Diagrammatic Modelling Tools for Grounded Theory Research: The Implementation of a Multi-Representational Approach

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Abstract
Grounded Theory (GT) researchers have an ever-expanding palette of digital tools available to further analyse complex phenomena with interrelated data sets. However, few GT researchers have systematically examined how the use of diagramming tools can enhance analysis. To advance the analytical process of GT, this study develops a multi-representational approach that integrates with research design. After diagrams supportive of GT are identified for their potential improvements to the analytical process, the research focuses on the experience of employing three diagramming tools (Flourish, Observable, and Pajek) in developing two complementary diagrams (Network and Arc diagrams). The use of these tools for analysis is explained in detail for conducting extensive constructivist GT study; illustrated via a case study examining a century of innovation in hospital design. Via this multiple-source case study, this paper demonstrates how the sagacious deployment of diagramming tools, when carefully aligned to research objectives, can complement GT analysis by facilitating systematic thinking and holistic interpretation of hidden patterns.

Keywords
mixed grounded theory (MGT), diagrammatic modelling tool, CAQDAS software, systematic thinking, big data analysis

Introduction
Over the last two decades, the fast-paced growth of technology has widely altered the nature of research data and analytical methods. A plethora of well-established Computer Aided Qualitative Data AnalysisS (CAQDAS) software packages has considerably decreased the time-burden of data analysis while increasing overall accuracy (Oswald, 2019; Robins & Eisen, 2017; Woods et al., 2016). This changing landscape has had a considerable impact on the highly data-driven nature of Grounded Theory (GT) methodology (Bryant & Charmaz, 2019). The increasing impetus for addressing complex phenomena and dealing with big data sets has given rise to ‘hybrid mixed grounded theory (MGT)’ research designs, involving new methods of data collection, analysis and interpretation (Bowleg et al., 2016; Constantiou & Kallinikos, 2015; Johnson & Walsh, 2019, p. 13; Mills, 2019). Novel developments in GT research design are not just the result of ‘the enormity of the data’ being analysed, for their emergence also addresses the ‘networked/connected nature’ of data sets (Mills, 2019, p. 2). This innovation has brought unprecedented opportunities for GT researchers, who have been marginalised in the discourse, to advance the analytical process of GT studies exploring complex real-world phenomena.

Diagramming is widely considered a credible approach to actively facilitate the process of making sense of qualitative data and encapsulating fresh concepts (Birks & Mills, 2015; Bryant & Charmaz, 2019; Charmaz, 2014; Gorra, 2019; Mills, 2019). However, the plethora of diagrammatic modelling...
approaches available to researchers can make it difficult for researchers to evaluate their comparative merits and choose the approaches best suited to their work. In recent studies, Ligita et al. (2020) and Buckley and Waring (2013) have clarified the significant role of diagrams, particularly in dealing with a considerable amount of interconnected qualitative data in GT analytical processes. While these authors have strongly suggested that GT researchers should benefit from new digital modelling tools to address the new complexities for the interpretation and presentation of big, networked data analytics, their focus has been limited to a few types of diagrams and commonly used modelling tools. Due to the considerable deficiencies of the modelling tools provided in CAQDAS programs (Friese, 2019; Gorra, 2019; Woods et al., 2016), lack of knowledge about other potential technological tools (Munzner, 2014), and the growth of digital approaches to qualitative analysis (Mills, 2019), it is crucial and urgent to explore the affordance of new research technologies promoting both ‘technical and theoretical efficiency’ of the analysis of many complex phenomena with interrelated data sets (Bowleg et al., 2016, p. 8).

Gorra (2019, p. 321) has recently argued that technology can impact the way GT researchers interact with data sets, and that researchers must ‘find their own way’ of adopting technology in the analysis process. The author believes that the expansion of new tools and software can significantly support the critical process of interacting with and making sense of the data. It is argued that the strongest approach to yield effective results is to augment the use of digital modelling tools with human analysis and interpretation abilities, instead of relying on machines for automated analysis (Barberis Canonico et al., 2018; Baumer et al., 2017; Friese, 2019; Lipton, 2018; Munzner, 2014; Wiedemann & Wiedemann, 2016). Here, specific digital modelling tools provide a wide range of distinct diagrams that can be customised by GT researchers. Some of the key attributes that characterise digital diagramming tools and make them particularly helpful for boosting GT analysis include associability, interactivity, editability, communicability, programmability, and openness (Kallinikos et al., 2013). These unique attributes allow GT researchers to engage with the data, modify the diagrams to fit with the research objectives, investigate the interconnections between concepts from a system approach through iterative adjustments, and discover and confirm the presence of patterns. Although creating hand-drawn diagrams in the early stages of the GT analysis is advised to help researchers interact physically/kinaesthetically with their data and generate preliminary ideas without the limitations of software (Buckley & Waring, 2013; Charmaz, 2012; Ligita et al., 2020), using digital diagramming tools can further the analysis through aiding systematic thinking and developing the reflexivity of GT researchers that leads to a significant increase in the validity of final grounded theory (Charmaz, 2014; Corbin & Strauss, 2014; Kallinikos et al., 2013; Mills, 2019).

