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ENHANCING DOCTORAL DISSERTATIONS WITH DATA VISUALIZATION – GUIDELINES AND FRAMEWORK DEVELOPMENT

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ABSTRACT

Aim/Purpose	To develop a framework aimed at effectively including data visualization in writing doctoral dissertation documents. Typical doctoral dissertation documents are divided into chapters and sections. Suggestions for the sections that are deemed more helpful to include visualized data are provided in this paper. The suggestions are going to be provided in a framework presentation.
Background	Presenting information visually in research writing has advantages if they are done correctly. If done incorrectly, including data visualization in research documents may be detrimental to what is written. In doctoral dissertations, this takes special importance as the students strive for correctness in all sections of their dissertation including when comprising visual elements.
Methodology	The paper reviews the literature on the issue of data visualization and includes them in different sections of the doctoral dissertation. It provides suggestions for the inclusion of data visualization elements in sections of the doctoral dissertation document. The suggestions are based on a developed framework named Data Visualization Framework (or DVL-FW).
Contribution	The contribution of this paper is that it provides guidelines that can be used as a reference for doctoral students on how to strengthen the dissertation sections by including data visualization that is more effective in delivering the intended messages. The data visualization can contribute to enhancing the

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	writing of the section in particular and to writing and completing the dissertation document in general.
Findings	This paper is intended to be used by mentors or advisors of doctoral dissertations when they guide their students in writing a dissertation document. Students can include effective visual components into their dissertation document provided they are done correctly. Visualizing data (or including data visualization) in a doctoral dissertation can be effective and it can contribute to the clarity of the dissertation document.
Recommendations for Practitioners	Practicing the inclusion of data visualization adds value to the dissertation document and will contribute to making the document more convincing. Mentors or advisors can use information from this paper to provide suggestions for effectively adding visual elements to dissertation documents and can pass the information to their students.
Recommendations for Researchers	The psychology of visual elements and their addition to research can be discussed in follow-up research studies to strengthen the findings of this paper here.
Impact on Society	The findings of this research aim to help doctoral mentors/advisors when they supervise their students in writing doctoral dissertation documents. It can also be used by doctoral students when they write their dissertation documents.
Keywords	data visualization, data visualization and doctoral dissertation, visual literacy and doctoral dissertation

INTRODUCTION

Data visualization is a topic that has been widely discussed in numerous research studies (McCrudden & Rapp, 2017; Zhao & Gaschler, 2022). In the simplest form, data visualization refers to using visual elements (such as charts, graphs, plots, matrixes, and others) to replace (or add to) text in research writing (Azzouzi, 2024; Noorain, 2024). We call these visual elements that can be placed in research studies "Visual objects". The inclusion of visual objects in a document can serve various purposes, such as, but not limited to, adding clarity to the text, convincing the reader of certain points, and highlighting characteristics of certain textual information included in the research.

It is important to note that for the intended purpose to be served, the inclusion of visual objects must be done correctly and properly (Börner et al., 2019; Hidayah, 2023). If done improperly, the inclusion of visual elements could be detrimental to the writing (Bresciani & Eppler, 2015). It could confuse the readers; it could give different messages than what is intended for the reader, and it could also give a negative impression about the author of the article (Cairo, 2019). This applies to writing doctoral dissertation documents as much as to any other document.

Doctoral students as part of completing their terminal degrees, have to write and complete a dissertation document. The dissertation document is typically divided into specific chapters and sections. The sections and chapters could vary in terms of their requirements for textual and visual information. However, in certain sections, writers can take advantage of including visual objects more than others (Biljon & Renaud, 2015). Students writing doctoral dissertations have to follow certain rules and adhere to guidelines in the inclusion of visual objects in their documents. Without adherence to these guidelines, including these visual elements may negatively affect the writing of the dissertation (Schöpfel et al., 2016).

This paper develops a framework that suggests the effective inclusion of visual objects in doctoral dissertation documents. It delves deeper into the steps that need to be followed to help secure the correct inclusion of visual objects in doctoral dissertations. Given the potential benefits that visual

objects provide and considering the underutilization (Midway, 2020; Verdinelli & Scagnoli, 2013) of visual display in research, the goal is to provide suggestions for correctly including visual objects in sections of doctoral dissertation documents.

The remainder of this paper is divided into the following:

- First, it reviews the literature about data visualization and its inclusion in research writing in general and in doctoral dissertation documents in particular
- Second, it explains the framework that is followed in this paper to reach the final recommendation
- Third, it provides a discussion of the sections that we deem more helpful to include data visual objects of the dissertation document.
- Fourth, it draws conclusions and suggestions for future research.

LITERATURE REVIEW

This section provides a review of the literature for the topics that are relevant to this paper to give clarification and background information to the issues that are being discussed here. In particular, the literature review includes coverage in the following sequence:

- About data visualization to clarify the terms and background information we deemed necessary to understand the remaining sections of this writing
- Theories of data visualization that provide suggestions for correctly placing dissertation objects in research writing
- The benefits that can be gained from the inclusion of visual objects in research writing in particular
- The persuasive value that data visualization potentially offers in writing
- The pitfalls of data visualization that likely make it detrimental to add visual objects
- About dissertation documents and dissertation writing and the sections that data visualization is typically included in

ABOUT DATA VISUALIZATION

In the simplest terms, data visualization in research writing refers to the inclusion of visual objects (such as graphs, plots, and matrices) to add to written text, replace written text, or supplement the written materials (Parsons, 2021; Unwin, 2020). Data visualization is not something new. Document writing (whether printed or digital) has included a lot of visual objects since the early days of research writing. The difference now is the extent to which data visualization is used in research. This significant increase in the inclusion of data visualization is attributed mainly to three factors:

- The staggering increase in the volume of data exchanged digitally or in printed format (Pedota, 2023)
- The ease at which data visualization objects are generated (Börner et al., 2019)
- The increase in visual literacy (Franconeri et al., 2021; Newfield, 2011) and Visual competency (Pauwels, 2008) among the public in general

Regarding the rate increase of data exchange, it is no secret that data is everywhere nowadays. The volume of data exchanged over the Internet (E-Commerce, social media, and others) is staggering. This is more clarified in the introduction of new terms to measure data capacity. Experts in this field keep introducing new terms to describe the staggering volume of data (whether storage, processing, or data exchange) being used. This volume of data is often described with five words that start with the letter V: Volume, Velocity, Variety, Veracity, and Value to describe a new field of study in big data analysis (Beerkens, 2021; Monino, 2021). These words are called the 5 V's of big data (Keskar et al., 2020).

