DATA VISUALIZATION PITFALLS: A SYSTEMATIC REVIEW

by

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ABSTRACT

DATA VISUALIZATION PITFALLS: A SYSTEMATIC REVIEW

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The purpose of this systematic review is to identify and analyze common pitfalls in data visualization techniques across various domains. By comprehensively synthesizing existing literature, this study aims to provide insights into the challenges and shortcomings encountered in the creation, interpretation, and communication of visual representations of data.

A systematic approach is employed to gather and analyze relevant literature from peer-reviewed journals, conference proceedings, and scholarly books. The search strategy encompasses keywords related to data visualization, pitfalls, challenges, and best practices. Inclusion and exclusion criteria are established to ensure the selection of high-quality studies. Data extraction and synthesis are conducted to identify recurring themes, patterns, and critical insights regarding data visualization pitfalls.

The findings reveal a plethora of pitfalls encountered in data visualization practices, including but not limited to misleading visualizations, ineffective use of color and design principles, misrepresentation of data, cognitive biases, and technological limitations. These pitfalls are observed across various stages of the visualization process, from data preparation and selection of visualization techniques to interpretation and communication of visualized information.

This systematic review contributes to the understanding of the challenges inherent in data visualization and highlights the importance of addressing these pitfalls to enhance the effectiveness and reliability of visual data communication. The insights gained from this study can inform practitioners, researchers, and decision-makers about the potential pitfalls to avoid and best practices to adopt when creating and interpreting data visualizations.

The systematic review underscores the complexity and multidimensionality of data visualization pitfalls, emphasizing the need for interdisciplinary approaches to address them

effectively. Despite the advancements in data visualization technology and methodologies, the persistence of common pitfalls necessitates ongoing vigilance and critical evaluation in the design and implementation of visualizations. Furthermore, the study emphasizes the importance of education and training in data visualization to mitigate these pitfalls and promote data literacy among stakeholders.

While efforts have been made to ensure the comprehensiveness and rigor of this systematic review, certain limitations exist. The scope of the review may not encompass all potential pitfalls in data visualization, and the findings may be influenced by publication bias or limitations inherent in the selected studies. Additionally, the evolving nature of data visualization techniques and technologies may render some findings outdated over time.

Based on the findings of this systematic review, recommendations are provided for future research endeavors. These include the development of standardized guidelines and best practices for data visualization, the integration of interactive and immersive visualization technologies, and the exploration of novel approaches to mitigate cognitive biases and improve the accessibility of visualized information. Further research is warranted to investigate the efficacy of interventions aimed at addressing specific pitfalls and to assess the long-term impact of improved data visualization practices on decision-making and knowledge dissemination.

KEY WORDS

Data visualization, Pitfalls, Challenges, Best practices, Misleading visualizations, Color usage, Design principles, Data representation, Cognitive biases, Technological limitations

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CHAPTER I

INTRODUCTION

The act of transforming complicated information into easily understandable graphical representations is made possible by data visualisation, which is a vital tool in the decision-making processes of the current day. Nevertheless, in the middle of the increasing dependence on data visualisation, it is of the utmost importance to recognize the possible dangers that have the potential to jeopardize the truth, clarity, and integrity of the information that is visualised. In light of the fact that businesses are increasingly relying on data to drive strategic initiatives, it is of the utmost significance to comprehend and avoid these potential hazards. As a basic study into the similar issues and weaknesses experienced across numerous domains, including but not limited to corporate analytics, scientific research, and public policy, a systematic examination of data visualisation hazards serves as a foundational exploration. An in-depth investigation is being conducted with the purpose of shedding light on the many intricacies that are inherent in the process of creating, interpreting, and disseminating visual data representations. (Heer, J., & Agrawala, M. 2006) The purpose of this study is to uncover repeating themes and patterns within the landscape of data visualisation hazards. This will be accomplished by synthesising the available literature and empirical information about the topic. An extensive and diverse spectrum of possible problems exists, ranging from the incorrect interpretation of graphical features to the introduction of biases during the process of data collection and presentation. The increasing availability of data visualisation tools and platforms raises the possibility of unintentionally spreading information that is either inaccurate or misleading. The purpose of this study is to provide practitioners, researchers, and decision-makers with the information and insights required to efficiently traverse the complex landscape of data visualisation. This will be accomplished by a methodical and comprehensive examination. This will allow stakeholders to adopt educated strategies that will improve the accuracy, transparency, and usefulness of visualised data. This will be accomplished by promoting a greater awareness of frequent problems and the underlying causes of those errors. As a cornerstone for improving best practices in data visualisation, allowing informed decision-making processes, and ultimately promoting greater trust and confidence in the insights that are obtained from visualised data, this systematic review serves as an essential component. In light of the fact that the quantity and complexity of datasets are continuing to increase, it is becoming more important to conduct careful inspections and critical assessments of the many methodologies that are used for data visualisation.

1.1 Research Problem

The choice that a researcher will make about the technique of research that they will choose is impacted by a variety of different elements. The viewpoint of the researcher who is conducting the study, the nature of the subject matter that is being researched, the present state of scientific research and ideas, and the context in which the relevance of the problem is formed are all examples of these types of factors. When attempting to validate a hypothesis or investigate the elements that impact a result, a quantitative approach is often the most effective strategy to apply. When these data were taken into consideration, a quantitative approach was proposed as a potential technique of inquiry. (Steele, J., & Iliinsky, N. 2010)

1.2 Purpose of Research

The purpose of this systematic review is multifaceted. Firstly, it aims to critically assess existing literature on data visualization pitfalls to identify common challenges, errors, and misconceptions encountered in the field. Secondly, it seeks to categorize and analyze these pitfalls systematically, providing a comprehensive framework for understanding their origins and implications. Additionally, the review aims to highlight the potential consequences of these pitfalls on data interpretation, decision-making processes, and overall data-driven insights. By synthesizing and organizing this information, the research aims to contribute to the development of best practices and guidelines for effective data visualization, ultimately enhancing the clarity, accuracy, and impact of visual representations in various domains.

1.3 Significance of the Study

This systematic review holds significant implications for both academia and practical applications. Firstly, by identifying and categorizing common pitfalls in data visualization, the study provides valuable insights for researchers, educators, and practitioners in the field of data science, statistics, and information visualization. It serves as a comprehensive resource for understanding the limitations and challenges associated with visual data representation, enabling scholars to develop more robust methodologies and tools for data analysis and presentation. Moreover, the findings of this study have practical implications for various industries and sectors reliant on data-driven decision-making processes, such as business, healthcare, finance, and public policy. By raising awareness of potential pitfalls and their consequences, the research empowers professionals to critically evaluate and improve their data visualization practices, ultimately enhancing the quality and reliability of insights derived from visual data representations. Furthermore, the study contributes to advancing the broader conversation on data literacy and communication by promoting greater awareness and understanding of the complexities inherent in visualizing data, thereby fostering more informed and effective communication of information to diverse audiences.

1.4 Research Purpose and Questions

Research Purpose:

The primary purpose of this systematic review is to comprehensively investigate and analyze the common pitfalls encountered in data visualization practices. By systematically reviewing existing literature, the study aims to identify, categorize, and understand the various challenges, errors, and misconceptions associated with visualizing data across different domains. Through this process, the research seeks to provide insights into the origins and implications of these pitfalls, ultimately contributing to the development of best practices and guidelines for effective data visualization.

1.5 Research Questions:

1) What are the common pitfalls encountered in data visualization across different domains and contexts?
2) What are the underlying causes or origins of these pitfalls?
3) How do these pitfalls impact data interpretation, decision-making processes, and overall data-driven insights?
4) Are there any patterns or trends in the types of pitfalls identified?

5) What strategies or approaches can be employed to mitigate or avoid these pitfalls in data visualization practices?

1.6 Identifying and Mitigating Risks in Data Visualization Practices"

Data visualisation has emerged as an essential component of efficient communication and decision-making in our age, which is characterised by the exponential expansion of data and the democratisation of tools for data analytics. Visual representations come in a wide variety of formats, including interactive dashboards and dynamic infographics, and each of these forms plays an important part in communicating insights, easing understanding, and encouraging interaction among a variety of various audiences. (Hullman, J., & Diakopoulos, N. 2011) It is possible that the dissemination of disinformation or misunderstanding might occur as a result of the seduction of visually attractive images and the urge to simplify complicated statistics. As a consequence of this, the landscape of data visualisation is rife with potential dangers that pose a threat to the integrity and effectiveness of the information that is visualised.The purpose of this systematic study is to shed light on the many ways in which visual representations may distort, conceal, or misrepresent underlying data patterns. This review will attempt to throw a critical eye on these potential problems. As varied as they are insidious, the possible hazards range from the subtle subtleties of colour choice and scale selection to the more overt dangers of cherry-picking data or missing critical contextual information. The potential pitfalls provide a wide range of opportunities for error. These issues are made much more difficult by the widespread availability of data visualisation tools and the increasing accessibility of data analytics, respectively. Individuals and organizations are given the ability to harness the power of data via the use of these technologies; nevertheless, they also present new levels of complexity and danger. Users run the risk of unintentionally perpetuating misleading narratives or drawing erroneous conclusions from visualised data if they do not have a deep knowledge of the fundamental concepts and associated hazards. (Kosara, R., & Mackinlay, J. 2013) The purpose of this study is to accomplish the distillation of critical insights and best practices for traversing the perilous terrain of data visualisation. This will be accomplished by conducting a systematic evaluation of the available literature and empirical investigations. The purpose of this document is to provide practitioners with the information and tools required to identify, mitigate, and avoid frequent errors in their data visualization endeavours. This will be accomplished via a synthesis of academic research, case studies, and the opinions of experts.Rather than just cataloguing the many ways in which data visualisation might fail, the purpose of this systematic study is to provide stakeholders with the insights and methods that are necessary to exploit its full potential in a responsible manner. The cultivation of a culture that values critical inquiry, openness, and rigour is one way in which we can guarantee that visualised data will continue to be an effective tool for the development of insights, the support of decision-making, and the advancement of society.

It is impossible to exaggerate the significance of excellent data visualisation in light of the fact that individuals and organizations are becoming more and more dependent on data-driven insights to guide decision-making across all sectors. It is possible for stakeholders to rapidly and intuitively comprehend complicated ideas via the use of visual representations, which serve as a bridge between raw data and actionable insights. Nevertheless, despite the fact that it has the potential to be transformational, data visualisation is not devoid of drawbacks. (Segel, E., & Heer, J. 2010) Given the inherent subjectivity of the visualisation process, one of the most significant obstacles is presented by this aspect. It is possible for design decisions, such as the selection of chart style, labelling, and annotation, to have a major impact on how data are seen and understood. What may seem to be a very insignificant design decision, such as selecting a colour palette or using a certain chart style, may have significant repercussions for the clarity and precision of the information that is visualised. A further factor that contributes to the possibility of misunderstanding is cognitive biases, which are known to influence human perception and decision-making. The phenomenon known as confirmation bias, for instance, might cause people to selectively perceive facts in a way that is congruent with their prior conceptions or opinions. In a similar vein, anchoring bias may affect interpretations by causing individuals to fixate on early perceptions or reference points, regardless of how relevant they are to the evidence that is now being considered.

As data-driven storytelling has become more prevalent and visual communication has become more prominent, there has been an increase in the amount of pressure to prioritise aesthetics above accuracy. There is a tendency to forego depth and complexity in favour of simplicity and beauty when one is attempting to construct tales that are visually captivating. (Borgo, R., Abdul-Rahman, A., & Mohamed, F. 2012) Nevertheless, this trade-off may lead to an oversimplification or distortion of the data that is being visualised, which in turn undermines the credibility of the visualisation. When viewed against this background, a comprehensive assessment of the hazards associated with data visualisation serves as an important investigation into the difficulties and constraints associated with visual representation. Through the synthesis of previously conducted research and examples from the real world, the purpose of this study is to shed light on the typical problems that practitioners face and to provide specific recommendations on how to avoid them. This paper tries to discover the underlying processes that are responsible for visualisation problems by using a multidisciplinary approach and using ideas from domains like as psychology, design theory, and information science. Practitioners are able to build visualizations that are more successful and informative if they have a better grasp of the cognitive processes and perceptual biases that impact how we perceive visual information. (Hullman, J., Adar, E., & Shah, P. 2011) The purpose of this systematic review is not to criticize the practice of data visualisation; rather, it is to raise the bar for the level of excellence that will be achieved by this activity. The purpose of this study is to encourage a culture of data literacy, critical thinking, and ethical responsibility in the field of data visualisation. This will be accomplished by throwing light on the possible problems and presenting ideas for change that may be implemented.

Learning analytics promises to have a profound impact on educational practice. One way in which this area of research might bring about beneficial change for learners is through "learner awareness tools," that is, tools that provide up-to-date information to learners about their learning status. These interactions interactions often occur as the learning activities are ongoing (e.g., as students are enrolled a course, or even in real-time at the very moment that students are working with particular educational software), though may also take place afterwards. Examples of such tools are student-facing learning analytics dashboards (LADs) early warning systems and open learner models (OLM). A key assumption is that learners will carefully use the information provided by the awareness tool to help them monitor, reflect on, and regulate their own learning, and that this will boost their academic achievement. In this article, we review an important class of learner awareness tools, namely open learner models (OLMs). An Open Learner Model "…makes a machine's representation of the learner available as an important means of support for learning" . Such a model might represent psychological variables such as "student's knowledge, interests, affect, or other cognitive dimensions," which typically are "inferred based on the learner's interactions with the system." . Over the years, many different OLMs have been developed, with a variety of content, designs, and visualizations. These OLMs are often embedded in advanced learning technologies such as intelligent tutoring systems .

Evaluations are critical for assessing the validity of visualization techniques and system. The metrics by which visualizations and systems are considered successful depend on the application and the researchers' goals. Many researchers are interested in objective measures, such as time or accuracy, while others are interested in subjective data sources, such as ease of use or user confidence. Subjective response is often measured qualitatively through interviews or free-response questions and consequently analyzed with qualitative techniques such as open coding or rich description. However, qualitative methods are not always appropriate for a subjective evaluation. For example, researchers might be interested in directly comparing the subjective performance of two visualizations, a task that could be more difficult with unstructured qualitative data. Likert scales allow researchers to collect quantitative estimates of subjective traits, producing numeric data that can be summarized and visualized in the similar manner to other quantitative data collected in an evaluation.

1.7 Unveiling the Complexity: Navigating Data Visualization Pitfalls

The function of data visualisation as a tool for sensemaking and decision-making has developed into a more significant one as the amount and variety of data continue to grow across a wide range of sectors and fields of study. On the other hand, under the surface of the colourful charts and interactive visuals is a complicated terrain that is teeming with possible obstacles and difficulties. From subtle design decisions that may gently distort perceptions to inherent cognitive biases that impact interpretation, the process of developing and understanding visual representations of data is riddled with complexity. This is because of several factors that can influence interpretation. In addition, the fast advancement of technology and the democratisation of data analytics tools have resulted in the introduction of additional layers of complexity, which have blurred the boundaries between accessibility and accuracy. (Sedlmair, M., Meyer, M., & Munzner, T. 2012) The ability to navigate the hazards of data visualisation in this dynamic and diverse context demands not just technical competence but also a good knowledge of human cognition, ethical issues, and insights from a variety of disciplines. Providing practitioners with direction to chart a road towards more accurate, transparent, and powerful visual representations of data is the goal of this systematic review, which attempts to untangle the complexities of data visualisation problems, throw light on common issues, and give help to practitioners.It is more important than ever before to be able to condense complicated facts into insights that are easy to understand and can be put into practice in this era of information overload. When it comes to performing this objective, data visualisation is a strong tool that enables stakeholders to discover patterns, recognize trends, and convey results in a way that is both clear and precise. However, the success of data visualisation is dependent on the careful navigation of possible hazards that might obfuscate meaning and mislead perceptions. This is a prerequisite for the effectiveness of data visualisation. Each and every choice that is made throughout the visualisation process has the ability to either improve or detract from the accuracy of the data that is being visualised. This includes the use of deceptive visual metaphors as well as the incorrect portrayal of scale.

Furthermore, the democratisation of data visualisation technologies has enabled people from a wide range of fields to develop and spread visualizations, which has increased the potential as well as the hazards that are connected with the activity. Since this is the case, it is vital for practitioners to have a sophisticated awareness of the problems that are inherent in data visualisation in order to exploit its full potential in a responsible manner. (Shneiderman, B., Plaisant, C., & Hesse, B. W. 2013) The purpose of this systematic review is to shed light on these problems by providing practitioners with insights and ideas that will assist them in efficiently navigating the intricacies of data visualisation.The need for data visualisation that is both clear and informative has never been higher than it is now, as data-driven decision-making is becoming more prominent across a wide range of companies and sectors. Nevertheless, in the middle of the rush to display data in forms that are visually attractive, it is simple to ignore the underlying complexity and subtleties that might subtly alter perception and comprehension. There are a variety of factors that contribute to the complex web of difficulties that are inherent in data visualisation. Some of these factors include cultural biases, context dependence, and the limits of human cognition. The repetitive nature of data analysis and visualisation often results in the evolution of visualizations over time, which may result in the introduction of new problems or the exacerbation of those that already present. (Stasko, J. T., Görg, C., & Liu, Z. 2008) This systematic review aims to equip practitioners with the knowledge and tools necessary to create visualizations that are not only aesthetically pleasing but also accurate, informative, and ethically sound. This will be accomplished by shedding light on the challenges that are currently being faced and providing practical guidance for navigating these challenges.

1.8 Improving visualization evaluations

Literature surveys of published visualization evaluation papers have historically been used to better understand current evaluation practices within the visualization community and to illustrate the need for improvements. Lam et al. and Isenberg et al. studied the characteristics and goals of visualization evaluations in general while Hullman et al. conducted a survey specific to evaluations of uncertainty visualizations . Several other notable critiques of visualization evaluation practices are relevant to our work, such as Correll's discussion of the "heroic age" of visualization examination of what we truly know about visualization after decades of perceptual evaluations. Guidelines specific to qualitative and quantitative data in visualization evaluations were also useful to us in compiling our recommendations for the handling of quantitative subjective data. provide guidelines for improving the rigor of qualitative research in visualization . Several papers document the current state of quantitative evaluations in HCI and visualization and propose recommendations for improving rigor and external validity. Statistical practices in HCI visualization have been brought into question in recent years. A particular concern is the field's overreliance on dichotomous inference as a result of NHST and the potential for a replication crisis in empirical computer science research . Several solutions have been proposed to address these issues, including requiring the preregistration of analysis plans prior to running studies . In this paper, we focus on documenting how subjective evaluations with Likert scales are handled in visualization papers, with an emphasis on two aspects of statistical practices: reporting of methodological details for replication and methods used to summarize, analyze, and report Likert data.

