A Novel Visualization Approach for Multiple-Case Analysis Using Sankey Diagrams

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Conflict of Interest Statement:

The authors declare no conflict of interest.

Ethics Statement

This study was approved by the Ethics and Research Committee of the Universidade Federal de São Paulo, under opinion number 6.957.080. All participants signed an Informed Consent Form before participation. This study was conducted in accordance with the Declaration of Helsinki.

Data Availability Statement

Interview data cannot be publicly shared due to confidentiality. All other data described in this manuscript are available at: https://osf.io/jv32y

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Abstract

Multiple-case studies are widely applied in biomedical and psychological sciences to investigate complex or rare conditions, yet their findings are often difficult to communicate using tables or conventional statistics. We propose the Sankey diagram as a novel visualization method for multiple-case research, highlighting replication logic across and within cases. A secondary analysis was conducted with patients diagnosed with borderline personality disorder (BPD) and their relatives, assessing attributional biases- personalization and intentionality- alongside BPD symptom severity. Data were categorized and visualized in a three-step Sankey diagram linking attributional biases, individual cases, and symptom severity, with flow widths representing numerical scores. Patients attributed higher intentionality to ambiguous social situations than relatives, and personalization significantly predicted symptom severity. The Sankey diagram made these associations visually accessible and highlighted one case that contrasted with our theoretical expectations, prompting refinement of the interpretation. Compared to traditional tabular formats, the Sankey approach offered a more intuitive and informative representation of both patterns and exceptions. This study demonstrates the potential of innovative visualization tools to enhance theory-building and the interpretation of complex case study data, particularly in psychiatry and psychology, and underscores their relevance for systematic application across multiple case studies..

Key-words: Multiple-case study; Sankey diagram; Attributional biases; Borderline personality disorder; Psychology; Psychiatry; Data visualization; Theory-building; Research methodology.

Introduction

Multiple-case studies are a common design to analyze complex or rare health conditions across fields of biomedical sciences. These studies treat each case as a complete entity, involving care-specific large amounts (in-depth) of data, usually acquired by mixed-methodologies, that are presented in individual reports and/or in integrated reports with cross-case comparisons (Eisenhardt, 1989; Yin, 2003). Multiple cases serve as experiments that contribute to the hypothesis generation, replication, contrast, and extension of an emerging theory (Eisenhardt & Graebner, 2007), and are therefore also highly relevant to theory building and improvement. Aligning with Open Science efforts to address the replication and theory crises, such designs offer a structured yet flexible framework that supports theory refinement through transparent, case-grounded evidence- resonating with recommendations to move away from vague theoretical claims and toward cautious interpretation of specific, context-rich findings (Korbmacher et al., 2023; Yarkoni, 2020). In psychology, by examining multiple cases, researchers can identify patterns across individual experiences while still attending to the uniqueness of each participant. This approach thus supports the development of theories that consider both individual experiences and connections across participants (Burgess-limerick & Burgess-limerick, 1998).

Given the characteristics of multiple-case studies or the rarity of the conditions usually involved, the use of tables and inferential statistics may be less effective for scientific communication and complex data interpretation. This is particularly evident in research involving participants with conditions shaped by multiple genetic, behavioral, traumatic, and epigenetic factors (Bozzatello et al., 2021), as well as diverse comorbidities and implications at both individual and public health levels (Biskin et al., 2011; Hastrup et al., 2019), such as borderline personality disorder. Issues with small sample sizes, statistical power, and representation reduce the breadth of common biostatistical analytical strategies, with extensive exploratory graphical analysis can shed light to aspects that might otherwise go unnoticed (Unwin, 2020) Furthermore, more visual approaches to data make understanding far easier compared to texts, numbers, and large tables (Gandhi & Pruthi, 2020), formats often employed in studies involving multiple cases.