The staggering volume of electronic data exchanged nowadays is growing at an astonishing rate. Data storage and processing hardware capacities have drastically increased to accommodate this increase in data volume. As a result, several new terms were introduced to describe recent storage and processing capacities including petabyte, exabyte, zettabyte, and others. The latest name of the storage device is zettabyte which is used these days to describe data volumes (Lynch, 2023). Zettabyte is written with 21 zeros to the right of the first comma in the number. This term with that many zeros is called sextillion and Spetillion (Fleming, 2024) – another new term introduced to describe staggering data volume. There is little doubt that this new term of zettabyte will be replaced with another name with more zeros to the right of the comma to describe another level of large data volume (Hofmann, 2017).

The term Velocity is used to describe the speed of data exchange. Again, this is no secret that data is being exchanged and processed at a very rapid rate and this rate is increasing. The speed of processing data is helpful depending on the quality and accuracy of the data exchanges (Samadi, 2022). This velocity of data exchange is necessary to help with the timely presentation of data analysis. The word Veracity is used here to describe the quality and accuracy of data exchange (Maseeh, 2023; Samadi, 2022). There has to be a mechanism to help ensure or maintain the accuracy of this volume of data generated so the result of analysis will be accurate too. Added to this, the different formats that are exchanged add another dimension to the exchange of data. Naming a few formats, data exchange can include text, audio, video, multimedia and other similar formats. This kind of diverse format poses a challenge to understanding and analyzing them. This latest description is explained through the word "Variety" of data exchanged over the Internet (Pedota, 2023).

Perhaps, the most relevant term among the 5 V's here is the word "Value". After seeing the overwhelming volume of data exchanged, there was a realization that there was a value that could be gained from this volume of data. However, the large volume of data has to be presented in different ways, in a more meaningful way to simplify understanding them. This led to the increasing need for data analysis and also for data visualization. Instead of presenting the data in row format or tabulating them, the data can be presented visually to show trends, summaries, directions, or other formats to help get value from this staggering volume of data (Monino, 2021).

Numerous tools were developed and used to help the creation of visual objects. Initially, data visualization was included in specialized packages such as SPSS and SAS, and there were specialized visualization software tools (Beerkens, 2021) like Microsoft Visio and Publisher. The creation of these tools to create visual objects went a long way. Nowadays, users can find these tools embedded in productivity software such as Word, Excel, and PowerPoint.

A quick look at the charts group in Microsoft Excel reveals the following objects that can be drawn in a typical spreadsheet document: column chart, line or area chart, pie chart, hierarchy chart, statistics chart, scatter diagram, waterfall funnel, maps, and so on. UniversalCPAreview (n.d.) lists many data visualization types, including waterfall chart scatter plots, bubble charts, Pareto charts, area charts, Gantt charts, treemap charts, geography charts, column charts, bar charts, line charts, pyramid charts, funnel charts, and many others. Taking another look at MS Word the WordArt group discloses a long list of categories that can be used for the creation of visual objects, such as hierarchy charts, Venn diagrams, pyramid charts, matrices, and many other similar tools.

The point here is the plethora of tools available to create, maintain, and include visual objects in research writing. This also led to increased understanding and knowledge of data visualization. This latest increase in knowledge is termed visual literacy or visual competency (Börner et al., 2019). The obvious advantage of these tools is the visual representation of data. This representation then results in an increased understanding of the data, better analysis and evaluation of the data, along an increased emphasis on ethical use of the data (Nair, 2024).

Including visual objects in a research document used to be an arduous task. It used to take enormous steps to collect the data, feed them into the input devices, and go through numerous steps to

generate simple output from given data (Zhao & Gaschler, 2022). Qualitative data had the same difficulty. Analyzing a passage and drawing a chart used to be challenging. That has changed over the past decade or so. Drawing something like a hierarchy chart or word map, for example, is now accomplished quickly (Lanters & Fantke, 2018).

There is a tendency often to refer to quantitative data when talking about data visualization. In other words, some may think about plotting numbers only when talking about data visualization. However, qualitative data can be visualized too. A quick look at Microsoft's "SmartArt" category shows numerous tools that can visualize qualitative data. In this paper, we use the term "Data Visualization" to refer to both qualitative and quantitative data. Most people interpret images better than they do words, that is images are often considered a more effective method of communication than text (Onwuegbuzie & Dickinson, 2008).

The developments that were discussed here (increase in data volume, the 5 V's, the simplification of visualization software, and the increase in visual literacy) have contributed to the development of a new field of study and a new term called "big data analytics" or "data science" which focus on finding meaning from the large volumes of data. Two other terms are introduced in this context: Information Visualization and Knowledge Visualization (Ahmed, 2024).

Information Visualization and Knowledge Visualization

The discussion in this paper thus far has focused on the meaning and development of data visualization. However, other similar terms are introduced in this field. A study conducted by Fadiran et al. (2018) introduced the term "Knowledge Visualization," which is the ability to use visual objects for the creation and dissemination of knowledge. Kavaz, et al. (2023) discussed "Information Visualization" as the practice of using visual aids to represent data in a way that's easy to understand. It was, according to Kavaz, et al., the natural result of an increase in the volume of data and the need to extract more helpful information from it.

If we follow the basic classification in the study of database management, we know that raw data consists of unprocessed facts, figures, or symbols that, on their own, lack meaning and context. When this raw data is organized, structured, or contextualized, it becomes information—data that is now meaningful and relevant, answering questions like who, what, where, and when. However, information alone does not result in understanding or application. Knowledge arises when information is processed, interpreted, and combined with experience and insights, allowing us to understand how and why something happens. Essentially, raw data transforms into information through context, and then information becomes knowledge through comprehension and application (The discussion thus far has focused on the meaning and development of data visualization The discussion has focused on the meaning and development of data visualization (Skender & Manevska, 2022).

This analogy can also apply to the visualization of data, information, and knowledge. The first level involves visualizing raw data (like numbers) to identify patterns, trends, summaries, outliers, and other key insights. Moving beyond this, the data can be combined with qualitative visualizations and guided by specific rules to help people understand the information at a broader level. This is what we call 'knowledge visualization.' While the distinctions between the three levels—data, information, and knowledge—are not always clear-cut, it's important to recognize these differences for effective visualization (Börner et al., 2019).

