Motion Instructions in Surveys:
Compliance, Acceleration, and Response Quality

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Abstract

The increased use of smartphones in web survey responding did not only raise new research questions, but also fostered new ways to research survey completion behavior. Smartphones have many built-in sensors, such as accelerometers that measure acceleration (i.e., the rate of change of velocity of an object over time). Sensor data establish new research opportunities by providing information about physical completion conditions that, for instance, can affect response quality. In this study, we explore three research questions: 1) To what extent do respondents accept to comply with motion instructions? 2) What variables affect the acceleration of smartphones? 3) Do different motion levels affect response quality? We conducted a smartphone web survey experiment using the Netquest opt-in panel in Spain and asked respondents to stand at a fix point or walk around while answering five single questions. The results reveal high compliance with motion instructions, with compliance being higher in the standing than in the walking condition. We also discovered that several variables, such as the presence of third parties, increase the acceleration of smartphones. However, the quality of responses to the five single questions did not differ significantly between the motion conditions, a finding that is in line with previous research. Our findings provide new insights into how compliance changes with motion tasks and suggest that the collection of acceleration data is a feasible and fruitful way to explore survey completion behavior. The findings also indicate that refined research on the connection between motion levels and response quality is necessary.

Keywords: Accelerometer, survey completion behavior, compliance, smartphones, SurveyMotion, response quality, web survey

Introduction

During the last decade, the Internet penetration rate and the ownership of mobile devices, such as smartphones and tablets, has increased continuously. According to the Pew Research Center (2018a, 2018b), this trend applies to most countries, but especially to developing countries.

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Simultaneously, the number of respondents taking part in web surveys using mobile devices, particularly smartphones, has increased (Revilla et al., 2016).[1] One reason for this phenomenon might be that people have their smartphone with them most of the time.

The rise of smartphones in web survey responding is accompanied by a large body of research investigating survey layout strategies, such as optimized and non-optimized, systematic measurement error, such as break-off rates and item non-response, and paradata, such as response times and device orientation (see, for instance, Buskirk and Andrus, 2012; Couper and Peterson, 2017; de Bruijne and Wijnant, 2013; Höhne et al., 2018; Mavletova, 2013; Mavletova and Couper, 2013; Revilla and Couper, 2018a, 2018b; Revilla and Ochoa, 2015; Schlosser and Mays, 2018; Wells et al., 2013). In addition, smartphones allow survey researchers the passive collection of so-called sensor data – i.e., data that are collected via a variety of built-in sensors, such as accelerometers, barometers, compass, Global Positioning System (GPS) trackers, and gyroscopes. Sensor data have the potential to complement survey responses (Höhne and Schlosser, 2019; Toepoel and Lugtig, 2015) by providing information about respondents physiological states, such as altitude level, motion, geographic orientation, and speed (see Elhoushi et al., 2017; Harari et al., 2016; Höhne and Schlosser, 2019; Toepoel and Lugtig, 2015). Data from these sensors can be collected either by JavaScript functions implemented in web survey pages or by apps installed on the smartphone.

Sensor data establish completely new research opportunities. Indeed, such data could be used for personalized feedback in mobile web surveys, to increase respondents' motivation and, thus, response quality. It is possible to determine respondents' real time motion level (i.e., the extent to which respondents engage in movements, such as standing and walking) during survey completion and provide them with immediate feedback. For instance, if a respondent exhibits a high motion level, he or she could be asked whether this is a convenient moment to complete the survey or whether he or she prefers to proceed at a later time. In addition, the collection of sensor data in mobile web surveys could be used as a more objective supplement to common fitness and health measures that are not affected by social desirability or recall bias. Sensor data could be also used to determine time-location profiles that can be linked with survey data to enhance our understanding of how people spend their time (see Elevelt et al., 2018).