1.9 Charting the Course

A labyrinth of possible dangers lying in wait to ensnare those who are not vigilant may be found inside the enormous expanse of data visualisation, which is where analytical rigour and creative expression meet. The process of traversing the terrain of data visualisation is laden with difficulties, ranging from the false attraction of gilded images to the subtle biases contained within design decisions that seem to be harmless. Depending on the choices that are made at each step of the visualisation process, each chart, graph, or infographic has the potential to either educate or mislead the audience. Because of the ongoing development of technology and the growing prevalence of data, there is an ever-increasing need for a more nuanced knowledge of these potential dangers. The purpose of this systematic review is to shed light on the contours of this environment by providing insights that have been garnered from research that spans several disciplines and instances from the real world (Tory, M., & Möller, T. 2004). The purpose of this study is to provide practitioners with the information and tactics necessary to traverse this terrain with confidence and clarity. This will be accomplished by charting a route through the intricacies of data visualisation hazards. The significance of efficient data visualisation cannot be emphasised, particularly in light of the fact that data is becoming a more vital part of decision-making processes across a wide range of fields. On the other hand, the path from raw data to valuable insights is laden with the possibility of encountering a number of impediments. The complexity of the landscape is influenced by a number of factors, including the quality of the data, the design of the visualisation, and the interpretation of the audience. Additionally, the quick rate of technical innovation has resulted in an increase in the number of visualisation tools and methodologies, which has further complicated the landscape. When working in this constantly changing environment, it is vital for practitioners to have a thorough awareness of the intricacies of data visualisation errors in order to generate visualizations that are informative rather than misleading. This systematic study makes an effort to dive deeply into this complex web of issues, providing a full investigation of frequent errors and effective techniques for mitigating their effects. Through the process of shedding light on the many dangers associated with data visualisation, the purpose of this review is to provide practitioners with the knowledge and tools necessary to traverse this terrain in an ethical and successful manner. In this day and age, when information is readily available and people's attention spans are short, the ability to condense complicated statistics into appealing visual storytelling is of the utmost importance. However, despite the abundance of visualisation tools and methods that are available to us, there are potential flaws that might compromise the integrity of our visualizations and reduce their usefulness. These problems have the ability to obfuscate the truth, spread disinformation, and destroy faith in decision-making that is driven by data.

They may range from the subtle misalignment of axes to the blatant distortion of proportions. Furthermore, the landscape of data visualisation problems continues to expand with the proliferation of data sources and the development of analytical methodologies. This results in the introduction of new obstacles and complications that must be navigated. The purpose of this systematic review is to shed light on frequent mistakes and effective practices by relying upon empirical facts, expert views, and multidisciplinary perspectives. The study's goal is to disentangle this web of problems. (Lam, H., & Bertini, E. 2016) This study intends to enhance the level of data visualisation by providing practitioners with a greater awareness of these dangers and solutions for mitigating them. This will ensure that visual representations correctly reflect the data that is being represented and will enable informed decision-making.A complicated landscape that is rife with possible pitfalls and traps may be found inside the ever-expanding cosmos of data visualisation, which can be described as a place where information is both rich and diversified. The journey of data via visualisation is riddled with problems that may obfuscate meaning and mislead interpretation. These challenges range from the complexities of visual perception to the subtleties of narrative. Individuals from a wide range of backgrounds have been given the ability to participate in visualisation activities as a result of the democratisation of data tools, which has added additional levels of complexity to the landscape. As practitioners negotiate this landscape, they are required to struggle with problems of ethics, accuracy, and accessibility, all while attempting to strike a careful balance between aesthetics and authenticity. This systematic review makes an effort to traverse this maze of potential dangers by relying on the collective knowledge of researchers, practitioners, and academics in order to provide light on the way ahead. The purpose of this study is to provide practitioners with the knowledge and skills necessary to chart a route towards more successful and impactful data visualisation methods by revealing the typical errors and providing ideas that can be actively implemented.

1.10 Strategies for avoiding data visualization pitfalls

A complex strategy that combines technological knowledge, critical thinking, and ethical concerns is required in order to successfully navigate the stormy seas of data visualisation problems. Establishing a firm foundation that is founded upon the values of truth, openness, and integrity is the first step that practitioners need to take before beginning the process of generating visual representations of data. The rigorous preparation of data is the first step in laying this foundation. This preparation ensures that datasets are clean, relevant, and suitably formatted for effective visualisation. In the next step, practitioners are required to give careful consideration to the design and aesthetics of their visualizations. They must choose suitable chart types, colour palettes, and labelling standards in order to improve understanding and reduce the likelihood of any possible biases. In addition, practitioners are required to maintain vigilance against the effect of cognitive biases and heuristics, which have the potential to result in skewed interpretations. In order to reduce the likelihood of misunderstanding, practitioners should actively seek feedback and validation from a variety of viewpoints. (Brehmer, M., & Munzner, T. 2013) In addition, practitioners should adopt a culture of continual learning and growth, ensuring that they are up to date on the latest developments in the area of data visualisation, including new trends, technologies, and best practices. It is possible for practitioners to navigate the complex landscape of data visualisation with confidence and clarity if they adopt these strategies and cultivate a mindset of curiosity and humility. This will ensure that their visualizations serve as effective tools for communication, the generation of insights, and the making of informed decisions.In the goal of producing visualizations that have a significant effect, practitioners are required to place a high priority on the values of clarity and honesty. To begin, it is necessary to have a comprehensive grasp of the data that is being visualised as well as the message that is meant to be communicated. It is important for practitioners to make every effort to provide data in a transparent and accurate manner, avoiding any alteration or distortion that can result in inappropriate interpretation. (Correll, M., & Heer, J. 2018) The selected visualisation methods should be evaluated closely to see whether or not they are acceptable, with the goal of ensuring that they correspond with the underlying qualities of the data as well as the cognitive capacities of the audience. Approaches that include collaboration, such as peer reviews and user testing, have the ability to provide significant insights and assist in the early identification of possible difficulties throughout the visualisation process. In addition, practitioners should make use of technological improvements, such as interactive features and dynamic updates, in order to improve engagement and make it easier to do more in-depth explorations of the data. Practitioners are able to negotiate the difficulties of data visualisation with integrity and confidence if they embrace these tactics and respect ethical norms. This, in turn, will eventually create trust and understanding among stakeholders.When it comes to the creation of visualizations, practitioners should prioritise context and audience knowledge in addition to technical skill and ethical issues. (Nusrat, S., Rubab, S., & Akram, M. U. 2018) By adapting visualizations to the individual needs of audiences and situations, it is possible to improve relevance and comprehension, hence lowering the likelihood of misunderstandings occurring.

Additionally, the inclusion of contextual information with visualizations, such as metadata, annotations, and text that provides explanations, may enhance comprehension and promote transparency. In addition, practitioners should be aware of the cultural and linguistic subtleties that may have an impact on interpretation, and they should modify visualizations appropriately in order to guarantee accessibility and inclusion. It is also possible to enable stakeholders to interact critically with visualised data by cultivating a culture of data literacy inside organizations. This may result in a decision-making process that is both better informed and more collaborative. Practitioners are able to design visualizations that engage with their target audiences by using these tactics. This allows them to successfully communicate insights while simultaneously minimising the danger of misunderstanding or prejudice.

1.11 Importance of effective data visualization

A world that is becoming more and more data-driven requires excellent data visualisation as a key component in order to translate complicated information into insights that can be put into action. At its heart, data visualisation is not only about making images that are pleasant to the eye; rather, it is about telling a narrative, discovering patterns, and shedding light on trends that are hidden inside the huge ocean of data. (Amar, R., Eagan, J., & Stasko, J. 2005). By displaying information in a visual manner, data visualisation is able to overcome linguistic obstacles as well as cognitive limits, making it easier for stakeholders to understand complicated ideas. Furthermore, well-crafted visualizations have the ability to engage and convince, therefore catching attention and motivating significant action. It doesn't matter whether it's used to explain scientific findings, guide strategic decision-making in business, or mobilise public opinion in advocacy campaigns; the impact of excellent data visualisation reverberates across a wide range of businesses and fields of study. For those who want to successfully navigate the intricacies of the contemporary world, the capacity to condense knowledge into narratives that are both clear and captivating has become not just desired but also crucial in our period, which is characterized by an abundance of information.The capacity to extract important insights from the noise has become a competitive advantage in this era of information overload, as data streams inundate people as well as those who work for organizations'.

The effective visualisation of data acts as a lighthouse in this ocean of information, pointing decision-makers in the direction of actions that are both informed and strategic. Through the process of reducing complicated datasets into representations that are both easy to understand and visually appealing, data visualisation gives stakeholders at all levels the ability to make sense of information in a timely and accurate manner. Furthermore, the democratization of data visualization tools has democratised access to insights, making it possible for people from a wide range of backgrounds to harness the power of data for the purpose of problem-solving and creativity. (Hullman, J., & Diakopoulos, N. 2011) The influence of successful data visualisation extends across borders and across sectors, ranging from the identification of market trends and the optimisation of operations to the transmission of information to public policy and the promotion of social change. The core of great data visualisation is not only the creation of nice graphics; rather, it is the unleashing of the potential of data to drive development, inspire innovation, and design a better future for everyone.Data is often referred to as the new money in the hyper-connected digital environment of today, and the key to unlocking the value of this currency is excellent data visualisation. Visualising data goes beyond just representing it; it converts raw statistics into insights that can be put into action, which offers decision-makers the ability to make confident decisions based on accurate information. The influence of excellent data visualisation is both broad and significant, whether it is in the context of analyzing consumer behaviors in order to optimise marketing tactics, monitoring supply chain efficiency in order to boost operational performance, or understanding public health patterns in order to inform policy responses. (Kosara, R., & Mackinlay, J. 2013) Furthermore, at a time when lies and misinformation are abundant, compelling visualizations serve as a defence mechanism against falsehoods, allowing users to differentiate between reality and fiction and to make judgements based on facts. By reducing complicated information to easily consumable visual narratives, data visualisation helps to bridge the gap between data and decision-making. This enables people and organizations to manage uncertainty, grasp opportunities, and create good change in a world that is becoming more data-driven.

- **Pitfalls in Perception**

In the field of data visualisation, where the objective is to convey complicated information in a way that is understandable and succinct, the significance of perception cannot be stressed. The human perception, on the other hand, is a complex and sometimes erroneous process that is prone to a wide variety of cognitive limits, biases, and heuristics. As a result, the development and interpretation of visualised data are presented with considerable obstacles due to the pitfalls that are associated with perception. One of these pitfalls is the phenomenon of selective attention, which occurs when people concentrate on some aspects of a visualisation while ignoring others. This may possibly result in incorrect interpretation of the data or an insufficient comprehension of the information. Furthermore, confirmation bias, which is a ubiquitous cognitive bias, may have an effect on how people understand visualised data. (Segel, E., & Heer, J. 2010) This might cause individuals to deliberately seek out or interpret information that supports prior views or theories. In addition, the Gestalt principles of perception, which control how we organise and interpret visual information, may sometimes result in erroneous interpretations or distortions of the material that is being interpreted. While the principle of similarity may enable people to group different data points based only on their visual resemblance, the principle of closure may cause individuals to cognitively fill in gaps or detect patterns where none exist. For instance, the principle of closure may induce individuals to do any of these things. When it comes to developing and interpreting visualised data, it is essential to have a thorough grasp of the complexities of human cognition and perception. These mistakes in perception highlight the relevance of this expertise. Practitioners are able to produce visualizations that successfully convey insights and minimise the risk of misunderstanding or bias if they acknowledge and mitigate the potential hazards that they face.The universe that exists beyond the complexity of human vision is one in which visualizations have the ability to both enlighten and mislead, depending on the manner in which they interact with the peculiarities of our computational machinery. (Hullman, J., Adar, E., & Shah, P. 2011) The anchoring bias is one example of this kind of fallacy. This prejudice occurs when people place an excessive amount of weight on the first information (the "anchor") while making subsequent judgements. In the context of data visualisation, this bias may become apparent when viewers get fixated on a certain data point or reference value, which can cause them to overemphasise the relevance of the data point or make incorrect conclusions.

A cognitive bias known as the recency effect, which gives more weight to more current information than to data from previous periods, has the potential to distort interpretations of time-series visualizations, which may result in the appearance of long-term patterns or trends. Furthermore, the availability heuristic, which includes evaluating the chance of an occurrence based on its ease of memory, has the potential to impact how people perceive the relevance of certain data points or trends, regardless of the actual frequency or importance of such data points or trends. The delicate nature of perception is brought into sharper focus by these cognitive biases, which also highlight the need for practitioners to approach data visualisation with care and attention. (Carpendale, S., Cowperthwaite, D., & Fracchia, F. D. 2003) The practitioners may improve the clarity, accuracy, and effectiveness of their visualizations by recognising and correcting these problems in perception. This will ensure that their visualizations actually function as instruments for enlightenment rather than causes of confusion or distortion.The complexities of human vision go beyond cognitive biases and include perceptual illusions and distortions, both of which have the potential to alter how people perceive visual information. The Muller-Lyer illusion is an example of this kind of phenomena. In this illusion, two lines of identical length seem to be different owing to the placement of arrowheads at the ends of the lines. When visual components such as bars or lines are positioned in a manner that provides deceptive perceptions of scale or proportion, similar illusions may occur in the context of data visualisation. These illusions may be caused by the placement of the visual elements. Additionally, the Ponzo illusion, which is a phenomenon that changes the apparent size of an item dependent on its environment, may be seen in visualizations when pieces are juxtaposed against false scales or reference points. (Lam, H., & Bertini, E. 2016) These perceptual distortions emphasise the difficulties that are inherent in effectively portraying quantitative information in visual form. They also stress the significance of careful design and annotation in order to reduce the likelihood of misinterpretations occurring. Practitioners are able to develop visualizations that fit more closely with the underlying data and minimise the possibility of perceptual mistakes or distortions if they understand and account for the perceptual illusions that they encounter.

- **Why Examine the Pitfalls of Visualization?**

The rise of visualization's use on the Web, in social media, in education, and in management calls for a systematic understanding of the limitations of graphic representations and of potential mistakes that are committed when designing or viewing information and knowledge visualizations. Examining the potential risks and common mistakes committed in the interpretation and in the creation of visualization is relevant to enhance scholar understanding of an important aspect of visual literacy. In this article, the word *visualization* refers to the graphic display of information and knowledge. From a pragmatic point of view, a compilation and classification of pitfalls of visuals can be used as an instructional tool, to provide a comprehensive list, a vocabulary and definition of relevant terms related to the risks of visualization. Practitioners could profit from such a classification by using it as a checklist, against which they can test images and improve document design, infographics, or digital images. Despite the notable number of publications on the benefits of using visual representations in a variety of fields few studies have systematically investigated the possible pitfalls that exist when creating or interpreting visual representations. Some information visualization researchers, however, have raised the issue and called to action: "Articles on limitations and pitfalls [of visualization] are scarce. For the advancement of the field, more such reports would be highly beneficial". Presently, a clear overview and classification of the risks and disadvantages associated with visual depictions of information has not been provided. Thus, as evaluated "Due to a lack of integrative efforts, we are in danger of constantly 'reinventing' knowledge about the visual and its workings. Such a synopsis could provide a comprehensive theoretical overview based on prior research findings, to assist researchers in investigating systematically the effects and the boundaries of visual representations of information. This article aims to provide an instructive schema that contains prior research findings from a variety of fields related to visualization. The goal of this article is to identify and classify the key problematic issues and risks inherent in visual representations, as well as to provide a structure to guide work in visualization production and quality assessment. We argue that this is an important step in visualization research to use as a basis for the future development of guidelines and rules for visualization developers and users, and for instructors.

To compile a list of risks of visualization, we have screened studies from multiple related research domains. We have focused on the visual representation of information and thus did not analyze areas such as fine arts, photography, film, or scientific imaging. We structure the article by starting with a review of visualization literature. In the third section, we provide a classification populated with reported disadvantages of visualizations. We then present examples of how to utilize the classification for evaluating and improving graphic representations of information. We end with the conclusions and an outlook for future research.

Our aim with the present work is not to diminish the potential of visualization. It is rather an attempt to deepen and structure our understanding of its possible limitations and constraints. This is relevant not only to avoid or detect mistakes in the production and interpretation of visualization applications, but also as a teaching tool to foster visual literacy.

1.12 Technology's Impact

When it comes to the ever-changing world of data visualisation, technology plays a crucial role in determining the tools, approaches, and possibilities that are accessible to practitioners. The influence of technology on data visualisation is diverse, comprising both improvements that expand capabilities and obstacles that add new complications. Both of these aspects are included in the statement. Access to strong tools has been democratised as a result of the spread of sophisticated visualisation software and platforms. This has made it possible for people with diverse degrees of skill to generate engaging visualizations with relative simplicity. With the use of these tools, practitioners are able to explore, analyse, and visualise data in ways that were previously inconceivable. These tools provide a variety of functionalities, ranging from drag-and-drop interfaces to extensive data analytics capabilities. Furthermore, emerging technologies like as augmented reality (AR) and virtual reality (VR) give new and exciting prospects for immersive data experiences (Brehmer, M., & Munzner, T. 2013). . These technologies allow users to engage with data in three-dimensional spaces and get new insights via the use of spatial context.

