

Concept Paper

AI-Generated Data as Epistemic Artifacts: Insights from Quantitative Methods Education

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Abstract

This article critically examines the use of generative AI (specifically ChatGPT-4) as a tool for designing teaching materials in university courses on quantitative social research methods. It is conceived as a concept paper grounded in an illustrative, AI-assisted co-design session. The purpose is not to evaluate learning outcomes or produce generalizable empirical findings, but to develop a theory-informed analytical framework for examining AI-generated materials as epistemic artifacts. The analysis illustrates how seemingly neutral AI outputs embed specific assumptions and can actively shape the way social research is approached, intensifying constitutive methodological conventions. By critically unpacking the simulated outputs, the article proposes a framework for integrating AI-generated content into quantitative methods education as an object of critical inquiry.

Keywords: critical data practices; generative artificial intelligence; epistemic artifacts; simulated datasets; AI-generated content; quantitative methods in social research

1. Introduction

The rapid diffusion of generative artificial intelligence (Gen-AI) in higher education has prompted growing interest in its pedagogical potential, alongside concerns about its practical and ethical implications (see, among others, [1–5]). While existing research has primarily focused on learning outcomes, assessment practices and institutional governance, increasing attention is being paid to how generative AI can reconfigure the conditions under which knowledge is constructed.

Recent scholarship has suggested that AI systems should be understood not merely as neutral tools but as epistemic technologies [6,7]. From this perspective, the relevance of generative AI in education relies on its capacity to structure what kinds of cognitive and interpretive actions become possible. This infrastructural view builds on insights from the philosophy of technology and cognitive science. Scholars have shown that technologies can actively shape perception and action and do not function as transparent intermediaries [8,9]. At the same time, theories of distributed cognition emphasize that epistemic activity extends across socio-technical systems composed of people, artifacts and routines [10]. Within this framework, the use of generative AI in education can be seen as a reconfiguration of distributed arrangements.

A key concern arising from this line of research is the risk of epistemic substitution. Generative AI performs operations that are constitutive of professional experts [7] and may displace activities such as interpretive judgment or critical evaluation. To analytically assess these dynamics, digital systems can be examined as socio-technical infrastructures



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according to interrelated conditions, such as the affordances they provide for skilled epistemic actions and their implications for habit formation over time [11].

This article offers a perspective on this debate by examining the use of generative AI within a specific disciplinary teaching practice, particularly in relation to social research methodology. It adopts a conceptual and reflexive approach to analyze how generative AI participates in the early stages of content design within methodological training and contributes to the construction of datasets, research questions, analytical routines and interpretive narratives. In this sense, the article aims to develop a theory-driven contribution focused on the implications of generative AI within quantitative methods education.

The article is grounded in an illustrative work session in which ChatGPT-4 was used to generate a simulated dataset and a sequence of instructional modules for an introductory university course in social research methods. The simulated data are treated as artifacts that illustrate how assumptions about variables, their distributions and relations are operationalized through AI.

The analysis is based on the use of a specific tool (ChatGPT-4) that was selected primarily for its accessibility and real-time generative capacity. Nonetheless, the article aims to illustrate more general dynamics of generative AI systems trained on large-scale methodological conventions. By examining how generative AI structures datasets, hypotheses, analytical routines and interpretive narratives within quantitative methods education, the study highlights how epistemic assumptions become embedded in AI-generated pedagogical content.

The study is situated within the challenges that characterize the teaching of social research methods. Students need access to data that are realistic enough to sustain interpretation. Yet, datasets suitable for instructional use (ethically safe, adaptable and aligned with students' interests) are often difficult to obtain. Generative AI tools can partly respond to these constraints by producing tailored datasets and exercises, but their adoption also demands attention to avoid uncritical use [12–15].

Existing models of technology-enhanced pedagogy, such as TPACK [16] and SAMR [17], have been used to conceptualize generative AI as a resource for transforming learning activities (see, for example, [18,19]). At the same time, research in social research methods teaching has emphasized the need to prioritize conceptual understanding over procedural execution [20–22]. Situating itself at the intersection of these strands, this article aims to interrogate the role of generative AI in the production and transmission of knowledge, using quantitative research methods learning as an empirical site.

2. Analytical Approach and Illustrative Material

2.1. AI Co-Design Procedure

The co-design session was conducted using ChatGPT-4 in September 2025. The interaction followed a sequential prompting strategy designed to simulate the preparation of introductory teaching materials for a university course in quantitative social research methods.

The prompting process was intentionally minimally specified in order to observe the model's default generative tendencies. Prompts progressively requested: (1) a modular course structure, (2) a simulated dataset, and (3) instructional worksheets corresponding to each module. Outputs were retained in their original form except for formatting adjustments required for publication.

The analytical interpretation was conducted through a theory-informed qualitative reading guided by the four analytical propositions presented in Section 3. These propositions oriented attention toward recurring patterns related to data construction, theory–data sequencing, interpretive standardization and the redistribution of agency.

The analytical propositions functioned as sensitizing analytical concepts used to structure interpretive attention within the examined co-design process. The objective of the procedure was not to evaluate the pedagogical effectiveness of AI-generated materials, but to examine how methodological assumptions become embedded within generated educational content.

The study does not claim that the identified tendencies are generalizable properties of generative AI systems. The analysis documents how these tendencies emerged within a specific co-design interaction under minimally specified prompting conditions.

2.2. Analytical Approach

This study focuses on the process of co-designing teaching materials with a generative AI system, treating this process itself as the object of investigation. Reflexivity is a constitutive feature of the research design, because the author is simultaneously the instructor involved in the development of the materials and the analyst interpreting the co-design process.