The current state of research on the usefulness and usability of the collection of sensor data in smartphone surveys is characterized by a few empirical studies that use acceleration data, GPS data, or other sensor-based data (see Bohte and Maas, 2009; Elevelt et al., 2018; Harari et al., 2016; Höhne and Schlosser, 2019; Stopher and Shen, 2011). Despite this small body of research, it seems that especially the collection of acceleration data of smartphones is a promising new way to investigate respondents' completion behavior and response quality in mobile web surveys (Höhne and Schlosser, 2019; Toepoel and Lugtig, 2015). Acceleration is the rate of change of velocity of an object over time. It is measured in meter per second squared (m/s^2). Acceleration can occur on three different axes: the x-axis (i.e., left and right), the y-axis (i.e., up and down), and the z-axis (i.e., back and forth). Figure 1 shows the sensitivity axes of an accelerometer implemented in a smartphone.

[1] Revilla et al. (2016), for instance, have also shown that not all respondents who have access to a smartphone or tablet are also willing to use their mobile device for web survey completion.

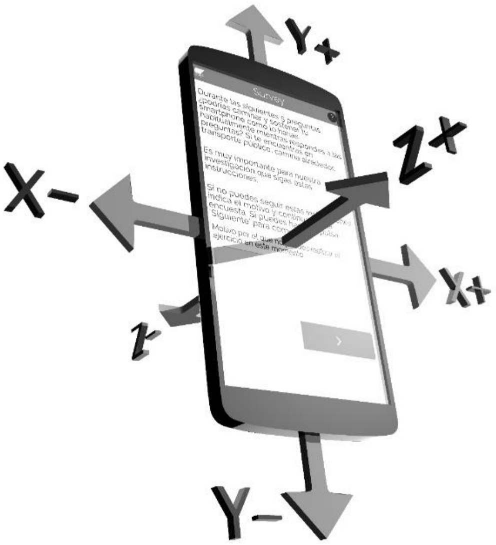

Figure 1. Sensitivity axes of an accelerometer implemented in a smartphone
Note. The accelerometer records the acceleration events on three axes with predefined directions. The x-axis indicates motions to the left and to the right, the y-axis indicates motions upwards and downwards, and the z-axis indicates motions backwards and forwards. The web survey page displays the original Spanish worded walking instruction.

Some studies have investigated respondents' stated willingness to share acceleration data. For instance, Revilla et al. (2018) reported a stated willingness of 37.4% among respondents of the Netquest opt-in panel in Spain and Wenz et al. (2017) reported a stated willingness of 31.0% (rate of those who were "very willing" only) among respondents of the Understanding Society Innovation Panel in the UK. Although the overall stated willingness for sharing acceleration data is low, it is considerably higher than the stated willingness for other passive data, such as GPS data and Uniform Resource Locator (URL) data (see Revilla et al., 2018; Wenz et al., 2017).

For instance, Höhne and Schlosser (2019) used acceleration data of smartphones to investigate respondents' completion behavior in mobile web surveys. The authors conducted a lab experiment with 89 university students where the students were assigned to one of four survey completion conditions: 1) sitting in front of a desk with the smartphone lying on the desk, 2) standing at a fixed point and holding the smartphone, 3) walking along an aisle and holding the smartphone, and 4) climbing stairs and holding the smartphone. In line with the author's expectations, the acceleration of smartphones increased with respondents' motion level indicating a "respondent-device link" (i.e., respondents motions are detected by using the sensors of the device). Furthermore, respondents with a higher motion level had significantly longer response times and significantly higher primacy effects than respondents with a lower motion level. Interestingly, this was only observed when respondents were presented with multiple questions per page but not when presented with one single question per page. This result indicates that question presentation (i.e., scrolling or paging) matters.

These results from Höhne and Schlosser (2019) suggest that acceleration data are useful in investigating completion behavior and response quality in mobile web surveys. However, considering the nature of the sample (i.e., university students), the artificial lab setting, and the associated small case number used, coupled with the limited number of existing empirical studies the relationship between respondents' motion levels and survey completion behavior and response quality merits further investigation.

