FORS GUIDES
to survey methods
and data management

# Making uncommon experiences visible in the survey life cycle

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**Abstract:**

This FORS Guide discusses how methodological practices and dissemination policies are likely to produce cumulative filters throughout the survey life cycle, acting as barriers to the representation of uncommon social experiences. A reflexive approach is proposed to researchers to observe how and why some of these filters make it less likely that minority populations become study samples, that non-normative events are reported by participants or noticed by researchers, and that “atypical” data are not stored, shared, and reused. This guide has been developed by members of the 'Data diversity and public good research’ group within the FORS-SSP scientific research program.

**Keywords:** survey data life cycle, minority populations, rare events, selective data sharing, cumulative bias, inclusive surveys

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**The FORS Guides to survey methods and data management**

The FORS Guides offer support to researchers and students in the social sciences who intend to collect data, as well as to teachers at the university level who want to teach their students the basics of survey methods and data management. Written by experts from inside and outside of FORS, the FORS Guides are descriptive papers that summarise practical knowledge concerning survey methods and data management. They give a general overview without claiming to be exhaustive. Considering the Swiss context, the FORS Guides can be especially helpful for researchers working in Switzerland or with Swiss data.

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# 1. INTRODUCTION

This FORS Guide proposes a reflective approach to researchers regarding how experiences that are statistically or socially perceived as uncommon tend to slip away throughout the survey data life cycle and remain unmeasured. Atypical or complex life trajectories, rare or non-normative events and situations, extreme opinions, minority groups, or vulnerable populations are often under-represented, and sometimes entirely excluded, during the process spanning from survey data production to data use and data sharing. As different but overlapping processes add up sequentially, they produce a cumulative outcome that is often as unconsidered as it is unwanted: they make the uncommon invisible.

The notion of uncommon experiences, our entry point into this reflection, is deliberately broad to facilitate a holistic and systemic approach. The term "uncommon" can be read both in its statistical sense – referring to relatively rare experiences – and in a normative sense, which also encompasses experiences that are positioned as marginal because they deviate from current social norms. Focusing on the *experience* rather than the *identity* of the individuals involved (for instance, focusing on migration rather than on the migrant), allows one to put the focus on the process itself, which is consistent across various atypical events or groups, rather than on a specific example as minority populations. Consequently, a broader perspective can be attained.

In this sense, the paper serves as an umbrella for different streams of previous work: on the representation of minority populations (e.g., Herzing, Elcheroth, Lipps & Kleiner, 2019; Laganà, Elcheroth, Penic, Kleiner & Fasel, 2013), sensitive life events (e.g. Morselli, Berchtold, Granell and Berchtold, 2016; Shattuck & Rendall, 2017), non-normative attitudes (e.g Cea D'Ancona, 2017), or statistical exclusion (Patiño, 2021; Yi et al., 2022). Cumulative filters can make uncommon experiences fully invisible (creating statistical exclusion) or partially invisible (creating statistical under-representation). *Full invisibility* can occur, for example, when there are too few cases left for the purposes of quantitative analyses, and data analysts choose to remove 'noise' or 'residual categories' from their data before testing their substantive models. *Partial invisibility* typically concerns the experiences of minorities, represented as smaller than they are. But in social settings where there is a strong discrepancy between descriptive norms (what most people are or do) and prescriptive norms (what they should be or do, according to socially influential sources), it can also extend to silent majorities turned into perceived minorities.

At every step of the research cycle, survey researchers – namely data producers, data analysts, data sharers, and data re-users – adopt methodological routines or decisions whose *consequences add up* to shape the overall scientific representation of certain types of experiences as systematic or exceptional, as normal or marginal, as social fact or social anecdote. Thus, uncommon experiences undergo filtering and invisibilisation at various stages of the data life cycle, and this can be attributed to different causes: direct researcher choices (e.g., selection of the sample to study); survey methodology (e.g. types of questionnaires and questions); data analysis techniques (e.g. weighting, recoding of categories); publication and dissemination policies (open science). These points are all related to the issue of costs. Indeed, the distribution of research funding plays a role in the processes leading invisibilisation, although limited funding alone does not explain the issue.

Survey methods and dissemination practices that make uncommon experiences invisible are problematic from different angles. From a standpoint of epistemological realism, social surveys should provide an accurate representation of social reality. If they are systematically biased against certain types of experiences, they have a major flaw, calling for methodological improvements. From a standpoint of epistemological constructivism, providing an accurate representation of reality might be an inherently difficult goal to reach, but at least we should aspire to be fair and responsible in the representations of reality that we contribute to create. From this perspective, "bias", in addition to its technical definition, also carries an ethical meaning: the core of the problem is not that social surveys tend to make *some* experiences invisible (as scientific representations of reality can never be exhaustive), but that they specifically reinforce the invisibility of social groups with less power, prestige or privilege than the groups whose experiences are (unwittingly) magnified.