However, the mixed-methodology approach in multiple case studies, such as interviews, questionnaires, observations, archival/documental sources- and draws on quantitative, qualitative mixed evidence (Eisenhardt, 1989), exploratory graphical analysis and data visualisation for this type of research presents a significant challenge. Effective data visualisation with in-depth high quality case study data can generate informative insights on a disease condition or phenomenon and support hypothesis generation (Gandhi & Pruthi, 2020; Minshall et al., 2022), thus demanding representations that facilitate understanding.

Recent multiple-case studies have employed comparative layouts with explicit encoding- that is, layouts enriched with additional elements to facilitate variable comparison (Bärenbold et al., 2024; L'Yi et al., 2020). While this approach offers advantages, particularly in detecting subtle differences, it is also prone to information loss (L'Yi et al., 2020). On the other hand, tables are also widely used (Biondi & Russo, 2022; Butt et al., 2024; Calandra et al., 2023). While they can mitigate the problem of information loss, they are far less intuitive and lack the visual appeal of graphical representations (Gandhi & Pruthi, 2020). Finally, we also found one study that used a framework matrix (Çetin et al., 2022). While this approach works well in qualitative research, it can be problematic in mixed-methods studies, as it may encourage researchers lacking a strong foundation in qualitative methods to inappropriately quantify qualitative data (Gale et al., 2013).

Given the challenges in representing complex data from multiple-case studies, it is useful to consider the methodological principles underlying this research design. In her influential paper "Building Theories from Case Study Research", Eisenhardt introduces this important research strategy that leverages the richness of case studies, which- unlike laboratory studies- emphasize real-world context (Eisenhardt, 1989). Among its distinctive features, the "Eisenhardt method" highlights constant comparison between theory and data, replication logic, and cross-case analysis (Eisenhardt, 2021). The first involves continuous iteration between the emerging theory and data to refine constructs and relationships; replication logic refers to repeating this process by treating each case as an independent observation rather than part of a pooled dataset for statistical analysis; and cross-case analysis employs different approaches to enhance creativity and reliability, particularly when developing theoretical explanations for patterns identified across cases (Eisenhardt, 1989; Glaser & Strauss, 1967; Yin, 2003). Capturing these dynamics in a visual format can be challenging, but the richness and structure of multiple-case data make them particularly suitable for innovative graphical representations.

As an approach to address the challenges in representing data in multiple-case studies, the Sankey diagram may offer a valuable visual alternative for presenting multiple-case studies. The Sankey diagram is a visualization method, first created to represent energy flows, that can also be applied to explore and interpret complex processes (Daniel & West-Mitchell, 2024), which are often characteristic of case studies. It is composed of nodes and arcs. As transitions take place, each arc connects a source node to one or more target nodes. In this type of diagram, the size of each node and the thickness of each arc correspond to the number of objects or members, thereby reflecting the magnitude of the flow (Otto et al., 2022). Various types of flow diagrams can be used to represent movements or transfers, but the Sankey diagram is unique in allowing the visualization of multiple steps while simultaneously conveying information about flows, volumes, and complex details of the variables involved (Lamer et al., 2020). Thus, beyond representing energy flows, the Sankey Diagram can be effective in understanding information related to protocol trajectories (Daniel & West-Mitchell, 2024), the evolution of measurement instruments (Azevedo & Bolesta, 2021) or patients' paths (Lamer et al., 2020). It can also aid in understanding data in psychiatry, including studies with patients with Borderline Personality Disorder, which will serve as the example case in this study.

Therefore, to better represent multiple-case studies and the logic of replication- thus reinforcing the strength of theories built from this type of research- we propose the use of the Sankey diagram as a graphical alternative. This proposal will be illustrated and tested through a secondary analysis of a multiple-case study involving patients with Borderline Personality Disorder (A. C. S. Marinho et al., 2025), aiming to provide a concrete example of how complex clinical trajectories and data patterns can be effectively visualized.