Our study addresses three research questions: First, to what extent do respondents accept to comply with different motion instructions? This is an important research subject because many health-related surveys, such as the interviewer-based "Health and Retirement Study (HRS)" and "Survey of Health, Ageing and Retirement in Europe (SHARE)", regularly ask respondents to engage in additional tasks, such as balance and walk tests (see Minicuci et al., 2019; Sakshaug et al., 2010), to collect information about respondents' fitness and health condition. Thus, this study informs about the general feasibility of asking such additional tasks in self-administered mobile web surveys.

Second, what external variables affect the acceleration of smartphones? As set out, the current state of research is characterized by a small but steadily increasing number of studies collecting acceleration data in mobile web surveys. However, until now, little information exists on what variables influence the acceleration of respondents' smartphone. For this reason, this study explores influencing variables to provide a conceptual framework for future mobile web survey research using acceleration data.

Third, do different motion levels affect response quality? Filling out a web survey while walking around may have a negative impact on response quality because respondents face additional effort in responding. More specifically, it is to assume that the higher level of response effort decreases respondents' motivation, which, in turn, decreases the quality of their responses. In this study, we use several response style indicators that were proposed by van Vaerenbergh and Thomas (2013).

In what follows, we describe the study design, the data collection conducted by the Netquest online fieldwork company (Spain), and the analytical strategy we use in our study. We then present the results and, finally, we discuss the practical implications associated with the use of acceleration data in mobile web survey research and address future research perspectives.

Method

Study Design

We conducted a field experiment within a smartphone survey to investigate survey completion behavior and response quality across different motion levels. First, respondents were asked to indicate their position (i.e., sitting, standing, lying, walking, or in another position). Then, they were randomly assigned to one of two experimental conditions. Respondents assigned to the first condition were asked to stand at a fixed point without moving away from it and to hold their smartphone as they usually do while answering five questions (standing condition). Respondents assigned to the second condition were asked to walk around and to hold their smartphone as they usually do while answering the same five questions (walking condition). The motion instructions were adapted in accordance with the respondents' initial position to avoid artificial-sounding instructions. All other parts of the instructions were held constant (see Appendix A for English translations of the instructions).

The five test questions asked about respondents' satisfaction with a client survey by Netquest that the respondents previously completed (see Data Collection). Each of the five test questions were displayed on a separate single screen with a vertically aligned, seven-point response scale including numerical values. All questions were asked in Spanish (see Appendix A for English translations of the questions).

After answering the five test questions, respondents in both conditions were informed that they could return to their previous position to answer the final seven follow-up questions. These follow-up questions mainly asked about the context in which respondents completed the test questions and about their experience with the motion instructions.

Data Collection

The data were collected by the online fieldwork company Netquest (www.netquest.com) in Spain from October 2 to October 6, 2018. The experiment was implemented just after a client survey about insurance that was expected to last about five minutes. The target population for this client survey were people aged 25 years or older who are involved in decisions about insurance. For this experiment, we only included respondents who used a smartphone, which were detected by the User Agent Strings of the devices. In total, 521 smartphone respondents were randomly assigned to one of the two experimental conditions (standing: n = 261; walking: n = 260).[2]

The respondents were between 25 and 74 years old with a mean age of 44.1 years (SD = 12.6 years). Of these respondents, 58% were female and 42% were male. We also evaluated the sample composition between the two experimental conditions with respect to age and gender. The results of the chi-square tests revealed no significant differences.

Netquest adapted the open-source JavaScript-based tool "SurveyMotion (SMotion)" developed by Höhne and Schlosser (2019) that collects the total acceleration of mobile devices, such as smartphones and tablets. Total acceleration is defined as follows:

$$\text{Total acceleration} = \sqrt{a_x^2 + a_y^2 + a_z^2}.$$

Equation 1. Calculating total acceleration

Note. Accelerations (a) along the x-, y-, and z-axis are defined as ax, ay, and az, respectively.

The total acceleration of smartphones was measured every 150 milliseconds, which means that approximately seven total acceleration measurement points were obtained every second. The reason for setting this measurement frequency restriction was associated with data storage limitations. In addition to acceleration, Netquest collected other kinds of paradata, such as response times and the (in)activity of the web survey page.