The examples we present in this paper to illustrate the process of invisibilisation come from the experiences with data from large quantitative surveys, where different stages of the work are carried out by a group of researchers whose respective fields of expertise cover the various stages of the data cycle. However, the discussion on invisibilisation applies to different forms and components of survey research, including small- as well as large-scale surveys, mixed methods, as well as purely quantitative designs. In this sense, one element that might seem like a limitation is that we could have chosen more stages, or stages with a more significant impact on the process of invisibilisation (e.g., fieldwork procedures). In this perspective, the examples drawn from the authors' experiences are merely a tool to describe a broader process that spans across different stages of the survey life cycle. Our aim is not to be exhaustive, but to provide a prism through which researchers can observe more situations than those described here.

In sum, the main purpose of this reflective paper is to achieve an understanding of the systemic problem of invisibilisation and serve as a guide for researchers in many ways: raising *awareness* about how certain groups or experiences are marginalized or excluded from research, providing insights into *methodological and analytical choices* that perpetuate invisibilisation, and suggesting *new practical options* for creating more inclusive and complex representations of reality. The paper also addresses the *ethical implications* of excluding certain experiences and aims to prompt reflections on research *policies and funding* priorities to promote equitable and inclusive practices. In summary, this paper offers researchers a framework for becoming more reflective about our (collective) impact as survey researchers on making uncommon experiences more or less visible.

The process of invisibilisation is described across three main distinct stages of the survey life cycle: (1) data production, (2) data analysis and (3) data sharing. In the first two chapters, the issue of the representativity of uncommon experiences is addressed through a micro perspective, which describes, with concrete and specific examples of the field, how the accumulation of small methodological decisions can impact data and results. In addition, the third part takes on a macro and more general perspective, and discusses how structural choices, related to research infrastructures and funding, influence the (in)visibility of uncommon experiences. Thus, on the one hand, we will have more concrete examples of invisibilisation experiences, such as atypical events and extreme opinions, while on the other hand, the process of invisibilisation will address elements on a broader level such as the inclusion of research projects from a broad spectrum, including independent low-resource projects. The common thread across these three seemingly different dimensions is the process that causes uncommon experiences to (unwittingly) disappear.

In conclusion, this paper does not aim to provide a systematic methodological account of how to reduce biases in surveys, although some examples will be given, and references for further reading will be provided. The main objective remains at a more epistemological level of discussion, aiming to stimulate reflection on *who* and *what* is very often made invisible in social surveys, *how* this happens, and *why* a systems perspective is needed to understand, and tackle, the problem. Finally, we will make some suggestions how the issue may be addressed by survey data producers, (re-)users, and archivists in the future.

# 2. DATA PRODUCTION

The first large stage of the data life cycle that we consider in this paper is data production, which unfolds in different sub-phases. Our discussion here focuses on how routine methodological practices and methodological decisions can contribute to making uncommon experiences invisible. We start with survey design issues and the problem of sample selection, in particular, related to the representation of certain subpopulations. We then focus on how the mode of survey questionnaire administration affects survey answers, especially about the reporting of sensitive events, and non-normative attitudes or behaviour. Next, we discuss how the methods used to access experiences retrospectively – notably life history calendars (LHC) – can lead to over-representing normative life trajectories and losing less normative events. We further address issues related to common practices of data cleaning, and how they can contribute to make some categories of experiences invisible, depending on (historical) time and (socio-cultural) space. We finally focus on methods used to adjust for (item and unit) non-response and discuss the benefits and pitfalls of the two main options to mitigate their impact on the accuracy of estimates: weighting and imputation.

## 2.1 SURVEY AND SAMPLING DESIGN

Sample selection is generally the first filter, which can result in giving more visibility to some people and experiences than to others. As researchers can almost never observe the whole target population, they need to select a subset of it. In Switzerland, it is possible, under specific circumstances, to use the register data of the Swiss Federal Statistical Office as a sampling frame to draw a survey sample. When membership of a rare subpopulation can be determined in the sampling frame, defining the required sample size of the sub-population and selecting the sample is relatively straightforward. In this case, various probability sampling designs based on unequal inclusion probabilities can be applied to oversample the desired subpopulation. But when there is no variable in the sampling frame that allows the identification of members of this subpopulation, the selection of a probability-based sample becomes more complicated. For example, when a survey is intended to study second-generation immigrants and the sampling frame doesn’t contain any information on parents’ origin (or it is unavailable for a specific research project), the members of this subpopulation cannot be identified in advance.

Sampling – or oversampling – then represents a major challenge. Working with two-phase sampling designs (Tao, Zeng & Lin, 2020), large-scale screenings (Deming, 1977) or multiple frames (Lohr & Rao, 2006) can improve the selection process and result in an appropriate raw sample (for a list of commonly used methods see Herzing et al., 2019). Unfortunately, such sampling methods often require additional information that is not always available or proves infeasible, costly or time-consuming. Besides the usual requirements concerning the size of the sample, based on desired levels of precision/accuracy or power analyses; a prominent rule of thumb concerning the sampling design goes back to Kish's (1987) recommendations. For major subgroups of population (10 percent or more of the population) general samples should produce precise estimates, and for minor subgroups (1-10 percent of the population) a specific sampling design is required. For mini-subgroups (0.1-1 percent of the population) specific statistical models are usually necessary, whereas for rare types (less than 0.1 percent) adequate estimation is in principle out of reach (Kish 1987). The problem with such rules of thumb, however, is that it does not consider that the raw sample is only a starting point and that subsequent data losses (including non-responses, but not only) regarding minority experiences are to be expected once the sample is drawn. As we will argue in this paper, selective filters tend to accumulate over the entire life cycle of the survey and to reduce, step by step, the size of the final sample.