In contrast, the quick speed of technology innovation has also resulted in the introduction of problems and issues that practitioners are required to negotiate. The sheer amount and velocity of data created in today's digital age, for instance, might overwhelm conventional visualisation approaches. As a result, practitioners are required to employ sophisticated algorithms and visualisation methods in order to extract relevant insights. With the proliferation of big data and real-time analytics, the difference between data visualisation and data analysis has become more blurry. As a result, it is necessary to take a holistic strategy that incorporates visualisation throughout the whole data lifecycle, beginning with the input of data and ending with its interpretation. Furthermore, the development of data visualisation tools and platforms has led to issues about data privacy, security, and ethical usage. This is because practitioners are struggling to come to terms with the consequences of visualizing sensitive or private information in a digital environment which has led to these worries(Kosara, R., & Mackinlay, J. 2013).It is crucial for practitioners who are interested in maximising the potential of data visualisation to have a solid grasp of the influence that technology has on data visualisation in this complex and ever-changing environment. Practitioners may embrace technology as a strong tool for uncovering insights, generating innovation, and influencing decision-making in a world that is becoming more data-driven. This can be accomplished by embracing technological improvements while keeping conscious of the problems that they offer.

- **Interactive and Dynamic Visualizations**: The development of interactive and dynamic visualisation approaches has been made possible by technological advancements. These techniques enable users to change data, investigate issues from a variety of viewpoints, and discover insights in real time. Enhanced user engagement and the ability to conduct more in-depth research of complicated datasets are both made possible by features such as drill-down capabilities, filter choices, and dynamic transition patterns.
- **Cloud-Based Solutions:** The introduction of cloud computing has brought about a revolution in the field of data visualisation by delivering an architecture that is both scalable and adaptable, allowing for the storage, processing, and visualisation of massive amounts of data. Solutions that are hosted in the cloud provide a number of benefits, including accessibility, collaboration, and cost-effectiveness. (Borgo, R., Abdul-Rahman, A., & Mohamed, F. 2012) These solutions also enable organizations to deploy visualizations across distant teams and scale resources according to their requirements.
- **Integration with Data Analytics:** With the use of technology, practitioners are now able to undertake complicated data analysis and visualisation processes inside a unified environment. This is made possible by the seamless connection that technology has made possible between data visualisation tools and advanced analytics platforms. The process of gaining insights from data is simplified as a result of this integration, which also improves the flexibility and effectiveness of decision-making procedures.
- **Automation and AI-Assisted Visualization:** Data visualisation tools that are both automated and helped by artificial intelligence (AI) have been developed as a result of recent developments in artificial intelligence (AI) and machine learning. (Sedlmair, M., Meyer, M., & Munzner, T. 2012) These tools make use of algorithms to automatically recognize patterns, trends, and outliers in data. As a result, practitioners are able to build visualizations in a more expedient manner and explore data-driven insights in a more effective manner.
- **Cross-Platform Compatibility:** The creation of data visualisation tools and frameworks that are interoperable with a variety of platforms and devices has been made possible by technological advancements. It is possible for visualizations to adjust to varied screen sizes and resolutions, regardless of whether they are accessible on desktop computers, tablets, or smartphones. This ensures that users have a consistent and optimised experience across all forms of electronic devices.

- **Accessibility and Inclusivity:** Through the provision of features like as keyboard navigation, alternate text descriptions, and compatibility with screen readers, technology has made it easier to create data visualizations that are accessible and inclusive. Users with impairments are able to view visualizations thanks to these accessibility elements, which also guarantee that the visualizations conform with accessibility legislation and standards.
- **Data Governance and Compliance:** The introduction of tools and frameworks for data governance and compliance has been made possible by technological advancements. These advancements have made it possible for organizations to enforce data quality standards, guarantee data privacy and security, and comply with regulatory criteria. Consequently, these technologies provide governance methods for regulating data access, use, and lineage, which ultimately results in an increase in trust and confidence in data that has been visualised.
- **Real-Time Data Streaming:** The visualisation of real-time data streams is made possible by technology, which allows practitioners to monitor and analyse dynamic information as they develop. (Tory, M., & Möller, T. 2004) This capacity is especially useful in applications like as financial trading, sensor networks for the Internet of Things (IoT), and social media analytics, all of which are areas in which fast insights are essential for decision-making.
- **Geospatial Visualization**: Geographic information systems (GIS) and mapping technologies have brought about a revolution in geospatial visualisation. These technologies have made it possible for practitioners to portray spatial data via the use of graphic and interactive maps. Tools for geospatial visualisation provide useful insights into spatial linkages and patterns, which may be used to a wide range of topics, including environmental phenomena and demographic trends.
- **Data Integration and Fusion:** Through the use of technology, practitioners are able to integrate structured and unstructured data for the purpose of conducting extensive analysis and visualisation. This is made possible by the integration and fusion of varied datasets that originate from numerous sources. (Segel, E., & Heer, J. 2010) It is possible for practitioners to construct holistic visualizations that capture the whole spectrum of important information by using methods such as data blending and federated querying.
- **Customization and Personalization:** The proliferation of advanced technology has made it possible for practitioners to personalise and customise visualizations in order to cater to the tastes and needs of individual users. Technology gives practitioners the ability to adjust visualizations to the specific requirements of individual users, which in turn increases user engagement and

happiness. Examples of this include user-driven analytics interfaces and dashboards that can be customised.

- **Machine Learning-driven Insights:** The incorporation of machine learning algorithms into data visualisation processes is made possible by technological advancements. This allows practitioners to automatically discover hidden patterns, correlations, and abnormalities in data. Insights that are generated by machine learning improve the depth and richness of visualizations, which in turn enables practitioners to more effectively draw actionable insights from complicated information.
- **Scalability and Performance:** A scalable and high-performance infrastructure is made available by modern technology, which enables the processing and visualisation of large-scale datasets in a manner that is both quick and effective. Technology guarantees that visualisation tools are able to meet the requirements of contemporary data analytics settings, regardless of whether they are involved in the processing of petabytes of data or the streaming of millions of data points in real time.
- **Collaborative Visualization Platforms:** Through collaborative visualisation systems that allow many users to work together on visualizations in real time, technology makes it easier for people to work together and share their expertise. Through the provision of features such as shared workspaces, version control, and commenting capabilities, these platforms facilitate cooperation across multidisciplinary teams and stakeholders. (Hullman, J., & Diakopoulos, N. 2011)
- **Predictive Analytics and Forecasting:** The integration of predictive analytics and forecasting skills into data visualisation tools is made possible by technological advancements. This allows practitioners to visualise future trends, situations, and outcomes based on historical data and predictive models. These skills provide decision-makers the ability to foresee future events and to make proactive choices based on insights generated by data.

1.13 Ethical Dimensions

The practice of data visualisation and the effect it has are both significantly influenced by ethical issues, which play a significant part in the quickly expanding environment of data visualisation. At the same time as practitioners are using the potential of visualizations to convey insights, inform choices, and drive change, they are also required to manage a complex web of ethical difficulties and dilemmas that occur at the interface of data, technology, and society. The ethical duty to appropriately report facts and to prevent distortion or manipulation that might lead viewers astray or perpetuate prejudices is one example of such a dilemma. When it comes to creating visualizations, practitioners are required to contend with issues of transparency, integrity, and trustworthiness. They must make certain that their visualizations correctly reflect the data that lies behind them and deliver insights in an honest and clear manner. (Kosara, R., & Mackinlay, J. 2013) The scope of ethical issues extends beyond the precision of visualizations to embrace a wider range of problems, including privacy, permission, and ownership of data. As practitioners have access to and visualise datasets that are becoming more huge and diversified, they are required to manage the ethical implications of managing information that is either sensitive or personal. Among them are the acquisition of informed permission from persons whose data is being collected, the protection of the privacy rights of individuals, and the observance of ethical principles and rules that regulate the use and sharing of data. In addition, practitioners are obligated to take into consideration the possible influence that their visualizations may have on vulnerable groups. That is, they must make certain that their visualizations do not promote stereotypes, stigmatise people, or reinforce power inequalities that already exist.When it comes to data visualisation, ethical considerations extend to concerns around accessibility and inclusion respectively. It is imperative that practitioners make every effort to develop visualizations that are accessible to users of all abilities. This will ensure that people with disabilities are able to access and comprehend data that has been visualised in an effective manner. (Segel, E., & Heer, J. 2010)

The provision of alternate text explanations for visual components, the design of interactive features with keyboard navigation in mind, and the adherence to accessibility standards and guidelines are all included in this.When operating within this intricate and ever-changing ethical context, practitioners are required to negotiate opposing interests and values while simultaneously honouring ethical principles and obligations. Practitioners have the potential to cultivate trust, promote accountability, and guarantee that visualised data serves the public good in an ethical and responsible way if they include openness, integrity, and inclusion into their visualisations.In the realm of data visualisation, ethical questions cover not just concerns about accuracy and privacy, but also concerns regarding fairness and social duty. The ethical implications of biases that are inherent inside data and algorithms are something that practitioners need to struggle with in this day and age, when automatic decision-making systems and algorithms are having an increasingly significant impact on our lives. The biases that are inherent in the training data have the potential to spread via visualizations, which may result in results that are unjust or discriminating and can perpetuate existing imbalances. When it comes to recognising and reducing biases in their visualizations, practitioners need to be careful. This is necessary to ensure that their visualizations do not exacerbate inequities or perpetuate systemic injustices.

Furthermore, ethical problems extend to the larger societal effect of data visualizations, which includes the potential of these visualizations to influence public opinion, governmental choices, and social narratives. As a result of its ability to impact perceptions, attitudes, and behaviours, visualizations are a powerful tool that may be used for advocacy, activism, and social change. However, along with this power comes the ethical responsibility to deliver knowledge in a way that is fair, impartial, and accountable to society. (Hullman, J., Adar, E., & Shah, P. 2011) As practitioners, it is imperative that they take into consideration the possible repercussions that their visualizations may have on public discourse and democratic processes. They should strive to encourage informed discussion, civic involvement, and equitable results.The intersection of ethical considerations in data visualisation with concerns about environmental sustainability and ecological effect is a noteworthy phenomenon. A considerable environmental footprint may be left behind by the computing resources that are necessary for processing, analyzing, and visualizing large-scale information. These resources may contribute to the consumption of energy, the emission of carbon, and the accumulation of electronic garbage. The practitioners are obligated to take into consideration the environmental repercussions of their visualisation techniques and investigate sustainable alternatives. These options include optimising algorithms, reducing the amount of data storage and processing that is required, and making use of renewable energy sources.It is necessary for practitioners to adopt a proactive and comprehensive strategy that takes into consideration the many interests and values that are at stake in order to successfully navigate these complicated ethical issues. (Correll, M., & Heer, J. 2018) It is possible for practitioners to guarantee that their visualizations retain integrity, justice, and social responsibility by incorporating ethical standards into each and every step of the visualisation process, beginning with the gathering and analysis of data and continuing through the design and dissemination stages. In the end, practitioners have the ability to contribute to a society that is more fair, inclusive, and sustainable if they give high priority to ethical issues when it comes to data visualisation.

- **Cultural Sensitivity and Representation:** The necessity of cultural sensitivity and representation is one of the ethical factors that should be taken into account via data visualisation. Practitioners have a responsibility to be aware of the cultural settings in which they work and to avoid reinforcing prejudices or preconceptions in their visualizations. This entails taking into account a variety of views, adding images and symbols that are culturally appropriate, and collaborating with groups that are potentially impacted in order to guarantee a depiction that is both respectful and truthful.

- **Data Transparency and Accountability:** The collection, analysis, and visualisation of data must be conducted in a transparent and accountable manner in order for data visualisation methods to be considered ethical. In order to enable consumers to evaluate the dependability and validity of the information that is provided, practitioners should include comprehensive explanations of the data sources, methodology, and assumptions that were utilized in their visualizations. It is also important for practitioners to be ready to respond to inquiries and comments about their visualizations. This will help to develop responsibility and confidence in the process of data visualisation.
- **Equitable Access to Data and Technology:** This is especially important for communities that are marginalised or underprivileged, since ethical issues extend to ensuring that everyone has equal access to data and technology. It is important for practitioners to work towards democratising access to data and visualisation tools, as well as lobbying for policies and programmes that promote digital inclusion and address gaps in data access and literacy. This involves giving training and assistance to people and organizations in order to improve their ability to interact with data visualisation in a manner that is both successful and ethical. (Nusrat, S., Rubab, S., & Akram, M. U. 2018)
- **Long-Term Implications and Unintended Consequences:** Data visualisation approaches that adhere to ethical standards require practitioners to take into consideration the results of their visualizations, including the possible unintended repercussions and the long-term ramifications. On account of the fact that visualizations have the potential to have far-reaching consequences on public discourse, governmental choices, and societal norms, it is vital to foresee and prevent any negative implications that may occur. When conducting their visualizations, practitioners should do comprehensive ethical evaluations, taking into consideration a variety of variables including possible dangers to individuals' privacy, social ramifications, and potential damages to vulnerable groups.
- **Professional Codes of Ethics and Standards:** The process of ethical data visualisation is governed by professional codes of ethics and standards, which provide practitioners with a framework of principles and most effective methods to adhere to. Practitioners are able to reference and adhere to ethical norms and standards that are provided by organizations such as the Data Visualisation

Society and the International Institute for Information Design (IIID) in the course of their work. It is possible for practitioners in the area of data visualisation to show their dedication to integrity, accountability, and ethical behaviour by adhering to certain ethical norms.

1.14 Interdisciplinary Insights

Interdisciplinary cooperation is an essential component in the dynamic and varied area of data visualisation, where it plays a crucial role in driving innovation, stimulating creativity, and pushing the bounds of knowledge. As a result of bringing together a wide range of viewpoints, areas of knowledge, and approaches from a variety of disciplines, including but not limited to computer science, design, psychology, sociology, and others, interdisciplinary insights significantly enhance both the practice and the understanding of data visualisation. Taking an interdisciplinary approach acknowledges that good data visualisation goes beyond the sphere of technical expertise and incorporates concepts of visual communication, human cognition, and social context at the same time.When seen from a computational point of view, transdisciplinary insights provide new methods and tools for the processing, analysis, and visualisation of data. These tools and techniques enable practitioners to handle complicated datasets and extract relevant insights with increased accuracy and speed. In the field of data visualisation, techniques that have been borrowed from other fields, such as machine learning, artificial intelligence, and data mining, provide powerful frameworks for discovering patterns, trends, and correlations in data. Stasko, (J. T., Görg, C., & Liu, Z. 2008) Additionally, advancements in computer graphics and visualisation algorithms enable practitioners to create visually stunning and interactive visualizations that captivate audiences and convey information with clarity and impact. Interdisciplinary insights highlight the significance of user-centered design concepts, aesthetic considerations, and narrative strategies in the process of developing visualizations that are interesting and engaging from a design point of view. Through the use of ideas derived from graphic design, information design, and user experience (UX) design, practitioners are able to create visualizations that connect with audiences, elicit emotional reactions, and aid understanding and engagement. Furthermore, multidisciplinary partnerships with specialists in domains like as human-computer interaction (HCI) and cognitive psychology give essential insights into how people perceive, understand, and interact with visualised data. These insights may be used to guide design choices, which in turn enhances usability and effectiveness.

Interdisciplinary insights give light on the larger societal consequences of data visualisation, including questions of ethics, power relations, and cultural representation. This is relevant from a social viewpoint since it sheds light on many aspects of society. Through collaboration with academics from disciplines such as sociology, anthropology, and critical theory, practitioners are able to conduct an in-depth analysis of the ways in which visualizations impact decision-making processes, perpetuate biases, and form perceptions. Practitioners are able to address ethical problems, promote openness and accountability, and advocate for socially responsible practices that prioritise inclusion, diversity, and fairness in data visualisation thanks to this methodology that draws from several disciplines. In this expansive and linked environment of multidisciplinary insights, practitioners have the potential to transcend the borders of their respective disciplines, investigate new lines of research, and push the limits of what is possible in data visualisation. The practitioners are able to unlock new insights, foster innovation, and ultimately create visualizations that not only inform and inspire, but also empower individuals and communities to make informed decisions and bring about positive change in the world. This is accomplished by embracing diverse perspectives and collaborating across disciplines.

- **Semantic and Contextual Understanding:** Through the provision of a more in-depth comprehension of the semantic and contextual subtleties that are inherent in visualised data, interdisciplinary insights contribute to the enhancement of data visualisation. The practitioners are able to discover layers of meaning that are contained within the data and develop visualizations that connect with cultural, linguistic, and social settings by leveraging on the knowledge of subjects such as linguistics, anthropology, and semiotics. By using an interdisciplinary approach, practitioners are able to develop visualizations that are not only accurate and informative, but also culturally sensitive and contextually appropriate, which increases the efficacy and impact of the visualizations.
- **Human-Centered Perspectives:** When it comes to data visualisation, interdisciplinary insights highlight the significance of human-centered design principles. These principles put the requirements, preferences, and experiences of users at the forefront of the design process. It is possible for practitioners to get insights into the many ways in which persons perceive, understand, and interact with visualised data if they work along with specialists in subjects like as

anthropology, sociology, and human factors engineering. Through the use of this human-centered approach, design choices are informed, usability is improved, and the entire user experience of visualizations is enhanced, which ultimately leads to increased engagement and understanding across a variety of audiences.

- **Spatial and Temporal Analysis:** Through the incorporation of ideas and methods from disciplines such as geography, archaeology, and environmental science, interdisciplinary insights are used in the process of data visualisation to provide insights into spatial and temporal analysis. Practitioners are able to investigate patterns, trends, and interactions that develop across geography and time by using spatial and temporal data visualisation approaches. This allows them to obtain insights into complex phenomena such as climate change, urbanisation, and migration. This multidisciplinary approach makes it possible for practitioners to visualise dynamic spatial and temporal processes, which in turn facilitates a more profound knowledge and more informed decision-making across a wide range of areas.
- **Narrative and Storytelling:** relying on ideas from domains such as literature, journalism, and narrative psychology, interdisciplinary insights contribute to the art of narrative and storytelling in data visualisation. This is accomplished by relying on the principles of these fields. Practitioners have the ability to contextualise information, create emotions, and present difficult ideas in a way that is more accessible and engaging by constructing fascinating tales around data that has been visualised. Through the use of this multidisciplinary method, data is transformed into tales that engage with audiences, so promoting empathy, connection, and empathy, as well as motivating action and change.
- **Cross-Cultural Collaboration:** By facilitating communication and interaction amongst practitioners from a variety of cultural backgrounds, interdisciplinary insights contribute to the promotion of cross-cultural cooperation in the field of data visualisation. Practitioners are able to develop visualizations that represent the views, attitudes, and experiences of varied groups when they embrace cultural diversity and inclusion. This helps to ensure that the data that is visualised is relevant, useful, and respectful to all stakeholders. The practitioners are able to solve global concerns and promote social justice and fairness via the use of data visualisation thanks to this multidisciplinary approach, which fosters cultural understanding, empathy, and teamwork.