Analytical Strategy

First research question: To investigate if respondents accept to comply with the motion instructions (standing or walking), we first looked at the proportion of respondents who did not provide any reasons for non-compliance when offered a chance to do so. In these cases, we

[2] The study contains data from 33 different smartphone manufacturers and from 173 different smartphone models.

assumed that respondents accepted to comply with the instructions, keeping in mind that not providing a reason does not constitute strong proof of compliance. To test whether the compliance rates differ across the two conditions, we conducted a chi-square test. In addition, we investigated respondents' stated reasons for non-compliance, which we classified into six categories.

Second research question: To investigate what external variables affect the acceleration of smartphones during web survey completion, we conducted an OLS (ordinary least squares) regression with the total acceleration as the dependent variable. To build the dependent variable, we aggregated the acceleration mean values of each respondent and web survey page, respectively. These mean values were based on the raw total acceleration data without checking for exceptionally low or high values because these values reflect specific characteristics of different motion levels that need to be preserved (see Höhne and Schlosser, 2019).

In general, the total acceleration of smartphones can be measured with and without gravity depending on the type of built-in acceleration sensor (see Appendix B for the SMotion JavaScript code with gravity and Höhne and Schlosser (2019) for the SMotion code without gravity). Some old and/or low-budget devices are not equipped with accelerometers that allow for the measurement of pure total acceleration without gravity. In these cases, only the total acceleration with gravity can be measured. The measurement of total acceleration with gravity results in a higher number of acceleration measurements, but they are less precise (i.e., the metric character of the data gets lost) than measurements of total acceleration without gravity. We conducted all analyzes of the total acceleration data both with and without gravity. The main results remained unchanged. For this reason and because their measurements are more precise, we chose to only report the results for the total acceleration data without gravity.

The total acceleration measurements to which we refer are aggregates of the total acceleration of the five test questions. As previously outlined, there are only few empirical studies on the usability and usefulness of sensor data in general and acceleration data in particular in mobile web survey research. Thus, there is little knowledge on what external variables affect the acceleration of smartphones. For this reason, we selected variables that explicitly and/or implicitly involve any kind of physical motions, such as body and hand motions (see Bedogni et al., 2012, Elhoushi et al., 2017; Miluzzo et al., 2012). Following the notion of a respondent-device link, such motions spread to respondents' smartphone and are detected by the built-in accelerometer. In this study, we expected the following variables to have an effect on the acceleration of respondents' smartphone: Experimental condition (standing = 0; walking = 1), completion outdoors (no = 0; yes = 1), moving around during completion (no = 0; yes = 1), and presence of third parties (no = 0; yes = 1). In addition, we used as independent variables several types of multitasking (no = 0; yes = 1), response times (in milliseconds), the stated questionnaire difficulty (from 1 = extremely easy to 7 = extremely difficult), and several respondent characteristics: age (in years), gender (female = 0; male = 1), respondents' restlessness (from 1 = extremely calm to 7 = extremely restless), smartphone usage (seven categories from “up to 30min” to “5h01 or more”), and iPhone (no = 0; yes = 1).[3] Except for experimental condition, response times, and iPhone, all independent variables used are based on self-reports that were obtained from the respondents.

For response times, we used an aggregate across the five test questions, and used a two-step outlier definition procedure (see Höhne et al., 2018; Höhne and Schlosser, 2018; Höhne et al., 2017). In a first step, we excluded as outliers all respondents who left the web survey page (e.g., switched between browser tabs to check emails) for a certain time. In a second step, we applied a distribution-sensitive outlier definition (Hoaglin et al., 2000): we excluded all respondents with response times below or above the median plus/minus the upper and lower quartile range multiplied by three. As a robustness check, we tested the lower and upper one percentile as thresholds (Lenzner et al., 2010). The main results did not change. All response time analyses were conducted with and without a log transformation. There were almost no differences in the main results. Thus, we decided to use the non-log transformed response time data. We did not adjust response times for baseline reading speed (see Couper and Kreuter, 2013).