## 2.2 SURVEY MODES AND QUESTIONNAIRES

In general, survey modes involving a reading act (paper & pencil or online) tend to exclude individuals with little formal education or literacy problems. In Switzerland, according to the Adult Literacy and Life Skills study, this concerns between 800'000 and 1 million people and varies according to education level, age, language, and social and national origin (Guggisberg, Detzel & Stutz, 2007). The CATI and CAPI (oral) modes tend to be more inclusive in this respect, unless materials such as vignettes, cards, or other written items are used for CAPI. The different modes therefore have an effect on the representation of different groups of the population and characteristics of the respondents, generally to the detriment of more socially disadvantaged groups, the latter displaying lower response rates (Oris, Roberts, Joye & Ernst Staehli, 2016).

The modes of data collection can also have an effect on the nature of the answers given by the respondents. Indeed, survey modes involving interaction with interviewers (CATI, CAPI) create stronger social desirability effects (Kreuter, Presser & Tourangeau, 2008). Thus, respondents may tend to minimise more extreme situations, such as poverty, in their answers. In terms of opinions, values and attitudes, respondents tend to give more compliant answers (to the norms, to the supposed expectations of the interviewers) and to hide discriminatory attitudes (Cea D'Ancona, 2017), such as racism or sexism. Measuring income is a multifaceted issue. The methods used to collect data can significantly influence the outcomes and, consequently, the interpretation of results. In the case of Swiss society, Voorpostel et al. (2020) have demonstrated that respondents reported higher incomes in web surveys compared with telephone interviews, this being mostly due to selection rather than measurement differences by survey modes. In contrast, Hermann and Krähenbühl (2019) have shown that in self-administered surveys (CAWI/paper & pencil) people tend to report financial problems more easily.

The questionnaire design too can affect how visible rarer or less normative life events are and, in particular, can result in over-standardised representations of life trajectories. Retrospective questionnaires are an effective means of discussing this issue. There are three main ways to collect information retrospectively: repeated questionnaires in longitudinal studies (asking about the time spent between one interview and the next), biographic questionnaires (administered once and composed of questions about the past asked sequentially (e.g. Scherpenzeel et al., 2002), or life history calendars (LHC; Belli, 1998) which allow the respondent to employ mnemonic techniques to ease their recall of events (Morselli & Berchtold, 2023). In all three types of questionnaires, and despite the demonstrated accuracy and quality of the retrospective data collected with the LHC (Belli, Shay & Stafford, 2001; Morselli, Dasoki et al. 2016), the retrospective orientation may lead to an invisibilisation process or over-standardisation. This may be the consequence of cognitive mechanisms or unintentional reproduction of the respondent's value system as well as of that of the researcher.

An example illustrating how retrospective questionnaires can lead to an over-standardisation concerns affective memory, specifically the distribution of positive events remembered retrospectively. Berntsen and Rubin have observed that the most cited events correspond to culturally expected and valued life trajectories, both in terms of the type and timing of events (Berntsen & Rubin, 2004; Rubin & Berntsen, 2003). Survey participants retrieve and report events and trajectories more quickly if they match with what these authors have called the internalized *cultural life script*: the shared memory representation of positive and normative events (e.g., births, marriages). While events that are socially categorised as sad (e.g., the death of a relative), less important (e.g., a concert), or “ill-timed” (for example unscheduled and out-of-sequence transitions (Furstenberg, 2005)) are less likely to be reported as significant events even if they could have been lived as positive. This standardization in the evaluation of positive events is manifested as a reminiscence peak when examining the distribution of events across different ages in life. It is a robust finding, with no significant differences in gender or age (Dasoki, 2017). Moreover, the normative reminiscence of events does not only depend on participants’ perceptions of socially important values or cognitive mechanisms, but can also be induced by the researchers, embedded themselves in social value systems (Lowes & Prowse, 2001) whose presence could lead to socially desirable responses (e.g., death being considered a negative event, even though it may be experienced as a relief in certain cases).

Given these considerations, to avoid the over standardisation of complex feelings and events, several strategies are proposed. In instructions, examples that fall outside normative values should be provided, such as stressful marriages or positively experienced bereavements. Additionally, presenting examples of trajectories that are non-linear, include rare life events, breaks, or transitions at atypical ages could lead to a less standardized answer. Moreover, the presence of interviewers and time constraints can narrow the scope of accessible experiences. Research has shown that the reporting of life events is influenced both by their perceived social desirability and by the time available to think about the answer (Berntsen & Rubin, 2004). Self-administered LHCs and/or prompts that repeatedly encourage respondents to consider life events or domains they might have forgotten could help counter these biases.