The present paper explains how using tools specifically designed for data visualisation offers opportunities to systematically represent as well as explore and identify semantic relations between different concepts through visual analysis. In this paper, the development of a multi-representational approach to advance the process of GT data analysis is discussed. Notably, as GT principally aims to develop theories grounded in data through constant comparison analytical processes, the proposed approach can be used by researchers adopting any school of GT to facilitate analysis and constant interactions with data. In our case study, we used this approach to propose a hybrid research design in the context of a constructivist GT study examining innovation in hospital building design. The approach developed aimed particularly with ‘showing patterns and connections’ (Charmaz, 2006, p. 130) and addressing the question of ‘What is going on here?’ (Charmaz, 2006, p. 24; Swanson & Holton, 2005) within the larger ecosystem of innovations in hospital building design. In this paper, we present our experience of adopting a multi-representational approach to aid systematic thinking to complement a more traditional approach to data analysis.

The prime aim of this paper is to represent a novel multi-representational approach to MGT methodology that gives the GT researcher a significant agency in the development of concepts and relationships while aiding the systematic thinking for enriched interpretations. Three research questions are addressed in the paper: 1) what core values can different types of diagrams add to the GT analysis process? 2) how can we best select the most useful diagrammatic modelling tools and adapt them to research objectives? and 3) how can we construct and actively interpret diagrammatic representations to address a complex phenomenon? Across three stages, we put emphasis on newly established tools, such as open web tools, to enhance the analytical and interpretive process. Recommendations are provided for GT researchers to guide the process of using analytical modelling tools.

**Background**

**Role of Diagramming to Aid GT Analysis**

Due to the fast pace of technological change, big data analysis has gained considerable impetus in generating innovative theories and insights in academic research by both qualitative and quantitative researchers (Jones, 2019; Mills, 2019; Strong, 2014). However, the complex nature of big data analytics is widely considered to challenge traditional methodologies and techniques in theory building and research design, giving rise to novel strategies and tools for the analysis process – such as text mining (extracting relevant information and patterns from unstructured document data), opinion mining (a type of machine learning, analysing (detection, extraction, and quantification) opinions or affect in large textual environments), information and data visualisation (making sense of data and its relations, primarily for the purpose of data exploration),
netnography (integrating big data analytic methods, using big data and digital environments), and multimodal analysis tools (potential spaces for the analysis of large and heterogeneous, digital data sets), etc. (Constantiou & Kallinikos, 2015; Jones, 2019; Mills, 2019, p. 34). Particularly in MGT studies, the adoption of a combination of analytical tools and strategies is widely suggested to creatively probe the data, increase researcher’s sensitivity, and move away from descriptive summation to conceptual explanations of the phenomenon. In this respect, diagramming is known as one of the most effective tools to show the scope and direction of categories and their interactions (Birks & Mills, 2015; Bryant & Charmaz, 2019; Charmaz, 2014; Corbin & Strauss, 2014; Glaser, 2003; Stern, 2007). Diagrams actively assist interpretive GT researchers to re-engage with data, gain ‘analytical distance’ to encapsulate fresh concepts from the chaos of links and codes, and analyse relationships (Birks & Mills, 2019; Buckley & Waring, 2013, p. 152).

Three prime approaches to mapping led to the development of different types of diagrams used in GT studies, namely mind mapping, knowledge mapping, and concept/cognitive mapping (Ligita et al., 2020; Silver & Lewins, 2014). Mind mapping acts as a tool to illustrate the main idea(s) in relation to the thoughts/aspects reflecting them (Buzan, 1995). Knowledge mapping aims to create novel and actionable knowledge through the manipulation/transformation of information (Hall & O’Donnell, 1996). Concept mapping (as conceived byNovak et al. (1984)) and cognitive mapping (as conceived by Eden and Ackermann (1998)) involve several causal or directional links, resulting in more complex diagrams. Concept maps demonstrate meaningful relationships between developed concepts in the form of propositions, whereas cognitive maps model a theoretical approach to solve a difficult problem. Here, Buckley and Waring (2013) represented a variety of diagrams used in GT studies that were developed from different mapping approaches. The authors argued that diagrams play distinct roles at different stages of GT research and proposed several types of diagrams: procedural clarification and articulation diagrams (useful in the early stages to clarify methodological process), diagrams to encapsulate emerging theories (to explore concepts and relationships), draw and write diagrams (to examine patterns), and emergent concept diagrams (to develop the grounded theory). Due to the potential of diagrams in the process of conceptualisation and communicating ideas, further research is needed to enhance their implementation in analysis processes.