Since the independent variables of the OLS regression are based on different units, we report standardized regression coefficients including standard errors.

Third research question: To investigate the link between respondents’ motion level and response quality, we investigated the occurrence of several response styles across the two motion conditions. We used four response styles proposed by van Vaerenbergh and Thomas (2013): primacy effects (i.e., attraction to the first response category of the scale), recency effects (i.e., attraction to the last response category of the scale)[4], middle attraction (i.e., attraction to the middle response category of the scale), and extreme responses (i.e., attraction to the first and last response categories of the scale). To build the response quality indicators, we calculated the number of responses to the first category (primacy), the last category (recency), the middle category (middle), and the first and last categories (extreme) across the motion conditions. To test if there are differences in the prevalence of each of these response styles across the standing and walking conditions, we conducted chi-square tests. In addition to these response styles, we looked at item-nonresponse and found that it did not occur. One reason might be that Netquest respondents are normally not allowed to skip questions without providing a response. We also compared response times between the two motion conditions but found no differences. This is in line with findings reported by Höhne and Schlosser (2019) for single questions.

[3] For “smartphone usage” we asked respondents to indicate how long they use their smartphone on a typical day and for “respondents’ restlessness” we asked respondents to indicate if they consider themselves a calm or restless person. For “iPhone” we extracted the device properties from the user-agent-strings; 20.3% of the smartphones were iOS-based (“iPhone”) and 79.7% of the smartphones were based on Android or another operating system.

[4] Although recency effects are more likely in aural than visual survey modes (see Krosnick, 1991), in smartphone surveys the next buttons are usually at the bottom of the screen. This might draw respondents’ attention to the lower part of the scale making it more likely that respondents select a response category at the bottom of the scale, which results in recency effects (see Revilla and Couper, 2018a for a discussion of the placement of next buttons and its impact on response behavior).

Results

Compliance with Motion Instructions

To answer our first research question, we analyzed respondents' compliance with the two motion instructions: either standing or walking. Table 1 summarizes respondents' compliance with the instructions for each motion condition.

Table 1. Percentage and frequency in parentheses of respondents complying with the motion instructions.

Standing condition	Walking condition	Difference
96.2	89.6	6.6***
(251)	(233)	(18)

Note. ***p < .001. Difference: standing condition minus walking condition.

The percentage of compliance is quite high in both motion conditions: 96.2% in the standing condition and 89.6% in the walking condition. This suggests that most respondents are both willing and able to comply with simple motion instructions if they are requested to do so. Nonetheless, the compliance rate is significantly higher in the standing condition than in the walking condition [$\chi^2(1) = 8.48$, $p < .001$]. This indicates that standing at a fix point during survey completion seems to be more convenient than walking around during survey completion. Correspondingly, it seems that, for instance, balance and walk tests are a feasible way to investigate respondents' fitness and health condition in self-administered mobile web surveys.

In a second step, we investigated respondents' stated reasons for non-compliance with the motion instructions. Based on the reasons stated by respondents, we identified six content-related categories: health issues, surrounding issues, situational issues, nonsensical reasons, other reasons, and refusals. Approximately two-thirds of the respondents who did not comply with the motion instructions reported either health-related issues, such as limited mobility, surrounding issues, such as being in a (public) transportation vehicle, or situational issues, such as charging the battery of the device. This finding applies to respondents in both the standing and walking conditions. Other respondents reported nonsensical reasons, such as "next", or refused to comply, such as "I do not want to comply". Three respondents in the walking condition gave other reasons that do not fall under a specific category, such as "I am painting nails". Although the rate of compliance differs significantly between the two motion conditions, the reasons provided for non-compliance are similar.

Explaining the Acceleration of Smartphones

In order to investigate our second research question, which investigates the external variables affecting the acceleration of smartphones during web survey completion, we ran an OLS regression with the total acceleration as the dependent variable. Table 2 shows the standardized (beta) coefficients and standard errors of the regression model [$F(16,365) = 5.83$, $p < .001$, adjusted $R^2 = .17$]. The intercept is not statistically significant.

