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How to enhance web survey data using metered, geolocation, visual and voice data?

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After briefly summarizing why there is a need to enhance web survey data, this paper explains how metered, geolocation, visual and voice data could help to supplement conventional web survey data, particularly when mobile participation is high. It presents expected benefits of these four data types in terms of respondents' burden, data quality and possible new insights, as well as a number of expected disadvantages, both on the respondents' and researchers' sides. Finally, the paper discusses what is still missing and the next steps to turn these new opportunities into realities.

Keywords: geolocation; measurement; metered data; web surveys; visual data; voice recording

1 Why do we need to enhance web survey data?

The use of surveys has been increasing for decades (Sturgis & Luff, 2021), making them the most frequently used method for collecting data across many disciplines (Saris & Gallhofer, 2014). Among others, surveys are used to collect information about values, attitudes, opinions, feelings and behaviours, in order to draw conclusions about a huge range of topics.

However, it is well known that survey data suffer from errors, both in the representation and measurement sides (see e.g., the Total Survey Error framework proposed by Groves et al., 2009). This paper focuses mainly on the issue of measurement. A lot of research suggests that there are large measurement errors (e.g., Alwin, 2007; Saris & Gallhofer, 2014). For instance, Andrews (1984, p. 425) found that "about two-thirds of the survey measures examined contained between 50 percent and 83 percent valid variance". This means that 17% to 50% of the observed variance was due to measurement errors. More recently, Poses, Revilla, Asensio, Schwarz, and Weber (2021) found an average measurement quality of 0.65 for 67 European Social Survey questions across up to 41 country-language groups. In other words, on average, 65% of the observed variance came from the latent concepts of interest while 35% was due to measurement errors. Thus, there is a large difference between what researchers want to measure (concepts used in their theories and hypotheses) and what is really measured with specific survey questions. These measurement errors can considerably affect results based on survey data (Saris & Revilla, 2016), leading to wrong conclusions and decisions.

The size of these measurement errors is affected by the many decisions made while designing a survey (Saris & Gallhofer, 2014), including the exact formulation of the request for an answer, its linguistic characteristics, the scale characteristics (when present) and the mode of data collection.

For the last 15–20 years, the internet has become more and more predominant. For instance, 91% of European households had an internet connection in 2020 versus only 55% in 2007.[1] To adapt to this new reality and given the relative simplicity of conducting surveys online in comparison with more traditional data collection modes (e.g., face-to-face or telephone), the number of web surveys has increased drastically too (Couper, 2017).

More recently, the widespread adoption of mobile devices, in particular smartphones, has produced a new change in the survey world, with a switch from PC survey participation to mobile survey participation (Revilla, Toninelli, Ochoa, & Loewe, 2016). For instance, on average, millennials answered 79% of the surveys using smartphones in the US Netquest opt-in panel in 2017/2018, and boomers

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[1] https://www.statista.com/statistics/377585/household-internet-access-in-eu28/

36% (Bosch, Revilla, & Paura, 2018b, 4). In European probability-based panels, these numbers are smaller, but still show a non-negligible mobile participation (Revilla & Höhne, 2020): for instance, in the CROss-National Online Survey (CRONOS) panel in 2017/2018, on average, millennials answered 23.3% (Estonia) to 44.7% (UK) of the surveys using smartphones, and boomers 9.6% (Estonia) to 17.6% (Slovenia). According to ESOMAR (2019), 35% of the money spent on research corresponds nowadays to research using (mobile) web, versus only 11% for telephone research or 8% for face-to-face research. With the Covid pandemic, these numbers probably increased further, since many surveys that used to be face-to-face were forced to consider alternatives, web surveys being usually one of them.

Web surveys differ at several levels (no interviewer, computer-assisted, visual stimuli, etc.) from surveys implemented in more traditional modes (for an overview, see e.g., de Leeuw, 2018). However, they suffer from similar error types as surveys using more traditional modes, even if the size of these errors might differ.

Overall, it is widely accepted that survey data suffer from non-negligible measurement errors. Huge efforts have already been made to study how to minimize such errors and a lot of knowledge already exists about how to best design surveys (e.g., Fowler, 2013; Groves et al., 2009; Tourangeau, Rips, & Rasinski, 2000) and more particularly web surveys (e.g., Callegaro, Manfreda, & Vehovar, 2015; Couper, 2008; Tourangeau, Conrad, & Couper, 2013). However, errors remain difficult to rein in. For example, DeCastellarnau and Revilla (2017) found estimates of measurement quality between 0.60 and 0.89 for questions of the fifth wave of the online probability-based Norwegian Citizen Panel (NCP). Thus, other alternatives need to be considered.