**Digital Tools to Create and Engage with Diagrammatic Representations**

Different approaches to the use of technology in GT research have resulted in the development of two different sets of tools under CAQDAS software packages that serve distinct purposes in the analytical process: (1) tools that aim to complement the method by helping the researcher relate words and concepts for technical efficiency; and (2) tools that focus on visual representation to aid in-depth interpretations of data for theoretical efficiency (Bowleg et al., 2016). The frequently used CAQDAS programs (e.g., ATLAS.ti, MAXQDA, and NVivo) largely focus on the application of the first set of tools. Here, it is highly recommended that GT researchers use the analytic options offered by such software (e.g., code co-occurrences, code-document tables/matrixes, and frequency clouds) to help develop theories by linking emerged textual interpretations (Friese, 2019; Olafson et al., 2013; Silver & Lewins, 2014). However, the diagramming tools offered – mind/concept maps and network view – vary little and can limit the capability for alternative interpretations of data. Seven prime deficiencies are identified in relation to the use by researchers of these tools for GT analysis. Woods et al. (2016) found that researchers did not usually use diagrams in data analysis, and only about 10% of researchers used software to visually represent their analytical process and conclusions, indicating that network view and modelling tools are not widely used to add value to the process of theorising conceptual relationships. Second, diagrams generated by using tools such as NVivo and ATLAS.ti were in some cases ‘hybrid’ outputs adapted or converted from other software applications (Ligita et al., 2020; Woods et al., 2016). Third, representing a dense network of linkages for big data analysis requires a large format, yet available network diagrams remain impractical for analysts to consider the whole picture of the relational context (Bringer et al., 2006; Friese, 2016). Fourth, Buckley and Waring (2013) highlighted that while NVivo can aid researchers to make sense of data and create different visual representations, the Microsoft Office diagramming tool was commonly viewed as better by researchers. Fifth, Gorra (2019) and Ligita et al. (2020) pointed out that the learning time and resources GT researchers need, as well as cost containment, have a substantial impact on their choice and use of tools. Sixth, CAQDAS representational tools provide researchers with only static diagrams, in which changes in different parts of the system do not impact the whole system. Last, the literature suggested the use of networks for manually visualising the links between concepts, which do not meet researchers’ interpretive needs and are not ‘yet living up to expectations’ for big data analysis (Friese, 2016, 2019). They provide limited functionality for focusing on organising data and exploring syntactic relations between theoretical concepts through textual analysis.

**Different Types and Features of Diagrams for GT Studies**

The diagrammatical representation a researcher chooses needs to suit their data and research questions and enhance the simultaneous processes of analysis and interpretation (Charmaz,
A set of appropriate diagrams can help GT researchers determine the representation pertinent to the context and data. Suggested in From Data to Vis (2021) is a decision tree based on input data (such as numeric variables, categorical variables, maps, network, and time series) (Figure 1). Given the data format of GT studies (codes, concepts and categories generated by one of the CAQDAS software packages), only diagrams classified in the categorical variables and network groups are examined in this paper because these are commonly the focus of a GT analysis (Buckley & Waring, 2013; Friese, 2019).

The diagrams depicted in Figure 1 are grouped according to the different relationships they can represent. In GT analyses, researchers can describe both hierarchical and non-hierarchical links (e.g., causal relationships) by using diagrams in ‘Flow’ and ‘Part of a whole’ categories. The main features of these diagrams are highlighted in Table 1.

Over the last two decades, these diagrams have been widely adopted in various fields and considered in relation to both quantitative and qualitative approaches. In quantitatively driven analysis, researchers capture and examine the structural properties of diagrams using sophisticated mathematical techniques. Qualitative analysis, though, puts emphasis on the context and content of structures to better interpret different aspects of a phenomenon (Decuypere, 2020; Venturini et al., 2015). The incorporation of these approaches has recently gained the attention of mixed method researchers, as it provides deeper understanding of the ‘story’ and the ideas behind structural properties to address many complex phenomena (Luxton & Sbicca, 2020). Likewise, GT researchers looking for hidden patterns and the meanings of a phenomenon can employ these analyses to examine the interactions between variables within the wider relational composition (Charmaz, 2014; Swanson & Holton, 2005).

While all of the eight aforementioned diagrams can be adopted in the process of GT analysis to visualise relational compositions and interpret the story, the key characteristics of 1) Network for representing the whole system, 2) Sankey for representing causal pathways, 3) Hierarchical Edge Bundling for representing bundled adjacency links, and 4) Arc...
Diagrams for representing sequence of concepts and links make them most applicable for the majority of GT studies. These diagrams can be analysed in terms of ‘why the user needs it, what data is shown, and how the visual representation is designed’ (Munzner, 2014, p. 23). The analytical framework of each diagram, defined by its key characteristics and attributes, informs GT researchers in selecting the best diagram in accordance with their research objectives.