Methods

Study overview

This study is a secondary analysis of a parent study (Marinho et al., 2025a) aimed to examine the relationship between the severity of borderline personality disorder (BPD) symptoms and attributional bias, from the perspectives of both the individual with BPD and a family member. Further information on the parent study can be found at https://osf.io/jv32y/. The parent study was a mixed-methods cross-sectional study with clinical participants recruited from the outpatient treatment program of the Personality and Impulse Disorders Clinic at the Hospital das Clínicas, Faculty of Medicine, Universidade de São Paulo. The family group refers to a relative nominated by the patient. The present sample included six female participants diagnosed with BPD (mean age = 23.8, SD = 2.7) and six family members (three males, three females; mean age = 34.2, SD = 16.4). The relatives identified were one mother, one father, and four siblings.

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Instruments

Borderline Symptom List (BSL-23)

The BSL-23 is a self-report questionnaire designed to assess symptoms of borderline personality disorder (Bohus et al., 2009). Items are rated on a five-point scale ranging from 0 to 4. In this study, we used the version translated by Catelan & Nardi (2021), adapted for online administration via Google Forms.

Attribution Bias Assessment Instrument (IAVA)

This is an experimental task based on a structured interview - that was recorded and transcribed-, designed to assess the degree of personalization and intentionality of the respondent when faced with socially ambiguous vignettes (Figueiredo & Marinho, 2025). The instrument includes four vignettes presenting social situations, along with four questions related to each vignette. The degree of personalization refers to the extent to which the respondent attributes the cause of the event to themselves, to another person, or to external factors. The degree of intentionality measures the extent to which the participant believes the action was performed on purpose.

Sankey diagram methodology:

With the aim of making explicit the replication logic of our multiple-case study- that is, assessing which cases converge with our emerging theoretical propositions and which diverge- we developed an adapted Sankey diagram in RStudio (*RStudio: Integrated Development Environment for R*, 2023). This visualization allowed us to track case-by-case confirmations and disconfirmations, thereby illustrating the iterative process of theory refinement across cases.

Data tabulation was carried out in Excel, and although the attribution bias scores are originally continuous, we grouped them into ranges (low, medium, and high personalization) to make the visualization clearer and more comprehensible.

For the categorization of the variables Personalization and Intentionality, we applied a fixed-interval range criterion, corresponding to the ordinal classification method with equal intervals. First, we identified the minimum and maximum values of each variable, and then divided the total range into three equal parts, corresponding to the categories Low, Medium, and High.

In the case of Personalization, scores ranged from 2 to 10, with values between 1 and 4 considered low, between 5 and 7 considered medium, and between 8 and 10 considered high. For Intentionality, with scores ranging from 1 to 16, values between 1 and 6 were considered low, between 7 and 11 medium, and between 12 and 16 high.

This procedure allows for a simple and intuitive separation, suitable for descriptive interpretations and comparisons between participants, without the need for more complex statistical calculations (see Table 1).

Table 1. Categorical and Continuous Scores of Attribution Biases and Symptom Severity by Participant

Family	**Role**	**Personalization**	**Categorical**	**Intentionality**	**Categorical**	**Severity**	**Continuous Severity**
Fam1	patient	9	High	16	High	Moderate	1,391304348
	sibling	4	Low	8	Medium	None or Low	0,3043478261
Fam2	patient	8	High	14	High	Moderate	1,695652174
	sibling	3	Low	3	Low	Mild	0,5652173913

Fam3	patient	9	High	10	Medium	High	1,913043478
	sibling	10	High	9	Medium	Moderate	1,391304348
Fam4	patient	6	Medium	8	Medium	Moderate	0,8260869565
	sibling	2	Low	1	Low	Moderate	1
Fam5	patient	8	High	6	Medium	High	2,217391304
	mother	7	Medium	8	Medium	None or Low	0,2173913043
Fam6	patient	8	High	10	Medium	Moderate	0,9565217391
	father	4	Low	2	Low	None or Low	0,2173913043

The Sankey diagram was constructed to visualize the relationship between attribution biases, each case studied, and symptom severity. We designed a three-step Sankey, comprising the origin, intermediaries, and outcome. The origin was represented by the attribution biases analyzed in our study- personalization and intentionality. The intermediaries corresponded to each case, that is, the participants (patients and relatives). Finally, the outcome was represented by the study's endpoint: BPD symptom severity. In this way, the Sankey was built to display the flow of data from attribution biases to participants and then to symptom severity.