In this context, it is important to stress that hidden trajectories not only concern minorities. Sometimes, very large parts of the population experience a systematic lack of coverage by the questionnaires. This is the case, for example, for the professional trajectories of women: women represent half of the population, but their trajectories are less linear and less homogeneous than those of men and therefore less well identified with standard questionnaires. This fact has been noticed during the income control of the Swiss Household Panel (SHP) survey: Implausible or problematic cases are checked by the survey team on a case-by-case basis. These checks have often revealed that women are disproportionally concerned, most likely because their careers are more characterized by interruptions, partial working hours and unpaid work, and more impacted by normative life events than those of men. This example suggests that the experience of half of the population (i.e., men’s careers) is likely to be over-represented as long as it is "easier" to survey. But it also shows that a greater focus on sensitive cases and manual recoding can help to make visible the more complex trajectories that concern “the other half”.

## 2.3 DATA PREPARATION

Once collected, data are usually not yet ready to be used or disseminated in their raw format. To make them suitable for research purposes, several treatments are needed. General data preparation techniques include data cleaning, which intends to correct manifest errors and highly implausible data, as well as the handling of non-response and missing data, the verification and sometimes harmonisation of response codes (which can include the coding of open-ended questions), and possibly the computation of sample weights to correct for unequal selection probabilities and/or nonresponse error. Applying these treatments modifies the distribution of the final data. In particular, the number of people estimated as belonging to a specific sub-population can be considerably different than expected.

These treatments are not always the result of objective and timeless criteria. Social norms and legislative rules that structure a given culture have their influence on the choices that researchers make when they prepare their data. In the *data cleaning process*, edits guided by assumptions based on cultural norms or current legislation may simplify classification, especially when “implausible” or “legally impossible” values or situations are “redressed”. However, assumptions related to legal working age, legal age of marriage, civil status, legal number of spouses, minimum age differences between mother and child, for example, differ from one population to another as well as across time. What was off limits yesterday is not necessarily so today, and what is highly implausible in one society might be less surprising in another.

Sometimes certain variables are distributed to data users only in a recoded format so that they can be compared with other (international) indicators. Therefore, some original response categories are hidden or merged with others, and sub-categories are not distinguishable anymore. For example, in the SHP, ties between family members are registered, and hence many different family structures could potentially be observed. But these variables are not distributed in their entirety. Instead, variables created with categories that fit internationally/officially defined schemes (Type of household (PACO); household typology of the Family and Fertility Surveys (FFS); Household typology Swiss census, Swiss Federal Statistical Office (CEN)) are available to researchers. For most research applications these variables are sufficiently detailed, but they do not convey the details that would be needed to make visible family structures that deviate from the assumptions on which established typologies are based.

Most social categories emerge and vanish over time due to social, technological, or medical evolutions. Some obvious examples of categories that emerged relatively recently are “internet users”, “electric car owners”, “long Covid patients”, or “persons who have undergone a medically assisted gender transition”. At the time of their apparition, new categories are typically less prevalent, less known, and less likely to be represented in official registers and in social surveys. During this period, they are hence statistically invisible. While their frequency, voice, public attention and/or scientific importance of emergent social categories increases, they are more likely to become response and coding categories as well and hence to become statistically visible.

## 2.4 HANDLING NONRESPONSE

Some data producers provide data that have been adjusted to handle non-response, using statistical methods. The aim of these methods is to treat missing values or missing participants to redress distortions in survey representativeness. Do these methods reach their goals? Do they sometimes add new biases and, if so, of which type?

First, unit nonresponse should be distinguished from item nonresponse. Unit nonresponse means that a whole unit – an individual, household, or organisation – did not participate in the survey at all. Item nonresponse arises when the unit did participate but did not respond to specific questions. These two types of nonresponses require different treatments, which affect the data distribution differently. The typical treatment to account for unit nonresponse is *weighting*. Weighting aims to compensate the loss of non-respondents by statistically restoring the original distribution of some chosen variables or categories in the target population. The procedure hence assumes that respondents and non-respondents are similar with respect to the other variables or categories (i.e., to any variable not included in the weighting process). Whenever this assumption is unrealistic, the resulting weighted estimates may give the impression of greater homogeneity in the target population on certain variables than is actually the case. Thus, the weighting procedure may contribute to masking the true heterogeneity vis-a-vis these variables. In fact, the effectiveness of the weight varies across estimates as a function of the correlation between variables used to compute the weight and variables on which the estimate is based. For example, Laganà et al. (2013) have shown that common weighting procedures, based on a binary distinction between Swiss nationals and foreigners, have resulted in a homogenizing representation of foreigners, in which nationals from more affluent and culturally closer neighbouring countries are largely overrepresented and most other origins largely under-represented.

Item nonresponse is typically treated by way of *imputation*, i.e., by replacing the missing information by either a value coming from the valid dataset itself (mean, median, modes or model-based approaches as in multiple imputation) or by an arbitrary value. These treatments can distort the distribution of survey variables, especially when values are not missing at random, i.e., when nonresponse behaviour is systematically related to the characteristics being measured of participants. Even multiple imputation, which involves sophisticated statistical procedures to estimate the range of uncertainty around the imputed estimate, may engender smoother distributions and underestimate the frequency or importance of less common values or categories.