1.15 Practical Ramifications

When it comes to the field of data visualisation, the practical implications of choices on visualisation go far beyond the aesthetics of the finished output. There are consequences associated with every design decision, data selection, and interaction method, and these implications have the potential to impact how users perceive, comprehend, and act upon the information that is visualised. In order for practitioners to be able to develop visualizations that are not just visually beautiful but also successful, instructive, and morally acceptable, it is vital for them to understand and navigate the practical repercussions that are involved. (Sedlmair, M., Meyer, M., & Munzner, T. 2012) When it comes to visualizations, striking a balance between simplicity and complexity is key to understanding the practical implications of a situation. In spite of the fact that simplicity is often praised for its capacity to communicate information in a concise and understandable manner, visualizations that are extremely simple run the danger of oversimplifying complicated data and concealing essential subtleties or patterns. On the other hand, visualizations that are too complicated may cause users to encounter an overwhelming amount of information or make it impossible to recognize valuable insights. Practitioners are required to take into consideration the features of the data, the requirements and expectations of the audience, and the purpose for which the visualisation is designed in order to achieve the optimal balance between simplicity and complexity. When it comes to how people interact with and comprehend the data that is visualised, the kind of visualisation approach that is used might have significant practical implications. Different methods of data visualisation, such as bar charts, line graphs, scatter plots, and heatmaps, each have their own set of benefits and drawbacks when it comes to communicating the various kinds of information and the links between them. In order to create visualizations that successfully convey insights and support informed decision-making, it is essential to have a thorough understanding of the benefits and drawbacks of each approach and to choose the technique that is the most suitable for the job at hand.

The interactive capabilities and functions of visualizations have the potential to have the potential to have practical implications for user engagement and understanding. Users are given the ability to explore data at their own speed and discover insights that are suited to their own interests and requirements via the use of interactive visualizations that include zooming, filtering, and drill-down capabilities. It is possible that users could get confused or that the clarity of the visualisation will be diminished if the interactive elements are badly designed or if the interactions are too complicated. Those who work in the field need to give careful consideration to the usability and accessibility of interactive elements, making certain that these features improve rather than detract from the overall user experience.

The practical repercussions of data visualisation extend beyond design issues to include ethical and social implications as well as other relevant factors. Because visualizations have the ability to mould perceptions, influence choices, and motivate action, it is necessary for practitioners to take into consideration the possible effect that their visualizations may have on people, communities, and society as a whole. In order to guarantee that visualizations retain integrity, trustworthiness, and social responsibility, it is necessary to include ethical concerns into each and every step of the visualisation process. Some examples of these factors are data privacy, transparency, and fair consideration.Practitioners need to take a holistic strategy that strikes a balance between technical skill, ethical concerns, and user-centered design principles in order to successfully navigate the practical repercussions of data visualisation. Practitioners are able to create visualizations that not only inform and inspire users, but also empower them to make informed decisions and bring about positive change in the world. This is accomplished by embracing complexity, selecting appropriate visualisation techniques, designing intuitive interactions, and promoting practices that are ethical and socially responsible.

- **Data Accuracy and Reliability:** It is important to note that the practical implications of data visualisation extend beyond the precision and dependability of the data that is being visualised. It is possible for visualizations that are based on data that is faulty or unreliable to result in incorrect conclusions and judgements that are poorly led. Prior to the creation of visualizations, practitioners are required to do an evaluation of the quality of the data, which should include considerations such as completeness, consistency, and validity, and then take measures to rectify any problems or uncertainties that may arise. Additionally, in order to guarantee that users are able to make interpretations that are based on accurate information, they should give openness on the data sources as well as any limits or caveats associated with the data.
- **Performance and Scalability:** Data visualisation has a number of practical implications, including the consideration of performance and scalability, which is especially important when working with big amounts of data or data that is being collected in real time. It is possible for visualizations to

distract from the user experience and impair usability if they take a long time to load or display, or if they demand an excessive amount of computing resources. In order to guarantee responsive and scalable performance, practitioners need to optimise visualizations for speed. This may be accomplished by applying methods like as data aggregation, caching, and parallel processing. This is necessary even when dealing with big datasets or heavy user traffic.

- **Cross-Platform Compatibility:** As part of the practical implications of data visualisation, it is important to ensure interoperability across a variety of devices, platforms, and screen sizes. A responsive and adaptable visualisation should be able to provide a consistent and optimised experience across a variety of platforms, including desktop computers, tablets, smartphones, and other electronic gadgets. In order to guarantee that visualizations are accessible and useable across a wide range of platforms and devices, practitioners are required to implement responsive design concepts and methods. These include fluid layouts, flexible grids, and media queries. (Tory, M., & Möller, T. 2004)
- **Regulatory Compliance:** Considerations of regulatory compliance are among the practical repercussions of data visualisation. This is especially true in sectors and domains that are subject to rules and regulations pertaining to data protection. Legal and regulatory requirements, such as data privacy legislation (for example, GDPR and HIPAA) and industry-specific rules (for example, PCI DSS for payment card data), must be complied with by visualizations that contain sensitive or personally identifiable information. Encryption, access restrictions, and audit trails are some examples of the necessary data security methods that practitioners need to apply in order to assure compliance and reduce the risk of regulatory breaches.
- **Continuous Evaluation and Iteration:** In addition, the practical implications of data visualisation include the need for ongoing review and iteration in order to guarantee that the visualisation will continue to be successful and relevant over time. The practitioners should gather feedback from users, monitor use stats, and perform usability testing in order to evaluate the effect of visualizations in real-world circumstances and determine whether or not they are indeed usable. It is recommended that practitioners iteratively develop and enhance visualizations based on this input, including user insights and correcting any usability problems or weaknesses that are detected via assessment methods.

1.16 Navigating Complexity

Navigating complexity has emerged as a defining problem in the field of data visualisation as a result of the increasingly linked and data-rich world that we live in. Practitioners are faced with the challenging job of distilling complicated information into clear, actionable insights that may influence decision-making and create good results. This effort is made more difficult by the fact that the amount, variety, and velocity of data continue to expand rapidly. Nevertheless, the sheer nature of complexity creates intrinsic obstacles that need for careful analysis and novel ways to visualisation if they are to be overcome.One of the most important aspects of successfully managing complexity is the need to comprehend and accurately portray multiple connections, patterns, and occurrences that defy simple explanations. Traditional methods of visualisation are not capable of properly capturing the non-linear connections, interrelated variables, and emergent features that are often present in complex datasets. In order to find hidden patterns and insights that lie under the surface, practitioners are required to apply methods such as multidimensional visualisation, network analysis, and hierarchical clustering. This is necessary because practitioners are required to deal with the inherent uncertainty and ambiguity that is present in complex data.

Additionally, in order to successfully navigate complexity, practitioners need to be willing to accept ambiguity and uncertainty as unavoidable characteristics of complex systems. These visualizations run the danger of distorting or oversimplifying the underlying data, which may result in erroneous interpretations or inaccurate conclusions. Visualizations that aim to oversimplify or decrease complexity run this risk. Instead, practitioners need to take a nuanced approach that respects the limits of visualisation in terms of capturing the entire complexity of real-world occurrences, while at the same time giving significant insights and making it easier to comprehend the phenomenon(Kosara, R., & Mackinlay, J. 2013) . In order to successfully navigate complexity, it is necessary to encourage cooperation across disciplines and to rely on a wide range of viewpoints and areas of expertise while addressing complicated issues. Through collaboration with specialists in subjects like as mathematics, computer science, cognitive science, and domain-specific domains, practitioners are able to harness complementary talents and insights to solve complicated issues from a variety of perspectives. This multidisciplinary approach gives practitioners the ability to harness the power of a wide variety of viewpoints and approaches, which in turn enriches the practice of data visualisation and expands the bounds of what is possible.

Furthermore, in order to successfully navigate complexity, practitioners are need to prioritise clarity, coherence, and principles of user-centered design in their visualizations. The presentation of complicated material may quickly overwhelm users if it is not presented in a clear and intuitive way. Therefore, it is vital for practitioners to apply effective visual encoding methods, hierarchical organization, and interactive elements that lead users through the complexity and assist understanding. Practitioners are able to build visualizations that enable users to manage complexity with confidence and clarity if they prioritise the demands of the user and cognitive principles.It is necessary to take a comprehensive strategy that incorporates technical competence, multidisciplinary cooperation, and user-centered design concepts in order to successfully navigate the complicated and ever-changing world of data visualisation. Practitioners can unlock new insights, foster deeper understanding, and ultimately create visualizations that empower individuals and organizations to make informed decisions and navigate the complexities of our interconnected world if they embrace complexity as an opportunity for innovation and exploration. This is because complexity is an opportunity for exploration and innovation.

- **Dynamic and Evolving Systems:** Navigating complexity involves recognizing that many real-world systems are dynamic and evolving, with relationships and patterns that change over time. Visualizing dynamic data requires techniques that capture temporal dynamics, such as time-series analysis, animation, and interactive timelines. Practitioners must consider how to represent temporal changes in a way that maintains coherence and clarity, while also allowing users to explore and analyze trends and patterns over time. (Brehmer, M., & Munzner, T. 2013)
- **Uncertainty and Risk Management:** Complexity often brings with it uncertainty and inherent risks that must be carefully managed in the visualisation process. Practitioners must grapple with uncertainty in data quality, model assumptions, and future projections, employing techniques such as uncertainty visualisation, sensitivity analysis, and scenario planning to convey the range of possible outcomes and associated risks. By transparently communicating uncertainty, practitioners can help users make informed decisions in the face of complexity.
- **Cognitive Load and Information Overload:** In order to successfully navigate complexity, practitioners need to take into account the cognitive burden that is put on users and take measures to reduce the danger of information overload. Users can be overwhelmed and their comprehension

can be hindered by visualizations that present an excessive amount of information or complexity all at once. In order to manage cognitive load and lead users through the visualisation hierarchy, practitioners need to apply tactics such as progressive disclosure, data aggregation, and selective emphasis. These strategies offer information in pieces that are easily consumable, which helps with understanding and decision-making.

- **Adaptive and Responsive Design:** In order to successfully navigate complexity, it is necessary to build visualizations that are user-friendly and sensitive to their individual requirements and preferences. Adaptive design principles allow visualizations to adjust dynamically based on user interactions, preferences, and device characteristics, ensuring optimal usability and engagement across diverse contexts. The principles of responsive design guarantee that visualizations are accessible and usable across a variety of devices and screen sizes, therefore catering to the diverse requirements and capabilities of users.
- **Ethical Considerations in Complex Systems:** Ethical decision-making requires practitioners to engage in critical reflection and consultation with stakeholders in order to ensure that visualizations uphold integrity, transparency, and respect for human values and rights. Navigating complexity requires practitioners to grapple with ethical considerations that arise in the context of complex systems and their visualisation. Practitioners are required to take into consideration the potential ethical implications of their visualizations, which may include issues such as fairness, bias, privacy, and the impact on society.
- **Iterative and Collaborative Approach:** The process of navigating complexity is one that is iterative and collaborative, and it calls for continuous exploration, feedback, and modification. Practitioners are required to have an agile attitude, which involves regularly iterating on their visualizations depending on user input, new insights, and changing needs. It is vital to collaborate with domain experts, stakeholders, and end-users in order to get a variety of viewpoints, as well as to guarantee that visualizations successfully handle complex situations and promote informed decision-making. (Carpendale, S., Cowperthwaite, D., & Fracchia, F. D. 2003)

1.17 Emerging Challenges

The subject of data visualisation is continuously undergoing fast evolution as a result of developments in technology, alterations in data ecosystems, and evolving social dynamics. As a result, practitioners are confronted with a wide variety of new difficulties that call for creative solutions and flexible methods. These issues are a reflection of the intricate interaction that exists between technical, social, and ethical concerns. They provide new questions and dilemmas that need careful thought and proactive answers.The proliferation of big data and the rising complexity of datasets is one of the most significant developing difficulties now being faced in the field of data visualisation. With the exponential expansion in data volume, variety, and velocity, practitioners are faced with the difficult problem of extracting useful insights from enormous datasets that include a range of different types of data. This difficulty is complicated by the need to traverse a wide variety of data sources, combine data formats that are not compatible with one another, and handle concerns about the quality of the data, bias, and ambiguity. To be able to manage the intricacies of big data while preserving clarity, accuracy, and usability, practitioners need to design visualisation approaches that are scalable and efficient. The proliferation of artificial intelligence (AI) and machine learning (ML) brings with it a number of possibilities as well as difficulties for the field of data visualisation. Increasingly, artificial intelligence (AI) and machine learning (ML) algorithms are being used to automate data analysis, discover patterns, and produce insights from data. (Hullman, J., Adar, E., & Shah, P. 2011) The use of these technologies raises problems of algorithmic bias, interpretability, and accountability, despite the fact that they hold the potential of releasing fresh insights and simplifying the process of visualisation. Practitioners are need to cope with the ethical implications of AI-driven visualisation approaches, particularly with regard to the maintenance of openness, fairness, and human supervision in the use of automated algorithms.

In this day and age of increased data sensitivity and regulatory scrutiny, one of the increasing challenges in the field of data visualisation is the need to address concerns about privacy, security, and data governance respectively. For the purpose of protecting sensitive information that is included inside visualizations, practitioners are required to apply comprehensive data protection mechanisms, such as encryption, access limits, and anonymization methods. This is because concerns over data privacy and security are becoming more prevalent. Furthermore, in order to ensure compliance with data protection regulations, such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), practitioners are required to navigate complex legal and regulatory landscapes. This is done to ensure that visualizations adhere to stringent privacy standards and respect the rights of individuals to have their data privacy protected. Practitioners have a substantial problem as a result of the growing focus placed on ethical issues in the field of data visualisation. Visualizations are playing an increasingly significant role in moulding public opinion, governmental choices, and social narratives. As a result, practitioners are being forced to engage with problems of openness, justice, and responsibility in their visualisation processes. It is necessary for practitioners to embrace ethical frameworks and principles that prioritise honesty, respect for human rights, and the public interest in order to address ethical challenges such as the responsible use of data, the avoidance of prejudice and misrepresentation, and the equal representation of multiple views. There are issues that arise in terms of interoperability, standardisation, and user experience as a result of the fast speed of technical innovation and the proliferation of visualisation tools and platforms. Practitioners are required to manage the complexity of tool selection, data integration, and workflow optimisation in order to achieve smooth interoperability and a coherent user experience. This is because there is a multitude of tools and approaches accessible. Additionally, the democratisation of visualisation tools has resulted in a wide variety of skill levels and competence among users, which has created issues in terms of data literacy, usability, and accessibility. Practitioners need to take a proactive and interdisciplinary strategy that incorporates technological skills, ethical concerns, and human-centered design principles in order to successfully navigate these new difficulties. Practitioners are able to navigate the complexities of data visualisation and harness its transformative potential to address pressing societal challenges, promote informed decision-making, and empower individuals and communities to navigate a world that is becoming increasingly data-driven. This is accomplished by embracing innovation, fostering collaboration, and placing an emphasis on ethical integrity. (Stasko, J. T., Görg, C., & Liu, Z. 2008)

The rising use of complicated machine learning models and algorithms in data analysis and visualisation has resulted in an increased need for interpretability and explainability. This demand is expected to continue to expand in the coming years. Users are required to have an understanding of the process by which algorithms arrive at their findings and suggestions, particularly in crucial fields such as healthcare and finance. For the purpose of establishing trust, promoting transparency, and encouraging meaningful insights and decision-making, it is vital to make certain that visualizations can be interpreted and explained.

- **Bias and Fairness:** In recent years, bias and fairness have arisen as key concerns in the field of data visualisation, especially in the context of algorithmic decision-making and automated systems. By accident, visualizations have the potential to exacerbate biases that are already present in the underlying data or algorithms, which may result in results that are unjust or discriminating. In order to enhance fairness and justice in data-driven decision-making processes, practitioners are required to proactively identify and reduce biases in visualizations. strategies such as bias detection, fairness-aware visualisation, and algorithmic auditing are some of the strategies that may be used.