Figure 1 visually explains the transition from data to information, from information to knowledge, and from knowledge to wisdom, which is the pinnacle of the triangle. In this example, raw data is the appearance of a red traffic light; information is the processing of data to conclude that the traffic light is red, as opposed to yellow or green; knowledge is the understanding that one must come to a stop when they see a red light at a traffic light. And finally, wisdom is applying the brakes to bring the vehicle to a stop.

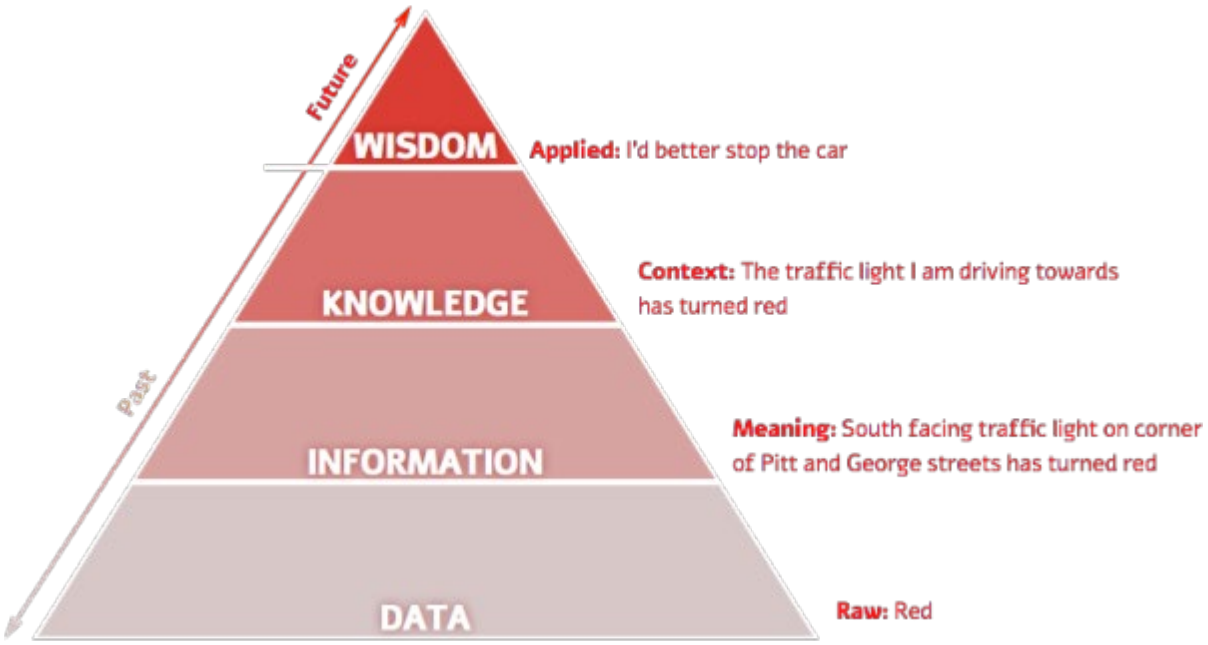

Figure 1 - Hierarchy of Data_Visualization (Mushon, 2014)

In this paper, we use these three terms (data visualization, information visualization, and knowledge visualization) interchangeably. More than the other two terms, we used the term "Data visualization" to mean any or all the three terms. But to help understand this further and to add some guidelines to effectively adding data visualization objects, we need to shed light on some theoretical backgrounds that guide these concepts. This leads us to the study of the theories of data visualization.

Theories on Data Visualization

Emerging practices usually begin without clear guidelines, evolving organically as they gain traction. Over time, as these practices become widespread, theories and guidelines emerge, consolidating findings into coherent frameworks that offer new insights or predictive power beyond existing models. As a practice, data visualization can be traced back to the early days of primitive maps and tally marks for record keeping (Hofmann, 2017). Over time, theories have developed to establish best practices for effectively designing and utilizing visualization objects, ensuring clarity, accuracy, and meaningful data representation (Kumar, 2024).

Nowadays, there are numerous theories of data visualization tools and applications, spanning multiple disciplines, including statistics, cognitive science, graphic design, human-computer interaction and real-time analytics (Midway, 2020). They shape best practices for designing effective, engaging, and ethical visualizations. Whether rooted in perception, statistics, design, interaction, or ethics, these theories provide a framework for making data more accessible and insightful (Chen et al., 2020). Here, we will cover only two of these throes: the 5C's and the Golden Rules of Data Visualization.

The 5 C's of data visualization

The 5 C's of Data Visualization provide a structured approach to creating effective and meaningful visual representations of data. These principles help ensure that visualizations communicate insights clearly and engage the audience effectively (Ahmed, 2024). The 5 C's are Clean, Consistent, Conformed, Current and Comprehensive. They are discussed below:

- **Clean:** Remove unnecessary elements, such as excessive labels, gridlines, and colors, to enhance the clarity and focus of the visual. Cluttered visuals can overwhelm the audience,

making it difficult to extract meaningful insights. Using white space effectively and maintaining a simple, well-structured design ensures that the data remains the primary focus. Clean visualizations also minimize distractions and improve readability, making them more effective for communication (Biljon & Renaud, 2015).

- **Consistent:** Consistent visualization maintains uniformity in design elements, such as colors, fonts, scales, and formats, across multiple charts and dashboards. This consistency ensures that users can easily compare and interpret data without confusion (Nguyen et al., 2021). For example, using the same color to represent a category across different visualizations prevents misinterpretation. Consistency also builds trust in the data, as audiences can recognize patterns and relationships more intuitively (Few, 2009).
- **Conformed:** A conformed visualization aligns data with predefined standards, categories, and structures to enable accurate comparisons. This means ensuring that similar data points are measured and displayed in the same way, avoiding inconsistencies in labeling or formatting. For instance, sales figures from different regions should follow the same currency and units to maintain comparability. Conformed data visualization ensures coherence across datasets, supporting more reliable analysis (Kimball & Ross, 2013).
- **Current:** A current visualization reflects the most recent and relevant data to support timely decision-making. Outdated or stale data can lead to incorrect conclusions and missed opportunities. Ensuring that visualizations update dynamically or are refreshed at appropriate intervals helps maintain their usefulness. In fast-moving industries, real-time or near-real-time data visualization is crucial for tracking trends and making informed decisions (Murray, 2013).
- **Comprehensive:** A comprehensive visualization presents all essential data points and context needed for a complete understanding without overwhelming the audience. It balances detail and simplicity by including key insights while avoiding unnecessary complexity (Cairo, 2016). For example, a dashboard should provide an overview of performance metrics while allowing deeper exploration if needed. A well-structured, comprehensive visualization ensures that users gain actionable insights without getting lost in excessive data (Segel & Heer, 2010).