This paper discusses one idea to further improve the quality of the information collected through web surveys that has not been investigated much yet: taking advantage of new measurement opportunities linked mainly to the growing use of smartphones to reduce measurement errors and/or to gain new insights. While most of the ideas proposed in this paper are especially relevant for mobile devices, they also often apply to the web survey mode in general.

2 Using new data types to enhance web survey data

The growing presence of mobile devices and the resulting ubiquitous connectivity (everyone is connected, everywhere, all the time) create both new challenges and opportunities for researchers. While quite a few studies have focused on the challenges (e.g., Couper, Antoun, & Mavletova, 2017; De Bruijne & Wijnant, 2014; Link, 2016; Mavletova & Couper, 2013; Peterson, Mechling, LaFrance, Swinehart, & Ham, 2013; Revilla, Toninelli, & Ochoa, 2016), little has been done yet about the new opportunities. Among the different opportunities (e.g., using Whatsapp to contact respondents, sending them a link to an online survey), this paper focuses on that of collecting different data types beyond conventional survey answers, especially (but not only) thanks to the presence of sensors and apps on smartphones. The new data types can replace some conventional survey questions or be used in addition to them.

More precisely, the following four new data types are considered:

- Metered data: data obtained through a tracking application (called a "meter") installed by the participants on at least one of their browsing devices and that registers at least the URLs of the webpages visited.
- Geolocation data: data obtained through a tracking application installed on participants' mobile devices that registers at least the GPS coordinates.
- Visual data: data obtained within the frame of web surveys by asking respondents to capture photos, videos or screenshots while answering the survey or to share visual data already saved on (or accessible from) the devices used to answer the survey.
- Voice data: data obtained within the frame of web surveys by asking respondents to record their voice.

Using these new data types could help reduce respondents' burden, improve data quality and extend measurement into new domains. This, in turn, could allow for better informed decisions of key players, such as governments, institutions and private organizations, and open the door to answer new research questions. However, while the general idea that these data could help enhance web survey results is often mentioned, little has been said about the mechanisms through which they could help, and the related pros and cons that researchers could expect.

Since each of these four data types has its own potential benefits and disadvantages, it is necessary to study them separately. However, they also have a lot in common, making it crucial to compare them as well. For instance, the first two are passive data. Thus, participants only have to accept and possibly set up a tracking application. Then, the data are collected and shared with the fieldwork company without participants' further intervention. On the contrary, the last two need to be shared actively by the participants within the frame of a survey.

These new data have already been used in substantive research. For example, metered data have been used to study fake news consumption (e.g., Guess, Nyhan, & Reifler, 2020) or time spent online (e.g., Festic, Büchi, & Latzer, 2021); geolocation data to study spatial context of physical activity (e.g., Krenn, Titze, Oja, Jones, & Ogilvie, 2011) or travelling (e.g., Lin & Hsu, 2014); visual data to study the presence of specific species of mosquitoes (e.g., Pataki et al., 2021) or plant diseases (e.g., Kaur, Pandey, & Goel, 2019); and voice data to study the level of literacy (asking respondents to read text out loud) or to survey the children of a group of panellists. Thus, these data on their own are not new. However, I speak about new data types because when compared to conventional survey answers, their use is much more recent and limited. Moreover, the idea of using them in a specific frame and in order to enhance web survey data has received little attention so far, even if a few reports or papers considering these topics already exist (see e.g., Link et al., 2014).

It is important to note that most of the new data types are not limited to mobile devices and can also be collected for PCs. For instance, metered data can be collected for PCs as well as smartphones and tablets. Similarly, visual data and voice recordings can be captured and shared both from mobile devices and PCs. However, it might be more complicated to capture such data from PCs (especially desktops) and might require extra equipment (e.g., not all PCs have a camera included).