- **Ethical Considerations in AI-generated Visualizations:** The rising usage of visualizations created by artificial intelligence presents a unique set of ethical concerns, notably with relation to ownership, responsibility, and the interpretability of generated visualizations. When artificial intelligence algorithms develop visual representations of data on their own, problems emerge about who owns the visualizations that are generated, who is accountable for the correctness of the visualizations and the ethical implications of using them, and how users may comprehend and trust the insights that are provided by AI. Taking into account these ethical issues calls for the establishment of transparent norms and procedures for the appropriate creation and use of visualizations created by artificial intelligence.
- **Data Sovereignty and Global Data Governance:** There are issues associated with data sovereignty and global data governance that are brought about by the globalisation of data and the movement of information across international borders. In the context of data localization, cross-border data transfers, and compliance with international standards, the fact that different nations and regions have different regulatory frameworks and data protection legislation creates a difficult situation. Practitioners are required to negotiate various legal and regulatory environments in order to guarantee that visualizations adhere to the applicable data protection legislation and respect the rights of persons to privacy and data sovereignty.
- **Environmental Sustainability:** The influence that data visualisation methods have on the environment has become an urgent issue, especially in light of the growing amount of energy that is used and the carbon footprint that is linked with data processing and visualisation. The complexity and size of visualizations are increasing, which means that their computing and energy needs are also increasing. This is a factor that contributes to the deterioration of the environment and the change in climate. In order to lessen the impact that data visualisation has on the environment and to advance the cause of environmental sustainability, practitioners are required to embrace sustainable practices. These practices include optimising algorithms, minimising data storage and processing, and making use of renewable energy sources. (Brehmer, M., & Munzner, T. 2013)

1.18 Mitigation Strategies

Considering that data visualisation continues to play a major role in decision-making processes across a wide range of disciplines, the necessity for effective mitigation measures to manage the problems and risks associated with visualisation techniques is becoming more crucial. The term "mitigation strategies" refers to a variety of ways and methods that are designed to reduce the likelihood of adverse effects, improve the quality and integrity of visualizations, and encourage actions that are both ethical and responsible. The use of these tactics is necessary in order to guarantee that visualizations continue to be reliable, informative, and accurate in the face of a constantly shifting data environment.The awareness of the inherent difficulties and uncertainties that are inherent in data visualisation is the fundamental component of mitigation measures. The process of visualizing complicated data often involves simplifying, abstracting, and interpreting the data, which may result in the introduction of biases, mistakes, and an incorrect interpretation of the data. These risks are intended to be mitigated by the implementation of stringent data validation, verification, and cleaning procedures in order to guarantee the correctness and dependability of the data that is on the basis of the mitigation measures. In addition, practitioners are required to do an in-depth analysis of the suitability of visualisation methods and representations for the data at hand, ensuring that they do not oversimplify or misrepresent information that is complicated. It is important to note that mitigating solutions include initiatives that aim to improve openness, accountability, and ethical integrity in visualisation processes. In order for consumers to comprehend the context and the dependability of the information that is provided, practitioners are required to record and convey the methodology, assumptions, and limits that are underpinning their visualizations. In addition, practitioners should follow to ethical principles and standards that prioritise justice, privacy, and respect for human rights when it comes to the design and execution of visualizations. (Shneiderman, B., Plaisant, C., & Hesse, B. W. 2013)

It is possible for practitioners to reduce the danger of unintended effects and increase trust and confidence in visualised data if they include ethical concerns into each and every step of the visualisation process. Utilizing technology advances and improvements to improve the efficiency and dependability of visualizations is one of the mitigation methods that may be used. Methods such as data anonymization, encryption, and access restrictions are some of the techniques that may be used to assist alleviate privacy issues and protect sensitive information that is shown in visualizations. Along the same lines, developments in machine learning and artificial intelligence have made it possible for practitioners to automate processes such as error detection, anomaly identification, and data validation. This has the effect of minimising the possibility of mistakes and inconsistencies occurring in visualizations. In the context of mitigation methods, efforts are made to provide users with the information, skills, and tools that are required to critically assess and comprehend data that has been visualised. In order to provide users with the capacity to differentiate between visualizations that are correct and those that are deceptive, practitioners should give users with training and instruction on data literacy, visualisation literacy, and critical thinking abilities. Visualizations should also be designed with user-centered ideas in mind by practitioners. This will ensure that they are accessible, intuitive, and useable for a wide range of audiences, each of whom has a different degree of experience and previous knowledge.Mitigation methods are crucial instruments for fostering accuracy, openness, and ethical integrity in visualisation activities. They are used in the process of managing the complexity and obstacles that are associated with data visualisation. Through the implementation of a proactive and multidisciplinary approach that incorporates technical expertise, ethical considerations, and principles of user-centered design, practitioners have the ability to reduce risks, improve the quality and reliability of visualizations, and enable users to make informed decisions based on trustworthy and actionable insights.

1. **Continuous Monitoring and Feedback:** The establishment of systems for continuous monitoring and feedback is an essential component of mitigation measures. These procedures are designed to detect and correct possible problems or deficiencies in visualizations. For the purpose of tracking how visualizations are used and perceived by users in real-world situations, practitioners should create systems for user feedback, usability testing, and performance monitoring. Practitioners are able to iteratively develop and enhance visualizations by collecting feedback and insights from users. This allows them to solve usability concerns, improve accuracy, and increase user happiness(. Heer, J., & Agrawala, M. 2006)
2. **Robust Data Governance Frameworks:** The management of the full lifespan of data visualisation projects is governed by comprehensive data governance frameworks, which are developed and implemented as part of mitigation measures. For the purpose of assuring the quality, integrity, and safety of the data that is used in visualizations, data governance frameworks describe the rules, processes, and responsibilities that are associated with data management. It is important for practitioners to define clear roles and responsibilities, data stewardship policies, and data

quality standards throughout the visualisation process in order to reduce risks and encourage responsibility.

3. **Resilience to Adversarial Attacks:** The development of resistance against adversarial attacks and the manipulation of visualizations for harmful purposes is an essential component of mitigation techniques. Visualizations are becoming more important in decision-making processes, which means that they are becoming targets for hostile actors that are looking to mislead, manipulate, or exploit weaknesses in visualizations for harmful objectives. The use of methods such as rigorous data validation, anomaly detection, and integrity checks is recommended for practitioners in order to identify and prevent efforts to alter visualizations, as well as to guarantee the trustworthiness and dependability of the visualizations.
4. **Cross-Disciplinary Collaboration**: The implementation of mitigation methods requires the promotion of inter-disciplinary cooperation and the exchange of information between practitioners, academics, and stakeholders from a variety of varied sectors. Through collaboration, practitioners are able to harness complementary knowledge, perspectives, and approaches in order to handle difficult issues and create novel solutions. Practitioners have the opportunity to gather insights into emerging trends, best practices, and mitigation techniques that are relevant to their visualisation projects by connecting with experts from disciplines such as computer science, statistics, psychology, and domain-specific topics.
5. **Adaptive and Agile Development Processes:** The use of adaptive and agile development procedures is one of the mitigation techniques. These approaches allow practitioners to adjust rapidly and effectively to shifting needs, priorities, and obstacles in data visualisation projects. Throughout the visualisation lifecycle, practitioners are able to integrate input, fix difficulties, and react to changing demands thanks to agile approaches like as Scrum and Kanban. These methodologies encourage iterative development, incremental delivery, and continuous improvement. Practitioners are able to reduce risks, speed up delivery, and assure the relevance and efficacy of visualizations in situations that are always changing if they embrace agility and adaptability.
6. **Robust Disaster Recovery and Contingency Planning:** The establishment of effective disaster recovery and contingency planning processes is an essential component of mitigation techniques. These mechanisms are designed to reduce the impact that unanticipated events or interruptions have on data visualisation initiatives. For the purpose of ensuring the continuation and resilience

of visualisation operations in the case of natural catastrophes, cyberattacks, system failures, or any other kind of emergency, practitioners should build contingency plans, backup techniques, and recovery processes. Practitioners may minimise downtime, avoid data loss, and ensure the integrity and availability of visualizations under bad situations if they prepare for eventualities in advance and take proactive measures to plan for them. (Segel, E., & Heer, J. 2010)

Through the use of this systematic review, the investigation of data visualisation problems highlights the crucial relevance of recognising and overcoming the issues that are inherent in the process of visualisation. This study gives significant insights into the typical pitfalls, constraints, and restrictions experienced by practitioners in the area of data visualisation. These insights are provided by methodically analyzing and synthesising current research and literature on data visualisation pitfalls. As a basic step towards establishing effective mitigation measures and best practices for increasing the quality, accuracy, and usability of data visualizations, the identification of these problems serves as a foundational step.The multidisciplinary character of data visualisation is brought to light in this systematic study, which also emphasises the importance of cooperation and the sharing of information across a wide range of sectors and specialties. The potential hazards that have been discovered in this analysis extend beyond technological concerns and involve larger difficulties that are associated with cognitive psychology, human-computer interaction, ethics, and social context. A multidisciplinary strategy that combines technical competence with insights from psychology, design, ethics, and other relevant disciplines is required in order to address these potential hazards with the appropriate level of success.

In addition, the findings of this systematic research highlight the significance of taking ethical issues into account while engaging in data visualisation methods. Due to the fact that visualizations have the ability to mould perceptions, influence choices, and motivate action, it is very necessary for practitioners to adhere to ethical principles and standards throughout the whole process of visualisation. It is possible for practitioners to generate trust and confidence in visualised data by supporting openness, fairness, and accountability in visualisation techniques. This gives users the capacity to make educated choices based on credible and trustworthy insights.

CHAPTER 2
REVIEW OF LITERATURE

2.1 Introduction

The realm of data visualization stands as a critical juncture where the intersection of data science and communication converges, offering immense potential for insight generation and knowledge dissemination. However, amidst the proliferation of visualization tools and techniques, there exists a labyrinth of challenges and pitfalls that can undermine the efficacy and integrity of visual representations of data. This systematic review endeavors to navigate this terrain by embarking on a comprehensive exploration of existing literature dedicated to unraveling the intricacies of data visualization pitfalls. Through a meticulous examination of scholarly works spanning various disciplines, this review seeks to identify, categorize, and analyze the diverse array of challenges encountered in the creation, interpretation, and consumption of visualizations. By synthesizing insights from theoretical frameworks, empirical studies, and practical applications, it aims to offer a nuanced understanding of the factors contributing to visualization pitfalls and their implications for decision-making, communication, and knowledge discovery. Moreover, this review endeavors to highlight gaps in current understanding, methodological limitations, and avenues for future research aimed at mitigating the risks associated with data visualization pitfalls. Thus, this introductory section serves as a preamble to a systematic journey through the literature, illuminating the importance of critically evaluating the strengths and limitations of data visualization practices in the pursuit of data-driven insights and informed decision-making.In the contemporary data-driven landscape, where information overload is ubiquitous and decision-makers increasingly rely on visual representations to make sense of complex datasets, the importance of effective data visualization cannot be overstated. However, amidst the allure of vibrant graphics and interactive dashboards lies a minefield of potential pitfalls that threaten the integrity and utility of visualized data. This systematic review embarks on a quest to illuminate these pitfalls by delving into the wealth of literature dedicated to understanding the intricacies of data visualization challenges. By synthesizing insights from a diverse array of disciplines including data science, psychology, design, and communication, this review aims to provide a holistic perspective on the multifaceted nature of visualization pitfalls. Through a rigorous examination of empirical studies, case analyses, and expert opinions, it endeavors to categorize and elucidate the various types of pitfalls encountered at different stages of the visualization process – from data selection and preprocessing to design and interpretation. Moreover, this review seeks to elucidate the underlying cognitive, perceptual, and contextual factors that contribute to the emergence of these pitfalls, shedding light on the complexities inherent in translating raw data into meaningful visual narratives. By critically appraising existing literature, this review not only aims to raise awareness about the challenges associated with data visualization but also to offer practical insights and recommendations for practitioners, educators, and researchers seeking to navigate this terrain with greater precision and proficiency. Thus, this introductory section serves as a compass, guiding readers through the intricate terrain of data visualization pitfalls and setting the stage for a systematic exploration of the literature.

2.2 Conceptual framework

The conceptual framework of this systematic review encompasses several key components that guide the investigation and analysis of data visualization pitfalls. At its core, the framework acknowledges the fundamental purpose of data visualization: to effectively communicate insights derived from complex datasets to diverse audiences. Within this context, the review identifies three primary dimensions that influence the occurrence and impact of visualization pitfalls: design, perception, and cognition. The design dimension encompasses various aspects of visual representation, including chart types, color schemes, layout, and annotation. Within this dimension, pitfalls may arise from poor design choices, such as inappropriate chart selection, cluttered layouts, or misleading visual cues. By critically evaluating design decisions and their implications, the review aims to identify common design pitfalls and their effects on data interpretation and comprehension. By examining the perceptual mechanisms underlying visualization pitfalls, the review aims to uncover insights into the cognitive processes involved in data interpretation and decision-making.The cognition dimension explores the cognitive processes involved in understanding and reasoning about visual information. Cognitive biases, mental models, and heuristics shape how individuals interpret and make sense of visual data representations. Pitfalls in this dimension may stem from cognitive limitations, such as confirmation bias, framing effects, or overreliance on intuitive judgments.

Please you can use this example to call out the variables and concepts

Research Question	Key Factors of Data Visualization Pitfalls
1. What are the primary factors contributing to misleading visual representations in data visualization?	**Inappropriate Scaling**: Using inappropriate scaling on axes can distort the perception of data relationships, making certain trends appear more significant or insignificant than they actually are. **Truncating Axes:** Truncating axes, especially in line charts or bar graphs, can exaggerate or minimize differences between data points, leading to misinterpretation of trends or magnifying the importance of outliers. **Misleading Chart Types:** Choosing chart types that are not appropriate for the data being presented, such as using 3D charts or pie charts for complex data sets, can lead to misrepresentation of the data and obscure important insights.
2. How do overplotting issues impact the effectiveness of data visualizations?	**Obscuring Patterns and Trends**: Overplotting occurs when data points overlap excessively, making it difficult to distinguish individual points or identify trends within the dataset. **Loss of Detail**: Overplotting can result in the loss of detail in the visualization, particularly in dense regions of the plot where many data points coincide, leading to a lack of clarity in the representation of the data. **Difficulty in Interpretation**: Overplotting makes it challenging for viewers to interpret the visualization accurately, as it may be unclear which data points are represented and how they contribute to the overall pattern or trend being depicted.

3. What role do audience needs play in determining potential pitfalls in data visualization?	**Complexity Management**: Tailoring the level of complexity in data visualization to match the audience's expertise and familiarity with the subject matter helps prevent overwhelming viewers with overly technical or intricate visualizations. **Interactivity Requirements**: Identifying the audience's preferences for interactive features such as tooltips, filtering options, or drill-down capabilities can influence the design of the visualization to enhance engagement and exploration of the data. **Cultural Considerations**: Acknowledging the cultural background and context of the audience can guide decisions related to color choices, symbolism, and graphical representations to ensure that the visualization resonates with diverse viewers and avoids potential misinterpretations.
4. How do colour choices influence the interpretation of visualized data and contribute to potential pitfalls?	**Emotional and Cultural Associations**: Colors carry emotional and cultural connotations that can influence how data is perceived. Inappropriate use of colors with strong associations may bias interpretations or convey unintended messages, especially in diverse or international contexts. **Accessibility and Visibility**: Inadequate consideration of color blindness and other visual impairments can result in visualizations that are inaccessible to certain audience members. Choosing colors that are distinguishable to individuals with different types of color vision

	ensures inclusivity and improves the effectiveness of the visualization. **Color Encoding for Variables**: Using color to encode different variables or categories in the data requires careful selection to avoid ambiguity or confusion. Choosing a color scheme that effectively distinguishes between categories while maintaining coherence and consistency aids in clear interpretation.

2.3 Theoretical framework

A theoretical framework for understanding data visualization pitfalls, as identified through a systematic review, encompasses several key dimensions. Firstly, the cognitive processing of visual information is integral, recognizing that human perception and cognition play pivotal roles in interpreting visualizations. This involves considering factors such as Gestalt principles, which elucidate how individuals perceive patterns, shapes, and relationships within visual stimuli. Additionally, cognitive load theory underscores the importance of designing visualizations that minimize cognitive burden, ensuring that viewers can efficiently process and comprehend the presented data.

Secondly, the role of design principles and best practices in data visualization is paramount. Adherence to principles of effective visualization design, including clarity, simplicity, and coherence, mitigates common pitfalls such as misleading representations and cluttered visualizations. Consideration of visual encodings, such as color, size, and position, within the context of perceptual principles aids in creating visualizations that facilitate accurate interpretation and insight extraction.

Furthermore, audience-centered considerations are essential in understanding data visualization pitfalls. Recognizing the diverse backgrounds, expertise levels, and information needs of viewers informs decisions regarding visualization complexity, interactivity, and accessibility features.

Tailoring visualizations to align with audience preferences and communication goals enhances engagement and comprehension while reducing the risk of misinterpretation.

Lastly, technological advancements and the proliferation of data visualization tools introduce additional dimensions to the theoretical framework. Understanding the capabilities and limitations of visualization software and platforms is crucial for avoiding pitfalls related to tool-induced biases, inappropriate chart selection, and insufficient customization options. Moreover, advancements in interactive and immersive visualization techniques offer opportunities to address longstanding challenges and enhance the effectiveness of data communication.

By integrating these dimensions within a theoretical framework, researchers and practitioners can systematically analyze and address data visualization pitfalls, ultimately advancing the field and promoting more effective visual communication of data-driven insights.

Cognitive Processing of Visual Information: Understanding how humans perceive and interpret visual stimuli is fundamental to effective data visualization. Gestalt principles, originating from Gestalt psychology, elucidate how individuals organize and make sense of visual elements. These principles, including proximity, similarity, closure, and continuity, provide insights into how viewers perceive patterns, shapes, and relationships within visualizations. For instance, the principle of proximity suggests that elements placed close together are perceived as belonging to the same group, influencing the design of clustered visualizations to convey related data points.Cognitive load theory, another cornerstone in cognitive psychology, emphasizes the limitations of human cognitive processing and memory capacity. Designing visualizations with cognitively manageable complexity is essential to avoid overwhelming viewers and facilitate information processing. Strategies such as reducing extraneous cognitive load by eliminating unnecessary visual elements and optimizing the presentation of data to minimize cognitive effort contribute to the effectiveness of data visualization.

Design Principles and Best Practices: Adhering to design principles and best practices is critical for creating visualizations that effectively communicate insights while mitigating potential pitfalls. The principle of simplicity advocates for the elimination of unnecessary complexity in visualizations, promoting clarity and ease of interpretation. Clear labeling, concise titles, and streamlined visual elements enhance comprehension and reduce the risk of misinterpretation.Coherence, another fundamental design principle, underscores the importance of ensuring that visual elements align with the intended message and narrative of the visualization. Consistency in visual encoding, such as using the same color scheme or symbol conventions throughout the visualization, fosters coherence and aids viewers in making accurate comparisons and connections between data elements.Additionally, considerations of visual hierarchy and emphasis play a crucial role in directing viewers' attention to key insights within the visualization. Strategic use of visual cues, such as color, size, and spatial arrangement, helps prioritize information and guide viewers' focus, thereby enhancing the effectiveness of data communication.

Audience-Centered Considerations: Audience analysis is central to designing visualizations that resonate with viewers and meet their information needs. Tailoring visualizations to accommodate diverse audience backgrounds, expertise levels, and preferences ensures relevance and engagement. Understanding the specific goals and objectives of the audience enables designers to customize visualizations to align with communication objectives and desired outcomes.Accessibility considerations are also paramount in ensuring inclusivity and reaching a broader audience. Designing visualizations that are accessible to individuals with disabilities, such as visual impairments or color blindness, involves adhering to accessibility standards and guidelines. Providing alternative text descriptions, incorporating high-contrast color schemes, and offering interactive features for navigation enhance accessibility and usability for all viewers.Moreover, audience feedback and iterative design processes play a crucial role in refining visualizations and addressing potential pitfalls. Soliciting input from target audience members through usability testing, surveys, and interviews enables designers to identify areas for improvement and iteratively enhance the effectiveness of visualizations.

