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How to Analyze Data and Evidence: The Third Stage of the Social Research Toolbox, QGAP

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Learning Outcomes

- Having read this guide, readers should be able to . . .
- prepare their data for analysis by removing errors and identifying information;
- understand the central role of categorization and comparison in social science data analysis and explain how these processes are used to test, refine, and develop theories; and
- recognize how software tools can assist the analysis stage.

Introduction

This guide forms part of the social research toolbox, or QGAP, series, which offers a simple way of conceptualizing the research process. You can learn about QGAP by watching a short animation titled 'What is the Social Research Toolbox?' (which is included in this collection), and instructors can download some teaching PowerPoints that support the series here:

Wheeler.Slides.QGAP3_AnalyseData.pptx

Within the toolbox, there are four stages; (1) questions, (2) gathering data and evidence, (3) analyzing the data and evidence, and (4) presenting answers to your research questions. The four stages occur in all social research projects (whether qualitative, quantitative, or mixed-method), and though they have been presented in a linear way for teaching purposes, the reality is that each stage is shaped by the others, and it is usual to move between stages at different points of the research journey, depending on the type of research you are doing.

In this guide, the focus is on the “analysis” stage of the social research toolbox. Once you have gathered your data /evidence (G) to address your research question (Q), you then need to analyze this (A)—in other words, systematically explore the data and evidence to reveal patterns, trends, and meaningful insights—before presenting your findings (P). As with the other parts of the toolbox, the analysis stage is closely tied to the other stages; analysis often happens at the data-gathering stage (in terms of the design of the research collection tool), and it can be implied by the form of the research question (e.g., whether a quantitative or qualitative question or one based on primary or secondary data). Through analysis the aim is to develop answers to your research question; therefore, the form of that research question and the types of data it has generated will guide the analytical strategy. But the key tasks of analysis (regardless of data type) are to *categorize* your data into a form that enables you to *compare* different observations, spot relationships between them, and generate insights that are linked to or generative of theory. Before considering the purpose of the analysis stage, the guide begins with the practical step of preparing and formatting your data and evidence for analysis, including the need to deal with data entry errors and for anonymization. You may decide to use computer software to store your data and to explore the relationships within it, so the guide closes with a discussion of how software can enhance analysis through its embedded tools and functions.

Preparing Your Data for Analysis

The data-gathering stage can produce lots of different types of data (spreadsheets, audio recordings, photos, notes, and documents), which will need to be organized and formatted before you will be able to systematically analyze them. Though this may seem like a practical task unrelated to analysis, decisions made in this phase—such as what is relevant and where to store it—will follow you throughout the analysis stage. You might decide to store things in separate files and folders or use a software program to place all files in one overarching database (more on this later in the guide). If you had to write a data management plan when you submitted your project for ethical approval, you will be obliged to follow these procedures. (To learn more about data management plans and best practice see Corti et al., 2020.) In this section, we focus on two important tasks when preparing data for analysis: cleaning to remove errors and anonymization.

Cleaning the Data

Data cleaning procedures depend on the type of data you have and the instrument used to collect it. If you have an audio recording of an interview, transcription is required to convert it into a textual form. How you do this will depend on the sensitivity of the data you have collected, the quality of the recording you have, and the analytical purpose your transcription needs to fulfill. Some data might be for your ears only, so using a service for transcription might compromise the confidentiality you promised—another reminder to consider this stage of the toolbox when negotiating consent to gather data. On recording quality, I remember doing an interview next to a coffee machine in a busy café and the resulting recording was very difficult to hear. This was in the days before automated transcription, but I don't think these services could have produced an accurate transcript for this interview and my own transcription had lots of "[inaudible]" parts, which affected the quality of that data. Recording equipment has advanced over time, as has software to process audio recordings (such as Otter.ai and online conferencing tools that can produce a reasonable transcript), but the validity and reliability of these transcripts must be carefully checked (see Brinkmann & Kvale, 2015, for more on validity and reliability of transcription). I would recommend listening back to the original audio recording alongside your transcript (whether produced by automated transcription or a human transcriber) to check for accuracy. This performs the dual function of cleaning your data for errors and reimmersing you into that interview to aid the familiarization needed for qualitative analysis. There are different styles of transcription and choices that need to be made about what is transcribed, which usually relate to how you intend to use the data. Verbatim transcription records all the "errs" and "umms" as well as sentence stops, whereas intelligent verbatim removes these features so the result reads more like a written than an oral format (see Morgan Brett & Wheeler, 2022, for a discussion of transcription styles).