3 How could the new data help?

The new data are expected to have some benefits, both for participants and researchers, as shown in Table 1 (first column). However, it should be clear that such benefits are not expected for all concepts of interest: when researchers want to measure opinions, attitudes, or feelings, the new data might be less helpful. Still, there is a large range of concepts where conventional survey questions can lead to poor measurements that could benefit in different ways from being measured using such new data.

3.1 Participants' side

First, on the participants' side, using the four new data types could lead to a reduction of the time and/or effort required to provide the information needed to measure some concepts of interest. This is especially expected in the case of passive data since, once set up, they are collected without further participant intervention. Answering through voice recording is also expected to be quicker and less burdensome than typing in a text box. In the case of visual data, a reduction of the time/effort can also be expected but only in some cases, mainly when one piece of visual data replaces several conventional survey questions (especially open questions) and when the visual data is produced during the survey. For instance, sending a photo of a bill is expected to require less effort than typing in all the products' prices. However, if the respondents do not have easy access to the bill and need to look for it, then answering through visual data might require more time and effort than answering the conventional survey question(s); it all depends then if respondents can recall the prices (so they can answer conventional questions without looking for the bill) or not. In the case of visual data already stored, the time/effort mainly depend on how much visual data the participants can access from their devices and how they store them. For instance, if they have a lot of visual data but organize them into folders, it might be easy to find the file they want to share to answer the survey question. On the contrary, if they have a lot of visual data but all in the same folder, it might take a long time to find the file of interest.

Second, participants might find it more natural and thus more enjoyable to share visual data or voice recordings in a web survey than to answer questions in a conventional way. Indeed, sharing visual data and using voice functions of the smartphone have become very popular activities. For instance, Duggan (2013) found that 62% of the respondents in a sample of adult internet users in the US stated that they post or share pictures online. Regarding the use of voice functions, almost half (46%) of the respondents of the US Deloitte Global Mobile Consumer Survey reported having used a voice assistant on their smartphones during the last week (Deloitte, 2018). Still, some participants might also feel uncomfortable recording their voice or might complete the survey in conditions in which they might not like to speak out loud (e.g., if answering from a public place).

3.2 Researchers' side

On the researchers' side, most of the expected benefits are related to improved measurements. More precisely, Table 2 summarizes how the new data types are expected to help tackle the following issues:

- Respondents do not know everything surveys ask about: researchers sometimes ask too much from their respondents, assuming that they know everything that is of interest to them. Then, high levels of non-substantive answers ("don't know") are expected and/or respondents might feel they should know (mainly when the "don't know" option is not offered explicitly) and provide an answer even when they are unsure. Both can lead to poor quality data.
- Remembering self differs from experiencing self: human beings forget most of what they do, and what they remember often differs from what actually happened. As Kahneman and Riis (2005, p. 286) explain, "it is not an experiencing self that answers, but a remembering and evaluating self, the self that keeps score and maintains records." Therefore, large measurement errors are expected, in particular when asking about past behaviours, opinions, attitudes or feelings.
- To err is human: human beings make mistakes. In the frame of surveys, this leads to random errors. Such errors are expected for all questions. However, their size can vary across questions, countries and languages, as can be seen for instance in the Survey Quality Predictor (SQP; see Saris et al., 2011) database.[2]
- Lack of effort/satisficing: respondents tend not to put in the maximum effort when answering survey questions. This lack of effort, often called "satisficing" (Krosnick, 1991),

[2] Available at http://sqp.upf.edu/.

Table 1
Main expected benefits and disadvantages of the new data types

Expected benefits	Expected disadvantages
Participants	
Reduced time/efforts	Privacy issues
More enjoyable	Loss of control
	New skills needed
Researchers	
Avoid participants not knowing	Selection bias in who participates
Avoid relying on remembering self	New types of errors
Reduced human error	Ethical and data protection issues
Reduced satisficing	Need specific resources & data collection tools
Reduced effects of social desirability	Need new skills for analyses
Increased amount of data	Dependence on private companies
Data for concepts not measured so far	More expensive

leads to the use of different shortcuts (e.g., always providing the same answer).

• Social desirability: respondents also tend to present themselves in what they think is a positive way in their society (Krosnick, 1991), under-reporting behaviours they believe are considered non-desirable (e.g., visits of adult websites or votes for extreme right candidates) and over-reporting behaviours that they believe are considered desirable (e.g., eating fruits or exercising).