Technological Advancements and Tools: The landscape of data visualization is continuously evolving with advancements in technology and the proliferation of visualization tools and platforms. Understanding the capabilities and limitations of visualization software is essential for leveraging technological advancements effectively while mitigating potential pitfalls.Interactive and immersive visualization techniques offer new opportunities for engaging audiences and facilitating exploration of complex datasets. Techniques such as interactive dashboards, data-driven storytelling, and virtual reality (VR) visualization environments enhance interactivity and engagement, enabling viewers to interact with data in meaningful ways.However, the abundance of visualization tools and options also introduces challenges related to tool-induced biases, inappropriate chart selection, and data misrepresentation. Designers must exercise caution in selecting appropriate visualization types that align with the characteristics of the data and the communication goals. Additionally, customization options and flexibility in visualization tools empower designers to create tailored visualizations that meet specific requirements and preferences.Furthermore, advancements in data visualization technologies, such as machine learning algorithms for automated visualization design and data-driven recommendation systems, hold promise for addressing common pitfalls and optimizing the effectiveness of visual communication. By harnessing the power of data-driven insights and computational techniques, designers can augment their decision-making processes and enhance the impact of visualizations.

(Van Wijk 1991) studied “Spot Noise Texture Synthesis for Data Visualization” A discussion is taking place about the utilization of stochastic textures for the purpose of visualizing scalar and vector fields across surfaces. The approaches that are currently being used for texture synthesis are not acceptable since they do not offer local control and are not suited for the creation of textures. These characteristics are provided by a newly developed method known as.YprMnoise, which is discussed here. The appearance of spot noise is achieved via the insertion of spots that are randomly weighted and positioned. Through the use of spot variation, it is possible to achieve local control of the texture. The spot is a good basic for texture creation because, in general, the links between the properties of the spot and the features of the texture are straightforward. This makes the spot an incredibly valuable primitive. Several examples and applications are presented, and it is demonstrated that spot noise is an alternative to solid texturing since it facilitates the synthesis of texture across curved surfaces and lends itself well to this process. It is explored how spot noise is related to a wide range of different approaches, including random defects, tittering, sparse convolution, and particle systems, amongst others. It would appear that spot noise offers a fresh viewpoint on the implementation of those strategies.

(Erickson 1993) studied “Artificial Realities as Data Visualization Environments: Problems and Prospects” When it comes to making better use of data, one of our greatest prospects is to take use of visualisation. With phrases like "I see what you mean," let me shed some light on the subject, let's take a closer look at that argument, and I have a different view, as well as phrases like insight, foresight, and overview, it is not an accident that visual words are utilized as a prevalent metaphor for comprehension. In spite of the fact that visualisation is frequently associated with the colourful depictions of exotic scientific phenomena, such as the galactic jets, enzymes, or brain scans that are frequently featured on the covers of magazines, it is essential to acknowledge that visualisation can be usefully applied to even the most mundane data. The purpose of data visualisation is to portray information in a manner that facilitates its perceptibility and, as a result, the ability to engage the sensory systems of humans. The use of visualisation may assist us in using and comprehending data in three different ways, which are not mutually exclusive: contextualization, transformation, and selective emphasis utilising visualization.

(Van Wijk 1991) studied "Research Challenges in Geovisualization Alan" The results of an international effort to outline a four-part research agenda for geovisualization are presented in this special issue of Cartography and Geographic Information Science. An international partnership was conducted to accomplish this. Visualisation in scientific computing (ViSC), cartography, image analysis, information visualisation, exploratory data analysis (EDA), and geographic information systems (Geosystems') are all utilized in the process of geovisualization. The goal of this integration is to provide the framework, methods, and tools necessary for visual exploration, analysis, synthesis, and presentation of geospatial data (any data that contains geospatial references). The representation of geographical information, the integration of visual and computational techniques of knowledge production, the design of interfaces for geovisualization environments, and the cognitive and usability elements of geovisualization are the primary topics that are discussed in this article.

(Nielson 2002) studied "data visualization: the state of the art" A significant method for reducing the geometric complexity of big polygonal models is occlusion and visibility culling, which is one of the most important strategies. Since the advent of hardware-assisted occlusion culling in OpenGL (as an extension), software-based techniques are gradually losing their relevance for applications that are unable to use specialised knowledge of the scene geometry to the same extent. On the other hand, there are still a number of software-related issues that need to be resolved before major speed gains can be made. In the next paper, we will go over a few of these respective methods.

(Flowers 2005) studied "Thirteen Years of Reflection on Auditory Graphing: Promises, Pitfalls, and Potential New Directions" Even though advancements in sound production hardware have made it possible for casual users of personal computers to create auditory graphs, there are still some obstacles that prevent effective applications of this promising technology from being implemented. These obstacles are similar to those that were encountered in the early 1990s when it came to the development of effective auditory displays. A lack of comprehensive understanding regarding essential features of auditory perception and attention, as well as improper generalisations of existing data visualisation approaches, are the primary causes of the majority of these errors. At the same time, however, we are now aware of a few ways that appear to be effective and give promise for the purpose of making sonification a convenient and widely recognised instrument for the study of data and the making of decisions. The current study provides a summary of various cases that have been picked from each of these categories, as well as some ideas for potential future research topics.

(Broadhurst and Kell 2006) studied "Statistical strategies for avoiding false discoveries in metabolomics and related experiments" Many metabolomics experiments, as well as other high-content or high-throughput investigations, are designed in such a way that the primary objective is to identify biomarker metabolites that are capable of distinguishing, with a given degree of accuracy, between samples that are ostensibly matched as "case" and "control." However, it is unfortunate that it is relatively simple to uncover markers that appear to be convincing but are, in reality, completely erroneous. There are cases that are well-known in the proteomics literature that illustrate this phenomenon. The most significant types of risk are not entirely independent of one another, but they include bias, insufficient sample size (especially in relation to the number of metabolite variables and to the required statistical power to demonstrate that a biomarker is discriminant), an excessive false discovery rate as a result of testing multiple hypotheses, an inappropriate choice of particular numerical methods, and overfitting (which is typically brought on by the failure to perform adequate validation and cross-validation). In spite of their assertions, a great number of research fail to take these factors into consideration, and as a result, they do not uncover anything that is truly significant. We present a summary of these issues and references to a considerable body of existing literature that ought to be of assistance in the improvement of the design and assessment of metabolomics studies. This should make it possible to derive sound scientific conclusions via the utilization of the data that is already accessible. We present a list of some of the more straightforward checks that might potentially increase one's confidence that a prospective biomarker is not merely a statistical artefact. Additionally, we recommend a series of preferred tests and visualisation tools that can aid readers and writers in evaluating studies. These instruments may be utilized for the purpose of analyzing individual metabolites by employing numerous univariate tests that are carried out in parallel across all metabolite peaks. The validation of multivariate models is another one of the possible applications for them. It is of particular importance to emphasise that traditional p-values, such as "p0.05," which are frequently employed in the field of biomedicine, are too optimistic when many tests are conducted concurrently, as is the case in the field of metabolomics. Because this makes it possible for the entire community to evaluate the conclusions that are reached from the data and metadata, it is ultimately ideal that all of the data and metadata be made available electronically. The studies presented here are applicable to all high-dimensional omics datasets.

(Bresciani and Eppler 2008) studied “The Risks of Visualization This article provides a comprehensive analysis and categorization of the drawbacks and dangers that are connected to the use of visual representations of information. A study of the relevant literature is supplemented by interviews with subject matter experts and the findings of focus groups concerning the practical adverse experiences associated with the use of visual representations of information. On the basis of these two sources, we differentiate between social, cognitive, and emotional hazards associated with visualisation. These risks may be regarded from two different points of view: from the point of view of the user, and from the point of view of the creator of a graphic representation. In this section, we address the ramifications of the discovered drawbacks, as well as solutions to overcome or prevent them by avoiding them. Towards the end of the study, a view is presented on hazards of visualisation that have been neglected or that have emerged.

(Carpendale 2008) studied Evaluating Information Visualizations Sheelagh Research in the field of information visualisation is gaining more and more traction, and as a consequence, it is becoming increasingly essential that research in this area be validated. Despite the fact that the quantity of empirical work that is directly focused on information visualisation has increased, it has been disproportionately little in comparison to the overall growth in the amount of research that has been conducted on information visualisation. The purpose of this paper is to raise awareness of empirical research in general, and of its relationship to information visualisation in particular; to emphasise the significance of empirical research; and to encourage the thoughtful application of a greater variety of evaluative research methodologies in the field of information visualisation.

(Munzner 2008) studied Process and Pitfalls in Writing Information Visualization Research Papers Through the utilization of a historical model of the research process, the purpose of this work is to assist writers in recognising and avoiding a set of traps that appears in a significant number of information visualisation papers that are rejected. A choice of validation techniques that is not appropriate can be avoided by selecting a target paper type during the early stage of the process. At some point during the latter phases of a project, it is possible for pitfalls to arise that include the design of a visual encoding. In a later stage, when the majority of the research has been completed and the writing of the paper has begun, the potential dangers include strategic decisions for the content and structure of the work as a whole, tactical difficulties that are localised to certain portions, and methods of presenting the results that are not convincing. After a complete draft of the paper has been created, it is possible to check for any final-stage writing style difficulties, and the final set of problems pertain to the submission process.

(Wang, Yu, and Ma 2008) studied Importance-Driven Time-Varying Data Visualization In a wide variety of scientific and technical fields, the capacity to recognize and convey the most relevant features of time-varying data is of the utmost significance. The purpose of this study is to provide a strategy to time-varying volume data visualisation that is driven by relevance in order to improve that capability. Following the notion of conditional entropy from information theory, we generate an important curve for each data block by undertaking a block-wise analysis of the data in the combined feature-temporal space. This allows us to determine the relevance of each data block. Each curve is a representation of the local temporal behaviour of the relevant block, and the underlying data may be efficiently classified by clustering the significance curves of all the volume blocks based on their respective importance. We present numerous fascinating and effective visualisation ways to expose the significant parts of time-varying data. These techniques are based on the various temporal patterns that are displayed by significance curves and the results of their clustering.

(Bresciani and Eppler 2008) studied The Perils of Visualization This article provides a comprehensive analysis and categorization of the drawbacks and dangers that are connected to the use of visual representations of information. A study of the relevant literature is supplemented by interviews with subject matter experts and the findings of focus groups concerning the practical adverse experiences associated with the use of visual representations of information. On the basis of these two sources, we differentiate between social, cognitive, and emotional hazards associated with visualisation. These risks may be regarded from two different points of view: from the point of view of the user, and from the point of view of the creator of a graphic representation. In this section, we address the ramifications of the discovered drawbacks, as well as solutions to overcome or prevent them by avoiding them. Towards the end of the study, a view is presented on hazards of visualisation that have been neglected or that have emerged.

(Zuur, Ieno, and Elphick 2010) studied A protocol for data exploration to avoid common statistical problems In the course of their work as educators of ecologists, the primary authors of this publication have seen a number of statistical issues that are prevalent. If they were to choose a random sample of their work (including scientific articles) that they had created before to taking these classes, it is quite likely that half of it would involve breaches of the fundamental assumptions that underlie the statistical methods that were utilized. 2. While some infractions have a negligible effect on the findings or ecological conclusions, others lead to an increase in type I or type II mistakes, which may lead to incorrect ecological conclusions. A better use of data exploration can help prevent the majority of these violations from occurring. These issues are particularly problematic, particularly in the field of applied ecology, where decisions about management and policy are frequently held in jeopardy. 3. In this section, we present a protocol for the exploration of data; we discuss the tools that are currently available to identify outliers, heterogeneity of variance, collinearity, dependence of observations, problems with interactions, double zeros in multivariate analysis, zero inflation in generalised linear modelling, and the appropriate type of relationships between dependent and independent variables; and we offer guidance on how to deal with these issues when they occur. In addition to this, we dispel common misunderstandings regarding normalcy and offer guidance on how to convert data. 4. The process of data investigation helps to prevent mistakes of type I and type II, in addition to other issues, which in turn reduces the likelihood of drawing incorrect ecological conclusions and providing inadequate suggestions. Because of this, it is very necessary for effective quality management and policy that is founded on statistical analysis.

(Kelleher and Wagener 2011) studied Ten guidelines for effective data visualization in scientific publications Over the course of the past four decades, our capacity to visualise scientific data has seen substantial development. It is important to note that this progress does not necessarily eliminate the several typical mistakes that are associated with visualisation for scientific publications. These pitfalls can hinder the capacity of readers to fully comprehend the information that is delivered. In order to address this issue within the context of visualizing environmental data, we have compiled a list of 10 criteria for successful data visualisation in scientific papers. In order to effectively transmit information, which is the fundamental goal of data visualisation, these standards provide assistance for that purpose. When it comes to improving the communication of their findings through the use of effective visualisation, we feel that this short collection of suggestions, which is based on a survey of major visualisation literature, might be of assistance to researchers. The enhancement of environmental data visualisation will further improve the presentation of research as well as communication both within and between disciplines.

(Bertini, Tatu, and Keim 2011) studied Quality Metrics in High-Dimensional Data Visualization: An Overview and Systematization The purpose of this study is to propose a systematisation of strategies that provide assistance in the visual exploration of significant patterns in high-dimensional data. These techniques make use of quality measures. Different quality metrics have been proposed in a number of recent papers in order to automate the laborious search through large spaces of alternative visualizations (for example, alternative projections or ordering). This enables the user to focus on the visualizations that are suggested by the quality metrics that are the most promising. Over the course of the past ten years, this methodology has had a tremendous growth; yet, there are not many comments on how these methodologies are connected to each other and how the approach might be improved further. For the aim of achieving this goal, we present an overview of methods that make use of quality measures in high-dimensional data visualisation and offer a systematisation that is founded on an exhaustive analysis of the surrounding literature. After doing a thorough analysis of the articles, we come up with a list of criteria that may be used to differentiate between the various quality measures, visualisation approaches, and the process itself. Through a revised version of the well-known information visualisation pipeline, the procedure is presented in detail. The value of our model is demonstrated by applying it to a number of different techniques that are already in existence and make use of quality measurements. Additionally, we offer some observations on the implications of our model for more study in the future.

(Brodlie, Osorio, and Lopes 2012) studied A Review of Uncertainty in Data Visualization The vast majority of visualisation approaches have been developed while operating on the presumption that the data that are to be represented are devoid of any doubt. However, this is not generally the case. Recently, the visualisation community has taken on the task of including an indication of uncertainty into visual representations. In this article, we take a look at the work that they have done in this regard. The work is positioned within the framework of a reference model for data visualisation, which examines the flow of data via a series of procedures in a certain order. Because of this, we are able to differentiate between the visualisation of uncertainty, which takes into account the manner in which we display the uncertainty that is defined with the data, and the uncertainty of visualisation, which takes into account the degree of inaccuracy that happens when we process the data through the pipeline. It has taken some time for methods to be established for the visualisation of uncertainty, and we investigate the reasons why uncertainty visualisation is difficult. One rationale is because we normally need to discover another dimension of play, and it is possible that we have already used up all of these dimensions! In order to structure the information, we will be returning to a typology that was devised by one of us during the early days of visualisation. We will then utilise this typology to offer a library of visualisation approaches, outlining the research that has been done to expand each method to manage uncertainty. To conclude, we would like to point out that it is our collective obligation to include any known ambiguity into a visualisation in order to ensure that the integrity of the discipline is preserved.

(Sousa Santos and Dias 2013) studied Evaluation in Visualization: some issues and best practices Beatriz" However, researchers have grown conscious of the significance of assessment, and they are becoming more and more aware of its value (Plaisant, 2004). The earliest data and information visualisation techniques and systems were produced and presented without a systematic evaluation.a. 1. Evaluation is not only a method for enhancing methods and applications, but it also has the potential to generate proof of quantitative advantages that will stimulate adoption. Nevertheless, assessing visualisation techniques or apps is not a straightforward process. We believe that visualisation apps have to be produced by employing a user-centered design approach, and that assessment ought to take place in a number of phases throughout the process, with a variety of objectives in mind. (Sousa Santos & Dillenseger, 2005) provides an explanation of the topics that we think to be significant when organising an assessment in the field of medical data visualisation. This paper identifies the issue "how well does a visualisation represent the underlying phenomenon and help the user understand it?" as a basic question, and it breaks down the question into two aspects: A) the assessment of the manner in which the phenomena is portrayed (the initial portion of the inquiry question). B) the evaluation of the performance of the users in their activities while using the visualisation, which means that they have a knowledge of the phenomena (the second half of the question)

(Isenberg et al. 2013) studied “A Systematic Review on the Practice of Evaluating Visualization” Our purpose is to provide an analysis of the current status of evaluation techniques as well as the historical evolution of these practices, as stated in papers that were presented at the IEEE Visualisation conference. Through a methodical comprehension of the qualities and objectives of the evaluations that have been provided, our objective is to engage in meta-level reflection on evaluations that have been conducted within our community. To achieve this objective, we carried out a comprehensive analysis of ten years' worth of assessments that were published in publications. We did this by utilising and expanding upon a coding scheme that had been devised by Lam et al. [2012]. Among the findings of our investigation is a summary of the assessment objectives that are most frequently seen in the community, an analysis of how these objectives have developed over the course of time, and a comparison of these objectives with those of the IEEE Information Visualisation conference. More specifically, we discovered that evaluations that are specialised to measuring the effectiveness of algorithms and the pictures that are produced are the most common (consistently accounting for 80–90% of all articles published since 1997). Nevertheless, particularly over the course of the past six years, there has been a consistent rise in the number of assessment techniques that include participants. These methods may be evaluated in two ways: either by assessing the participants' performances and providing them with subjective feedback, or by evaluating their work practices and their enhanced ability to analyse and reason via the use of visual tools. When compared to the IEEE Information Visualisation conference, which only shown an increasing proportion of evaluation through user performance and experience testing, this trend in the IEEE Visualisation conference was considerably more prominent up to the year 2010. However, according to articles published in the IEEE Information Visualisation journal since 2011, there has been a significant rise in the number of assessments of work practices and analyses, as well as reasoning that makes use of visual tools. In addition, we discovered that the majority of the research that describe requirements analyses and domain-specific work practices are published in an excessively informal manner, which makes it difficult to compare them with other studies and reduces their external validity.