The Golden Rules of Data Visualization

The golden rules of data visualization refer to suggestions that enhance the chances of effectively achieving the intended purpose by including data visualization. They include four suggestions: Build for a targeted audience; Select the right method; Use proper labels and colors; and keep it simple. Figure 2 shows these data visualization rules.

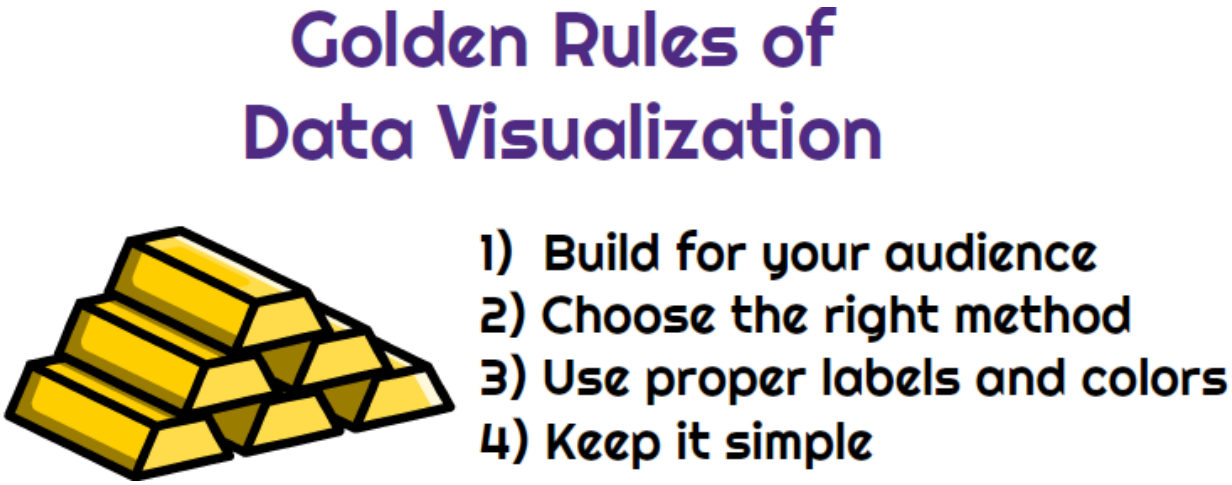

Figure 2 – The Golden Rules of Data Visualization (UniversalCPAreview, n.d.)

- **Build for a targeted audience:** Data Visualization should be tailored to the needs and expertise of its intended audience (Savage et al., 2014). For example, a financial dashboard for executives should highlight key performance indicators (KPIs) in an easy-to-read format, while a report for data analysts might include raw figures and detailed trends. If the content were swapped, in other words, if raw figures and details were presented to executives, this could result in information overload, and loss of focus on strategy (Similarly, if high-level KPIs were presented to analysts, the analysts may miss important trends, anomalies, or inefficiencies that could otherwise be addressed). Understanding one's audience could help make the visualization both engaging and actionable (Kelleher & Wagener, 2011; Khasnabish et al., 2020).
- **Select the right method:** Choosing the appropriate visualization method is crucial to effectively convey information. The key question to ask is: What type of visualization best represents the data being presented? In many cases, multiple visualization techniques may be suitable, but the best choice depends on the nature of the data and the message being communicated (Bredbenner, 2021). For example, pie charts are useful for displaying proportions within a dataset, such as demographic distributions, percentage-based spending, or gender ratios in a population (Zhao & Gaschler, 2022). Selecting the right visualization enhances clarity, facilitates comprehension, and ensures that key insights are effectively communicated (Hubbe & Millan, 2023).
- **Use proper labels and colors:** Proper labeling and color selection are essential for clarity and readability. While intricacies of color theory are beyond the scope of this paper, research highlights the importance of legibility, readability, and color coordination both within the visualization and in relation to the overall document (Stone, 2006). Poorly chosen colors or ambiguous labels can create confusion, misinterpretation, and cognitive strain. Thoughtful color choices, clear axis labels, and meaningful legends contribute to a more intuitive and accessible visualization (Fadiran et al., 2018; Stone, 2006).
- **Keep it simple:** Perhaps the most important principle of effective visualization is simplicity. A common rule of thumb is to keep it simple, ensuring that the visual representation remains clear and focused on the core message. Unnecessary complexity can obscure key insights, confuse the audience, and reduce the overall effectiveness of the visualization. Simplicity does not mean omitting critical details; rather, it involves presenting information in a way that aligns with the audience's needs and avoids unnecessary distractions (Bredbenner, 2021). The concept of the "lowest common denominator of knowledge" applies here—visualizations may be designed to align with the foundational understanding shared within a particular field, ensuring accessibility without oversimplification (Few, 2009).

DATA VISUALIZATION ADVANTAGES

Biljon and Renaud (2015) described "Visualization", in general terms and suggested data visualization could serve as a powerful communication mechanism. The communication mechanism here refers to explaining ideas, in formats other than text format. We use the "visual objects" to refer to the representation of data in a visual format. The purpose of including visual objects in research could include the following:

Enhancing understanding

The saying "A picture is worth a thousand words" suggests that viewers can often grasp a message more effectively through an image than by reading an extensive description. In the context of data visualization, we adapt this idea to say, "A chart is worth a thousand data points." This means that a well-designed chart allows readers to quickly perceive patterns, classifications, trends, and structures more intuitively than if they were to examine raw data or follow detailed procedural steps (Hockley, 2008).

The two images in Figure 3 illustrate this concept. The image on the left presents a chart, demonstrating how raw data is better illustrated in tabular form. The image on the right provides the same data visualized by a line graph overlayed on a bar chart. This immediately conveys the overall trends and relationships, interpreting far easier than scanning through a dense table of numbers (Azzouzi, 2024).

This enhanced comprehension is not limited to charts alone—it applies to various forms of visual representation, including images, plots, and infographics. Visual elements can either replace raw data or complement textual explanations, reinforcing the material being presented. This phenomenon, known as the Picture Superiority Effect, highlights how visual representations improve retention and understanding compared to text or numerical data alone (Hockley, 2008).