Alternatively, you may have survey data that either has been collected by hand or has been entered into a computer-assisted platform by the participant themselves or a survey interviewer. If your survey data was collected by hand, it will need to be manually entered into a digital format, which can lead to errors due to poor handwriting or data entry mistakes. You may have funds to employ two people to enter the data separately and then compare, but if not, checks can be done to ensure that the data is as free from error as possible. Even if data was entered using a computer platform, it may still contain errors or skipped questions. Sometimes errors can be spotted because answers across several questions are not internally coherent—for example, when I recently analyzed a survey that asked separately for age and level of education, I found one participant had entered their age as 12 and also stated they had a degree-level qualification. I looked at the data from their survey responses to help me determine which answer seemed most likely. You may make the decision to delete both answers to create missing data excluded from analysis. If you have lots of missing data, perhaps because a participant has left the survey after only a few questions, a decision needs to be made about whether this indicates withdrawal. The consequence of withdrawal will directly relate to the terms upon which you negotiated consent with the participant. If consent for data contributed was stated to be *up to the point of* withdrawal, what was contributed can be used, but if withdrawal was possible *at any point* with no details on data already contributed, then you may need to delete that entry completely.

Cleaning data to remove errors is important for all types of data, and I recommend recording the changes made in a project journal to keep track of these decisions. Your changes should be about increasing the validity of the data so that you can trust your findings as you move through the analysis process.

Anonymizing the Data

Another key consideration when preparing your data for analysis is the removal of identifying information. Most participants are offered anonymity in social research, but when data is first gathered—for example, raw data—it will still contain information that could reveal identities. Identities can be revealed through direct identifiers—such as names, addresses, zip codes, telephone numbers, and pictures—and indirect identifiers—information like workplace or occupation, which if revealed *in combination* with other information like sociodemographic characteristics might identify a person (Corti et al., 2020). It is common practice to remove all direct identifiers (such as using pseudonyms instead of real names) and store these separately from the rest of your data (perhaps in a secure folder or locked filing cabinet). But do also think about other identifying information. We often want to keep the context, so it is better to replace rather than remove entirely. As an example, suppose a sociology professor from Essex University was interviewed; rather than provide those details of status, workplace, and subject, they could be described as a "UK higher education academic" to retain the context but widen the potential pool of participants. With quantitative data, aggregate precise values of variables to prevent identification (e.g., use year of birth rather than date of birth, report data in categories rather than as discrete values). If you have zip code or geospatial data, you might want to transform that data into an alternative variable such as deprivation index position, population density, or a larger area coordinate. If removing the precise data will affect your research question, it might be that you need to secure access provisions for its use so that analysis is carefully controlled and results produced checked to ensure that confidentiality is maintained.

Section Summary

- It is important to organize the various types of data gathered before you start analyzing it. This initial organization serves the dual purpose of familiarizing yourself with your data and evidence.
- You should "clean" your data to minimize errors—such as data entry errors created by transcription processes or manual entry validation of survey data.
- Remove all direct identifiers and modify indirect identifiers (as necessary) from raw data to protect participants' confidentiality while maintaining useful context.
- All changes and choices made at the stage of data preparation should be documented in your research journal to track key decisions.

What Is the Purpose of Your Analysis?

Once your data and evidence are organized and in a form ready for analysis, your task is then to thoroughly familiarize yourself with their contents to identify elements that will be of interest to your research objectives. The word "analysis" has its origin in ancient Greek language where it meant "breaking up" or "taking apart." Analysis will always involve breaking down data and evidence into its constituent parts to understand it better and to systematically identify patterns and trends. This is then paired with "synthesis" (also a Greek word), which means bringing those parts back together to make connections and draw out meaningful insights and conclusions that are relevant to your research question. Most analysis (regardless of theoretical and methodological approach) therefore involves the processes of categorization and comparison. How these processes are realized varies depending on the type of data you have and the goal of your analysis—whether it is to generate new theories and insights, to test existing theories, or to add to an evidence base to inform policy decisions. This section is broken into two main parts: the first describes how researchers categorize and compare qualitative and quantitative data, while the second considers the role of theory within the stage of analysis. Here is not the place to give detailed step-by-step guidance, but I do point you in the direction of some sources to learn more.