• Limited amount of data: comparatively long surveys are associated with several negative effects. For instance, Galesic and Bosnjak (2009) found that questions close to the end of the survey had higher item non-response rates, shorter answers to open-ended questions, and less variability in answers to grid questions. Moreover, as individuals are confronted with more and more survey requests, survey fatigue can appear (Callegaro et al., 2015). Thus, researchers need to limit both the number of questions in each survey and the number of surveys administered overall. Moreover, the level of details that respondents are able to report in a conventional survey frame is often limited.

• Some concepts not measured yet: there is a range of concepts that researchers have not measured yet because no adequate tools exist for measuring them.

Due to their passive nature, both metered and geolocation data can help reduce the different issues. Indeed, the data are collected without relying on the respondents doing anything else than accepting and/or setting up the tracking application at the beginning. The researchers simply observe what people are doing. Thus, problems related to respondents not knowing, not remembering properly, making mistakes, or satisficing are avoided. Moreover, social desirability is expected to affect the answers less when using passive data compared to conventional surveys, because presenting oneself in what one considers a socially desirable way is much harder when data are collected passively. Indeed, participants really need not only to think about it but also to change their behaviours if they do not want the researchers to observe them (e.g., they should stop visiting given websites, or they should think about visiting them from a device in which they did not install the meter, or they should remember to turn off the meter before doing such visits – but this will also be registered). In addition, passive data are usually collected in a continuous way, leading to a massive amount of data. Finally, passive data can be used to measure new concepts and to answer new research questions due to their granularity, but also by comparing them with survey answers, since the difference between the two measurements can be informative.

Visual data are also expected to reduce the above-mentioned issues. Indeed, participants can share visual data without having a full understanding of the information contained in the files. For instance, they can send a picture of their moles without knowing if they are dangerous or not. Then, an expert can look at the pictures and assess the moles' harmfulness. Moreover, if researchers are interested in the experiencing self, one solution to avoid getting data from the remembering self is to ask for visual data (in particular videos) captured in the moment the respondents experienced something of interest. The availability of such data might be limited (i.e., participants might not have visual data captured during the event of interest). However, for some events, for instance a wedding, we can expect that many participants would have some available data that could be shared. In addition, human mistakes can be reduced if visual data are shared, mainly compared to answering open questions: for instance, a respondent could easily type in a price of 15 euros instead of 150 euros without noticing it. By sharing a photo of the bill, such mistakes are prevented. However, one should keep in mind that the information needs to be extracted from the photo, either by a human or automatically

Table 2
How the new data types are expected to help tackle different issues

Passive data[a]	Visual data	Voice data
Participants do not know everything		
Only accept/set up, so no need to know (e.g., total time spent on WhatsApp per week)	Participants need to share a file but not to be fully aware of its content (e.g., dangerous moles)	Information respondents are not aware of (e.g., surrounding noise)
Remembering self differs from experiencing self		
Do not rely on human memory (e.g., how long did it take you to find and buy this product?)	Do not rely on human memory (e.g., video of the feelings on a wedding day)	-
To err is human		
Avoid respondents' mistakes (e.g., did you read political news online yesterday?)	Reduce respondents' mistakes (e.g., typing in a price of 15 euros instead of 150 euros without noticing it)	-
Lack of effort/satisficing		
No effort once set up (e.g., list of websites visited)	Might reduce effort when replacing several questions or open questions (e.g., bill with all prices)	Might reduce effort compared to conventional text box, open narrative questions
Social desirability		
Harder to present oneself in a socially desirable way; need to think about it and change behaviours (e.g., stop visiting a given website)	Need to capture visual data in a specific way or look for false data, etc. (e.g., illegal plants in your garden)	-
Limited amount of data		
Real time/ continuous data collection, leading to massive amount of data	Provide very detailed information ("A picture is worth a thousand words")	Respondents expected to provide longer answers when speaking than typing
Some concepts not measured yet		
Can measure new concepts (e.g., difference between survey answers and what we observe using metered data provides new information about what participants recall)	Can measure new concepts (e.g., visual aspects that participants cannot describe properly with words such as landscapes or colours)	Can measure new concepts (e.g., emotions that can be detected when speaking but not when writing)

[a] Passive data include both metered and geolocation data. However, for the sake of simplicity, I present only one example based on metered data each time