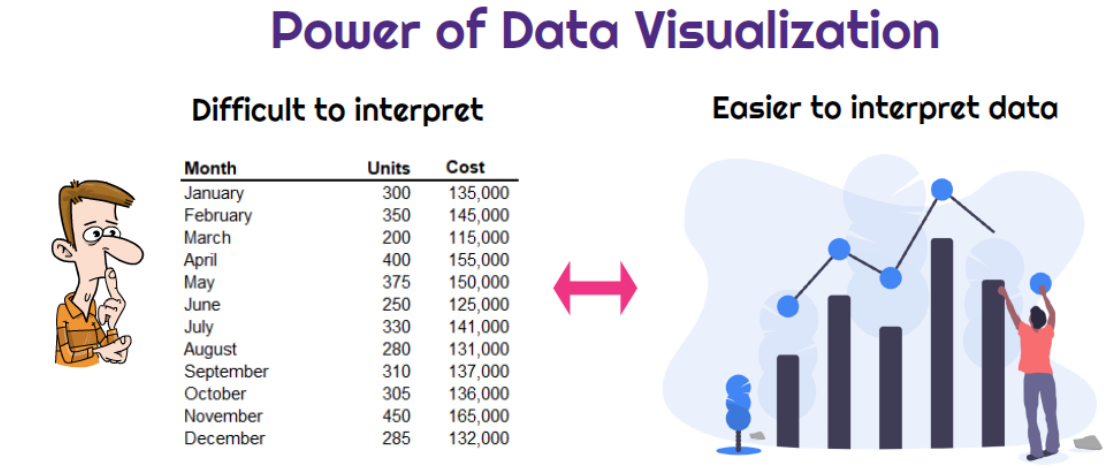

Figure 3 – The Power of Data Visualization (**UniversalCPAreview, n.d.)**

Focusing attention

It has been known for some time that text (especially long text) does not always effectively work to get the attention of readers. Instead, text typically if long may make it boring to follow and as a result, it may drive the audience away from reading the text. A better strategy to grab attention is through including visual elements. Visual elements can work to get the attention of the readers and may lead to improving the chance of approving the presented information (Schraw & Richmond, 2022).

Visual objects help with focusing attention which is termed "pre-attentive processing" (Shander, 2016). Take things that catch attention, such as a red flag, a blinking light, or a big image. Attention can be drawn to other related objects. If that visual object is supplemented with other explanatory text, it may even work better to deliver the intended message.

Conveying complex ideas more effectively

Complex ideas cannot always be explained just through text. Instead, it can be broken down, illustrated, and further clarified through visual objects. Complex ideas can be further clarified through something that the human mind can relate more to and that is visual objects. It is known that the human brain can be drawn to visual objects earlier than text. This plays a bigger role in complex ideas when it involves multiple steps and different illustrations that are connected or linked to each other. In these cases, the ideas are better explained through visual objects or by combining them with text (McCrudden & Rapp, 2017).

Making communication more engaging

Visual aids make communication more engaging and effective than plain text. Instead of relying solely on lengthy text, incorporating meaningful images can enhance comprehension and retention

(Reimers & Harvey, 2024). Research shows that our brains process images more efficiently than words, a phenomenon known as the picture superiority effect. This occurs because when we see an image, we encode it both visually and verbally, strengthening memory and recall (Hubbe & Millan, 2023). Combining words and visuals such as pictures, diagrams, and graphics increases engagement. Providing two different representations of the information, both visual and verbal, to help students understand the information better (Hockley, 2008).

The Persuasive Messages of Data Visualization

When someone reads a long, text-heavy document, they are likely to lose interest quickly. To make the content more engaging, incorporating visual elements can be more effective (. More importantly, visuals often communicate messages more persuasively than text alone. Unlike plain text, visual objects bring a sense of liveliness to the content, making the message more compelling and easier to understand. This is because visual displays inherently engage the audience, enhancing both attention and retention (Pandey et al., 2014).

Figure 4 illustrates this concept by presenting a line chart that depicts a downward trend in a data series. Such a trend is difficult to convey effectively through text or tables alone. In this case, the image not only enhances comprehension but also strengthens the persuasive impact of the message. According to the picture superiority effect (Markant et al., 2022), readers are naturally drawn to images first, allowing them to grasp key insights at a glance.

Figure 4: The Persuasive Message of Data Visualization (Falkowitz, 2019)

The Pitfalls of Data Visualization

While incorporating visual elements in research documents offers significant benefits, there are also potential pitfalls. Improper use of visual objects can lead to confusion or even annoyance for readers (Cairo, 2019). Bresciani and Eppler (2015) emphasize this point, noting that experts in the field agree that poorly integrated visuals can detract from the reading experience rather than enhance it.

McCrudden and Rapp (2017) further explained that humans react differently to visual elements based on their design. When visuals are well-designed, they facilitate engagement, making it easier for viewers to interpret the intended message. However, ineffective visual design can create confusion, making it difficult for readers to understand the content and discouraging them from engaging with the material (Bresciani & Eppler, 2015; Krok, 2021).

This raises an important question: What constitutes an effective use of visual communication? Various theories, concepts, and guidelines contribute to best practices in visual integration. Earlier in this

paper we introduced two key frameworks: the **5 C's** and the **Golden Rules of Data Visualization**. These will serve as reference points throughout our discussion.

About Doctoral Dissertation Document

Doctoral students (or students enrolled in doctoral programs) are required to complete a document that represents the culmination of their research study. The document typically is lengthy and completing it is faced with different challenges and typically represents a first-time publishing by the student. A dissertation document characteristically is divided into named chapters and sections that the students adhere to and follow in their writing (Ali et al., 2024). The student has to successfully defend the dissertation document with a committee of educators or experts. Without these two steps (completing the dissertation document and defending the dissertation) the students cannot complete the degree requirements and will not add the "Dr." title. Instead, the student has to be content with what is called ABD or "All But Dissertation".