Categorization and Comparison

Comparison forms the core of social science analysis. Whether it is comparison within a case or across groups of cases, comparison is a necessary precondition to understand the different elements within your data. To systematically compare these different elements, you need to transform (or break up) your data into categories or chunks—or, more scientifically, “codes”—which will enable you to view your data according to key features of interest. The process of coding your data does differ between qualitative and quantitative projects, but essentially the purpose of this coding remains the same.

In qualitative research, you will have texts (interview transcripts, field notes, newspaper articles, videos, photos, or other documents) that need to be sorted into meaningful units of analysis. There are different approaches to analyzing qualitative data, from thematic analysis (Braun & Clarke, 2006, 2022) to qualitative content analysis (Hsieh & Shannon, 2005; Schreier, 2012), grounded theory (Charmaz, 2014; Glaser & Strauss, 2017), discourse analysis (Fairclough, 2009; Keller, 2013; Taylor, 2013), visual analysis (Pauwels, 2019; Rose, 2001), and narrative analysis (Holstein & Gubrium, 2012; Riessman, 2008), to name a few (and point you in the direction of some key texts so you can learn more). While there are differences between these approaches and your choice of approach will be shaped by your research question, they all share the requirement of categorizing data and then comparing these categories to reach an interpretive understanding. This involves carefully reading and immersing yourself in the data and either developing a coding frame from that immersion (bottom-up) or applying a set of criteria (top-down) or both to better understand what the text *says* (about social worlds beyond the data) and/or what the text *does* (use of language/visuals, construction of talk or narrative, symbolism, key messages within the data). This process usually involves breaking data into chunks and labeling them based on key analytical concepts, often called "codes" (but terminology varies across approaches). As the analysis develops, you'll compare how these concepts are applied and used between your units of analysis (e.g., transcripts, participants, texts, visual material) while also incorporating your interpretive reflections and notes, commonly referred to as"memos."

In quantitative research, decisions about categorizing data are usually made at the data entry stage (or much earlier at the questionnaire design stage) and involve converting raw data into numerical categories for statistical analysis. In developing your data collection tool or gathering secondary evidence, you will have thought carefully about the concepts that need to be measured. In order to perform basic through to advanced statistical analysis, you need to create a dataset that is composed of a series of variables; a variable is “an image, perception or concept that is capable of measurement” (Kumar, 2014, p. 386). There are different ways of coding your data into variables depending on the unit of measurement. There are four main types of scale: (1) nominal variables categorize data without any order (e.g., different categories like ethnic group or occupation); (2) ordinal variables categorize ordered data with no consistent intervals between these categories (e.g., level of education, Likert scales); (3) interval variables categorize data that have consistent intervals but no true zero point (e.g., IQ scores, temperature); and (4) ratio variables categorize data with consistent intervals and a true zero point (e.g., age, income). Different types of variable demand different statistical methods of analysis. For example, ordinal data, such as Likert scales, can be analyzed using nonparametric tests (like chi-square or Spearman’s R correlations) or ordinal regression, while interval and ratio data often allow for more advanced techniques like linear regression (see Field, 2024, for a good overview of what forms of analysis are appropriate for your data). A codebook needs to be developed to record how variables have been measured and to provide a key for what the numbers represent. Once data has been categorized, the different categories can then be compared for descriptive analysis within variables (frequencies of categories, measures of central tendency and dispersion) and more complex bivariate and multivariate analysis across variables (crosstabs, correlations, t-tests, regression) (see Kumar, 2014, and Williams et al., 2021, for a good introductory overview). The purpose of this analysis is usually to identify differences, relationships, patterns, and trends within our data that can be inferred to the general population from which our sample was drawn (see MacInnes, 2022, for an introduction to inferential statistics). This leads us to the role of theory in analysis. In quantitative approaches, it often involvestesting the probability that our hypotheses (a priori theories) about relationships between variables are false (the null hypothesis). This can only be achieved by comparing categories.

In mixed-methods research, data analysis involves applying standard qualitative and quantitative techniques of categorization and comparison, but the key difference lies in the integration of these findings. For a convergent design, such as in my study of fair trade consumption, qualitative and quantitative data were analyzed separately and then compared to draw complementary insights. I analyzed a national attitude survey to explore how individuals rated the effectiveness of fair trade consumption compared to other individual actions, while qualitative interviews and focus groups provided deeper context to these perceptions. In this case, the integration and comparison of results revealed that fair trade consumption is often perceived as a valuable action but not a substitute for organized political efforts to address poverty (Wheeler, 2012). In addition to convergent designs, sequential designs use one type of data to inform the collection or analysis of the other—such as using the findings from a focus group to craft the questions in a survey—with integration of analysis techniques occurring progressively. Embedded designs involve nesting one type of data within the other—such as selecting a subsample of participants from a quantitative survey to interview so as to better contextualize the patterns and trends observed—enabling close comparison between different method-types and data (see Creswell, 2013, for a discussion of mixed-method designs).