As Table 2 shows, the variables of experimental condition, completion outdoors, moving around during completion, and presence of third parties have a significant effect on the total acceleration of smartphones. This implies that respondents who were in the walking condition, completed the survey outdoors, moved around during survey completion, and had other people around produced a higher total acceleration. Comparing the effect size of the standardized coefficients of these four variables, we observe the following relationship: the effect of being in the walking condition is larger than that of being outdoors, the latter of which is larger than both the effect of moving around and the effect of having third parties around.

Table 2. Standardized OLS regression coefficients of different independent variables on the total acceleration of the five aggregated test questions including standard errors.

Independent variables	Beta coefficients	Standard errors
Experimental condition	.270***	.034
Completion outdoors	.143**	.052
Moving around during completion	.109*	.034
Presence of third parties	.100*	.020
MT: listening to music	.040	.056
MT: off-device	–.025	.079
MT: on-device	.037	.068
MT: watching TV	.085	.042
MT: others	.050	.048
Response times	.087	.001
Stated questionnaire difficulty	–.083	.010
Age	–.048	.001
Gender	.070	.033
Restlessness	–.022	.012
Smartphone usage	–.006	.010
iPhone	–.089	.035

Note. *p < .05, **p < .01, ***p < .001. The intercept of the regression model is not statistically significant. Coding of the independent variables: Experimental condition (standing = 0; walking = 1), completion outdoors (no = 0; yes = 1), moving around during completion (no = 0; yes = 1), presence of third parties (no = 0; yes = 1), several types of multitasking (no = 0; yes = 1), response times (in milliseconds), stated questionnaire difficulty (from 1 = extremely easy to 7 = extremely difficult), age (in years), gender (female = 0; male = 1), respondents' restlessness (from 1 = extremely calm to 7 = extremely restless), smartphone usage (seven categories from "up to 30min" to "5h01 or more"), and iPhone (no = 0; yes = 1). Abbreviation: MT = multitasking.

To investigate whether respondent characteristics play a role, we added age, gender, respondents' restlessness, smartphone usage, and iPhone in the OLS regression model as main effects. We found that these characteristics did not have a statistically significant effect on the total acceleration.

We also tested for several interaction effects (e.g., between stated questionnaire difficulty and age), but the interaction terms were not statistically significant and did not improve the model fit. Thus, we report the regression model without them.

Motion Impact on Response Quality

To investigate our third research question, we compared the response quality between the two motion conditions. We used several response style indicators that were proposed by van Vaerenbergh and Thomas (2013). Table 3 reveals that the differences in response quality between the motion conditions are low. Running chi-square tests, we found no significant differences: Primacy [$\chi^2(1) = 1.86$, $p = .173$], recency [$\chi^2(1) = 1.06$, $p = .303$], middle [$\chi^2(1) = .11$, $p = .737$], and extreme [$\chi^2(1) = .58$, $p = .445$]. Hence, it seems that the motion level of respondents has no impact on the quality of responses to single questions, a finding that corresponds with those reported by Höhne and Schlosser (2019).

Table 3. Prevalence of response styles across the five test questions in percentages and frequencies in parentheses.

Response styles	Standing condition	Walking condition	Difference
Primacy	13.9	15.9	–2.0
	(181)	(206)	(25)
Recency	3.3	2.6	0.7
	(43)	(33)	(10)
Middle	28.0	27.2	0.8
	(361)	(351)	(10)
Extreme	17.3	18.5	–1.2
	(224)	(239)	(15)

Note. Difference: standing condition minus walking condition.