The analysis distinguishes between the documented empirical material generated during the co-design interaction (prompts, datasets, instructional outputs) and the interpretive reasoning developed through the theoretical framework adopted in the study. The empirical material provides a traceable basis for analysis, while interpretation remains theoretically mediated and explicitly situated within the author's analytical perspective.

The empirical material derives from a work session in which ChatGPT-4 was used to co-generate teaching materials for an introductory course in social research methodology. ChatGPT-4 is approached as a socio-technical actor and not as a neutral instrument (see Introduction). The interaction with the model is conceptualized as a co-production process between human and machine agency. The instructor specifies objectives and the model responds by mobilizing implicit assumptions.

The illustrative material consists of instructor prompts used to request the generation of teaching content and the corresponding AI-generated outputs. The resulting teaching materials are described in synthetic form in the main text of the article and are fully reported in Appendix A. The analysis follows an analytical strategy guided by a set of propositions derived from the theoretical framework.

Table 1 summarizes the methodological positioning of the study, including the nature of the empirical material, the prompting strategy, the analytical approach and the scope and limitations of the contribution.

Table 1. Methodological Structure of the Study.

Component	Description
Type of contribution	Concept paper grounded in an illustrative AI-assisted co-design case
AI System	ChatGPT-4
Context	University course in quantitative social research methods
Empirical material	AI-generated dataset, instructional modules, prompts and generated outputs
Prompting strategy	Sequential and minimally specified prompting to observe default generative tendencies
Analytical approach	Theory-informed interpretive analysis guided by analytical propositions
Objective	To examine how epistemic assumptions become embedded in AI-generated pedagogical content

Table 1. *Cont.*

Component	Description
Role of the appendix	Documentation of prompts and outputs to ensure analytical transparency and procedural traceability
Replicability	The prompting sequence, analytical structure and interpretive procedure are documented so that the co-design process can be reproduced
Scope and limitations	Illustrative and conceptual rather than statistically generalizable; the study does not evaluate learning outcomes or causal effects

3. Theoretical Framework and Analytical Propositions

Within the sociological tradition, data and analytical research methods have been understood not as neutral instruments but as constructed artifacts that participate in the production of knowledge. Empirical facts do not pre-exist analysis but emerge through practices of measurement and interpretation. This insight, articulated early on by Berger and Luckmann [23] and further developed in contemporary scholarship, treats data as outcomes of theoretical decisions and operational conventions. As Gitelman [24] argues, “raw data” is an oxymoron because data are always shaped by prior assumptions.

From this perspective, the use of generative AI can be seen as intensifying the constructed nature of data. AI-generated datasets suggest a model of the social world embedded in algorithmic conventions rather than reflecting social reality. For this reason, generative AI can contribute to what Kitchin [25] terms “data imaginaries”, i.e., narratives about social life that take the form of data.

Insights from science and technology studies further support this view by emphasizing processes of co-production of data between human actors and technical systems [26–28]. From this standpoint, interaction with generative AI cannot be reduced to the transmission of content. Moreover, this interaction tends to redefine the instructor’s role, which increasingly involves the critical interrogation and mediation of AI-generated outputs.

Critical data studies extend this argument by drawing attention to the simplifications and reductions embedded in automated content production [24,25,29]. AI-generated data may foreground regularity and coherence, and potentially downplay social inequalities and power relations. Such representations may constrain the capacity to recognize the contested nature of social phenomena.

Related concerns have long been articulated within critical pedagogy. Educational approaches that privilege the passive reception of ready-made content risk limiting engagement with uncertainty and interpretation. As Biesta [30] has argued, education also involves maintaining spaces of ambiguity and judgment. When generative AI supplies well-structured materials, there is a possibility that learners may substitute critical inquiry with the acceptance of prefabricated narratives. This scenario echoes the “banking model” of education criticized by Freire [31].

Drawing on these perspectives, the present study formulates a set of analytical propositions that guide the reading of the illustrative case. The analytical propositions were constructed through a theory-informed interpretive process grounded in the theoretical perspectives discussed above.

These are the analytical propositions:

1. The constructed nature of data: AI-generated datasets embed imaginaries that may orient how social phenomena are described and perceived.

2. The relationship between data and theory: Starting from simulated datasets can encourage data-driven questioning and weaken the role of theory in problem formulation.
3. Interpretive standardization: Generative AI may produce uniform narratives that limit interpretive diversity.
4. Redistribution of agency: Generative AI contributes to defining what appears meaningful and the instructor's role shifts toward that of curator and critical mediator.

Each proposition guides attention toward specific aspects of the co-design process, including the construction of datasets, the sequencing of theory and data, the standardization of interpretive outputs, and the redistribution of agency between human and AI systems. This analytical structure provides a framework for examining how epistemic assumptions become embedded across the different stages of AI-generated pedagogical content production. This approach is consistent with interpretive and socio-technical traditions of inquiry in which reflexivity is understood as a component of analytical transparency rather than a methodological weakness [32].

4. Analytical Insights

The co-design process is situated within a university course offering a first exposure to social research methodology. At each stage of the process, ChatGPT-4 was prompted using minimally specified instructions in order to observe the model's default generative tendencies. The full set of prompts and AI-generated teaching materials are reported in Appendix A.