(e.g., through optical character recognition, a technique that transforms the letters and words contained in an image into machine-encoded text). Mistakes can occur in this extraction step. Nevertheless, the researchers can implement different checks to minimize these errors (e.g., it is common practice to use at least two human coders instead of just one). Visual data have also the potential to reduce in some cases the effort participants have to put forth in order to provide the information of interest to the researchers (see Section 3.1). Reducing the participants' effort might, in turn, reduce the level of satisficing. Finally, visual data could help reduce the number of answers affected by social desirability because it is often harder to hide reality when sharing visual data. For instance, if respondents want to hide that they have illegal plants when asked to share a photo of their garden, they need to capture the visual data in a specific way, to make sure that these plants do not appear, or look for fake data, whereas in a conventional survey, they just need to omit mentioning they have such plants. However, there is also a tendency to create and share visual data in order to present oneself in a positive way. In particular, in the social media environment, there is a growing phenomenon of false self-presentation. For instance, a significant number of Facebook users stated that they exaggerated their positive aspects in their profile (Gil-Or, Levi-Belz, & Turel, 2015). The same occurs for Instagram (see e.g., Mun & Kim, 2021). In addition, filters are available in most mobile devices. Thus, it is quite easy to change the appearance of (part of) an image, for instance by altering the shades and colours in some manner. Therefore, social desirability can still affect the measurements based on visual data, but it requires more effort and sufficient technical skills. Furthermore, visual data provide much more detailed information than conventional survey answers (as the famous adage says, “a picture is worth a thousand words”) and it can be used to measure concepts that have not been measured yet because of a lack of adequate tools (e.g., visual aspects that participants cannot describe properly with words such as landscapes or colours). However, it is necessary to extract the information of interest from the visual data. Thus, the amount and quality of information depend on how the classification is done (Iglesias, Ochoa, & Revilla, 2022).

Regarding voice data, voice recordings might include information that the respondents are not aware of, such as information about the nature and/or level of surrounding noise (e.g., a respondent might say if he/she is answering from a noisy place, but it is not likely that he/she can provide a proper estimate of the level of noise). It is also expected that speaking requires a lower level of effort than typing in a text box. This could, in turn, lead to longer and more complete answers when voice recordings are used, and thus to a larger amount of data. However, a larger amount of data is not always an advantage. Researchers should also consider how they will extract the information of interest. Overall, the advantages for voice data are expected to be lower than for the other data types.

Finally, we should keep in mind that there might be important differences depending on the exact concepts to be measured, the target population of interest or the exact type of data used. For instance, within visual data, the levels of benefits might differ between a screenshot and a video created while answering a survey. Thus, the researchers need to consider the expected benefits for each concrete study, concept of interest and exact data type that they plan to ask for.

4 Expected disadvantages of the new data

Even if the new data types sound promising at different levels, there are also expected disadvantages that should be considered and balanced with the potential benefits when deciding whether to use such data or not. These disadvantages are summarized in Table 1 (second column).

4.1 Participants’ side

Some disadvantages are expected for the participants when the new data types are used. In particular, privacy issues might be even more important than in the case of conventional surveys. This is mainly because of the massive amount of data shared and the lower control that participants have over the shared data, especially in the case of passive data. However, this is also the case for visual and voice data. Indeed, it is easy to share an image, let alone a video, without realizing that there are some personal data somewhere in the background. Similarly, when sharing a voice recording, one might not realize that some surrounding noise is recorded (e.g., the voice of one’s children). Moreover, the voice can reveal the responent’s identity. Finally, sharing these new data types often requires some new skills from participants, in comparison to those needed to answer conventional surveys, such as setting up a tracking app or using the camera or microphone of their devices. However, we can expect that more and more participants will have these skills in the near future.

4.2 Researchers’ side

On the researchers’ side, there are also some expected disadvantages. Again, it is important to keep in mind that even if a general discussion is provided here, these should be evaluated for each concrete study and concept of interest, accounting for potential differences within a category of data (especially for visual data).

First, participants who share the new data types might differ from those who do not on key variables, creating a selection bias. Researchers should consider using methods to correct for this bias, such as weighting techniques (see e.g., Bethlehem, 2010). However, weighting might not be sufficient to eliminate all the bias (Keusch, Bähr, Haas, Kreuter, & Trappmann, 2020). In particular, researchers are limited by the information available. Mainly when the target population is very specific, which is the case in most surveys implemented in online opt-in panels (Revilla, 2017), it is often not possible to find any information about the target population composition.