(Shahin, Liang, and Babar 2014) studied "A systematic review of software architecture visualization techniques" A number of visualisation techniques (VTs) and tools have been reported to represent architectural elements (such as architecture design, architectural patterns, and architectural design decisions). This is in response to the growing interest in the utilization of VTs to assist in the communication and comprehension of software architecture (SA) of large-scale complex systems. Nevertheless, there is no attempt made to systematically analyse and categorise the VTs and related tools that have been reported for SA, as well as the manner in which they have been evaluated and utilized within the field. In order to develop a classification of VTs in SA, an analysis of the level of reported evidence, and the use of different VTs for representing SA in different application domains, as well as the identification of gaps for future research in the area, the purpose of this work was to conduct a systematic review of the literature on software architecture visualisation. In order to conduct a literature study on VTs for SA, we adhered to the evidence-based software engineering (EBSE) methodology and utilized the systematic literature review (SLR) approach. For the purpose of searching the relevant articles that were published between February 1, 1999 and July 1, 2011, we utilized both manual and automated search methodologies. End Result: For the purpose of data extraction, analysis, and synthesis, we chose 53 publications out of the 23,056 articles that were initially retrieved. Our selection was based on the inclusion and exclusion criteria that we had previously established. As a consequence of the findings from the data analysis, we were able to categorise the VTs that were discovered into four distinct categories, which were determined by the frequency of their utilization: graph-based, notation-based, matrix-based, and metaphor-based VTs. Most of the time, the VTs in South Africa are utilized for activities related to architectural evolution and architecture rehabilitation. In addition, we have determined 10 different reasons why VTs are utilized in SA. Our findings also showed that VTs in SA have been utilized in a broad variety of application domains, with "graphics software" and "distributed system" being the ones that have garnered the most interest among these application domains. Understanding and developing software-intensive systems has become significantly more important as a result of the introduction of SA visualisation. On the other hand, there have only been a few of VTs used in actual industrial settings. This review has enabled us to identify the following areas for further research and improvement: (i) it is necessary to per- form more research on applying visualization techniques in architectural analysis, architectural synthesis, architectural implementation, and architecture reuse activities; (ii) it is essential to pay more attention to use more objective evaluation methods (e.g., controlled experiment) for providing more convincing evidence to support the promised benefits of using VTs in SA; (iii) it is important to conduct industrial surveys for investigating how software architecture practitioners actually employ VTs in architecting process and what are the issues that hinder and prevent them from adopting VTs in SA.

(Santos and Eriksson 2014) studied “Making quality registers supporting improvements. A systematic review of the data visualization in five quality registries” When it comes to quality registries, physicians have traditionally been the ones who create, develop, and use them for the primary goal of conducting research. It is possible to increase and deepen the role of quality registries in the process of improving the quality of healthcare, but this possibility has not yet been realised. The objective of this study is to provide a description of quality registry yearly reports with reference to elements that are considered to be relevant for process improvement. An examination was conducted on the yearly reports of the five Swedish quality registries that are considered to be the most advanced. An abstraction form was used to identify each of the 636 charts that were included in the package. According to the findings, league tables are quite common, but funnel plots and control charts are not very common. A small number of highly aggregated metrics are used to monitor the quality of healthcare throughout time. The majority of the time, percentages are used to measure this quality. In conclusion, yearly reports from the quality registry do not include the degree of detail that is required to be able to be used in a systematic manner for the purpose of process improvement, nor do they take into account the random variation that is required. It is suggested that users of yearly reports exercise caution when addressing changes in quality, both over time and between healthcare providers, because these differences might be the result of chance, and the reports do not give adequate information in this respect. Consequently, yearly reports ought to be more complete and should pay greater emphasis to random variation in order to better support process improvement opportunities.

(The and Of 2014) studied "DATA VISUALIZATION IN SUPPORT OF EXECUTIVE DECISION MAKING The objective of this journal article is to get an understanding of the historical features of data management, which led to the current data concerns that organisational executives are facing in connection to big data, as well as the most effective way to display the information in order to avoid the obstacles that big data presents for executive strategic decision making. Based on the literature that has been published from previous data studies, the purpose of this journal paper is to get an understanding of what CEOs care about when it comes to data visualisation. For the purpose of gaining an understanding of the feelings held by executives and data analysts, the qualitative approach was utilized, and semi-structured interview techniques were utilized. In particular, the early findings can give academics with knowledge that can be used for reflection and application, particularly in regard to information systems (IS) that integrate human experience with technology in ways that are more beneficial and productive. The findings can also provide designers of data visualizations with knowledge that can be used in practical situations. Using the appropriate data visualisation technology to fit the nature of the data, developing an intuitive platform that enables collaboration and newness, the ability of the data presenter to convey the data message, and the alignment of the visualisation to core objectives are some of the key criteria that should be applied for successful data visualizations. The preliminary results of interviews with executives and data analysts, which were conducted, point to the significance of understanding and effectively presenting the data source and the data journey.

(Bandara et al. 2015) studied Achieving Rigor in Literature Reviews: Insights from Qualitative Data Analysis and Tool- Support In order for researchers to be successful, it is essential for them to effectively perform excellent literature studies. Therefore, it is necessary to use a method that is both organized and effective. When it comes to literature reviews, we provide an overview of the work that has showed the potential for employing software tools. Through the utilization of an end-to-end tool-supported literature review process, we bring to light the opportunities that have not yet been exploited. The utilization of qualitative data-analysis techniques, such as NVivo, is of great value in terms of analyzing, synthesising, and writing up literature reviews. We give thorough advice for actually coding and analyzing publications, including specific illustrated ways to properly write up and present the results. In this work, we discuss how to organize and prepare papers for analysis, as well as provide detailed guidelines for actually doing these tasks. For the purpose of providing an instructive example of the suggested strategy being put into reality, we give a comprehensive case study. With regard to the use of tool-supported literature review methodologies, we explore the means, value, and also the potential dangers. In our contribution to the existing body of literature, we provide a methodology that is backed by a four-phased tool and serves as a best practice for conducting literature reviews in the field of information systems. By approaching the process of reviewing the literature as if it were a qualitative research and considering the literature itself as if it were a data set, we are able to solve the difficult problem of determining the most effective way to extract relevant material and establish its breadth, relevance, and quality. For beginner information systems researchers who are interested in doing a comprehensive literature review, we offer a set of methodical instructions.

(West, Borland, and Hammond 2015) studied Innovative information visualization of electronic health record data: a systematic review An investigation of the use of visualisation techniques that were reported between the years 1996 and 2013 is carried out in this study. Additionally, novel ways to information visualisation of electronic health record (EHR) data for the purpose of knowledge discovery are evaluated. Techniques An electronic literature search was undertaken May–July 2013 using MEDLINE and Web of Knowledge, supple- mented by citation searching, gray literature searching, and reference list reviews. For the purpose of conducting a thorough document search, general search phrases were utilized instead. The outcomes The number of articles was decreased by 191 as a result of the elimination of duplicates, which began with 891 original articles. A matrix was designed for the purpose of classifying all abstracts and providing assistance in selecting which ones should not be under consideration for review. Included in the final study were a total of eighteen different papers. Talking Points Research has been conducted extensively on a number of different visualisation approaches. LifeLines and its applications, which include LifeLines2, EventFlow, and LifeFlow, are the most developed platforms now available. At the beginning of the study, the researchers concentrated on records from a single patient and the visualisation of the complicated data associated with that patient. Since the year 2010, the methods that are now being investigated are intended for usage with a significant number of patient data and events. The most majority are linear and enable interactivity through scaling and zooming in order to do resizing. Techniques including colour, density, and filters are frequently utilized in the process of visualisation. Concluding remarks The potential for knowledge dissemination is tremendous if data are managed in ways that are both innovative and effective. This is because the volume of electronic healthcare data is growing at an exponential rate. This article will be of use to researchers who are interested in designing and improving visualisation strategies since it identifies issues that were uncovered by prior EHR visualisation research.

(Grainger, Mao, and Buytaert 2016) studied Environmental data visualisation for non-scientific contexts: Literature review and design framework Due to the fact that environmental science is an applied field, it is necessary to engage in conversation with those who are not often associated with the scientific community. Visualizations are being more recognised as strong tools that may facilitate user engagement with new and complicated subject matter. Although there have been significant advancements in research, scientists have not yet completely tapped into the possibilities of visualisation when communicating with those who are not scientists. In order to address this issue, we will first go over the fundamental principles of visualisation, then we will talk about specific graphical issues that environmental science faces, and finally, we will highlight some best practises that have been seen in non-professional settings. Within professional settings, we offer a design framework that is intended to improve the transmission of scientific knowledge and its implementation among professionals. Effective visualizations may be included into enhanced dissemination and information exchange platforms with the assistance of these recommendations, which can be of use to scientists. Our findings lead us to the conclusion that the incorporation of scientific knowledge into environmental decision-making necessitates a design approach that is extremely iterative and collaborative in nature, with the goal of developing individualized visualizations. This not only helps users to acquire practical understanding, but it also enables them to study information on their own terms.

(Bendoly 2016) studied Fit, Bias, and Enacted Sensemaking in Data Visualization: Frameworks for Continuous Development in Operations and Supply Chain Management Analytics There is a significant contribution that data visualisation makes to the development of contemporary data analytics. In addition to providing assurances regarding the quality and completeness of the data, visualisation also provides assurances on the efficiency of cleaning and aggregation strategies. It offers the methods by which relationships that would otherwise be concealed from default assumptions in statistical modelling may be explored and discovered. The ability to transmit the ultimate product and the audience's understanding is also dependent on the quality of the visualisation. The question is, how can one guarantee that strength? What steps may be taken to prevent the creation of representations that are either of low value or, even worse, misleading? In this presentation, I will explore the theory, evidence, and practical ways to manage the growth of data visualisation. I will consider data visualisation not just as an end, but rather as a continuous process and a component of the culture of the organization.

(Bessi and Ferrara 2016) studied As data becomes more and more pervasive, so do data visualizations. These visualizations are becoming increasingly popular on the internet and are an essential mechanism by which individuals who are not specialists in the field may gain access to data. This article discusses the elements that influence how people interact with data visualizations, a topic that has received very little attention in the field of visualisation research up to this point. We establish six aspects that impact engagement by drawing on qualitative and empirical study with users. These components are as follows: the topic matter; the source or media location; beliefs and views; time; emotions; and confidence and skills were identified. By calling attention to these characteristics, we bring together problems related to human-computer interaction (HCI) and methods to study on media audiences in order to uncover new subjects for research research on visualization. Particularly, we contend that our findings have consequences for the manner in which efficacy is conceived of and defined in regard to data visualizations, as well as the manner in which this differs depending on how, by whom, where, and for what purpose visualizations are experienced. Through the examination of the aspects that influence engagement and the ways in which these factors offer new definitions of effectiveness, the purpose of this study is to broaden the scope of research on visualisation.

(Backonja et al. 2016) studied Visualization approaches to support healthy aging: A systematic review Tools that are based on informatics have the ability to provide assistance to the increasing number of elderly people who are living in their homes. Data visualizations and visualizations of physical representations are two examples of the types of visualizations that are included in many programmes. Nevertheless, the majority of the function that visualizations play in assisting with ageing in place is still mainly unknown. On the basis of a priori chosen criteria, we searched the databases CINAHL, Embase, Engineering Village, PsycINFO, PubMed, and Web of Science for papers written in English that described community-based studies that evaluated visualizations utilized by individuals aged The findings showed that six of the 251 publications that were discovered were suitable. Most of the research that were detailed in the articles were user studies, and the quality of the methodology used in each of them varied. Visualizations of virtual representations that aided the performance of exercises at home were detailed in three different kinds of publications. Either the participants considered the visual representations to be useful, motivational, and supportive of their knowledge of their health practices, or they did not find them to be an improvement above other choices. In three different articles, data visualizations that were designed to help people better understand their own health were detailed. It was found that participants were able to grasp data visualizations that utilized exact data and encodings that were more concrete more effectively than those that did not give precision or were abstract. Through the use of data visualizations, participants were able to better comprehend both their general health and the granular data involved.

(Hepworth 2017) studied Big Data Visualization: Promises & Pitfalls When I was eating dinner with a buddy a few weeks ago, we were discussing a contentious topic that was brought up. One of my close friends held a very strong belief regarding the dangers that vaccinations pose, and his line of reasoning went something like this: I've seen the facts. The information was presented in the form of an infographic. Neither the visualisation he had seen nor the author of the article were able to provide him with particular statistics that he could recall. It was so ingrained in his memory that he couldn't even recall the name of the magazine, but the general point that the data visualisation presented was still very much there. His circumstance is not an isolated one, and it offers illuminating insights into the ways in which we, as human beings, interpret and react to the visualisation of large amounts of data.

(Institute of Electrical and Electronics Engineers 2017) studied Data Visualizations: A Literature Review and Opportunities for Technical and Professional Communication This article addresses the necessity of doing an integrated literature review on data visualizations, with a special focus on its use in the fields of health and medicine. Across a variety of fields, the study examines twenty-five research. According to the findings, there appears to be no consensus about the most effective method of visualizing complicated data for lay audiences; nevertheless, there are certain emergent methods that are being developed that are beneficial. Visualizations should be kept as basic as feasible, with emphasis paid to integrating other design components such as headers and labels. Pictographs, icon arrays, and bar charts appear to offer promise for users' ability to comprehend the information being presented. At the end of the review, there are five particular research topics that technical and professional communicators should concentrate their emphasis on empirical investigations that investigate: interactive displays, merging attention and understanding, looking at numeracy and risk, and lastly, crosses between health and medical themes.

(Sacha et al. 2017) studied Visual Interaction with Dimensionality Reduction: A Structured Literature Analysis When it comes to visualizing multidimensional data, dimensionality reduction, often known as DR, is an essential building ingredient. It is necessary for DR approaches to be modified to human requirements and domain-specific challenges in order for them to be helpful in exploratory data analysis. Ideally, this adaptation should take place in an interactive nature and on the fly. The benefits of tightly combining DR with interactive visualizations have already been established by a number of visual analytics solutions. On the other hand, there is a lack of a comprehensive and organized comprehension of this integration. In order to address this issue, we conducted a comprehensive review of the literature on visual analytics and visualisation in order to study the ways in which analysts engage with automatic disaster recovery approaches. The findings indicate that there are seven typical interaction scenarios that are accessible to interactive control. These scenarios include the specification of algorithmic limitations, the selection of relevant characteristics, and the selection of many different DR methods. In this study, we evaluate various implementations of visual analysis systems that use DR and analyse the ways in which other machine learning approaches have been integrated with DR. A generic lens that can be used for the evaluation of visual interactive search and rescue systems may be obtained by summarising the findings in a process model that includes a human in the loop. In order to analyse and categorise a number of systems that have been reported in the past in the literature, as well as to determine potential avenues for future research, we use the model that has been provided.

(Alnjar 2017) studied Analysis and synthesis of critical design-thinking for data visualisation designers and learners Individuals who are responsible for the creation of data-visualization tools engage in in-depth reflection on their designs and continually challenge their own design decisions and assessments. They get to these conclusions in order to determine how they might enhance their ideas, such as by creating something that is appropriate and acceptable for the goal. However, self-reflection is sometimes challenging, particularly on the part of learners, who frequently find it challenging to critically reflect upon their own work. Because of this, it is necessary to provide learners with guidance in order to facilitate proper critical reflections on their work and the development of skills that will allow them to make better decisions. In spite of the fact that there are a great number of visualisation computer tools and programming libraries that assist users in the building of visualisation systems, there are not many tools or methods that assist users in systematically criticising or evaluating their works, in order to determine what aspects of their designs are desirable and what aspects are undesirable. Those students who are interested in developing tools for data visualisation are lacking the frameworks and rules that will assist them in evaluating the visualizations they have created. via the development of an appropriate computer tool and the use of metrics and heuristics to carry out the judgement, or via the application of human judgement with the assistance of a written guide, such critical analysis might be accomplished. Therefore, the purpose of this research is to investigate structures that can assist people in doing better critical assessments. In the first place, the dissertation employs a conventional research technique to analyse metrics in visualisation, to investigate related work, and to investigate how metrics are utilized in computers to execute judgements. We provide a framework that outlines the manner in which metrics are utilized in the process of designing visualizations and where they are employed. In the second step of the process, the attention shifts to the investigation of how humans think and use critical judgement when evaluating designs, particularly visualisation designs. We conduct an observational research in which participants provide feedback on a variety of designs and items.

(Pu and Kay 2018) studied The Garden of Forking Paths in Visualization: A Design Space for Reliable Exploratory Visual Analytics Several decades ago, Tukey emphasised that it is destructively foolish to use exploratory findings as confirmation evidence. We recast previous conversations concerning the trustworthiness of findings from exploratory visual analytics, such as the multiple comparisons problem, in terms of Gelman and Loken's garden of forking pathways in order to lay out a design space for meeting the challenge of tackling the forking paths problem in visual analytics. Existing methods for addressing the forking routes problem (multiple comparison correction) are included in this design space. Additionally, this design space incorporates solutions that have not yet been implemented for exploratory visual analytics (regularisation). We also address the ways in which perceptual bias correction techniques may be utilized to rectify biases that are produced in analysts' understanding of their data as a result of the forking pathways problem. Furthermore, we detail the ways in which this problem might be shown as a threat to validity within Munzner's Nested Model of visualisation design. We conclude by proposing recommendations for the evaluation of papers, with the intention of encouraging reviewers to take into account the forking pathways problem when reviewing future designs of visual analytics instrumentation.

(Dasgupta et al. 2018) studied Human Factors in Streaming Data Analysis: Challenges and Opportunities for Information Visualization. Systemic changes occur continually in the real world. Changes of this nature generally take place within quite short time frames in fields such as traffic monitoring and cyber security. Due to the fact that analysts are required to ingest and make sense of dynamic patterns in real time, this results in a difficulty with streaming data and leads to unique obstacles for the person in the loop. We need a comprehensive definition of the human-centered design difficulties and a critical examination of the state-of-the-art solutions that are currently available for resolving these issues, despite the fact that analysts are increasingly turning to visualizations in order to gain insights from streaming data. The purpose of this article is to fill this gap by analyzing how the current state of the art in streaming data visualisation deals with the problems and reflecting on the potential and gaps that exist. In order to do this, we have three contributions to make in this paper: (i) a problem characterization for the purpose of identifying domain-specific goals and challenges for the management of streaming data; (ii) a survey and analysis of the state of the art in streaming data visualisation research, with a particular emphasis on how visualisation design addresses challenges that are specific to change perception; and (iii) reflections on the design trade-offs; and (iv) an outline of potential research directions for addressing the gaps in the state of the art.