Some of the sections in the dissertation document require a show of data to deliver a clearer message. In these cases, it will be helpful to use data visualization to get the points across more effectively. We identified five sections in the dissertation document that could help with presenting more data and also with data visualization. These sections include:

- The problem statement section in Chapter One
- The conceptual model in Chapter One
- Chapter two about the literature review
- Introducing participants' demographic information after data collection
- The final result of the dissertation finding

Research Methodology

This paper followed the approach that is endorsed by Börner et al. (2019) when designing the typology of data visualization learning framework (DVL-FW). The framework is intended to provide helpful information for categories of data. Figure 5 shows a copy of this typology with seven columns. These seven columns of the DVL-FW framework are explained in the following:

Column one is about insight needs or what is the purpose (or insight) that needs to be visualized. For example, if the purpose is to sort or tank, this combined with other factors can lead to suggesting a visual object – A chart

Column two selected data scales, the type of data under consideration

Column three is about analysis, what type of analysis is followed in this case

Column four is the suggested visualization by this framework

Column five determines the graphical symbol (Details of the graph) to be used in the suggested graph

Column six suggests the graphical variables, which are the details of the variables in the suggested graph

Colum seven suggests the method of interaction, or how the data are extracted for this suggested chart

Table 1. Typology of the DVL-FW

Insight needs	Data scales	Analyses	Visualizations	Graphic symbols	Graphic variables	Interactions
Categorize/cluster	Nominal	Statistical	Table	Geometric symbols	Spatial	Zoom
Order, rank, sort	Ordinal	Temporal	Chart	Point	Position	Search and locate
Distributions (also outliers)	Interval	Geospatial	Graph	Line	Retinal	Filter
Comparisons	Ratio	Topical	Map	Area	Form	Details on demand
Trends (process and time)		Relational	Tree	Surface	Color	History
Geospatial			Network	Volume	Optics	Extract
Compositions (also of text)				Linguistic symbols	Motion	Link and brush
Correlations/relationships				Text		Projection
				Numerals		Distortion
				Punctuation marks		
				Pictorial symbols		
				Images		
				Icons		
				Statistical glyphs		

Figure 5 - the Typology of Visual Literacy (Börner et al., 2019)

As can be seen from presenting the DVL-FW, it requires some information to suggest the type of visualization, the graphic symbol, and the interactions. However. Some columns do not apply to this research. For example, we do not intend to provide suggestions about the symbols, graphic variables, or interactions, instead, our study focuses on similar information that is presented in the first four columns of the DVL-FW framework. Thus, we modified the original framework to take out the columns that are not needed in this study. Our modified version of the typology contains four columns and is presented in Table 1 below. In column one, we list the section of the doctoral dissertation document that we suggested including the visualization object. Column two, notes the type of analysis that is typically practiced in this section. Column three suggests the visualization object that we suggest based on our discussion and findings. The last column (column four) lists any additional information we deem necessary to be presented to clarify the inclusion of the visual object in the listed section of the dissertation document.

Table 1 –Empty Framework of Data Visualization in Doctoral Dissertation to Be Completed

DISSERTATION SECTION	ANALYSIS	VISUALIZATION OBJECT	NOTES
Problem statement			
Conceptual framework			
Literature review planning			
Demographics section			
Final section			

DISCUSSION AND FINDINGS

This section provides a discussion of the literature that was reviewed to introduce recommendations about what type of visualization objects to be included in the sections that were discussed earlier. We take three steps in explaining each of the sections we identified earlier.

- We first explain the section to show some understanding of it
- We discuss how the section can be helped by including data visualization
- Later, we suggest some data visualization tools that can help the section discussion

- At the end of this section, we give our suggestions for the inclusion of visual objects following the guidelines in the sections of the 5 C's and the Golden Rules sections that were discussed earlier in the literature review.

A point to be noted here is that our suggestions of visual objects to include are based on our experience and searching Google images. A better way to find more suitable visual objects is to search Google's images (https://images.google.com/) and many images can be found.

Visualization in the Problem Statement

The problem statement section is in the first chapter of the doctoral dissertation document. In it, the student explains the problem that the dissertation document is working on. Two points are particular to this section. The problem statement has to be explained in terms of a cause-and-effect relationship, that is there is a cause and effect to the problem being studied (Ali & Pandya, 2021). A common diagram that describes this cause and effect is the Fishbone Diagram. Figure 6 shows an example of the fishbone diagram which gives room for identifying multiple causes for an effect.

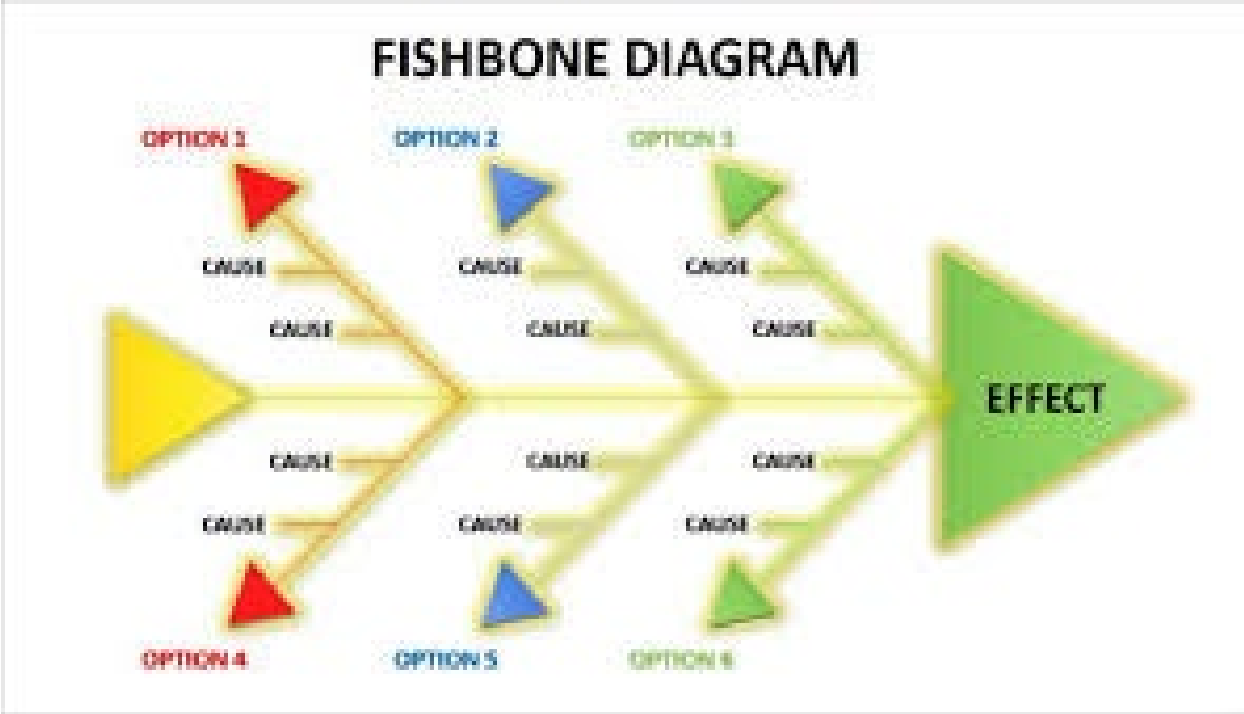

Figure 6: Isakawa Diagram - Cause and Effect Model (Kajal, 2022)

The researcher may need to convincingly articulate the problem. One of the effective ways to achieve this is by providing supporting data. A particularly compelling method is visualizing historical data using charts, with line charts being especially effective. Among the various sections of a dissertation, the problem statement often requires the most persuasion, as it must demonstrate that the issue under investigation is both significant and research-worthy (Ali & Pandya, 2021).