Second, the new data suffer from their own errors: some of them are similar to conventional survey data errors (although their size can differ), while others are specific (e.g., technological errors or device-related errors). It might be difficult for researchers to deal with these new error types because a) very little is known yet and b) the presence and size of these errors can vary depending on the devices, operating systems and browsers used by the participants. Thus, researchers should not only consider all error types in order to decide if using the new data types is beneficial or not for their research, but they should also take into account that these errors can differ depending on the exact devices/operating systems/browsers used by their participants. For instance, what is tracked in the current Netquest metered panels is not the same for Android and iOS devices. Thus, different levels of tracking coverage are expected depending on the operating system of each participant’s devices.

Third, it might be more complicated for researchers to comply with all the ethical and data protection requirements when using the new data types. This is especially true because of the huge amount of data that can be produced, and the fact that participants might easily share data without fully controlling their content (see Section 4.1). Thus, even if the participants provide consent, one might doubt that this consent is always truly informed. These issues might improve when both researchers and participants gain experience in dealing with these new data types, but we still expect them to be tricky.

Finally, there are several potential disadvantages linked to the fact that these new data are not commonly used yet that should disappear or at least be reduced if researchers start using them more frequently. For instance, researchers need specific resources (e.g., servers) as well as data collection tools that are not yet included in the most popular web survey software. However, some tools have already been developed and can be used with limited extra programming. Additionally, a few of them are available freely to the research community (see e.g., Höhne, Gavras, and Qureshi, 2020 or Revilla, Iglesias, Ochoa, and Anton, 2022b for voice recording; and Höhne, Qureshi, and Gavras, 2020, or Revilla, Iglesias, Ochoa, and Anton, 2022a for visual data). Similarly, new skills are needed for analyzing the new data types. However, as soon as researchers start using such data more frequently, they will learn these skills and add them to their repertoire of conventional survey data analyses. Related to this, collecting the new data types might also currently mean a high dependence on private companies because of the lack of skills, availability of resources and tools and/or high costs to collect the data without contracting them. Nevertheless, it might soon become easier to collect the new data types without the need to contract a private company. Also, the total cost for collecting such data, which is currently often higher than that of conventional web surveys, is expected to go down if the tools and skills for such data collection are further spread.

5 What is still missing?

Not much is known so far about whether and to what extent the expected benefits and disadvantages presented in Table 1 occur in practice. First, most of the previous research about the four new data types considered in this paper has focused on the stated willingness to share such data (e.g., Höhne, 2021; Keusch, Struminskaya, Antoun, Couper, & Kreuter, 2019; Revilla, Couper, & Ochoa, 2019; Struminskaya, Lugtig, et al., 2021; Struminskaya, Toepoel, et al., 2021; Wenz, Jäckle, & Couper, 2019) or on evaluating the level of actual participation in studies asking to share such data (e.g., Bosch, Revilla, & Paura, 2018a; Bricka, Zmud, Wolf, & Freedman, 2009; De Reuver & Bouwman, 2015; Gavras, 2019; Ilić, Struminskaya, & Lugtig, 2020; Lütters, Friedrich-Freksa, & Egger, 2018; McCool, Lugtig, Mussmann, & Schouten, 2021; Ohme, Araujo, de Vreese, & Piotrowski, 2020; Revilla, Couper, Bosch, & Asensio, 2020; Revilla, Couper, Paura, & Ochoa, 2021; Scherpenzeel, 2017; Struminskaya, Lugtig, et al., 2021). Overall, these studies found that both the stated willingness and actual participation are clearly lower than the participation in conventional survey questions. However, large variations are observed in the above-mentioned studies across data types, but also depending on different aspects such as the sponsors, incentives or interest generated by the topic. This research is highly relevant since most of the benefits can only materialize if participants agree to share such data. Moreover, who agrees or not to participate also affects the bias of the results. However, it does not directly address the question of whether and to what extent the expected benefits and disadvantages occur.