The Role of Theory in Analysis

All analysis is driven, at least in part, by theoretical assumptions drawn from the existing evidence base. No researcher gathers data without at least some idea about what social phenomena are interesting and what mechanisms might explain why things happen in the way they do. A literature review is precisely about learning how your research question fits within an existing body of evidence and how your research might contribute. When it comes to data analysis, the insights gained through exploring existing evidence will help you spot links within your data to connect your findings to those of others and to generalize (often in a limited way) from your data to broader populations or processes. This moves us to the synthesizing stage of the analysis process, which is about bringing our analysis together to make connections with theoretical frameworks and draw out relevant conclusions. Theory is not an add-on but integral to all social science research. As we touched on in the first guide in the series, research questions come from different epistemological and ontological orientations, which shape research design, data gathering, and analysis (Wheeler, 2025). Research questions from the interpretivist tradition are more likely to be exploratory in their nature, with theory being developed through the process ofdata analysis (sometimes referred to as an inductive approach) (Braun & Clarke, 2013; Ritchie et al., 2014). Alternately, research questions from a positivist tradition are likely to start with a theoretical framework from which hypotheses about relationships between measurable phenomena are generated, with data gathered and analyzed to test these theories (sometimes referred to as a deductive approach) (Kumar, 2014; Williams et al., 2021). Though it is common to hear that theory plays either a deductive or inductive role, it is rarely as simple as this in practice (Clark et al., 2021). What is important is that researchers pay attention to the theories and assumptions that have shaped how data has been gathered and in so doing acknowledge the synergies between theory and research findings. Theory is critical for understanding and drawing conclusions from data.

Section Summary

- The key tasks associated with data analysis are categorization and comparison. These processes break down data into smaller parts so the researcher can identify patterns, trends, and relationships relevant to the research question.
- Categorization and comparison are essential for both qualitative and quantitative projects, but how these processes are achieved does differ depending on data type.
- Theory is integral to all stages of the social research toolbox and helps us connect research findings to broader frameworks and existing knowledge.

Using Computer Software to Aid Analysis

In this section, we consider some of the advantages and limitations of using software to assist the analysis of your data. Most researchers will use computers to store research data and write up their analysis. This may seem obvious, but it was not always the case, and norms around the safe handling of participant data have shifted as technology has evolved. I am old enough (just) to remember a time when interviews were stored on tapes and reports written on typewriters. Some of your data may be in a paper format, such as hand-filled questionnaires or signed consent forms (and we previously discussed the need to digitize survey responses and mitigate against data entry errors). Increasingly data is digital, and it is produced in all sorts of spaces, not always for research purposes but because of how company infrastructures operate online—and there is a growing literature on using this sort of data for social science research (Castellani & Rajaram, 2021). Technology is not a deterministic force, but it does shape what is possible, influencing how data analysis is performed.

Before the availability of packages like SPSS, STATA, R, and Excel, advanced statistical analysis was less possible, or it required mathematical knowledge that took a great deal of time to perform. Nowadays, social researchers with quantitative data will use statistics software and computers as standard. Undergraduate training across the social sciences will require students to be familiar with at least one of these programs. The same is not yet true for qualitative software or computer-assisted qualitative data analysis software (CAQDAS) packages, like MAXQDA, NVivo, and ATLAS.ti. Here there is both a skills gap and a reluctance among some qualitative researchers to embrace the opportunities of these packages, which are many and evolving (Silver, 2023; Silver & Woolf, 2015).

Packages for both types of data enable data management, categorization, and comparison features as well as visualization tools. Being able to store all observations and different data types/files in one place is one of their key benefits. You can also keep a record of decisions made about coding data and the procedures undertaken (in project logs or memos or by keeping the syntax of commands), and your project file could be the place where you store your project journal, which records key decisions throughout the research journey. There are also opportunities to explore relationships within your data and to use visual tools to display those relationships, which is very useful when it comes to presenting your findings at the last stage of the social research toolbox.