# 3. DATA USE

The second large stage of the data life cycle concerns data use. Once the data have been collected – and in some cases prepared, as seen in the previous section – substantive data analysis involves another round of treatments. At this stage, data users decide on the way the data are recoded, organized, and modelled, whether to apply weights, and how the results are reported. In this section, we discuss common practices for aggregating original survey responses into broader response categories suitable for statistical modelling. We notably consider the trade-off between working with complex, disaggregated data versus aggregating data for substantive analysis at the cost of excluding experiences that do not fit into the main categories. Another point that we tackle is how certain experiences risk being "interpreted away" when theoretical grids are applied on empirical results.

## 3.1 INDIVIDUAL AND GROUP LEVELS OF ANALYSIS

For all research questions, researchers must decide about the unit of measurement and analysis. In the case of surveys which collect information about all members of one group, such as household panel surveys, the unit of analysis can be either the individual respondent or the household.

Considering the household as the unit of analysis comes with its own challenges. Indeed, considering the whole while ignoring the specificities of every part can be a problematic shortcut (Casimir & Tobi, 2011). In particular, Tillmann (2020) critically discusses the practice of assigning a similar class position to all household members. He notes that the consideration of the household "as a place of pooled resources" in fact hides differences among household members in accessing and contributing to the resources. With regard to the problem considered here, it can notably contribute to making invisible the situation of the most precarious household members.

On the other hand, considering individual characteristics at the household level can considerably complicate the matter as shown in the following example: Imagine you aim to consider the situation of both partners in describing the couple's participation in the labour market, using the percentage of paid work activity as the defining variable. Let's imagine further that this variable is defined in three categories (full-time, part-time, null-time). When combining the two partners' responses together, the new variable hence includes nine possibilities. Should all nine categories be kept and treated separately? Should some of them be merged and, if so, on what basis: by merging low frequencies, by creating meaningful joint configurations (e.g., full-time/part-time), or by grouping similar individual configurations (e.g., both part-time and both full-time)? Things become even more complicated as similar configurations do not necessarily carry the same social meaning: for example, "full-time/null-time" is not equivalent to "null-time/full-time" in a gendered world.

## 3.2 DATA RECODING AND ANALYSIS

Recoding is part of the research process, because in some cases it is pointless to keep response categories with too low frequencies (de Singly, 1992). A classic example is education level: in the SHP, data users can choose between several variables, which display between ten and nineteen categories to describe the level of education. These detailed categories are usually reduced to three major levels: basic (low), intermediate (middle), or advanced (high). Another example of univariate recoding concerns income, when collected as a continuous variable (Kuhn, 2019). To perform group comparisons, this continuous variable is also recoded into a limited number of categories with labels either based on a quantitative feature (e.g., deciles, or ranges of amounts) or on a qualitative one (e.g., low or high incomes, economically disadvantaged or privileged groups). A question that frequently arises is how data users should handle extreme values or rare observations at this stage: create separate, tiny categories (e.g., a separate category for the happy few, very rich) or merge them into larger but highly heterogeneous categories.

The necessity of recoding is even more relevant in the case of bi-variate or multi-variate analysis. Indeed, the more response categories are kept, the higher the possible combinations, with consequently a lower number of observations for each of them. This consequence requires then to combine some responses together in order to have a valid test. For instance, for Chi-square tests, the statistical analysis of independence between two variables is conventionally considered valid only if the expected values are equal or superior to five observations for each cell created by crossing the two variables. When the condition is not met, the concerned categories are supposed to be merged with another category and the independence of the two variables retested.

Data aggregation, at other times, lies simply in the method itself. In cluster analysis, for instance, the goal is to identify common traits and general tendencies. This method aims for minimum intra-group differences and maximum inter-group differences. Like in the recoding process, rare or marginal, counter-normative cases can either be integrated in dominant categories or be treated separately. It also happens in such analyses that cases without a clear profile are grouped together. Such a classification can be found in Levy, Gauthier & Widmer (2006), where the masculine sequences of occupational activity in Switzerland were classified into two groups: a dominant and a residual category. These authors still offered a brief description and analysis of the residual category, but such is not always the practice. Creating a residual category can be a strategy chosen to deal with unexpected, infrequent cases which do not fit into the theoretical frame and to avoid splitting and “drowning” them across the other clusters.

While data aggregation, through recoding or clustering the data, is often unavoidable, this practice can be problematic when rare or marginal cases (social groups, events, or practices) are systematically integrated into dominant categories or put aside as a residual category. Both processes, integration and residual categories, have similar consequences: As uncommon experiences are merged within broader categories, they become invisible. In the North American context, several researchers therefore advocate for the disaggregation of data, especially those about race/ethnicity (Patiño, 2021; Yi et al., 2022). These authors show how grouping individuals who have distinct experiences contributes to their statistical exclusion and social misrepresentation. Indeed, some categories can be deceiving and favour the perpetuation of false perceptions (Patiño, 2021).