The initial interaction asked ChatGPT-4 to assist in designing materials for the quantitative component of an introductory social research course. In response, the model proposed a modular sequence with a list of objectives, contents and exercises for each module. The suggested path closely mirrors classical textbook representations of quantitative inquiry: dataset introduction, hypothesis formulation, descriptive analysis, bivariate analysis and reporting (Appendix A, Table A1).

This sequence was presented as self-evident without any explicit justification or acknowledgment of alternative strategies. The research process proposed appears linear and cumulative and tends to support an image of quantitative inquiry as a standardized progression. In this sense, starting from this very first interaction, the AI-generated output implicitly normalizes a specific methodological imaginary and a uniform and traditional narrative.

The co-design work continued by asking ChatGPT-4 to implement the modular sequence, starting with the creation of a simulated dataset and then proceeding with worksheets. The structure proposed by AI was respected in the prompting, and no further specifications or modifications were introduced by the instructor, in order to allow ChatGPT's way of working to emerge clearly.

4.1. The Dataset as a Pedagogical Artifact (Module 1)

When asked to generate a simulated dataset, ChatGPT-4 produced a dataset of 200 cases and eight variables centered on sociodemographic characteristics, income, working hours and subjective well-being. The prompt deliberately avoided specifying substantive domains or variable structures in order to examine which conventions would be mobilized by AI. The resulting dataset reproduces a highly conventional inequality-oriented framework that tends to pre-structure the kinds of questions and type of analysis that can be performed (Appendix A, Table A1). If requested, the system allows for rapid modification of cases and variables through additional prompts. This starts suggesting the role of curator that can be played by the researcher. At the same time, the flexibility and

convenience of the tool risks framing datasets as interchangeable artifacts rather than as theoretically grounded constructions.

Once generated, the dataset acts as an epistemic anchor, that implicitly influences subsequent analytical activities. The initial exploratory exercises proposed by AI to become familiar with the dataset are clear and detailed, but they do not involve any kind of reflection on the implicit choices that structure the dataset (Appendix A, Worksheet A1). Variables such as binary gender, hierarchically ordered learning attainment, and normally distributed income values embed specific assumptions about social structure and measurement. They embody a representation of the world, which needs to be problematized.

4.2. *When the Dataset Precedes the Theory (Module 2)*

The worksheet generated for the module on research questions and hypotheses formulation was produced by prompting ChatGPT-4 to design guided exercises based on the existing simulated dataset (Appendix A, Worksheet A2).

The resulting materials are technically coherent and well aligned with introductory learning objectives. However, this configuration shows the tendency of reordering the relationship between theory and data. Because the generated exercises begin from the dataset and invite students to identify relationships among the available variables, hypothesis formulation is framed as a reactive process. This may reduce theoretical reasoning to a justificatory level. This exemplifies how AI-generated materials can privilege pattern recognition over conceptual reasoning when datasets precede theory, especially in introductory learning contexts. It promotes a reduced reading of social complexity and requires intervention to mitigate this simplification.

This dynamic can be further interpreted considering the distinction between deductive and inductive reasoning in quantitative research pedagogy. Traditionally, quantitative methods pedagogy has been organized around a deductive logic in which theoretical frameworks guide the formulation of hypotheses prior to data analysis [33] (Blaikie 2007). Statistical education research has similarly emphasized the importance of connecting analytical procedures to conceptual reasoning [20]. When inquiry begins from pre-structured datasets, as in the case of AI-generated materials, there can be a tendency to shift toward a more inductive or data-driven logic, in which hypotheses emerge reactively from available variables. While this approach may facilitate engagement with empirical patterns, it risks weakening the role of theory as an autonomous source of problem formulation.

4.3. *When the Data Are Too Perfect (Module 3)*

In response to a prompt requesting a worksheet on descriptive statistics and data visualization, ChatGPT-4 generated exercises and solutions that rely on established measures such as frequencies, means, standard deviations and usual model of data visualization (Appendix A, Worksheet A3). Because the underlying dataset was produced by default using standardized statistical distributions, the resulting descriptive outputs display a high degree of regularity. For instance, occupational status categories (employed, unemployed, student) exhibit near-equal proportions, while age, income, and education display regularized ranges with limited skewness.

The generated content seems to convey a vision of social reality characterized by symmetry and smooth distributions. While these properties facilitate technical instruction, they risk detaching quantitative reasoning from the empirical complexity of societies and normalizing an intuitive understanding of social processes.

4.4. *Artificial Relationships and the Risk of False Confidence (Module 4)*

The bivariate analysis module was generated by prompting ChatGPT-4 to introduce basic techniques for examining relationships between variables, including contingency

tables, *t*-tests and correlations (Appendix A, Worksheet A4). Given the structure of the simulated dataset, these analyses consistently yield weak associations.

These results are not analytical failures but artifacts of the modeling assumptions embedded in data generation. They are technically rigorous but at the same time encode an overly simplified representation of reality. The issue is not whether the generated materials are “right” or “wrong”, but how they normalize specific methodological conventions through their apparent naturalness. The module thus illustrates how generative AI may contribute to expectations about social regularity and uncertainty. In this sense AI-generated datasets require explicit contextualization.

4.5. *Communicating with Creativity (Module 5)*

In response to a prompt requesting guidance on communicating results, ChatGPT-4 produced a well-structured mini-report using highly standardized interpretive language (Appendix A, Worksheet A5). The generated text emphasizes coherence and closure, but it seems to omit interpretive uncertainty or alternative explanations.