Second, the few studies that more directly address this question provide empirical evidence for only some of the possible benefits/disadvantages. For instance, several studies asked participants to share images (Bosch et al., 2018a; Bosch, Revilla, Qureshi, & Höhne, forthcoming; Ilić et al., 2020; Jäckle, Burton, Couper, & Lessof, 2019), screenshots (Ohme et al., 2020; Sewall, Goldstein, Wright, & Rosen, 2021) or videos (Struminskaya, Lugtig, et al., 2021) in the frame of web surveys. However, these studies do not consider, for instance, whether data quality is improved by not relying on the remembering self or because of reduced satisficing. Similarly, a few studies asked for voice recordings (Gavras, 2019; Lütters et al., 2018; Revilla & Couper, 2021; Revilla et al., 2020; Schober et al., 2015) but they mainly focus on the feasibility of using such a tool (level of nonresponse, frequency of technical errors, etc.) and on the increased amount of data. Furthermore, many studies mention some of the benefits and/or disadvantages of geolocation data. For example, Keusch, Struminskaya, Kreuter, and Weichbold (2021) study the concerns of participants regarding sharing their geolocation, while Toepoel, Lugtig, and Schouten (2020) discuss the presence of problems such as signal loss in a travel app. In addition, geolocation data and technology have been used through all the survey life cycle, from sampling and measurement to weighting and analysis (see e.g., Eckman, Butt, & English, 2017, 3). Moreover, a few studies focus more specifically on the measurement quality issues of geolocation data (Bähr, Haas, Keusch, Kreuter, & Trappmann, 2022; Krenn et al., 2011), showing that even if geolocation data can help improve data quality, they are far from being error-free. However, these studies do not consider other aspects presented in Table 1 (e.g., social desirability). Finally, there are only very few studies providing empirical evidence on the different benefits and disadvantages of using metered data to replace or in combination with conventional web survey data (Barthel, Mitchell, Asare-Marfo, Kennedy, & Worden, 2020; Jürgens, Stark, & Magin, 2020; Revilla, Ochoa, & Loewe, 2017).

Third, the results of these few studies are sometimes mixed. For instance, regarding the expected benefits of proposing voice recording as a way to answer open-ended survey questions, Schober et al. (2015) found more precise answers for text than voice respondents, whereas Revilla et al. (2020) found more elaborated answers for voice than text respondents.

Overall, there is still a lot to be done to assess how and to what extent the new data types can really help enhance web survey data. In particular, research regarding the following aspects should be urgently developed:

Better understand the errors of those data It is crucial to further investigate the types of errors of the different data types, their size, and how they affect the results. For instance, Bosch and Revilla (2021) developed a total error framework for metered data. However, evaluating the size of the different errors in concrete studies is still missing. Moreover, the existing substantive research (e.g., Festic et al., 2021; Guess et al., 2020) still mainly ignores the presence of these errors. It is also crucial to develop ways to reduce and/or correct for them. This has been done already for conventional survey data (see e.g., Saris & Gallhofer, 2014; Saris & Revilla, 2016), but further research is needed to assess whether and how it can be extended to each of the new data types.

Better understand when to use such data The new data types cannot be used to measure all the concepts of interest to researchers. Thus, guidelines about when it could be beneficial for researchers to consider these new opportunities would be useful. Before providing such guidelines however, it is necessary to identify for which kind of concepts the benefits are higher than the disadvantages, balancing those for researchers and participants. This, in turn, requires a better understanding of the mechanisms behind some of the already observed behaviours. For instance, high non-response rates have been found when asking for visual data in the frame of web surveys (see e.g., Bosch et al., 2018a; Jäckle et al., 2019). Is this due to technological failures, a lack of skills, non-availability or non-willingness? Iglesias and Revilla (2021) started disentangling this. Their results suggest that the main factor behind the high non-response rates is the non-availability of visual data. Similar research is needed for other data types and behaviours. Moreover, even if it is beneficial for the research, one should take into account the participants' experience when deciding whether to use such data. In particular, data protection and privacy issues should always be considered (Stier, Breuer, Siegers, & Thorson, 2020). More knowledge on the different ethical issues is really needed to help researchers evaluate whether there are risks at this level. For instance, future research should investigate how to guarantee a truly informed consent in the case of the new data types.