Additionally, we determined that the width of the flows between attributions, participants, and symptom severity should represent the numerical scores of each case. This provides a more detailed visualization of the magnitude of the results, as a wider flow corresponds to a higher score in that domain.

The diagram was customized with the exact colors we defined for each type of node, making the visual analysis more intuitive and clear, following (Hehman & Xie, 2021) recommendations. The R package utilized was the RColorBrewer with the Dark2 palette, once it's indicated to categoric variables such as ours and is both colorblind safe and print friendly

(Brewer et al., 2003; *ColorBrewer: Color Advice for Maps*, s. d.; Hehman & Xie, 2021). Furthermore, all cases in the clinical group were represented with one specific color and those in the family group with another. The case that, following the replication logic, disconfirms our theory was represented with a lighter shade.

Results

Study main results

The non-parametric analysis showed a significant difference in the total intentionality degree between patients and family members, $\chi^2(1)=4.410$, $p=0.0357$. Individuals in the BPD group attributed higher intentionality to the vignettes (Mean = 10.67; Median = 10.00), whereas family members showed lower scores (Mean = 5.17; Median = 5.50) (Table 2).

Table 2. Difference in personalization and intentionality between patients and family members (adapted from Marinho et al., 2025a).

	χ^2	**df**	**p**	**ε^2**	**Mean (BPD vs. Family)**
IAVA P	3.169	1	0.0750	0.288	BPD (8) > Family (5)
IAVA I	**4.410**	**1**	**0.0357**	**0.401**	BPD (10.667) > Family (5.167)

Furthermore, linear regression analyses were performed to investigate whether attributional variables predicted symptom severity as a continuous outcome. The model with IAVA P (personalization) explained 39.6% of the variance in BSL scores, $R^2 = 0.396$, and revealed a statistically significant association, $\beta = 0.160$, SE = 0.063, $p = 0.0283$ (Table 3).

Table 3- Linear Regression Analysis of IAVA P predicting BSL Severity (adapted from Marinho et al., 2025a).

Predictor	**Estimate**	**SE**	**t**	**p**	**95% CI**
Intercept	0.016	0.437	0.036	0.9722	[-0.957, 0.988]
IAVA P	**0.160**	**0.063**	**2.563**	**0.0283**	**[0.021, 0.300]**

Visualization Results

Firstly, the diagram (Fig 1) highlights the role of intentionality in differentiating between patients and relatives. By tracing intentionality flows across the different participant types, distinct patterns become visible: patients, for example, show a more prominent flow toward higher levels of intentionality, whereas relatives tend to display greater flow toward lower levels. This visually supports the conclusion that intentionality varies distinctly according to family role.

Secondly, the diagram visualizes the predictive association between personalization and severity: thicker flows toward higher levels of Personalization (in the first column) tend to be associated with substantial flows toward higher severity levels in the last column. This graphical representation illustrates findings identified in the analyses, in which personalization proved to be a significant predictor of symptom severity.

On the other hand, the case of the sibling from Family 4 exemplifies an instance that contradicts our theory, as it refers to a participant who scored low on personalization but nevertheless had a moderate score for symptom severity.

Additionally, the Sankey diagram can be made interactive. By enabling an HTML function, hovering the mouse over a flow displays the exact score for each case, as well as the total sum for each node. This enhances not only the visualization but also the richness of the information conveyed. The interactive version of this visualization is available online at https://osf.io/jv32y/.