Up to this point, the process of co-design had remained within the framework of the sequence proposed by the AI. In this last step, a deliberate deviation was introduced in order to observe the AI response when agency is assumed by the instructor. When the prompt was modified to explicitly request creative forms of presenting results, the model generated more imaginative outputs, including narrative portraits and dramatized graphs (Figure A1). This contrast shows that interpretive plurality is not excluded by the system but seems suppressed by default conventions. Following a clear instruction to encourage diversity and complexity, AI gradually becomes able to produce less standardized outputs.

The results suggest that generative AI does not necessarily impose a structural limitation on interpretive plurality. It appears to default to methodological conventions, which seem to be reproduced unless explicitly challenged through targeted prompting. The supposed standardization of interpretation appears like an emergent effect of its training and default optimization toward coherence. Interpretive plurality remains possible but requires deliberate intervention to be activated. This passage once again illustrates the instructor’s key role in AI-generated content as a curator and critical mediator.

4.6. *Synthesis: The Analytical Propositions*

Through a combined evaluation of the different steps, the analyses show how the four analytical propositions operate across the co-design process. The constructed nature of data (Proposition 1) emerges most clearly at the moment of dataset generation but continues to shape subsequent analytical routines. The reordering of theory and data (Proposition 2) becomes fully visible when operational tasks are derived from available variables. Interpretive standardization (Proposition 3) permeates both analytical outputs and narrative reporting, while the redistribution of agency (Proposition 4) cuts across the entire process and redefines the instructor’s strategic role for reopening spaces of judgment and ambiguity.

5. Discussion

The analysis of the co-design process examined in this article reinforces key insights from critical data studies by illustrating how AI-generated datasets within quantitative methods education operate as epistemic artifacts [24,25]. The simulated data produced by ChatGPT-4 embed specific modeling assumptions, such as binary gender classifications, hierarchically ordered categories and smooth statistical distributions. This illustrates that data do not pre-exist their modes of production but emerge from classificatory and operational conventions [23,24]. In this sense, AI-generated datasets function as performative

devices that foreground certain dimensions of social life and marginalize others. AI contents contribute to the formation of data imaginaries that may be mistaken for empirical facts when introduced into teaching contexts without explicit interrogation [25].

Moreover, the outputs highlight how the sequencing of data prior to theory can place conceptual reasoning under pressure. Compared to situations in which data scarcity requires strong theoretical framing, the availability of ready-made simulated datasets may encourage inquiry to begin from observable variables. This dynamic risks reversing the logic in which theory guides problem formulation and data collection [20–22]. This tendency is not unique to generative AI, but the immediacy and apparent neutrality of AI-generated datasets may intensify data-driven modes of inquiry.

The analysis also illustrates a tendency toward interpretive standardization in AI-generated teaching materials. Across modules, ChatGPT-4 produces coherent and well-structured narratives. This clarity reflects conventions embedded in generative systems trained on dominant methodological representations [25]. In educational settings, however, such outputs may reinforce procedural rather than interpretive understandings [20]. The observation that more plural and creative interpretive forms emerge only when explicitly requested suggests that interpretive diversity is not excluded by generative AI, but requires deliberate human intervention.

The investigation enlightens how generative AI systems shape the horizon of plausible research actions even before human actors intervene and exemplify dynamics consistent with accounts of technological mediation [8,9]. It further suggests that the redistribution of agency entails a transformation of instructor authority [10]. Within AI-mediated contexts, agency is co-produced through interactions between human judgment and algorithmic generation. Overall, these patterns support the view of AI as an epistemic infrastructure that reconfigures the conditions under which epistemic agency is exercised [7].

These dynamics can also be interpreted in relation to concerns about cognitive off-loading in AI-mediated environments [34]. The delegation of analytical tasks may reduce cognitive load and facilitate access to methodological procedures [35] and may also limit engagement with evaluative and interpretive reasoning [36]. Similar concerns emerge in earlier discussions of the “Google effect,” which suggest that the increasing availability of externalized information can reshape processes of memory and critical engagement [37].

Within quantitative methods education, this does not imply that generative AI necessarily weakens critical reasoning. Rather, the analysis suggests that the pedagogical implications of AI-generated materials depend on how these systems are mediated and contextualized within teaching practices. The instructor’s role involves maintaining spaces for interpretation and ambiguity within AI-assisted learning environments [38].

Table 2 summarizes the key epistemic tensions identified across the co-design process and maps them onto the critical counterpoints discussed in the analysis.

Table 2. Epistemic Tensions and Critical Counterpoints Identified in the Co-Design Process.

Epistemic Tension	Manifestation in AI-Generated Materials	Critical Counterpoints Emerging from the Analysis
Data as Socio-Technical Artifacts	AI-generated datasets appear neutral but embed modeling assumptions (binary gender, balanced categories, smooth distributions, limited heterogeneity). These artifacts risk naturalizing specific visions of the social world.	The dataset can be treated as an object of critique through which implicit choices and assumptions become visible. Contrasting simulated and real datasets foregrounds what is emphasized or obscured and open reflection on what renders data “social”.

Table 2. Cont.

Epistemic Tension	Manifestation in AI-Generated Materials	Critical Counterpoints Emerging from the Analysis
Theory Under Pressure	Research risks becoming data-driven: questions and hypotheses tend to arise reactively from available variables rather than from conceptual reasoning. Weak associations can limit the role of theory.	Starting from theoretically grounded questions emerges as a way to face the limits of data-driven inquiry. Situations in which available datasets cannot address the research question render visible the autonomy of theory from data.
Esthetic Regularity	AI-generated data can normalize noise-free patterns that obscure real-world variability, inequalities and outliers.	Juxtaposing simulated and empirical data accentuates irregularity as a constitutive feature of social life.
Standardization of Interpretation	The model tends to standardize narrative templates and privilege coherence over interpretive uncertainty.	Exploring multiple readings of the same outputs helps make visible the contingency of explanation and the plurality of interpretive possibilities.
Redistribution of Epistemic Agency	The model supplies datasets, exercises and explanatory structures, in which meaning is partially pre-structured.	This configuration highlights the instructor's role as curator and critical mediator of AI-generated reasoning.