The literature to date has only employed the networked GT approach, focusing mainly on the quantitative techniques of Social Network Analysis (SNA) as a completely separate methodology in research design (e.g., Brailas, 2014; Guzek, Lovrić & Lovrić, 2018; Solhi & Koshkaki, 2016; Sullivan et al., 2019). In other words, qualitative GT has commonly been considered to be only a part of the main sequential mixed methods, whereby GT analysis is widely used to determine concepts and links and SNA is employed to develop categories and examine the structural properties of networks. The sections that follow describe how we have attempted to construct, refine and analyse two diagrammatic representations of data as an integral part of a MGT methodology. Through our complex case study, the use of different diagrams is explained in relation to the required outputs at different stages of the GT analysis.

### Table 1. The Main Features Of Diagrams Useful To GT Research (Author - compiled from From Data to Vis (2021); Observable; RAWGraphs).

| Type of Diagram          | Application                                                                 | Benefits                                                                                     | Drawbacks                                                                                                   |
|-------------------------|------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------|
| Tree-map Circular-packing | To display the hierarchical organisation and the way each entity (higher level) is divided into smaller parts (lower levels); the main nodes of the tree are depicted as sets of nested rectangles/circles, the size of which allow compare values | As tree-maps make efficient use of space, it is appropriate for representing large data sets; circular packing displays the hierarchical ordering better than tree-maps | Tree-maps are able to show less than three levels; the precise comparison between values of circles is not feasible |
| Dendrogram Radial-dendrogram | Tree-like diagrams that represent the distribution of a hierarchical clustering that starts from one node spawning several nodes | Dendrograms illustrate the direct links between nodes in a hierarchical architecture; Radial variant show node-link diagrams with leaf nodes at equal depth is less compact than tidy trees, but are useful for dendrograms, hierarchical clustering and phylogenetic trees | — |
| Sunburst                 | Similar to tree-map, it shows hierarchical structures, but in a radial layout; the main node locates at the centre of a circle with higher levels added as additional rings; numeric values can be included in each section | —                                                                                             | The comparison between sections of rings in relation to their size, particularly outer with inner parts, cannot be accurate; adding labels to leaves and rotated sections is hard that make diagram hard to understand |
| Sankey diagram Alluvial diagrams | To display weighted flows and relationships between a wide range of variables (categorical dimensions); it is useful to depict different stages and links between variables from a start point to the end | The thickness of links and arcs is related to their value | — |
| Network                  | Displaying the interrelationships between nodes                              | The thickness of links and the size of nodes are related to their value; the direction of links can be shown; extra information can be added to each node | A layout algorithm is needed to determine the optimal position of each node |
| Arc diagram              | Displaying the interrelationships between nodes; a special kind of network diagram in which nodes are located along a single axis | It shows the order between categories; there is enough space to show the label of each node; the thickness of arcs is related to their value | Do not provide the overall picture of relationships and nodes like networks |
| Cord diagram             | Displaying the interactions between several nodes by lines in a circular layout | The thickness of arcs is related to their value; eye-catching representation | Not a good representation for large data as it gets cluttered |
| Hierarchical edge bundling | Displaying the interactions between several nodes by arcs in a circular layout using arcs instead of lines | Reducing the visual clutter by bundling the adjacency arcs; useful for large data visualisation | — |
**Case Study: The Implementation of the Multi-Representational Approach**

The data used in this paper to demonstrate the significance of diagramming in the analysis process is from a completed GT study on *Innovation in Hospital Building Design*. Innovation in hospital building design is a complex ecosystem, comprising different forms of interactions between heterogeneous factors that are not mutually exclusive. Here, insufficient understanding of this complexity has been acknowledged as one of the prime critical factors in the shortage of timely design innovations in this field (Sal Moslehian et al., 2022). A holistic understanding of the complex innovation ecosystem evolved through GT analysis using a novel systematic way of constructing and interpreting the interconnections between the very wide range of contextual factors triggering design innovations over the past 100 years (Sal Moslehian, Kocaturk, et al., 2022). Here, the critical contribution is highlighted of the multi-representational approach to the analysis of the interrelated data sets; informing the development of a context-based, explanatory innovation framework grounded in real data that delineates the nature of design innovation.

Our philosophical stance in this case study was derived from the constructivist GT of Charmaz (2014); adopting the interpretivism/constructivism paradigm, we were concerned with values and meanings that people themselves assigned to events, as well as the examination of incidents within a wider relational composition (Charmaz, 2006; Guba & Lincoln, 2005). Critical texts on the historical analysis of the evolution of hospital building design were analysed - largely books examining the events and incidences from different perspectives. The process of content analysis and data collection was conducted concurrently until the categories were sufficiently saturated. The saturation point was recognised after the analysis of the 11th data source (Francis et al. (1999), Willis et al. (2018), Sloane and Sloane (2003), Verderber (2010), Rivett (2017), Wagenaar et al. (2018), Prasad (2008), Schrank and Ekici (2016), Verderber and Fine (2000), Kisacky (2017), and Guenther and Vittori (2013)), when the process of constant comparison yielded to neither new properties of each category nor new conceptual ideation in relation to the nature of design innovation. As a result, we developed 617 connections between 146 codes of different nature; the number of connections for each pair of decades and copying connections for each code ranged from 2 to 29. Considering the plethora of factors classified in several categories, examining the individual and collective impacts of codes (contextual factors) within and across categories was not feasible without the application of different diagrammatic modelling tools.