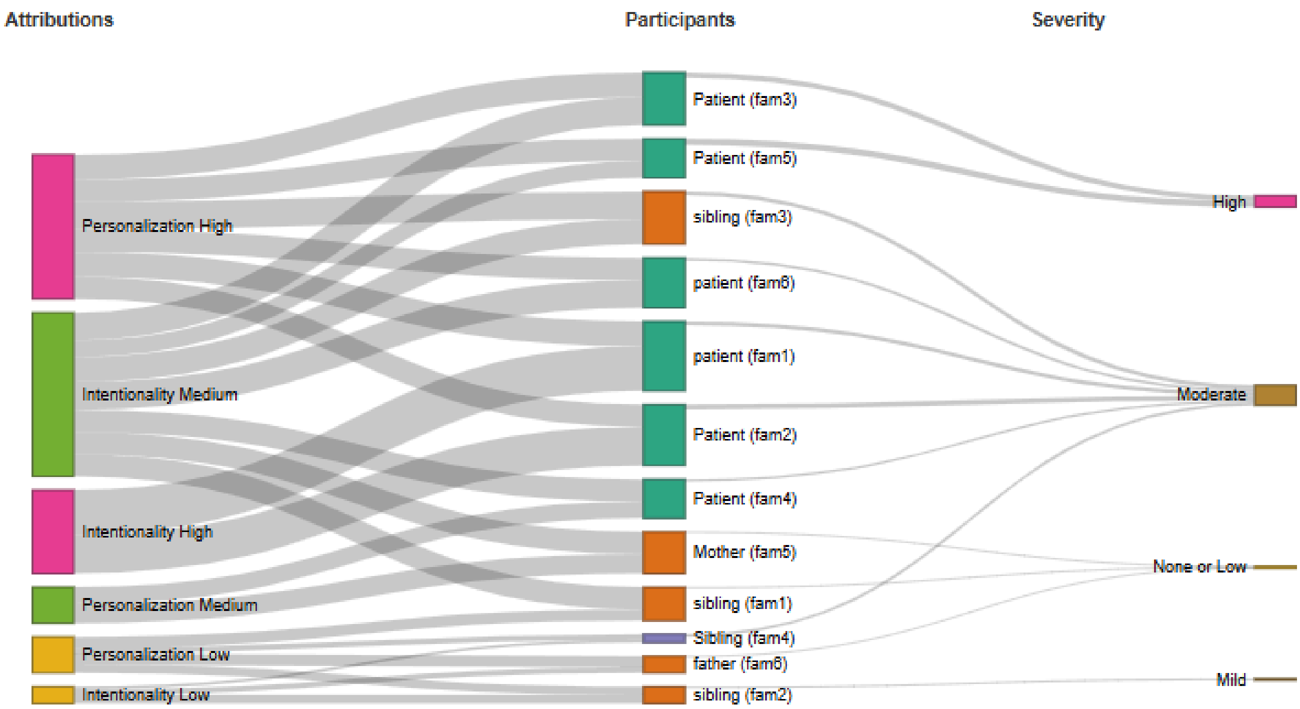

Fig. 1. Sankey Diagram for multiple-case research (Marinho et al., 2025a).

Discussion

In this study, we propose a new approach to data visualization in multiple-case studies, emphasizing replication logic and supporting both intra and cross-case analyses, as well as comparisons between theory and data (Eisenhardt, 2021).

The Sankey diagram proved to be an effective visualization strategy, allowing us to clearly observe the relationship between attribution bias, each individual case, and symptom severity. In this way, the width of the flows, their paths, and the chosen colors make it evident that our quantitative findings were confirmed in eleven cases, thus demonstrating a literal replication of our theory. Conversely, we see that in a single case, our results were contrasted, indicating a theoretical replication of our theory.

If we were to use a tabular visualization strategy to present the same amount of information provided by the Sankey diagram, the result would resemble the example shown in Table 4, constructed based on studies such as Jensen et al. (2023) and Maragno et al. (2023). Although it contains rich information, the presentation is far from intuitive. Data displays composed of numerous lines of text, numbers, and large tables with many rows and columns are generally harder to interpret than visual formats (Gandhi & Pruthi, 2020).

Table 4. Example of a Tabular Display of the Data Represented in the Sankey Diagram.