6. Conclusions

This article aims to contribute to the literature on Gen-AI as a socio-technical infrastructure by offering an illustrative analysis of how simulated data operate as epistemic artifacts in social research training. Its primary contribution lies in the reflexive use of the co-design process as analytical material, which helps to clarify how methodological assumptions and social imaginaries become embedded in generated data. The study also draws attention to the reversal of the theory–data relationship and explores a reconceptualization of the instructor's role as an epistemic curator.

These dynamics raise broader pedagogical concerns regarding the long-term consequences of AI-mediated methodological training. If students become progressively accustomed to pre-structured analytical paths, standardized interpretive templates and readily available explanatory schemas, there is a risk that engagement with theoretical reasoning and plurality may weaken over time. In this sense, the issue is not only whether AI-generated materials simplify representations of social reality, but whether repeated exposure to such simplifications may gradually normalize reduced forms of inquiry. This could contribute to the formation of methodological habits in which complexity and reflexivity become increasingly marginalized. This article does not assume that such outcomes are inevitable. The analysis suggests that the consequences of generative AI depend significantly on how these systems are integrated into pedagogical practices. Critical mediation, reflexive interrogation of generated outputs, and explicit engagement with alternative interpretations remain essential.

In conclusion, the analytical insights suggest that Gen-AI participates in quantitative methods education by affecting the conditions under which methodological reasoning is learned and practiced. These effects emerge under minimally specified prompts, suggesting that they reflect default generative conventions. Plurality emerges when the instructor actively intervenes. Attending to these dynamics is essential for preserving full responsibility and interpretive openness in the education of social researchers.

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Appendix A

The materials reported in this appendix are included as epistemic artifacts produced through interaction with a generative AI system (ChatGPT-4). They are presented in order to document the assumptions, narrative structures and methodological conventions mobilized by generative AI in the design of quantitative methods education.

Table A1. ChatGPT-4 generates a modular course structure following the initial co-design prompt.

Prompt: I am a university lecturer teaching a course in social research methodology, both qualitative and quantitative. I would like your help in generating materials for the practical part of the course (quantitative focus). I want to teach students how a quantitative dataset is organized and how to use this dataset to answer research questions, support or disconfirm hypotheses and teach them how to comment and present data.

Response: A social research methodology course with a practical quantitative component is essential for equipping students with concrete tools to read, analyze, and produce empirical research. I can help you create a complete package of teaching materials. Here is a modular structure for the quantitative practical component of the course, with examples and activities we can build together:

Module 1: Introduction to the Quantitative Dataset

Objectives:

Understand the structure of a dataset (variables, cases, coding).

Distinguish between categorical, ordinal, and continuous variables.

Contents:

What a dataset is and how it is organized (rows = units, columns = variables).

Data coding (e.g., 1 = male, 2 = female).

Real datasets (e.g., ISTAT data, Eurostat data, social surveys such as ESS or GSS).

Exercise:

Download a simple dataset (e.g., simulated or from public data) and describe:

- number of cases,
- number and type of variables,
- minimum and maximum values, and categories.

Module 2: Research Questions and Hypotheses

Objectives:

Write a research question.

Formulate quantitatively testable hypotheses.

Contents:

Difference between a research question and a hypothesis.

Types of relationships: group differences, correlations, causal effects.

Operational construction of hypotheses.

Exercise:

Starting from an existing dataset:

Write a question such as: "Are there differences in life satisfaction between men and women?"

Formulate one or more testable hypotheses.

Module 3: Descriptive Analysis

Objectives:

Calculate and interpret frequencies, means, and standard deviations.

Present data graphically (bar charts, histograms, boxplots).

Contents:

Indicators for categorical and metric variables.
 Data visualization.
 Use of Excel, SPSS, or R (depending on level and preferred tools).

Exercise:

Create frequency tables for categorical variables.
 Calculate the mean and standard deviation of a metric variable.
 Graphically represent a distribution.

Module 4: Bivariate Analysis**Objectives:**

Examine relationships between two variables.
 Interpret results of association or correlation tests.

Contents:

Contingency tables and chi-square test (categorical variables).
 Pearson correlation (metric variables).
 T-test for mean differences between two groups.

Exercise:

Test the hypothesis “Education level is associated with type of occupation” (chi-square).
 Test “Do men have a higher average income than women?” (*t*-test).
 Calculate and interpret the correlation between age and satisfaction.

Module 5: Writing and Presenting Results**Objectives:**

Communicate data effectively.
 Comment on charts and tables.
 Write a mini-report with introduction, analysis, and conclusion.

Contents:

Descriptive and interpretative language.
 How to present charts and statistics in reports.
 How to discuss results in light of hypotheses.

Exercise:

Write a short report including:

- research question,
- descriptive data,
- bivariate analysis,
- conclusion regarding the initial hypothesis.

Recommended Datasets for Practice

ESS (European Social Survey): broad coverage of socio-demographic and attitudinal variables.
 World Values Survey.
 ISTAT data (e.g., Multipurpose Survey).
 Alternatively, simulated datasets on social topics (e.g., well-being, work, education).