Discussion and Conclusion

In this experimental study, we used data from the online opt-in panel Netquest in Spain to investigate the compliance of respondents with motion instructions and the external variables that affect the acceleration of smartphones. In addition, we compared response quality across motion conditions. To answer our first research question, we compared respondents' acceptance to comply with standing at a fix point or walking around. Although the compliance rate is significantly higher in the standing condition than in the walking condition, the overall compliance rate is high in both conditions. Moreover, the stated reasons for non-compliance do not differ substantially between the two motion conditions. Most respondents report issues related to health, surrounding, or situation. Note, however, that only 10 respondents in the standing condition and 27 respondents in the walking condition provided reasons for non-compliance. This small number of respondents providing reasons makes it difficult to draw robust conclusions about the distribution of the stated reasons. Nevertheless, the high acceptance of compliance indicates that motion instructions can be employed in mobile web surveys. This also indicates the general feasibility of asking additional tasks, such as balance and walk tests, in self-administered mobile web surveys to draw conclusions about respondents' fitness and health condition.

Regarding our second research question, we found that four external variables had a significant effect on the total acceleration of smartphones. These variables were the experimental condition, completion outdoors, moving around during completion, and the presence of third parties. Respondents who were in the walking condition, completed the survey outdoors, moved around, and had other people with them exhibited a higher total acceleration. In particular, the significant effect of the experimental condition points towards two conclusions. First, most respondents actually complied with the motion instructions to which they were assigned. Second, the tool "SurveyMotion (SMotion)" seems to measure total acceleration properly. In addition, these results present supporting evidence for the existence of a respondent-device link – i.e., respondents' motion levels manifest themselves in the total acceleration of smartphones. This implies that smartphones can be used to distinguish respondents on the basis of their motions to draw conclusions about completion behavior in self-administered mobile web surveys.

To investigate our third research question on response quality, we compared the two motion conditions in terms of four response style indicators: primacy effects, recency effects, middle attraction, and extreme responses. We found no statistically significant differences in response quality between the two motion conditions. This finding is in line with Höhne and Schlosser (2019), who found that primacy effects are less common when a single question per survey page was presented than when multiple questions per survey page were presented. One explanation might be that single question pages – in contrast to multiple question pages – do not require respondents to pinpoint question stems and response categories by vertical scrolling and screen taps for selecting response categories, making it easier to respond to single questions even while walking around.

Our study has some limitations that could be addressed in the future. First, our target population was specific: Netquest panelists who were aged 25 years or older and involved in decisions about insurance. However, we did not find any effect by the demographic variables on the total acceleration and, thus, the specific target population may not have affected our results. Nevertheless, further research using more general target populations would be useful to test the robustness of our results. Second, we only employed five test questions that asked about a specific topic – satisfaction with a Netquest client survey that the respondents had previously completed. Future research could test whether the results change when asking questions on different topics and/or asking a larger number of questions. This would allow us to draw more robust conclusions about compliance, total acceleration, and data quality. Third, we only employed simple questions (i.e., short rating scales with radio buttons) that were presented as single questions. We expect response quality, however, to be affected by the motion level in surveys that employ multiple question pages (e.g., a scrolling design instead of a paging design), more complicated response formats (e.g., if respondents must enter responses to open-ended questions or drag and drop their responses into a box), and more difficult topics (e.g., topics that require deep cognitive processing to determine a response). Thus, future studies on the link between motion levels and response quality could vary the type of questions and response formats and employ a scrolling instead of a paging design. Fourth, we only investigated a limited number of response quality indicators. While no significant differences between motion conditions were found for the four response styles proposed by van Vaerenbergh and Thomas (2013), we expect that other response quality indicators – that could not be investigated in the current study (e.g. drop outs and item missing data) – exhibit substantial differences across motion conditions. Therefore, research that uses further response quality indicators is required. Fifth, it would be desirable if future studies employ more refined situational factors, such as noisy or quiet environments (see Wenz, 2019), to explain total acceleration of smartphones during web survey completion. Finally, we only focused on two motion conditions (standing or walking). Future research could test more motion conditions. For instance, it would be also possible to ask respondents to take part in a kind of motion or fitness task (e.g., doing knee bends) during mobile web survey completion to draw conclusions about the fitness level of respondents.