To support the analysis process, NVivo was used to organise data sets, constantly compare codes and explore both hierarchical and non-hierarchical connections between codes, as well as two diagrams constructed and analysed using three diagrammatic modelling tools. In the following subsections four main stages of the methodology are described with a focus for application in similarly complex studies on the selection and use of diagrammatic representations:

1. In the first stage, the methodological steps, defined by the Charmaz (2014) interpretive GT, were translated to be computer-assisted in line with Friese (2019). This translation informed and facilitated the use of NVivo for initial and focused coding processes.

2. Next, the most appropriate diagrammatic models were identified in accordance with the research objectives. The selection process is explained in relation to the potential improvements added to the GT analysis process. The study started with the use of a Network diagram to facilitate the process of ordering different concepts in correct relation to one another - both horizontally and vertically. Analysing the first three data sets and developing the Network incrementally led to the generation of new ideas and questions, leading to the development of the second diagram (Arc diagram);

3. The next stage describes in detail the use of different diagramming and associated analysis techniques. Explanations are provided for how two complementary methods of analysis were merged into Chramaz’s suggestions for focused coding. Here, different web platforms and open-source programs are introduced and their specific capabilities for GT research are highlighted. Next, the process of adoption and adaption of Flourish studio, Observable, and Pajek is explained through the case study. The imbrication processes taking place due to the interaction of human agency with the digital agency are also described.

4. Diagrammatic representation contributed to the eventual construction of an explanatory innovation framework. At the final step, we interpreted the framework to meet the prime aim of the case study (i.e., who and what played a key role in design innovations, how their interplay triggered design innovation and when the incidents occurred). However, as these explanations are specific to the case, it is beyond the scope of this paper to discuss them. Instead, we provided some recommendations for other grounded theorists trying to make sense of relational compositions in the discussion section.

**Step 1: Data Collection and Coding Process**

To examine the interrelationships between contextual factors triggering innovations in hospital building design, the raw data from the selected texts were imported into NVivo and classified according to the decades in which innovations occurred (by creating separate files for each pair of decades and copying relevant text into them). *Initial open coding*, to look for implicit and explicit factors and their interconnections, started.
immediately after the collection of the first data set (Francis et al. (1999)). We started with pre-structuring the material, using the annotation function to tag the data, allowing quick access to the material for the next stage of analysis. The initial tags were applied to data incidents using line-by-line analysis. Then, via comparing tags to the fresh data incidents, initial codes were generated to cover a broader range of incidents using the coding function. Codes generated at this stage of the analysis were reconsidered for further exploration if they could be combined with other codes, risen to a higher level of conceptualisation, or simply eliminated. At this point, 59 context-specific codes were determined.

Through focused coding, the list of codes was refined and synthesised in relation to new data sets, resulting in the generation of concepts. Having used the coding function, vertical and horizontal analyses of concepts were conducted. Via vertical analysis, codes with similar properties were categorised under the best fit conceptual label, leading to the development of eight categories. In parallel, the interrelatedness of concepts was explored through a horizontal analysis, resulting in 86 links. During the initial and focused coding, analytic memos were created to capture the emergent ideation of theoretical codes in NVivo.

Having connected 91 codes through 190 interrelationships, by conducting the vertical and horizontal analysis for the first two datasets - Francis et al. (1999) and Willis et al. (2018) - using NVivo, we faced the main challenge of this data analysis. While at this stage memos were sorted analytically to make a comparison between concepts, textual analysis was not adequate to describe the several relationships explored. Considering the importance and complicatedness of cross-sectional analysis, utilising an appropriate diagrammatic modelling tool helped organise and make sense of concepts and their linked impacts on design innovations. Here, the network function of NVivo was employed. Based on the relationships discovered during the analysis, interconnecting lines were drawn between the codes to construct a network diagram.

After conducting the analysis for the next dataset using the network graph provided by NVivo, it became evident that creating networks manually was not the most appropriate strategy to make sense of semantic relationships between a wide range of concepts (Brailas, 2014; Solhi & Koshkaki, 2016). Having used the network function of NVivo to depict interactions between various concepts classified in different categories, almost all codes were connected to one another. While a detailed and extensive set of concepts and relationships was necessary to explore and explain how and why a phenomenon occurs, the considerable number of codes made manual networking impossible for relational data. Indeed, it was difficult for the human eye to identify the underlying structure interconnecting codes. This situation was exacerbated after conducting equivalent analyses for the next data sets. To address this problem, and in line with Charmaz’ and Johnson’s recommendations, two complementary analysis techniques and methods were added, namely diagramming and social network analysis (SNA) (Charmaz, 2014; Johnson & Walsh, 2019).