Lone parenthood is a good example of a category that groups under one term a variety of specific experiences: It can be due to widowhood, single parenting by choice or not, or it can involve co-parenting across several households, among other examples. Data disaggregation, as a way to acknowledge diversity and describe groups in their specificities, has been a strategy chosen for the construction of a new household typology in the SHP (Morel, 2023). This household typology distinguishes between couples with common children (nuclear families) and couples with children from previous relationships (i.e., step and blended families). This distinction contributes to the visibility of alternative couple-with-children configurations. However, it encounters the statistical challenge of a very low number of observations which prevents from doing extensive statistical analyses or comparisons: The newly created household types represent less than 2.5 percent of all households in the SHP – a proportion which is similar, on average, to the prevalence shown in official statistics (Morel, 2023). Should diversity in the types of couples with children and in family-household configurations therefore be ignored? Of course, the researcher's sensitivity to consider such marginal cases depends on the research question, but failure to take diversity into account depends also on the lack of information, knowledge and theory about the experiences of minorities, whether prior, during or after the analysis.

### 3.3 INTERPRETATION AND PUBLICATION OF RESEARCH FINDINGS

The selection of a few patterns in a wealth of data, or the description of only a fraction of the available information, are parts of the research process, but also a consequence of limited time and publication space. Which findings or cases should be presented? The most frequent or the most instructive? Those that confirm established wisdom or those that challenge it? Those that focus on the most clearly visible patterns or those that shed light on what is more difficult to see?

Billig (2013) has argued that the continuous pressure to publish and be quoted creates conditions that are detrimental to the diversity and quality of publications. More specifically, social stereotypes as well as theoretical preconceptions (Yi et al., 2022) can guide data users in favour of what they already know or expect, leading to confirmation bias in the interpretation and publication of research findings. Furthermore, results which do not reach collectively expected conclusions run a heightened risk of being ignored later on. Citation bias hence adds to publication bias, and both seem to be reinforced by the tendency to consider results in line with research hypotheses and/or statistically significant as more noteworthy than those which prove them wrong (Pannucci & Wilkins, 2010; Gøtzsche, 2022; Leng & Leng, 2020).

When null results are kept in the dark, the literature becomes skewed (Peplow, 2014). In particular, formal or informal rules that encourage researchers to present and/or discuss only statistically significant coefficients have been firmly criticised by Hoem (2008) for at least two reasons. First, even if a model presents some statistical significance, the multiple steps which are required to fit a given model at best (e.g., splitting or combining the level of co-variates; backwards, forward or stepwise procedures) leave much room for data analysts to influence which findings pass the threshold and which do not. Second, the 0.05 p-value threshold for statistical significance can lead the researcher to unduly ignore results relating to practices or events experienced by a minority of the population, namely those who compose (very) small datasets for which the 0.05 threshold is unrealistically high. In addition, insufficient statistical power deters the testing of interesting hypotheses, out of fear for not meeting publication standards (Peplow, 2014).

## 4. DATA SHARING AND REUSE

In this chapter, the discussion will shift to a macro-level observation, where the process of invisibilisation is less linked to direct researcher choices, and more influenced by broader science policies and their impact on the representation of diverse realities. The third large stage of the data cycle we examine concerns data sharing, and in particular the impact of new open science practices on the (in)visibility of uncommon experiences. This leads us to discuss the potential of full openness as well as the potential drawbacks of half-measures and a culture of partial openness.

In the social sciences, open research data tend to become the new international norm: prescriptive codes of good practices are institutionally endorsed (e.g., Concordat on Open Research Data, 2016) and, even in subfields where data sharing is traditionally controversial, not sharing your data becomes an exception to the rule that requires justification (Bishop & Kuula-Luumi, 2017). Sometimes, the rationale for more open science comes as a principled, ethical and political stance: public money for public science. Sometimes, it takes a more concrete and epistemological shape: influential voices have called for more transparent research practices as an antidote to cherry-picked analyses, nonreplicable research findings or “sloppy science” (e.g., Nosek et al., 2015; Ioannidis, 2012).

Our focus here is more specific and concerns the potential impact of open research practices on the visibility of rare or counter-normative social phenomena. Does the promise of a more transparent, robust and self-reflective science also imply that it will be easier to see the manifold processes that traditionally make uncommon experiences invisible? Or is there a risk that the new standards of open science could unwittingly exaggerate social norms even further? In this section, we will envisage both possibilities, discussing first the potential of open data sharing, and then its risks, with regard to making uncommon experiences (in)visible in the social sciences.