I can help you generate:

Simulated datasets (.csv).
 Student guide sheets (PDF or Word).
 Commented examples of analysis (in R, SPSS, Excel).
 Exercises with solutions.
 Mini practical exams.

Report templates.

Table A1. ChatGPT-4 produces a case–variable matrix ready for analysis.

Prompt: I want to start by creating a simulated dataset. Create a file that can be imported into one of the main statistical packages for the social sciences.

Response: Here is the simulated dataset in .csv format, ready to be imported: “life_conditions_and_well-being.csv.”

Variables included:

ID, Gender, Age, Educational_Attainment, Occupation, Monthly_Income, Life_Satisfaction, and Weekly_Working_Hours

Appendix A.1 Worksheet A1 ChatGPT-4 Produces Module 1

Prompt: Create a worksheet for students. It should contain tasks and solutions using the file you created. Let's start with Module 1: Introduction to the Quantitative Dataset. Objectives: understand the structure of a dataset (variables, cases, coding); distinguish between categorical, ordinal, and continuous variables.

Response: Worksheet for Module 1

Worksheet—Module 1

Introduction to the Quantitative Dataset

Learning Objectives:

- Understand the structure of a quantitative dataset.
- Distinguish between categorical, ordinal, and continuous variables.
- Learn how to read and describe a dataset systematically.

Dataset to use: *life conditions and well-being.csv*

If you have not already done so, download the file here:

[*life conditions and well-being.csv*] (insert local link provided by the instructor or download from the course platform)

PART 1—Understanding the Structure

1. How many units of analysis (rows) does the dataset contain? How many variables (columns)?
2. Read the variable names. For each variable, specify:
 - Whether it is categorical, ordinal, or continuous.
 - Whether it is coded or contains text labels.
 - The hypothesized level of measurement (nominal, ordinal, interval, ratio).

Fill in the following table:

Variable Name	Type (categorical, ordinal, continuous)	Level of Measurement	Notes on Coding
ID			
Gender			
Age			
Educational_Attainment			
Occupation			
Monthly_Income			
Life_Satisfaction			
Weekly_Working_Hours			

PART 2—Data Exploration

Use SPSS to answer the following questions:

3. What are the minimum, maximum, and mean values for the variable Age?
4. How many distinct categories does the variable Gender have? Which is the most frequent?
5. What categories are present for the variable Educational_Attainment?
6. What is the distribution of the variable Occupation? (Provide a frequency table)
7. What are the minimum, maximum, and mean values for the variable Monthly_Income?

Solutions (*to be provided to students later*):

1. The dataset contains 200 units and 8 variables.
2. Example of completed table:

Variable Name	Type	Level of Measurement	Notes on Coding
ID	Categorical	Nominal	Unique labels
Gender	Categorical	Nominal	Text
Age	Continuous	Ratio	Numeric
Educational_Attainment	Ordinal	Ordinal	Text
Occupation	Categorical	Nominal	Text
Monthly_Income	Continuous	Ratio	Numeric
Life_Satisfaction	Ordinal	Ordinal	Scale from 1 to 10
Weekly_Working_Hours	Continuous	Ratio	Numeric

3. Age: min = 18, max = 69, mean \approx 43.7
4. Gender: 2 categories (Male, Female), most frequent \approx Female (depends on sample)
5. Educational_Attainment: 4 categories (Lower Secondary, High School Diploma, Bachelor's Degree, Postgraduate Degree)
6. Example frequency table for Occupation:
 - Unemployed: 15
 - Student: 35
 - Employee: 60
 - Self-employed: 45
 - Retired: 45
7. Monthly_Income: min \approx €0, max \approx €3800, mean \approx €1800

Assignment:

Save your answers and the completed table in a Word or PDF file. Upload the file to the course platform before the next lesson.

Appendix A.2 Worksheet A2 ChatGPT-4 Produces Module 2

Prompt: Create a worksheet based on the simulated dataset for Module 2: Research Questions and Hypotheses. Learning objectives: formulate a research question; develop hypotheses that can be quantitatively tested. Content: distinction between research questions and hypotheses; types of relationships (group differences, correlations, causal effects); operationalization of hypotheses.

Response: Worksheet for Module 2

Worksheet—Module 2

Research Questions and Hypotheses

Learning Objectives:

- Learn how to formulate a clear and meaningful research question.
- Develop hypotheses that can be tested through quantitative analysis.
- Distinguish between different types of relationships: group differences, correlations, and causal relationships.

Reference Dataset: *life conditions and well-being.csv*

PART 1—Understanding the Concept

1. In your own words, what is the difference between a *research question* and a *hypothesis*?
2. Review the following variables from the dataset: Gender, Life_Satisfaction, Age, Monthly_Income, Educational_Attainment.
For each, answer:
 - Is it suitable as an *independent variable*, a *dependent variable*, or both?

- What kind of relationship could be studied with it?

PART 2—Formulating Research Questions

3. Write two research questions based on the dataset. Example:
“Are there differences in life satisfaction between men and women?”
 Research Question 1: _____
 Research Question 2: _____
4. For each question, formulate a testable hypothesis. Specify:
 - Dependent variable
 - Independent variable
 - Type of expected relationship (difference, correlation, effect)

Hypothesis for Question 1:

Hypothesis for Question 2:

PART 3—Guided Application

5. Analyze the following hypothesis:
“Individuals with higher monthly income report greater life satisfaction.”
 - What variables are involved?
 - What type of relationship is hypothesized?
 - How could you test it using SPSS?