Better understand how to use such data So far, this paper mainly considered the new data types as a way to replace one or a few conventional survey questions. However, the new data can also be combined with conventional surveys in different ways. For instance, if we consider combining conventional surveys with metered data, many options can be considered:

- Both measures can be used as indicators for a latent concept of interest.
- Metered data can be used as a gold standard to examine how distant the survey answers are from it (Revilla et al., 2017).
- Survey data can be used to evaluate and try to correct for some of the metered data errors (Bosch & Revilla, 2022).
- Metered data can be used to detect events of interest for the researchers and trigger a survey at a specific moment (Ochoa & Revilla, 2021). Such "in-the-moment surveys", by reducing the time between the event of interest and the survey completion, could help improve data quality (Ochoa, Revilla, & Versteeg, 2016).
- Metered data can be used to check respondents' behaviours during the survey: for example, to control if respondents look for information on the internet when asked knowledge questions during a web survey.

Summing up, very different ways of combining survey and metered data exist. Further research is needed to identify all these possibilities and assess their performance. Since there are different data types, each one with its own specificities, research is needed for each of them separately. Nevertheless, research considering the different data types together is also needed since it is crucial to better understand their similarities and differences. Moreover, the different new data types could also be combined themselves (e.g., metered data could be combined with visual data).

6 Conclusions

A lot of knowledge already exists about conventional survey data, its types of errors, their size, and even how to correct for them. However, current estimates of measurement quality in survey data suggest that overall conventional survey questions are far from measuring perfectly the concepts of interest for researchers. Thus, there is a need to enhance conventional survey data in other ways than those proposed so far. This paper focuses on the possibility of enhancing web survey data taking advantage of four new types of data: metered, geolocation, visual and voice data.

Such data have expected benefits for both participants (e.g., reduced efforts, more enjoyable) and researchers (in particular, reducing measurement errors in different situations and providing more detailed data). However, the new data types also have expected disadvantages, again both for participants (e.g., privacy issues, loss of control) and researchers (e.g., selection bias, new types of errors). Therefore, researchers need to balance all these benefits and disadvantages to decide whether to use these data. Moreover, they should do so on a case-by-case basis, since each data source has its own specificities, and the benefits and disadvantages vary depending on the concepts to be measured and the target population, among others.

However, there is currently a lack of empirical evidence concerning the occurrence of the expected benefits/disadvantages for the four types of data, making it hard to take informed decisions about their use. Most of the existing literature has focused on the stated willingness and/or actual participation when asking participants to share such data, but few studies have investigated to what extent the expected benefits and disadvantages really occur, and the results of the few studies doing so are sometimes mixed.

Thus, there is still a lot to be done to provide researchers with sufficient information so they can reach informed decisions about the use of such data in their studies. In particular, we need to: 1) create frameworks for all the different data types, 2) get empirical evidence about the size of these errors across different countries and for different concepts of interest, and 3) provide guidelines to help researchers use these new data types to answer key research questions. I believe that this methodological research is worthwhile considering the broad potential applications across different disciplines (e.g., health, social sciences, economics), and that new relevant insights could be obtained.

Finally, it is important to keep in mind that any data collection method suffers from errors. Even when measuring physical states using well-developed tools (e.g., when using thermometers to gauge the corporal temperature), measurement errors occur. Thus, when measuring more abstract, subjective concepts, it is not realistic to aim for perfect measures. What we need is to be aware of the errors present in our data and their consequences, try to minimize them, and if possible correct for them, while keeping in mind that even the “corrected” results will contain errors.

Thus, I think it is crucial to study the concepts of interest using different perspectives, in order to get different but complementary information. Conclusions based on data collected in one way (e.g., surveys) can be accurate but still will not reflect the full reality. Using different sources of information allows us to gain access not only to more knowledge, but to more accurate knowledge. For instance, if a respondent is asked if he/she has read some newspaper article and answers “no”, while according to metered data he/she has read it, the difference can be due to the person lying but also to the person really not remembering. The fact that the person does not remember can in and of itself be useful additional information (the article was not interesting/impactful for the person), that can only be obtained by combining information from two sources.

This idea of combining different data sources (sometimes called “data fusion”) has become popular in the past few years. Conventional survey answers are increasingly linked with other data sources, with the hope that new and enhanced measures and conclusions can be achieved in a cost-efficient way. However, even when using more than one source of data, since any measurement suffers from errors, we should be very careful about not concluding too much from a single given study. In this regard, dedicating time to check the robustness of the results and implementing replication studies is crucial. Furthermore, meta-analyses are very much needed to identify the main trends across studies.

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