable responses in online surveys. The first part of the study examined the characteristics of two extreme groups: current panel participants and non-participants, while the second part investigated the relationship between Big Five personality traits and propensity to provide the socially desirable responses in survey. Given the limited research in this area, an exploratory research approach was utilized.

The results revealed that panel participants and non-participants differed significantly on two personality characteristics: Extraversion and Conscientiousness. High levels of Extraversion and low levels of Conscientiousness were found to predict group membership, indicating that these traits may contribute to the decision to sign up for non-probability participant panels. These personality traits were found to be moderately effective at predicting group membership. Additional findings indicated that lower scores in Openness and Conscientiousness predict the tendency to produce more socially desirable responses. While there is no significant overrepresentation of individuals with lower Openness traits in online panels, the tendency to have more individuals with lower Conscientiousness might impact data validity by providing more socially responsible responses. At the same time, the participants with lower scores on Conscientiousness and Openness were more likely to provide socially responsible responses. With overrepresentation of individuals with lower scores on Conscientiousness in online participant panels, this might impact the validity of scores and overall quality of data collected.

The results of the present study have important implications for both academic researchers and practitioners who rely on non-probability online panels for online data collection. Low scores on Conscientiousness personality traits can impact data quality in survey research. This personality trait is characterized by the predisposition to self-control, responsible behavior, hardworking, orderly, and rule-abiding (Roberts et al., 2014). Individuals with low Conscientiousness may exhibit tendencies towards carelessness and a lack of attention to detail, which can lead to a number of challenges in survey research. The preference of individuals with low Conscientiousness to participate in non-probability consumer panels may harm the quality of data collected. These individuals may be more likely to provide inaccurate or inconsistent responses, complete surveys without thoroughly reading or understanding the questions, or not maintain coherence in their responses which can affect the quality of survey data. Additionally, individuals who participate in professional panels with the primary motivation of gaining a reward may not pay adequate attention to the quality of their responses, further impacting the quality of survey data. Participants who exibit a low Conscientiousness trait can undermine the validity and reliability of survey data, thus compromising the integrity and value of research findings.According to the ESOMAR report (2020), the amount of money spent on online research in research agencies is continuously rising, and an increasing number of quantitative survey studies are conducted via commercial research panels. However, the increased utilization of commercial research panels can influence the quality of the research, particularly when non-probability online samples are used (Brüggen et al., 2016). Therefore, the generalization of such results might be questionable, and researchers should consider this, especially considering the tendency of both academic and commercial researchers to rely on panel data for survey research.

Researchers should apply stringent quality control measures and pre-screening techniques to mitigate these risks.. They should exercise caution when using non-probability online panels due to the number of certain limitations that can compromise data validity and quality. The composition of online panels may not accurately reflect the target population, and number of panel participants are motivated by incentives, which can introduce response bias and affect the quality of their responses. Researchers should consider these limitations and carefully evaluate the suitability of nonprobability online panels for their specific research objectives, noting potential biases and limitations associated with such methods of data collection Adding additional information or using more rigorous statistical methods can help reduce these limitations and researchers can enhance the reliability and validity of findings. Before proceeding with data analysis, the careful quality check of the collected data should be conducted.

The main limitation of the present study is that it is conducted as a quantitative survey study, so the opinions of the survey non-respondents and their attitudes and potential interest in participating in the commercial online panels could not be explored. An additional limitation is the survey sample's non-representativeness due to the nonprobability sampling approach taken for the exploratory research. Therefore, the results should be taken as indicative and further research could explore a more representative sample of Internet users. To overcome the limitation of being unable to assess non-respondent's attitudes, qualitative research could be conducted in the future with a sample of individuals who never participated in online survey research. Future research in this area can also explore the motivation for participation in non-probability online panels, comparing the data quality of extrinsically and intrinsically motivated participants.

The shift toward online research is notable in business, academic research, and political polling, especially during the COVID-19 pandemic. As more focus is placed on online research, understanding the characteristics of participants in online surveys is becoming more critical. Before deciding to use an online panel as a source of research participants, companies should understand the methods used for panel recruitment and the mechanisms for panel data quality control. Therefore, it is especially important to understand the characteristics of panel participants in the context of their habits, personality traits, and overall behaviour in the digital environment. Ultimately, these findings contribute to a better understanding of the factors influencing participation in online research panels and can inform future research and practice.

In the years to come, despite all methodological imperfections and challenges, the number of studies conducted through online panels will most likely increase. Nevertheless, the limitations of online panel research can directly influence the quality of collected data and, consequently, conclusions and recommendations based on potentially biased data with limited generalizability. Considering the business community's need for valid and reliable information for data-driven decision-making, understanding the potential problems that contemporary survey research is facing and finding adequate solutions and methods to overcome these challenges will be very important in the coming years.

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