Solutions (for instructor or later distribution):

1. A research question is a broad inquiry (“what do I want to know?”), while a hypothesis is a specific, testable prediction (“what do I expect to find?”).
2. Examples:
 - Gender → independent; group comparison
 - Life_Satisfaction → dependent; continuous outcome variable
 - Age → independent or control; possible correlation
 - Monthly_Income → independent or dependent; correlation or regression
 - Educational_Attainment → independent; ordinal group comparison

3–4. Examples:

 - Question: *“Are self-employed workers more satisfied with their lives than employees?”*
 Hypothesis: *“Self-employed workers have higher average life satisfaction scores than employees.”*
 DV: Life_Satisfaction
 IV: Occupation
 Relationship: mean difference between groups
 - Question: *“Does the number of weekly working hours change with age?”*
 Hypothesis: *“There is a negative correlation between age and weekly working hours.”*
 DV: Weekly_Working_Hours
 IV: Age
 Relationship: correlation
3.
 - Variables: Monthly_Income (IV), Life_Satisfaction (DV)
 - Relationship: positive correlation
 - Analysis: Pearson correlation or simple linear regression

Submission:

Write your answers in a Word or PDF file and upload it to the course platform before the next lesson.

Appendix A.3 Worksheet A3 ChatGPT-4 Produces Module 3

Prompt: Continue and prepare Module 3 using the simulated dataset. Module 3: Descriptive Analysis. Learning objectives: calculate and interpret frequencies, means, and standard deviations; present data visually (bar charts, histograms, boxplots). Content: indicators for categorical and metric variables; data visualization; use of Excel, SPSS, or R (depending on level and preferred tools).

Response: Worksheet for Module 3

Worksheet—Module 3

Descriptive Analysis

Learning Objectives:

- Calculate and interpret frequencies, means, and standard deviations.
- Graphically represent categorical and metric variables.
- Gain familiarity with basic tools for data analysis: SPSS, Excel, or R.

Reference Dataset: *life conditions and well-being.csv*

PART 1—Descriptive Statistics

1. For each of the following categorical variables, create a frequency table:

- Gender
- Educational_Attainment
- Occupation

Include:

- Absolute frequencies
- Relative frequencies (%)
- Most frequent category (mode)

2. For each of the following metric variables, calculate:

- Mean
- Standard deviation
- Minimum and maximum values

Variables:

- Age
- Monthly_Income
- Weekly_Working_Hours
- Life_Satisfaction

PART 2—Data Visualization

3. Create a bar chart for the distribution of Occupation.
4. Create a histogram for the distribution of Age.
5. Create a boxplot for Monthly_Income, split by Gender (Male/Female).

Tip: In SPSS, use the command “Boxplot → Group by Category.”

Submission:

Export the tables and graphs into a Word or PDF file. Save the file as: *Module3_FirstNameLastName*. Upload it to the course platform before the next lesson.

Solutions

Descriptive Statistics

1. Frequency tables for categorical variables:

Gender

Category	Frequency	%
Male	100.0	50.0%
Female	100.0	50.0%

Educational Level

Category	Frequency	%
High school diploma	81.0	40.5%
Middle school	54.0	27.0%
University degree	43.0	21.5%
Postgraduate	22.0	11.0%

Occupation

Category	Frequency	%
Retired	47.0	23.5%
Unemployed	43.0	21.5%
Student	41.0	20.5%
Freelancer	36.0	18.0%
Employee	33.0	16.5%

2. Descriptive statistics for metric variables:

Variable	Mean	Std. Deviation	Min	Max
Age	44.4	15.4	18.0	69.0
Monthly income	1827.4	634.0	482.0	3585.0
Weekly working hours	30.7	16.8	0.0	59.0
Life satisfaction	5.2	2.9	1.0	10.0

[...Part 2 Data Visualization...]

Appendix A.4 Worksheet A4 ChatGPT-4 Produces Module 4

Prompt: Continue with Module 4. Create a lesson worksheet and include solutions. Learning objectives: examine relationships between two variables; interpret the results of association or correlation tests. Content: contingency tables and Chi-square test (categorical variables); Pearson correlation (metric variables); t-test for mean differences between two groups.

Response: Worksheet for Module 4

Worksheet—Module 4

Bivariate Analysis

Learning Objectives:

- Examine relationships between two variables.
- Understand and interpret tests of association and correlation.
- Apply statistical techniques to test hypotheses about group differences or linear relationships.

Reference Dataset: *life conditions and well-being.csv*

PART 1—Contingency Tables and Chi-square Test

1. Examine the relationship between Educational_Attainment and Occupation:
 - Create a contingency table.
 - Apply the chi-square test.
 - Interpret the result.
2. Examine whether Gender is associated with Life_Satisfaction (transform *Life_Satisfaction* into three levels: low = 1–4, medium = 5–7, high = 8–10):
 - Create a contingency table.
 - Apply the chi-square test.

PART 2—Mean Comparisons (*t*-test)

3. Test whether there is a significant difference in Monthly_Income between Males and Females:
 - Calculate the mean income for both groups.
 - Apply an independent samples *t*-test.
 - Interpret the *p*-value.

PART 3—Correlation

4. Calculate and interpret the correlation between:
 - Age and Weekly_Working_Hours
 - Monthly_Income and Life_Satisfaction
 - Use Pearson's correlation coefficient.

Submission:

Write your answers and insert the tables and test results into a Word or PDF document.

Upload it to the course platform before the next lesson.