**Step 2: Selection and Creation of Diagrammatical Representations to Support the Analysis Process**

**Generation of relational composition.** To meet code visualisation challenges and address the project objectives, the codes and links defined by the analysis of the first two data sources were imported into a diagrammatic modelling tool. The tool helped build relational composition from codes and their cross-sectional relationships, meaning there was no need for adding nodes into the network one by one. Next, interactions between codes were imported for the rest of the data sets. Representing data in Networks during the focused coding process of 11 data sets in total led to the development of 11 related yet distinct relational compositions. The final innovation network (Figure 2) renders all the interactions related to each factor, facilitating the further analysis of the nature of the ecosystem.

Web-based and open-source license tools can be used to construct free digitally optimised diagrams and one open-source software to analyse Networks. In our case study, Networks were created in the Flourish Studio web tool. Two sets of data were imported into Flourish: a table of ‘Points’ that indicate codes, and a table of ‘Links’ that indicate relationships between codes within and across categories. In the tool: the value of points illustrates the position of each code in the hierarchical ordering, where higher levels of abstraction are given higher-value points; different colours show codes belonging to each category; and directional relationships highlight the way codes have impacted one another.

The diagramming tool allowed us to record design innovations in relation to contextual factors and key code information (such as associated years, key players, design examples, etc.) in the table of Points, and descriptions of the connections between different factors in the table of Links (refer to: https://public.flourish.studio/visualisation/8063689/ to explore the information). Figure 3 represents the contextual factors and interactions between them developed after analysis of the third data source. The tables of Points and Links were revised at this stage and beyond as concepts and relationships developed. This iterative process is inevitable to GT analysis, and is enhanced by digital diagramming able to clearly represent the evolution of a grounded theory from one data set to the next.

**Classification of concepts and links.** GT study aim is to provide new perspectives during the process of data analysis. In our case study, analysing the first three data sets and developing the Network diagram incrementally led to the generation of new ideas and questions, such as the nature of the progression of these relationships over time. That is, the analysis process led to an incremental increase in the
understanding of the nature of design innovation. While the detachment of the Network diagram from chronological conceptions of time helped in the reading of multiple factors at the same time (Miles & Huberman, 2014), it was critical to capture trends based on time as well. To achieve this, we created an Arc diagram, for this is able to represent a wide picture of interactions between concepts within and across categories while indicating the sequence of concepts (Figure 4). Arc diagrams describe interactions between concepts with higher levels of generalisation (called parents) rather than focusing on individual codes (children), and contain both direct and indirect relationships between concepts.

Figure 5 displays a snapshot of Observable, a web-first, collaborative, computational notebook used to create the Arc diagrams in our case study. We used the Observable's ready-to-use (but also editable) visualisation components by finding a pre-published sample in its extensive JavaScript library and forking the provided programming sheet. Data sets were imported to the program via File Attachment. Similar to Network diagrams, to create this diagram, two main sets of data were required: 1) Nodes indicating contextual factors, and 2) Links representing relationships between them within and across categories. With respect to the research problem, analysts can import either the first-degree linked codes of each category, or all the links regardless of their level of generality. In our case study, integrating more specific codes (lower-level concepts in categories) and representing the links between more abstract concepts (higher-level concepts) helped to simplify the interactions between a wide range of factors already represented in the networks (refer to: https://observablehq.com/@researcherhbd/arc-diagram to explore the links).

Step 3: Analysis of Diagrams

Network diagrams. While in-depth knowledge of empirical data is essential for a GT researcher, utilising specific analysis techniques and methods facilitates the process of exploring semantic relations and explaining the phenomenon (Luxton & Sbicca, 2020; Newman, 2003). Here, to creatively analyse and interpret design innovation Networks, and in line with the suggestions of grounded theorists, qualitatively and quantitatively driven techniques of SNA were employed. This level of analysis goes beyond the simple visualisation of relationships in a diagram to an understanding of the underlying structure and the complex interactions within the innovation ecosystem and examines the role of various contextual factors in the whole picture (Borgatti et al., 2018; Scott, 2017).

In our case study, we used Pajek, an open-source software, to visualise and compute the structural properties of the Network diagrams, in line with De Nooy et al. (2018). All the codes and links generated after analysing each data source were imported to Pajek. Here, three datasets were needed: 1) a list of codes and relations (called Network); 2) a list of
codes and associated categories (Partition); and 3) a list of code values in relation to their level of abstraction in the category (Vector). To create the Network diagram, Pajek uses different force-driven algorithms to give meaning to the disposition of nodes based on the links among them (Burt, 1992; Panetti et al., 2019). In our case study, we used the Louvian algorithm to reach the best balance of constant interactions between forces of attraction and repulsion between codes (Blondel et al., 2008; Newman, 2004). Once the networks were constructed, some of their statistical properties were analysed in accordance with our research objectives. Here, three prime variables of the network structure (centrality measures, subgroup measures, and cohesion measures) were computed. In parallel, the nature of ties was qualitatively examined based on the memos and annotations. Table 2 represents the research objectives and associated analysis metrics.