### 4.1 HOW MORE OPEN RESEARCH PRACTICES CAN HELP MAKING UNCOMMON EXPERIENCES MORE VISIBLE

One of the strongest arguments in favour of a more open science is the expectation that it will limit scientific cherry-picking. When complete research protocols, data and findings are open to peer scrutiny, this should discourage researchers from presenting hand-picked findings that confirm their preferred theory or worldview as if they represented the general pattern and, instead, encourage them to reveal the specific circumstances under which they obtained their findings. Researchers are expected to become more cautious about the quality of their findings when they know that half-truths can be exposed more easily. And even if individual cherry-pickers persevere, science can correct itself more easily at a collective level and, over time, will be able to keep more robust findings. So, if opening research protocols and research data is promoted as an antidote to biased research findings in general, can it also help to limit findings biased against uncommon experiences in particular? *Open research protocols* can function as effective safeguards against over-generalized research findings. Making research procedures, materials, questionnaires and analytic scripts publicly available reveals the exact circumstances under which a given finding has been observed, documents the efforts required to separate signal from noise and hence opens a window into the boundary conditions of research findings. (Klein et al., 2018). Sharing research protocols should make it easier to show in full light the myriad of small methodological decisions, from sampling design to data handling, through which uncommon experiences are put aside. Vice versa, they will make it more difficult to take dominant patterns in easy-to-reach populations for the general picture. *Open research data* are certainly the most emblematic feature of open science. Storing and sharing research data paves the way both to direct replication of published research findings and to creative secondary analysis for purposes beyond those envisaged by the original data producers. It can hence promote more robust, but also less wasteful research. In addition, secondary analyses create a second chance to look more closely at the data, to “re-contextualise” them (Moore, 2007), and to search for alternative patterns and moderating factors - in short, to be less centred on the most normative patterns only.

### 4.2 HOW NEW RESEARCH STANDARDS COULD MAKE UNCOMMON EXPERIENCES EVEN MORE INVISIBLE

If research practices in the social sciences were one day to become fully open, it is very plausible that this would have a positive impact on the representation of uncommon experiences for the different reasons mentioned in the previous subsection. But what about the impact of partial (as opposed to full) steps toward a more open research protocols and data, as they are currently taking place? Does a dose of open science result in a dose of inclusivity?

Not necessarily. Previous research on survey non-response shows that partial measures can have paradoxical consequences. Whereas perfect response rates would logically imply the absence of nonresponse bias, small steps towards higher response rates do not necessarily lead to less bias in surveys. For example, as shown by Laganà et al. (2013), many measures designed to enhance overall response rates result in increased minority bias. More specifically, in their case, increased efforts to reach and recruit respondents within the same survey routines resulted in including more respondents of the same type. Additional efforts can produce a selective increase in the participation of "easy-to-reach" participants, but still leave out "easy-to-ignore" participants, as long as they are implemented in the framework of established survey routines and assumptions. Is there a risk that additional efforts to make the social sciences more open might result in a similar "more-of-the-same" paradox?

There are different reasons to take such a cautionary tale seriously. The open science movement creates new expectations on what counts as good science. When new quality criteria sum up with old criteria, the consequence can be *higher standards*, which require additional resources to conduct a research project successfully; for example, to implement a data management plan and meet the demands of open science journals, research archives and public repositories (Klein et al., 2018). As a consequence, larger research consortia are in a better position to meet the challenges. Furthermore, the gatekeeper role of research funders (able to provide the needed additional resources) increases, and the researchers' efforts might be drained away from other priorities – such as making samples more diverse or engaging with minority communities.

In addition, not all research data are equally shareable or perceived as such. Some *data archives* (such as SWISSUbase run by FORS) actively promote the storage of atypical data. However, dynamics of self-selection, academic subcultures and unequal resources for adequate data management can result in very unequal probabilities of effective data storage, documentation, visibility and reuse across different research fields. Drawing on decades of expertise, the team at FORS archives has observed that whereas the big social surveys typically rely on functional data preparation routines and established networks of users, for many smaller research projects all the different steps required before data reuse are possible but can act as deterrents. Consequently, if the social sciences collectively move toward more secondary analyses, one cannot rule out the possibility that this will also result in larger proportions of research publications based on smaller subsets of original studies and hence in less diversity of study populations and methods.

In sum, while the current movement toward more open research practices, and data sharing, is full of interesting opportunities for social scientists, its actual impact on the visibility of uncommon experiences is likely to depend on the concrete grounds on which scientific policymakers, universities and research teams embark on the journey. Without adequate *public investments* in public repositories, and data management facilitators, there is a genuine risk that the movement eventually deepens the gap between largely reused canonical studies and increasingly marginalized alternatives. Such a situation would result in ever larger shares of findings based on the same samples from the same populations.

# 5. IMPLICATIONS FOR SURVEY RESEARCHERS

In this paper, we have exposed a myriad of ways how survey practices can contribute to a representation of uncommon experiences as rarer than they are. A critical point is that, when considered in isolation, most of the practices discussed in the previous sections are well justified from the perspective of individual methodological decision-making. Yet, as a whole, they risk creating a distorted social science, which magnifies social norms and masks social diversity. It takes a systems perspective to understand such consequences of cumulative filters, as well as to conceive relevant alternatives. The latter requires both individual scientific imagination and adequate science policies. Were adequate public investments to be made, researchers would gain more freedom to make more sound methodological choices. They can then choose their tools to make visible otherwise forgotten social worlds, knowing that "research methodology is inherently about inclusion and exclusion: choosing a specific method, often unwittingly, implies accepting to ignore certain facets of the social world, which might have become visible with other methods" (Perrenoud, Bataille & Elcheroth, 2023). To create and use the spaces within which such choices can be made takes more than a toolbox: it requires a certain reading prism. In the concluding paragraphs of this paper, we will hence try to identify the backbone of such a reading prism, phrased as a set of heuristic suggestions for survey practitioners.