In addition to the limitations specific to our study, there is the more general issue that researchers using sensor data face ethical considerations. Although we encourage researchers to make use of sensor data to improve and enhance survey research methods, these data should not be used to surveil respondents or to frivolously adapt respondents' final responses (see Heerwegh, 2002). In addition, we encourage researchers to investigate respondents' actual willingness to share sensor data (see Revilla et al., 2018; Wenz et al., 2017). This also applies to the aggregation or combination of different kinds of sensor data, such as acceleration, compass, and gyroscope, to build new measures that, for instance, inform about respondents' geo-location (see Schlosser et al., 2018). Thus, we highly recommend that future research on informed consent does not only focus on the permission of sensor data collection, but also on the permission of sensor data processing. This is a crucial prerequisite to ensure that sensor data are used in an ethical manner and to guarantee respondents' full online privacy.

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Appendix A

Questions on respondents’ position and motion instructions (only if respondents indicated that they are standing or walking), and the five test questions used in this study.

Position question:
Are you currently …
1 sitting, 2 standing, 3 lying, 4 walking, or 5 in another position than those mentioned above

Standing instruction (only if respondents indicated that they are standing or walking):
While you complete the next 5 survey questions, could you please stand at a fixed point without moving away from it and hold your smartphone as you usually do while answering the questions? It is very important for our research that you follow this instruction. However, if you are not able to follow the instruction mentioned above, please indicate the reason below and continue the survey. Otherwise, please click on the Next button and continue the survey while following the instruction.
Reason for not being able to follow the instruction: *Open answer field*

Walking instruction (only if respondents indicated that they are standing or walking):
While you complete the next 5 survey questions, could you please walk around and hold your smartphone as you usually do while answering the questions? It is very important for our research that you follow this instruction. However, if you are not able to follow the instruction mentioned above, please indicate the reason below and continue the survey. Otherwise, please click on the Next button and continue the survey while following the instruction.
Reason for not being able to follow the instruction: *Open answer field*

Test question 1:
How easy or difficult was it to fill out this questionnaire?
1 Extremely easy – 7 Extremely difficult

Test question 2:
How boring or interesting was the topic of this questionnaire for you?
1 Extremely boring – 7 Extremely interesting

Test question 3:
How much did you like or dislike filling out this questionnaire?
1 Totally liked it – 7 Totally disliked it

Test question 4:
To what extent do you think that this survey was too long or too short?
1 Extremely too long – 7 Extremely too short

Test question 5:
To what extent do you trust or distrust that this survey guarantees anonymity?
1 Totally trust it – 7 Totally distrust it

Note. The presentation order of the questions and instructions corresponds to the order in Appendix A. All questions and instructions were displayed on a separate single screen and all response scales had a vertical alignment. The original Spanish wordings of all questions are available from the second author on request.

Appendix B

JavaScript-based "SurveyMotion (SMotion)" code to measure the total acceleration with gravity of mobile devices containing an accelerometer.

```
var start = now();
function SurveyMotion(e) {
    this.acceleration = new Object();
    if (e.acceleration !== null) {
      this.acceleration.x = Math.sqrt(Math.pow(e.acceleration.x,2)+
                            Math.pow(e.acceleration.y,2)+
                            Math.pow(e.acceleration.z,2)).toFixed(2);
      this.acceleration.g = abs(Math.sqrt(Math.pow(e.accelerationIncludingGravity.x,2)+
                            Math.pow(e.accelerationIncludingGravity.y,2)+
                            Math.pow(e.accelerationIncludingGravity.z,2))-
                            9.80665).toFixed(2);
      this.acceleration.t = Math.round(now() - start);
    } else {
        this.acceleration.x = null;
        this.acceleration.g = null;
    }
    this.interval = null;
    if (e.interval !== null) { this.interval = e.interval;
    }
    return (this);
};
window.addEventListener("devicemotion", update_accel, false);
```

 Although the application of the JavaScript-based SMotion code with gravity was tested in several pretest studies, we wish to state clearly here that the use of the code is completely the user's own responsibility. There is no warranty of any kind that the tool works properly and users are encouraged to test its functionality before utilization. We and/or our affiliations cannot be held responsible for any possible malfunctions and/or damages, even if SMotion is the responsible source.