In our case study, we considered innovation as a systemic and evolutionary process that destabilises one state of the network and opens a new process of self-organisation leading to a new stable state. Thereby, as the analysis of each data source introduced new contextual factors and relationships (based on the main thesis of each book and their specific temporal and geographic scope), the structure of the network changed, and in turn, our understanding of the nature of design innovation evolved. Notably, analysing the chronology of transformations of those relational compositions indicated the importance of using grounded theory methodology to accumulate an understanding of a complex phenomenon like innovation in hospital building design.

**Arc diagrams.** Figure 4 represents about 540 interactions between 78 unique contextual factors within and across categories while indicating the sequence of concepts. Analysis of several prime characteristics and attributes of Arc diagrams added to our understanding of this complex picture: 1) the total number of arcs incoming to and
outgoing from each code indicated the importance of that factor at each time bracket; 2) the presence of the grey arcs connecting similar codes across different decades indicated constant impacts of factors over a long period of time; 3) the absence of grey arcs over the time brackets previous to each concept indicated when a concept emerged; and 4) the total number of contextual factors and associated links in each time bracket was easily discernible.

**Step 4: Interpretation and Narrative Explanation of the Phenomenon**

The knowledge acquired from the diagrammatic analyses led to the construction of the ultimate goal, namely an explanatory innovation framework. A narrative interpretation was provided to address: who and what played a key role in design innovations, how their interplay triggered design innovation and when the incidents occurred by considering the position of inhabitants of the innovation ecosystem, as well as intensity, direction, and the number of ties between them. The knowledge elucidated the properties of multi-faceted processes triggering design innovations via an explanatory framework that spans ecosystems. Thus, the whole of the relational compositions of the Network and Arc diagrams shaped and enabled understanding of how design innovations have occurred.

The relational understanding gained from the combined use of Network and Arc diagrams allowed us to interpret data at a level that would be impossible to describe without them. Commencing with NVivo for open coding and then developing these diagrams made feasible the analysis of 617 interactions between 146 codes. As GT researchers, we moved iteratively between the qualitative data (codes, categories, memos and annotations), Network and Arc diagrams, and the measurements of network structural properties to further explore the semantic relationships acquired from the initial and focused coding processes. Thus, the understanding deducted from the diagrammatic analysis was built on top of the information obtained from reading each data source. The following subsection discusses the learnings gained from our complex case study for the construction and development process of using the Network and Arc diagrams.

**Discussion**

While GT methodology offers a set of well-structured strategies, it is important to be creative in choosing how to indicate relationships between concepts during the analytical process. This study, in line with the suggestion of Johnson and Walsh (2019), developed a novel hybrid research design to MGT, which expands the possibility of alternative interpretations for
complex and interrelated data sets. The proposed multi-representational approach enables a discovery process and promotes systematic and systemic thinking, advancing the process of grounded theorising.

As Friese (2019) has discussed, learning the various features of software does not necessarily result in selecting the best tool for a particular methodological framework. To address this problem, we have explicated how selection and adoption can be undertaken in relation to research objectives, and how systematic interventions at different stages of analysis can complement commonly used methodologies and techniques. This process can be followed both to further explore different dynamics of complex phenomena (for long-term use in an explanatory analysis) and, more importantly, to support the use of big and networked data in developing theories and insights in GT studies. As illustrated by our case study, the specific properties of in-motion Network and Arc diagrams can enhance GT analysis in the following ways:

Network Diagrams

1. Networks represent codes/concepts as well as vertical and horizontal links related to each code and provide a two-dimensional layout of the overall structure regardless of chronological patterns. Indeed, connections are demonstrated at specific sorts of times/places that are not confined to temporal/physical understandings of spatiality. This feature helps develop relational compositions that go beyond the simple identification of main categories by examining interactions between factors regardless of time and place.

2. Networks facilitate the discovery of patterns within a wider relational composition. Seeing these patterns detail reveals relationships that are hidden when simply recording factors and links.

3. Using network diagrams increases the possibility of searching and selecting certain components, thus...
helping researchers overcome the limitations of cognition and memory.

(4) The qualitatively and quantitatively driven techniques provided by SNA help quantify qualitative codes, explore hidden patterns, and prompt new questions about the data. In our case study, analysing the form and structural properties of networks revealed: 1) the most influential factors in the design innovation process; 2) the most interrelated contextual factors; and 3) the cohesion and density of the innovation ecosystem, helping us understand the system behaviour.