RESULTS AND SOLUTIONS

1. Chi-square test: Education Level × Occupation

Contingency table:

Education Level	Unemployed	Employee	Freelancer	Retired	Student
High school diploma	22	11	17	15	16
University degree	5	13	10	9	6
Middle school	13	4	6	17	14
Postgraduate	3	5	3	6	5

Chi-square = 19.55, *p* = 0.0760.

2. Chi-square test: Gender \times Life Satisfaction (categories)

Contingency table:

Gender	Low	Medium	High
Female	45	39	16
Male	38	29	33

Chi-square = 7.96, $p = 0.0187$.

3. T-test: Monthly income by Gender

- Mean (Male): 1870.50
- Mean (Female): 1784.40

T-test: $t = 0.96$, $p = 0.3381$

4. Pearson Correlations

- Age and Weekly working hours: $r = 0.19$
- Monthly income and Life satisfaction: $r = -0.05$

Appendix A.5 Worksheet A5 ChatGPT-4 Produces Module 5

Prompt: Learning objectives: communicate data effectively; comment on graphs and tables; write a mini-report with introduction, analysis, and conclusion. Content: descriptive and interpretive language; how to present graphs and statistics in reports; how to discuss results in relation to hypotheses.

Response: Worksheet for Module 5

Worksheet—Module 5

Presentation and Interpretation of Results

Learning objectives:

- Communicate the results of a statistical analysis effectively.
- Interpret quantitative data in light of formulated hypotheses.
- Write a short report with a logical and scientific structure.

Reference dataset: life conditions and well-being.csv

PART 1—Writing a Mini-Report

Choose one of the hypotheses formulated in the previous modules, for example:

“Individuals with a higher monthly income report greater life satisfaction.”

Complete a brief report including the following sections:

1. Introduction

- Briefly describe the research question.
- State the hypothesis to be tested.

2. Method

- Explain which variables you analyzed.
- Specify which statistical test you used and why.

3. Results

- Present the results concisely: mean values, t -test, p -value, or correlation.
- Include a table and, if useful, a graph.

4. Discussion

- Was the hypothesis confirmed or not?
- How do you interpret this result in light of the social phenomenon?

Example Report

1. Introduction

This analysis investigates whether there is a positive relationship between monthly income and life satisfaction.

Hypothesis: *As income increases, subjective satisfaction also increases.*

2. Method

Two continuous variables were analyzed: Monthly_Income (in euros) and Life_Satisfaction (scale 1–10).

A Pearson correlation was used to measure the linear relationship between the two.

3. Results

The correlation coefficient is $r = 0.03$, indicating a very weak positive relationship.

The table below summarizes the descriptive statistics:

Variable	Mean	Std. Dev.
Monthly_Income	1793.8	570.1
Life_Satisfaction	5.6	2.6

The graph shows the data dispersion:

(insert scatter plot)

4. Discussion

5. The initial hypothesis is not significantly confirmed. The correlation between income and satisfaction is weak, suggesting that other factors (e.g., social relationships, health, security) may influence perceived quality of life.

6. This result invites reflection on a simplistic view of well-being based solely on income.

Assignment:

Write your own mini-report following the above structure. Include at least one table and one graph. Save the file in Word or PDF format and upload it to the platform.

Data Postcard—A Socio-Demographic Portrait

“Carla is 48 years old. She holds a university degree and works as an office employee.

She works 27 h per week and earns approximately €1649 per month.

When asked, ‘How satisfied are you with your life?’, she replied 3.9/10.”

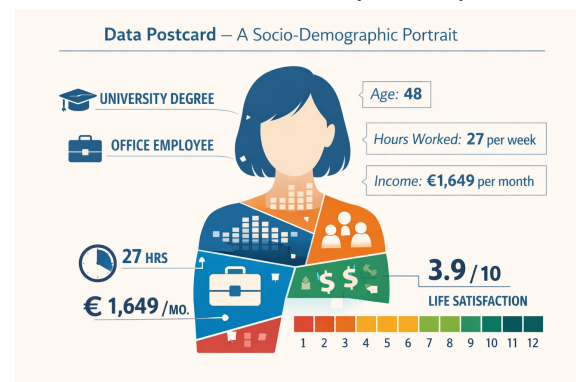
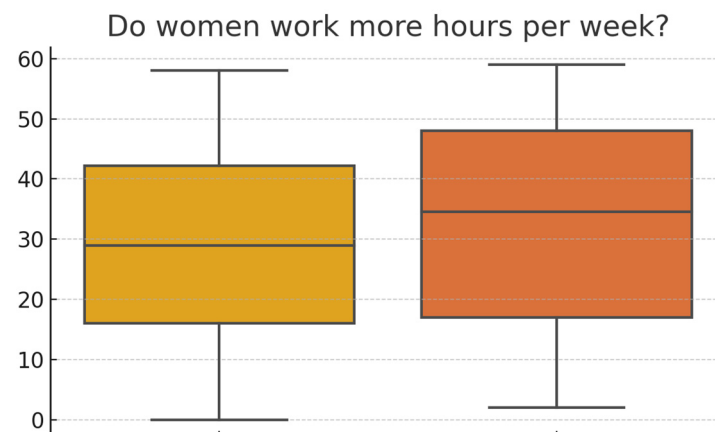


Figure A1. Cont.

Dramatized Graph—Hours Worked by Gender

A boxplot that tells a story: Who works more?



On average, women work more hours.

But who takes care of the house?

Figure A1. ChatGpt suggests creative presentation of results (Advanced Stage).**References**

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