To strengthen this argument, visual representation plays a crucial role. A well-designed line chart can effectively illustrate historical trends, making it easier for readers to grasp the progression and magnitude of the problem over time. When presenting numerical data, line charts offer a clear and intuitive way to highlight patterns, fluctuations, or emerging concerns, reinforcing the necessity of the research (Divecha et al., 2023).

VISUALIZATION OF THE CONCEPTUAL MODEL

The Conceptual Model section of a dissertation is designed to structure the research findings into distinct components, often referred to as constructs. This section provides a conceptual framework—an "empty shell" or blueprint—illustrating the anticipated structure of the final research outcome (Ali et al., 2024).

A strong starting point for this section is a hierarchy chart, which visually organizes the different constructs. Conceptual models can be represented using various formats, including hierarchical structures, relationship diagrams, pyramids, and other similar visualizations. In this case, we have chosen a hierarchy chart to depict a widely recognized conceptual model in doctoral dissertations: the Unified Theory of Acceptance and Use of Technology (UTAUT). Figure 7 presents a visual representation of the UTAUT model.

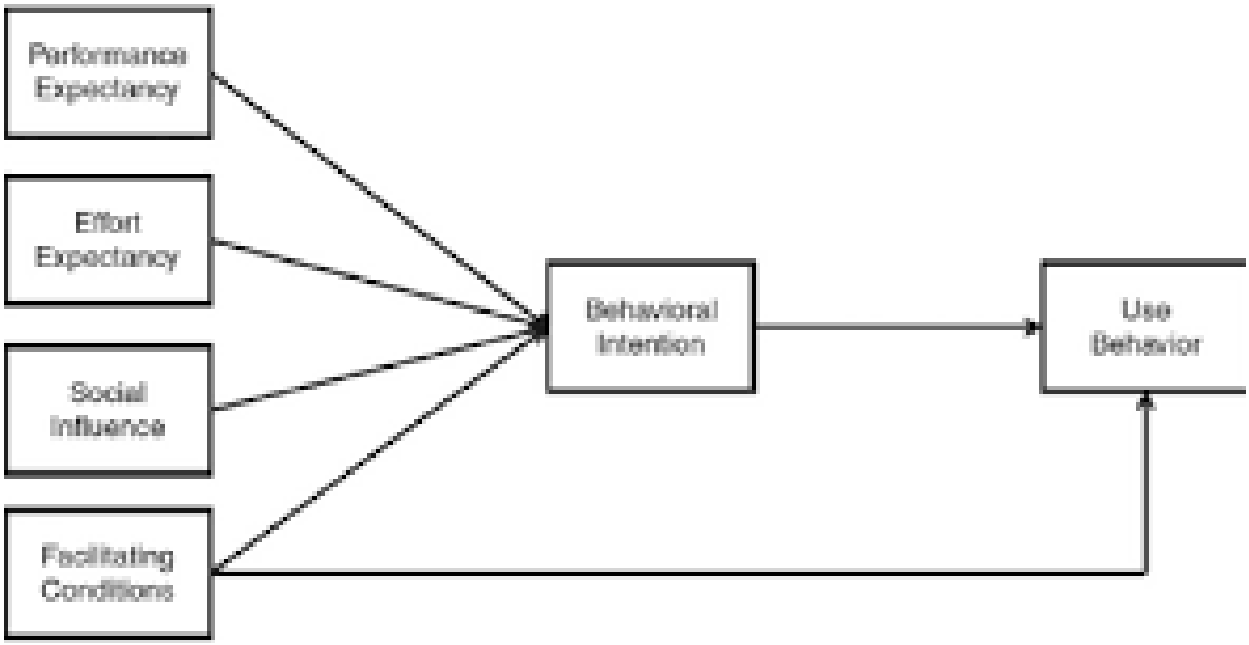

Figure 7: Visualization of the conceptual model, Example of UTAUT (Venkatesh et al., 2003)

The UTAUT model is widely used in research and doctoral dissertations (Chakraborty & Al Rashdi, 2018). Each of the rectangle shapes in Figure 7 represents a construct. The main purpose of the UTAUT model is to provide a framework that helps to determine the factors that influence the use of new technology. Figure 7 shows the first four constructs that influence behavioral intentions and then the behavior of the users of the new technology. The point to clarify here is that the model contains constructs and the purpose of the conceptual model in the doctoral dissertation is to determine how each of the constructs are influenced. Thus, some hierarchy may need to be followed here. We suggest including the hierarchy chart to help explain the conceptual model that the dissertation document is using.

VISUALIZATION IN THE CHAPTER OF LITERATURE REVIEW

According to Ali et al. (2022), the literature review chapter is a very time-consuming chapter of a dissertation. One reason for this is its open-ended structure—unlike other chapters, it does not follow a predefined format. Two key points could be included to clarify at the outset. First, the literature review is cyclical. It is not a linear or one-step process but rather involves continuous refinement and iteration. Figure 8 illustrates the cyclical nature of the literature review.

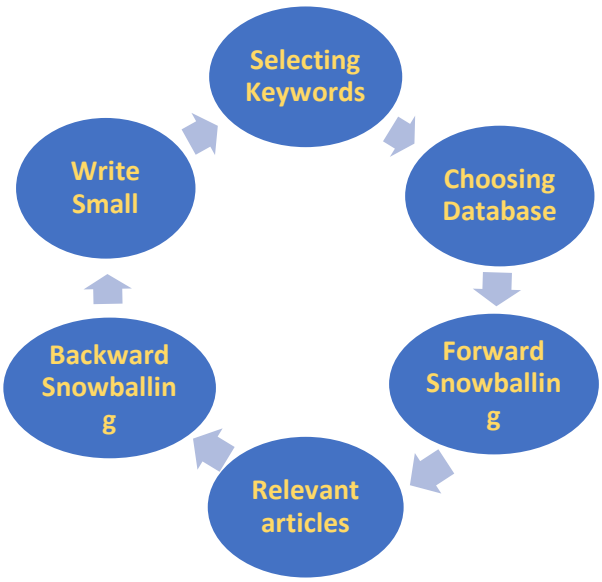

Figure 8: The Cyclical Nature of Literature Review (Ali et al., 2022)

Second, while the literature review follows a cyclical process, distinct steps can still be identified. Figure 9 presents a visual representation that helps explain the structured approach to planning a literature review.