Focusing on the more specific problem of the representation of national minorities in Swiss social surveys, Elcheroth et al. (2011) already made five suggestions that we see as still relevant today: *be critical* (encourage critical reflection on routine survey practices); *be specific* (make target-population-centered decisions about your survey design); *be consistent* (align the design of your survey with its research objectives, and the interpretation of its outcomes with its design); *be holistic* (consider how specific measures to handle survey bias interact with other relevant design parameters); *be creative* (accept that no perfect solution exists, try out new avenues, test empirically and openly discuss their impact). In the same pragmatic spirit, we wish to complement these suggestions here with seven practical implications of the more systemic perspective to the full survey data life cycle that has oriented the present contribution.

*Recommendation 1 – Be curious – do your best to know your data.* Sincere curiosity is the necessary foundation for any constructive action; nothing can be done about bias in survey as long as we are blind to it. If you have the chance to collect you own survey data, re-reading section 2 of this guide might help you ask relevant questions about sources of bias in your survey design. If you use data produced by others, read the methodological documentation, use this guide to read between the lines, and try to exchange with someone who was there when methodological decisions were taken, to understand how priorities were set.

*Recommendation 2 – Be humble – don't over-claim the representativeness of your findings.* Once you have followed recommendation 1 wholeheartedly, you are likely already inoculated against too broad claims regarding representativeness. Try always to replace them with more precise statements, which will truly inform your readers on which parts of your reference population, and which kinds of experiences, your survey allows measures with the greatest highest precision, and where are its likely blind spots. Keep these statements in mind yourself when analyzing your data and interpreting your findings.

*Recommendation 3 – Be transparent – help others to know their data.* If you contribute to the production of data that will likely be used by other researchers, you can do much to make it easier for them to follow recommendations 1 and 2. If you document the survey design process and fieldwork in a clear and descriptive manner, it will be easier for them to understand your work and make good usage of your data, than if you opt for much conceptual jargon or write as if you need to praise and market your data.

*Recommendation 4 – Be generous – share what you can.* When you have to decide which data and meta-data to share with other researchers, don't be blocked by the question whether they are likely to meet standard expectations. From a systemic view, standard expectations can actually be a serious source of systematic bias in the data that circulate and inform the scientific consensus. The more you share, the more likely you will hence contribute to remove systematic bias, especially if your data are "different". If you have ethical reservations, try to overcome an all-or-nothing approach, seek competent ethical advice and let yourself help with those obstacles that can be removed without infringing on the protection of research participants, or other stakeholders.

*Recommendation 5 – Be fair – don't assume uncommon experiences away.* The fact that certain social groups have not participated in a survey, that survey participants did not report certain types of events, or that your analyses do not reveal certain relations, is not yet proof that these groups, events or relations do not exist. Re-reading section 3 of this paper might inspire you not to interpret or write down your findings as if the question of their existence is irrelevant, but to give fair consideration to both substantive and methodological interpretations of empirical absences.

*Recommendation 6 – Be original – worry first about not reproducing existing biases.* Survey researchers are intuitively inclined to worry first about new biases they might introduce when deviating from established survey practices (which are more likely to be visible, and finger-pointed by peers). From a systemic perspective however, reproducing the same biases as everyone else is much more damaging than creating new biases: The former contributes to entrenched systematic bias, while the latter is more likely to increase variability in aggregate research outcomes. Thinking about this aspect might encourage you to weigh risks differently next time you consider departing from beaten tracks.

*Recommendation 7 – Be purposeful – choose one uncommon experience and make it visible.* After having read this paper, you might feel a vague sense of discouragement: If there are so many ways in which the experiences of minorities are masked in surveys, sensitive events or non-normative behaviors, the challenge might be too huge to tackle. But you might try to turn things upside-down: If so many blind spots are our baseline, you can already make a difference by tackling one of them earnestly. Unless you are leading one of the few very high-resourced surveys, focusing on one specific group or experience, giving yourself the methodological means to let it appear in open daylight, and then pursuing this goal throughout the different stages of the research cycle, is certainly your best chance to take the field a step further without dispersing limited resources – including your own cognitive focus – over many tiny battlefields.

# 6. FURTHER READINGS

If you are interested in the topic of surveying national minorities, we recommend articles by Herzing et al. (2019) and Laganà et al. (2013).

Concerning the field of environment-migration, the article by Borderon et al. (2021) illustrates the stages of the research process in which invisibility may be introduced and aims to guide researchers through a consideration of invisibility in their own work.

Concerning the life history calendar and the collection of life course data, see Morselli and Berchtold (2023).

On autobiographical memories and the structure of recall, especially the cultural life script, see Berntsen and Rubin (2004) and on the representations of affective memories see Dasoki (2017).

On populations that are reputed hard-to-reach and how mixed methods can help to approach them differently, you might read Perrenoud et al. (2023).

On survey and sampling design and methodology see Groves et al. (2009) and Blair, Czaja and Blair (2014).

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