The drawbacks of software relate to the learning required to effectively use the tools within these programs. It is often a steep learning curve, and from my experience teaching both qualitative and quantitative software to undergraduates, I have found that many students feel they would rather not invest this time. Though timetabled sessions introduce students to software, the real learning happens through repeated practical application and trial and error. The cost of software packages can also be a barrier as institutions may not subscribe to preferred packages, though freeware like R and RQDA is available and standard operating packages like Word and Excel can performs some analysis functions. From a critical point of view, software does embed a range of functions and promotes a particular way of "doing analysis"—just because something can be done does not necessarily mean that it ought to be. While statistical analysis is often a process of "following the rules," qualitative analysis is usually more flexible and iterative, which is one of the reasons some qualitative researchers are reluctant to use it. Qualitative analysis can be and often is done without special analysis software. Silver and Woolf's (2020) five-level QDA approach offers tips on how to harness CAQDAS for purposeful qualitative analysis.

In sum, software offers lots of opportunities for assisting and enhancing data analysis and can be used to manage processes of categorization and comparison. But it should be used strategically in the pursuit of research objectives rather than researchers being led by its capabilities. This is especially pertinent in an era of generative artificial intelligence, which has been embedded into some CAQDAS packages and can be used to assist with the writing of code for statistical analysis. These tools cannot do the analysis for you, but they can be harnessed to enhance your processes.

Section Summary

- Computer software has transformed the possibilities for data analysis with tools for managing, categorizing, and comparing both qualitative and quantitative data.
- While software use is common for quantitative data analysis, its use in qualitative analysis projects varies.
- Though software can enhance data analysis, these tools should be used strategically rather than allowing software functions to dictate the research process.

Conclusion

In this guide, we have considered the third stage of the social research toolbox and some of the key tasks to be executed when “analyzing the data and evidence” (A). While it can be tempting to think about analysis as something that happens once data has been gathered, as with the other stages of the toolbox, it is informed by the earlier stages (research question formulation [Q] and research design choices [G]) and shaped by the intended audience for the presentation of findings (P). The guide began by considering the importance of preparing your data and evidence for analysis. We discussed removing data entry errors and direct and indirect identifiers to ensure confidentiality. The mechanics of how to do data analysis will depend on the type of data you have and the approach to analysis you are taking, but the key tasks in all forms of analysis will be to categorize your data and evidence and to make comparisons. These two features form the core of data analysis processes and will be applied in tandem with theoretical frameworks to draw out key findings and conclusions that are pertinent to your research question. The guide concluded by discussing how computer software can assist the analysis of both qualitative and quantitative data, highlighting some of the opportunities it offers for data management, categorization, and comparison. It was pointed out that software can take time to learn, and its use should be strategic so you are research objective–led rather than allowing software to dictate the research process. The next guide turns to the final (maybe) stage of your research toolbox—presenting your findings—and it considers how we communicate our answers to our research question to different audiences.

Multiple Choice Quiz Questions

1. Which of the following steps are required when preparing data for analysis?

- **a.** Choosing a research topic

Incorrect Answer

Feedback: This is not the correct answer. The correct answer is B.

- **b.** Correcting data errors and removing confidential information

Correct Answer

Feedback: Well done, correct answer

- **c.** Writing the final report

Incorrect Answer

Feedback: This is not the correct answer. The correct answer is B.

2. Which of the following is a key advantage of using software for qualitative data analysis?

a. It completely automates coding, thus eliminating the need for researcher involvement.

Incorrect Answer

Feedback: This is not the correct answer. The correct answer is C.

b. It simplifies the data-gathering stage of the research process.

Incorrect Answer

Feedback: This is not the correct answer. The correct answer is C.

c. It allows researchers to store, categorize, and visualize data, aiding in systematic comparison.

Correct Answer

Feedback: Well done, correct answer

3. In social science data analysis, what is the primary purpose of categorization?

a. To group data into manageable units to aid the identification of patterns and relationships

Correct Answer

Feedback: Well done, correct answer

b. To eliminate any duplicate information that might affect results

Incorrect Answer

Feedback: This is not the correct answer. The correct answer is A.

c. To protect participant anonymity by removing identifiable information

Incorrect Answer

Feedback: This is not the correct answer. The correct answer is A.

SUBMIT

CLEAR

START OVER

Further Reading

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Publications.

Web Resources

CAQDAS Chats with Christina (podcast series). https://open.spotify.com/show/28usVeqag9q7irrrAgJTBh?si=7e44fcf1362c441d

Getting Help with R: The R Project for Statistical Computing. https://www.r-project.org/help.html

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