Family	**Role**	**Personalization**	**Categorical**	**Literal replication**	**Intentionality**	**Categorical**	**Literal replication**	**Severity**	**Continuous Severity**	**Literal replication**
Fam 1	patient	9	High	✓	16	High	✓	Moderate	1,391304348	✓
	sibling	4	Low	✓	8	Medium	✓	None or Low	0,3043478261	✓
Fam 2	patient	8	High	✓	14	High	✓	Moderate	1,695652174	✓
	sibling	3	Low	✓	3	Low	✓	Mild	0,5652173913	✓
Fam 3	patient	9	High	✓	10	Medium	✓	High	1,913043478	✓
	sibling	10	High	✓	9	Medium	✓	Moderate	1,391304348	✓
Fam 4	patient	6	Medium	✓	8	Medium	✓	Moderate	0,8260869565	
	sibling	**2**	**Low**	✖	**1**	**Low**	✓	**Moderate**	**1**	✖
Fam 5	patient	8	High	✓	6	Medium	✓	High	2,217391304	✓
	mother	7	Medium	✓	8	Medium	✓	None or Low	0,2173913043	✓
Fam 6	patient	8	High	✓	10	Medium	✓	Moderate	0,9565217391	✓
	father	4	Low	✓	2	Low	✓	None or Low	0,2173913043	✓

Moreover, the possibility to clearly identify the case that contradicts our quantitative findings enables us to return to the qualitative data and refine our theory. For example, the contrasted case- the sibling from Family 4- may provide important insights into the functioning of attribution bias and symptom severity among relatives. Upon revisiting our transcripts, we noted that this participant was the only one among the twelve to report having completed a postgraduate degree. This observation suggests that education level may play a relevant role in how personalization is manifested.

We may also consider other possibilities that influence our theory. For example, the BSL-23 assesses symptoms present over the last two weeks, whereas attribution biases- although subject to temporary changes (Marinho et al., 2025b)- may be more stable than the symptoms measured by the BSL-23. Additionally, we can revisit the IAVA transcripts and the responses to each individual BSL-23 item, supporting new propositions and further refining the theory.

Finally, with advances in open-source software, computational power, and data visualization science, the ways of visualizing data and the tools available for doing so have improved (Hehman & Xie, 2021). The codes and packages used to build strategies such as the Sankey diagram can be used, reproduced, and adapted. Although a basic understanding of programming was necessary to construct the Sankey presented in this study, there are other online tools- such as Flourish and SankeyArt (*Flourish | Data Visualization & Storytelling*, s. d.; *Sankey editor*, s. d.)- that can be used without prior programming knowledge, albeit with some limitations.

The Sankey diagram also has its limitations. For example, the greater the number of steps, the harder it becomes to achieve a clear interpretation- and case studies, given their complexity, often involve more than two steps. Moreover, in its current form, the diagram does not allow for tracking the flow from the very first to the final node- in this case, from attributions to symptom severity in BPD (Lamer et al., 2020).

Nevertheless, we are aware that this is a descriptive study and that there is still much to explore regarding case studies and their forms of visualization. Case studies can be rich in data, thus requiring constant enhancement in data visualization.

Conclusion

This study proposed a novel approach to data visualization in multiple-case studies, demonstrating how Sankey diagrams can enhance the clarity and interpretability of complex data by emphasizing replication logic across and within cases. Our visualization enabled a more intuitive and immediate understanding of the relationships between attribution bias, case characteristics, and symptom severity, successfully illustrating literal replication in eleven cases and theoretical replication in one. Compared to traditional tabular formats, which often overwhelm with excessive textual and numerical detail, the Sankey diagram allowed for a more accessible and wide view of the findings. This approach not only facilitated pattern recognition but also highlighted exceptions- such as the single contrasting case- which can serve as valuable entry points for refining existing theories. As open-source tools and user-friendly platforms continue to evolve, researchers can increasingly leverage sophisticated visualizations- even without advanced programming skills- to support robust case-based reasoning and theory development. In sum, while this is a descriptive study, it demonstrates the value of innovative visualization methods in making sense of rich, multi-layered case study data. Future research should continue to explore, adapt, and validate these techniques, particularly in fields where theory building from complex datasets is essential.

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