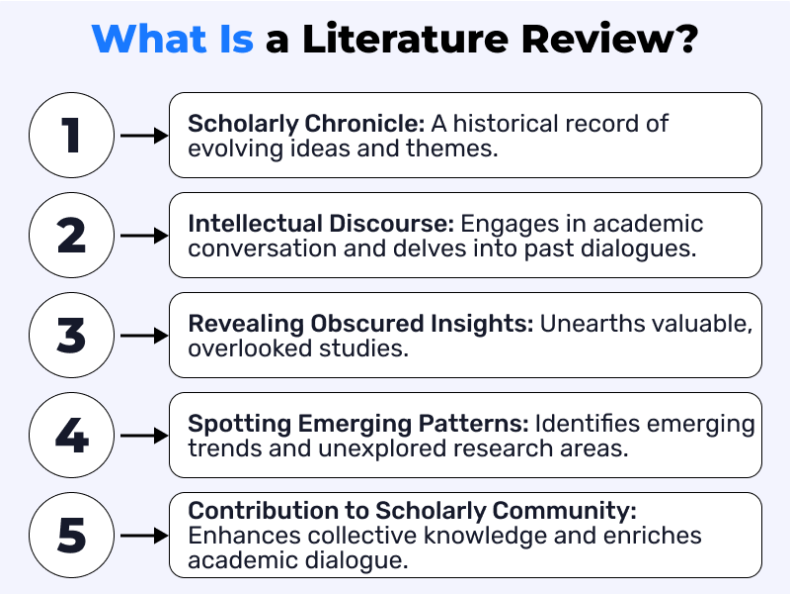

Figure 9: Literature review planning (Gunbold, 2024)

The Demographics Section in Chapter 4

In data collection, demographic questions are often included to provide insights into participants' backgrounds and highlight the diversity within the dataset. When presenting demographic data visually, the choice of chart depends on the level of detail required. For a simple demographic breakdown, a pie chart is an effective tool, as it clearly illustrates the proportion of each group relative to the whole. However, for a more detailed demographic representation, a doughnut chart can be more useful, as it allows for additional data to be incorporated while maintaining clarity (Hill, 2024).

The Final Section of the Dissertation

The final section represents the final findings of the research. It represents what was achieved based on the conceptual model that was planned in Chapter One. A new drawing of the conceptual model drawn in Chapter One will be reasonable, after filling in the different sections of the chart. A relationship chart may help also to establish the final view of the different components of the research.

Application of the 5 C's

We recommend following all the 5 C's guidelines that were discussed earlier. However, we recommend paying more attention to the consistency of the image being plotted. Consistency not only in the image being drawn itself but between the image being drawn and the other sections, with the section of the research purpose and research questions. This consistency plays a crucial point in solidifying the explanation of the problem and then paving the way for a more solid understanding of other sections in the dissertation document (Ali et al., 2023).

Application of the Golden Rules

The four golden rules presented earlier in this paper may need to be applied here as well. Below is a brief description of each rule and its proper application:

Targeted Audience: The primary audience for a dissertation is the dissertation committee, particularly during the dissertation defense. It is reasonable to assume that committee members have prior knowledge of the topic and are familiar with the requirements for writing a dissertation. However, there is also the possibility that the dissertation will be published, making it the student's first academic publication. The post-publication audience could include future students, researchers, or anyone referencing the work for review or citation.

While identifying the target audience may seem straightforward, it contrasts with the approach used for visualizations designed for a broad audience. In academic writing, visual elements should be tailored to enhance comprehension without oversimplifying complex ideas.

Choosing the right visualization method: As discussed in previous sections, selecting the appropriate visualization method is essential for effectively presenting information. When making this choice, students may need to ask themselves: *What type of visualization best represents the data or concept being conveyed?* (Bredbenner, 2021)

In many cases, multiple visualization options may be suitable. While personal preference plays a role, adherence to best practices—such as the 5 C's of effective visualization—could help ensure clarity and consistency.

Appropriate Use of Colors and Labels: The selection of colors and labels is another important consideration. While this paper does not delve into detailed color theory, research highlights key principles for effective color design, emphasizing legibility, readability, and harmony between visual elements and the document as a whole (Stone, 2006). Thoughtful color choices can enhance data interpretation, while poor color selection may lead to confusion or misrepresentation.

Keeping it Simple: The principle of "Keep it simple" is widely recognized in communication and design. In academic contexts, this means focusing on a single topic without introducing unnecessary complexity. Overcomplicating a visualization or including excessive details can obscure the key message, potentially confusing rather than clarifying the subject matter (Bredbenner, 2021). Keeping visuals concise and well-structured ensures that they effectively support the dissertation's arguments without overwhelming the reader.

CONCLUSION

After the discussion, we can list the following table to provide guidelines for including data visualization in doctoral dissertations. In the first column, we list the section/chapter of the dissertation document that we deem that visualization is helpful. The second column tells whether the data presented in the row are more likely to be qualitative or qualitative. The third column is our suggested visual objects to show the data. This is based on the discussion and findings we had in the previous section of this paper. The fourth and last columns show additional notes that we deemed helpful in the decision to select a data visualization object.

Table 2: A Framework for Including Data Visualization Objects in Dissertation Documents

DISSERTATION SECTION	ANALYSIS	VISUALIZATION OBJECT	NOTES
Problem statement	Quantitative	Fishbone diagram	Consistency with research purpose and research questions to be emphasized
Conceptual framework	Qualitative	Hierarchy chart	Understanding the constructs and how to outline the steps in the circular fashion that represents it.
Literature review planning	Qualitative	Circular object like text cycle or block cycle Also listing the steps or outline of the steps	A clear outline of the steps to be followed need to be explained here
Demographics section	Quantitative	A pie chart or doughnut chart	This depends on the level of detail presented in the demographic data
Final section	Qualitative	Similar to the hierarchy chart	It follows the same format as what was drawn in the explanation of the conceptual model, but with filled information

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