(5) For us, understanding the topology and structural properties of networks helped identify who and what played a role in a complex design innovation ecosystem, and the nature of the relationships between these actors. Our experience proved the use of two functions of Network diagrams defined by Decuyper (2020, p. 13): an ‘explorative function’ (by which we scrutinised how the phenomenon was composed, providing new insights for the analytical process), and a ‘narrative function’ (by which we constructed particular narratives of the formed networks).

**Arc diagrams**

(1) Arc diagrams represent the interplay between codes/concepts within and across categories by considering chronology as the second variable. Their use demonstrated both the most influential contextual factors at each decade and the critical role of some factors with constant influence on the structural formation of the process. The aim was to explore what happened when.

(2) Researchers might use this diagram to display the interplay between parents with higher levels of generalisation rather than focusing on individual nodes. We used this specific feature to reduce the inevitable clutter generated in the networks and examine the interplay between more abstract concepts.

(3) An interactivity changing display provided by most web-based tools facilitates the analysis of big datasets. The GT researcher can interact with the visual representation to change the view to explore different aspects and levels of the dataset (from very detailed information to the structural overview of relationships). In the arc diagrams, for example, putting the cursor on each concept highlighted all the links related to that node.

While there has recently been a slight growth in studies investigating digital agency and automation for GT analysis (Nelson, 2020), in the approach we have described the researcher has greater agency in the development of concepts, inclusion/exclusion of codes, the hierarchical positioning of codes within categories, and making horizontal connections between codes across categories. Moreover, unlike the existing literature employing quantitatively driven techniques of SNA to detect categories and functional concepts, the Network diagram can be used to represent the interrelationships and categories already developed through the initial and focused coding process, and to compute the structural properties of the final network to explain and interpret hidden patterns. In this, as Gorra (2019); Paulus et al. (2017) argued, it is critical to consider the significant position of research methodology over software functionality, even in the analysis of big data. The aim should be to address complex phenomena and leverage the big data analysis through the development of a human-centered approach that bridges the limitations of computer capacities, human perceptual and cognitive capabilities, and display capacities by keeping both human and computational decision-making methods in the analysis loop (Barberis Canonico et al., 2018; Lipton, 2018; Munzner, 2014).

We recommend that GT researchers consider the research objectives they wish to address before selecting the most appropriate diagrammatic representation/s. Given the vast array of dissemination digital tools and growing availability of complex interconnected data, the most appropriate use and mix of tools might be unique to the research problem at hand. As it is critical for GT researchers to work smoothly with different functions of a tool to manage, manipulate and analyse data, checking the accessibility, time, cost, editability, openness and communicability of a tool is crucial before conducting the research. Due to significant time saving involved in the process of using web-based platforms, GT researchers without coding skills can easily select a specific diagram, upload their data into predefined spaces, and customise the visualisation options. Although, researchers still need to use professional tools for quantitative analyses. To this end, it is worth highlighting that GT researchers with limited programming skills or related technical know-how can benefit from many online free tutorials to conduct analyses in professional programs, such as for Pajek. Further, we, in line with Davidson et al. (2016), suggest that vibrant communities of GT researchers from different disciplines should be created to support each other in working with an increasing range of computer-assisted analysis tools.

It should be stressed that we have not delineated the process followed in our case study of refinement and synthesis of concepts, and the categorisations of codes. For the prime point here was to highlight the process of selecting a combination of diagrams in relation to study aims, and in doing so make an argument for the key role of diagrams in addressing research challenges. Further, following this representational approach is limited to big data analyses focusing on one type of relationship between codes. In our case study, for instance, the causalities between codes were demonstrated via directional links.
Conclusion and Recommendations

Diagrammatic visualisations facilitate thinking in non-linear ways, promote researcher scrutiny and aid the analysis process by precisely and concisely representing what GT researchers do and do not know. While the GT methodology has considerably evolved in the past decade, the use of diagrammatical representations has remained an area of unexplored potential for the development of theory. This paper described a multi-representational approach to MGT that enables the human GT researcher to use digital tools to transcend the constraints of human analysis and digital tools abilities, resulting in enhanced visualisation, creativity, advanced analysis, enriched interpretation, and emergence of transparency in addressing complex phenomena.

Due to the various advantages of the diagrammatic representations discussed, GT researchers need to wisely select the most appropriate type of diagram, or a combination of graphs, to the research objectives to advance the analytical and interpretative capabilities necessary to conduct sound qualitative research. Notably, diagrams and the tools chosen to create them must build on and complement each other during the process of data analysis.

Finally, as research design is commonly seen to be a reflexive process reshaping through different stages of a qualitative study, we encourage researchers to build upon and extend the research designs we have provided based on their specific research objectives. Moreover, this new approach to GT analysis supports the need for advancing qualitative research methodology in relation to the growing use of big data. Future research might examine the process of GT analysis using a combination of other diagrammatical representations related to specific research objectives. Moreover, a diagrammatic modelling tool that concurrently explores different relationships in one diagram might be developed.

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