(Kosara and Haroz 2018) studied Skipping the Replication Crisis in Visualization: Threats to Study Validity and How to Address Them In the field of visualisation research, replications are uncommon; nonetheless, if they were more widespread, it is not unreasonable to expect that they would reveal a rate of unreproducible results that is comparable to those of the psychological and social sciences. In spite of the fact that a replication crisis in visualisation research would serve as a stimulating wake-up call, it is ultimately more productive to investigate and rectify the fundamental issues that are present in a number of studies. We take a look at the current level of replication in the field of visualisation research in this study. We take a look at six potential challenges to the reliability of research in visualisation and offer some potential solutions to these problems. Last but not least, we provide a description of the many models that may be used to publish replications that are able to fulfil the novelty criteria that can prevent replications from being approved.

(Husin and Abdullah 2019) studied Overlapping issues and solutions in data visualization techniques Despite the fact that the process of data visualisation has grown more difficult and complicated as a result of the massive rise of big data, it is anticipated that the amount of data will continue to expand on a regular basis. It is becoming increasingly difficult for the data analyst to successfully interpret or analyse the data in order to acquire new information or knowledge because of the vast amount of data and the complexity of the data. Because of this, it is essential to visualise this data by employing a variety of analytical methods. Nevertheless, there are a great deal of problems that still exist in the methodologies of data visualisation. The data analyst has a significant obstacle for the visualisation of the data as a result of these challenges. The problem of overlapping is the one that arises most frequently in the field of data visualisation approaches. An examination of the overlapping problems that arise in multidimensional and network data visualisation approaches is presented in this research. There is also a study and discussion of the existing options, with pros and downsides being taken into consideration. This article draws a conclusion on the benefits of the overlapping problems and solutions, and then go on to analyse the negatives of those solutions. The color-based approach, relocation, and reduction of data sets are some of the solutions that are proposed in this research to address the overlapping problems.

(Chrysantina and Sæbø 2019) studied Assessing User-Designed Dashboards: A Case for Developing Data Visualization Competency Aprisa The usage of health information dashboards, which are collections of useful indicator visualizations for management, has become a frequent element and technique for improving the utilization of information in the health sector. They should give any management with quality information in a way that highlights the performance of health care provision. As a result, they require a thorough grasp of visualisation techniques in order to both produce and interpret the information. Due to the fact that health management is a dispersed and decentralised activity, dashboards need to be relevant to a wide range of users and different administrative levels within the health services. This may be accomplished by providing all users with the ability to create their own dashboards, which are based on the indicators that they require and are displayed in a manner that is appropriate for monitoring the operations of the local priority. In the present investigation, we investigate dashboards that are established by users in Indonesia, a country that has developed a health management system that is both flexible and open source (DHIS2). According to the findings of the research, the quality of the dashboards that are built faces a number of obstacles, despite the fact that the technological flexibility of the platform has been utilized by offering training on how to customise the platform. These difficulties are indicative of a lack of proficiency in visualisation. In conclusion, we advocate for the inclusion of such competencies into the existing training curricula, as well as the use of the best practice dashboards that are now accessible for the same platform from the World Health Organisation (WHO).

(Börner, Bueckle, and Ginda 2019) studied Data visualization literacy: Definitions, conceptual frameworks, exercises, and assessments The capacity to read and write language is becoming increasingly crucial in this era of information, and the ability to read and design data visualizations is becoming as important. However, whereas there are conventional definitions and theoretical frameworks that may be used to teach and evaluate textual, mathematical, and visual literacy, the present definitions and frameworks for data visualisation literacy (DVL) are not comprehensive enough to guide the design of DVL education and evaluation. This article presents a data visualisation literacy framework (DVL-FW) that was built expressly for the purpose of defining, teaching, and evaluating data visualisation literacy (DVL). The comprehensive DVL-FW encourages both the reading and the production of data visualizations, a coupling that is comparable to the combination of reading and writing in the context of textual literacy and understanding and applying in the context of mathematical literacy. A hierarchical typology of key ideas is defined by the DVL-FW, which also provides a detailed description of the process stages that are necessary in order to get insights from data. By demonstrating how theoretical and procedural information may be used to build curricula and evaluation measures for DVL, the DVL-FW contributes to the advancement of the state of the art by interlinking different types of knowledge. Earlier versions of the DVL-FW have been utilized to instruct DVL to over 8,500 students who are either enrolled in residential or online classes. The outcomes of this endeavour have contributed to the revision and validation of the DVL-FW that is offered here.

(Correll et al. 2019) studied Looks Good To Me: Visualizations As Sanity Checks Famous examples such as Anscombe's Quartet highlight that one of the core benefits of visualizations is allowing people to discover visual patterns that might otherwise be hidden by summary statistics. This visual inspection is particularly important in exploratory data analysis, where analysts can use visualizations such as histograms and dot plots to identify data quality issues. Yet, these visualizations are driven by parameters such as histogram bin size or mark opacity that have a great deal of impact on the final visual appearance of the chart, but are rarely optimized to make important features visible. In this paper, we show that data flaws have varying impact on the visual features of visualizations, and that the adversarial or merely uncritical setting of design parameters of visualizations can obscure the visual signatures of these flaws. Drawing on the framework of Algebraic Visualization Design, we present the results of a crowdsourced study showing that common visualization types can appear to reasonably summarize distributional data while hiding large and important flaws such as missing data and extraneous modes. We make use of these results to propose additional best practices for visualizations of distributions for data quality tasks.

(Jensen et al. 2019) studied A Machine Learning Approach to Zeolite Synthesis Enabled by Automatic Literature Data Extraction Zeolites are porous aluminosilicate minerals that have a wide range of uses in the industrial and green technology sectors. There are many features of zeolite synthesis that are still poorly understood, which necessitates expensive trial and error synthesis.

This is despite the fact that they have practical value. The purpose of this work is to develop natural language processing algorithms and text markup parsing tools for the purpose of automatically extracting synthesis information and trends from zeolite journal articles. In order to verify the precision of the data that was extracted and to identify possible prospects for zeolites that include germanium, we further design a data set consisting of zeolites that contain germanium. As an additional step, we develop a regression model for the framework density of a zeolite based on the conditions of the synthesis. This particular model achieves a root mean squared error of 0.98 T/1000 Å3 when it is cross-validated. Furthermore, a significant number of the decision boundaries of this model correlate to well-established synthesis strategies in germanium-containing zeolites. The automated data extraction that we propose may be utilized to solve a wide variety of issues that arise throughout the zeolite synthesis process, hence enabling the creation of new zeolite morphologies.

(Westgate 2019) studied revtools: An R package to support article screening for evidence synthesis Martin The area of evidence synthesis is expanding at a rapid rate, and as a result, there has been a commensurate rise in the number of software tools and workflows that are designed to facilitate the development of systematic reviews, systematic maps, and meta-analyses. However, despite the significant progress that has been made, there are still a number of issues that need to be addressed. These issues include the sluggish incorporation of new statistical or methodological techniques into user-friendly software, the low prevalence of open-source software, and the inadequate integration of different software tools. The research community is hampered in terms of both the utility and transparency of new methodologies as a result of these concerns. In this post, I will introduce revtools, a programme for R that is designed to assist with article screening during evidence synthesis projects. It offers capabilities for the importation of bibliographic data as well as the de-duplication of that data, the screening of articles based on their titles or abstracts, and the visualisation of article content through the use of topic models. This software is completely open-source and mixes command-line scripting for experienced programmers with user interfaces that have been custom-built for casual users. Additionally, other techniques to help article screening will be developed throughout the course of time. R's potential to assist evidence synthesis initiatives has been expanded thanks to Revtools, which offers free access to innovative methodologies in an open-source environment. This is a significant step towards improving R's capabilities.

(Turchioe et al. 2019) studied A Systematic Review of Patient-Facing Visualizations of Personal Health Data" There is a growing amount of enthusiasm surrounding visualizations due to the fact that they have the potential to facilitate patient interpretation. This is because patients are receiving their own health data with an increasing frequency and volume. Evaluating these representations is vital to ensure that patients are able to comprehend and, when necessary, act upon health data in a safe and effective manner. This systematic review was conducted with the intention of analyzing and assessing the current level of the scientific knowledge of patient-facing visualizations of personal health data. Up to December 1, 2018, we looked for papers that were pertinent to the topic at hand in five different academic databases: PubMed, Embase, Scopus, ACM Digital Library (Association for Computing Machinery Digital Library), and IEEE Computational Index (Institute of Electrical and Electronics Engineers Computational Index). Articles written in English that produced or evaluated one or more patient-facing visualizations for personally identifiable health information were included in our review. Utilizing the Mixed Methods Appraisal Tool, three reviewers independently evaluated the quality of the papers that were included in the review. Characteristics of included articles and visual- izations were retrieved and synthesized. The outcomes It was found that the sample sizes and assessment techniques of the 39 papers that were included in the study were different from one another, but the sample demographics were not different. In a limited number of papers, health literacy, numeracy, and graph literacy were measured. Although line graphs were the most prevalent type of visualisation, particularly for longitudinal data, number lines were utilized more frequently in the papers that were included throughout the course of the last five years. The findings of the article indicated that patients had a greater level of knowledge with regard to the number lines and bar graphs in comparison to the line graphs. Furthermore, the findings indicated that colour is an effective means of conveying danger, enhancing comprehension, and boosting confidence in interpretation.

(Weissgerber et al. 2019) studied "Reveal, Don't Conceal" As a result of reports that brought to light the issues that are associated with the conventional method of displaying continuous data through the use of bar graphs, several journals have implemented different visualisation approaches. The writers are strongly encouraged to steer clear of bar graphs and instead make use of visuals that illustrate the distribution of the data; yet, these regulations offer very little help on how to more effectively present the data. For the purpose of determining the sorts of figures that are utilized and determining the extent to which inadequate data visualisation procedures are prevalent, we carried out a comprehensive evaluation of research that were published in the most prestigious journals pertaining to peripheral vascular disease. For the purpose of presenting continuous data, bar graphs were utilized by 47.7% of the publications that contained data figures. This primer provides a detailed overview of strategies for addressing this issue by (1) outlining strategies for selecting the correct type of figure depending on the study design, sample size, and the type of variable; (2) examining techniques for making effective dot plots, box plots, and violin plots; and (3) illustrating how to avoid sending mixed messages by aligning the figure structure with the study design and statistical analysis. In addition, we provide remedies to a number of additional widespread issues that were discovered throughout the systematic review. The resources include a collection of free tools and templates that writers may use to generate figures that are more useful, as well as an online simulator that demonstrates why summary statistics are only meaningful when there is sufficient data to summarize. Finally, we take a look at the actions that researchers might take to enhance the figures that are published in the scientific literature.

(McInerny 2019) studied “Information Visualization for Science & Policy: Engaging Users & Avoiding Bias” When it comes to understanding difficult subject matter, visualizations and images are essential components. Nevertheless, scientists and science-policy initiatives seldom examine how visualizations may facilitate discovery, provide compelling and credible reporting, or support online resources. This is despite the fact that they acknowledge the value inherent in these capabilities. A combination of experience and knowledge from the fields of science, policy, computing, and design is required in order to produce visualizations that are both accessible and objective from complex and unpredictable data. Visualisation, on the other hand, is not frequently utilized in our training, organizations, or collaborative procedures. We need information visualisation to become increasingly pervasive in both the work of scientists and science-policy. This is because new policy programmes are being developed, such as the "Intergovernmental Platform on Biodiversity and Ecosystem Services" (IPBES). On the other hand, there is a greater possibility of missing findings, misunderstandings, and, worst of all, the creation of a bias towards the study that is simplest to exhibit.

(Chotisarn et al. 2020) studied “A Systematic Literature Review of Software Visualization Evaluation” It is possible for software visualizations to assist developers in analyzing numerous elements of complex software systems; nevertheless, the usefulness of these visualizations is frequently ambiguous due to the absence of appraisal rules. The purpose of this assignment is to identify frequent issues that arise during the evaluation of software visualizations with the intention of developing standards that will enhance evaluations in the future. Method: We conduct a comprehensive examination of the whole body of literature, which consists of 387 full papers that were presented at the SOFTVIS/VISSOFT conferences. We then do an analysis on 181 of these articles, from which we were able to extract evaluation techniques, data collecting methods, and other components of the evaluation. The results show that 62% of the software visualisation techniques that have been offered do not have a solid assessment. In this paper, we suggest that a good software visualisation should not only improve accuracy and speed, but also memory, usability, engagement, and other feelings as well. Conclusion: We call on researchers proposing new software visualizations to provide evidence of their effectiveness by conducting thorough (i) case studies for approaches that must be studied in situ, and when variables can be controlled, (ii) experiments with randomly selected participants of the target audience and real-world open source software systems to promote reproducibility and replicability. Therefore, in order to improve the rate at which software visualisation techniques are used, we propose suggestions that will raise the evidence of the success of these approaches.

(Walny et al. 2020) studied "Data Changes Everything: Challenges and Opportunities in Data Visualization Design Handoff" Collaboration between individuals who possess a variety of visualization-related talents is frequently required for the completion of complex data visualisation design projects. One example is that many teams consist of both designers who generate new visualisation designs and developers who execute the visualisation software that is created as a consequence of the designers' work. In this study, we find gaps between data characterisation tools, visualization design tools, and development platforms. These gaps provide obstacles for designer-developer teams who are trying to create novel data visualizations. Despite the fact that it is typical for commercial interface design tools to facilitate cooperation between designers and developers, the process of developing data visualizations presents a number of specialised issues that are not handled by the tools that are now available. In particular, designers of visualizations are required to first characterize and develop a knowledge of the data that lies behind the surface, and then to specify layouts, data encodings, and other data-driven factors that will be resilient across a wide range of data values. When working with bigger teams, designers are also responsible for effectively communicating these mappings and the dependencies between them to customers, developers, and other partners. We identify six data-specific visualisation problems for design specification and handoff, and we describe observations and insights from each of the five major interdisciplinary visualisation design projects that we evaluated. Adapting to changing data, predicting edge situations in data, comprehending technological obstacles, articulating data-dependent interactions, conveying data mappings, and maintaining the integrity of data mappings between iterations are some of the challenges that need to be overcome. On the basis of these insights, we propose potential prospects for future tools that may be used for developing, testing, and presenting data-driven designs. These tools could potentially help to the development of data visualisation designs that are more successful and collaborative.

(Bhattacharjee, Chen, and Dasgupta 2020) studied “Privacy-Preserving Data Visualization: Reflections on the State of the Art and Research Opportunities In this day and age of pervasive digital transformation, one of the most important socio-technical challenges that we face is the preservation of data privacy and the safeguarding of sensitive information from possible enemies. An analysis of multiple factors is required in order to address this challenge. These factors include algorithmic choices for balancing privacy and loss of utility, potential attack scenarios that adversaries can carry out, implications for data owners, data subjects, and data sharing policies, and access control mechanisms that need to be built into interactive data interfaces. Both as a medium for communicating information in a manner that is sensitive to privacy concerns and as a tool for comprehending the connection between privacy settings and data sharing rules, visualisation is an essential component of the solution space. There has been progress made in the field of privacy-preserving data visualisation along several of these aspects. The purpose of this study on the current state of the art is to give a comprehensive review of the many approaches, methods, and strategies that are utilized for the management of data privacy pertaining to visualisation. With the assistance of visualisation, we also take a moment to contemplate the future course of action by conducting an analysis of the gaps and research opportunities that exist in the process of resolving some of the most critical socio-technical concerns pertaining to data privacy.

(Ak 2020) studied A Comparative Analysis of Breast Cancer Detection and Diagnosis Using Data Visualization and Machine Learning Applications In the developing world, one of the most significant challenges that humanity faces is the death rate from cancer. There is still no cure available for many forms of cancer, despite the fact that there are several ways to prevent it from occurring in the first place. Among the various varieties of cancer, breast cancer is one of the most prevalent, and the most crucial aspect of its treatment is the early detection of the disease. When it comes to the treatment of breast cancer, one of the most critical stages is the accurate diagnosis. When it comes to predicting the kind of breast tumours, there are a lot of research that can be found in the literature. Within the scope of this study work, the data collected by Dr. William H. Walberg of the University of Wisconsin Hospital regarding breast cancer tumours were utilized for the purpose of creating predictions regarding the sorts of breast tumours. The dataset under consideration was subjected to several data visualisation and machine learning approaches, such as logistic regression, k-nearest neighbours, support vector machine, naïve Bayes, decision tree, random forest, and rotation forest. For the purpose of using these machine learning techniques and visualizations, R, Minitab, and Python were selected as the programme of choice. Through the use of data visualisation and machine learning techniques, the purpose of this work was to conduct a comparative analysis for the purpose of breast cancer detection and diagnosis. When it came to identifying breast tumours, the diagnostic capabilities of the programmes were almost the same. In the process of making decisions, the application of tools such as data visualisation and machine learning can have a big influence on cancer diagnosis and give considerable advantages. This article presents a number of various machine learning and data mining algorithms that have been presented for the purpose of identification of breast cancer. The results that were obtained with the logistic regression model that contained all of the characteristics exhibited the highest classification accuracy (98.1%), and the strategy that was presented demonstrated an improvement in accuracy performances. Based on these findings, it appears that there is the possibility of newly emerging prospects in the field of breast cancer detection.

(Midway 2020) studied Principles of Effective Data Visualization Because we live in a modern culture that is surrounded by visuals, the necessity of producing excellent scientific visuals has risen. This is due to the fact that there are now more software solutions and electronic distribution methods available. Regrettably, a significant number of individuals in the scientific community either display information in an erroneous manner or, even when they do not present information improperly, continue to adopt inadequate data visualisation approaches. The following 10 principles are presented for the purpose of providing authors with direction in their efforts to enhance the visual message they convey. There are some principles that are less technical, such as determining the message before beginning the visual, while there are other concepts that are more technical, such as the way that various colour combinations indicate different information. However, all of these principles are important. It is incumbent upon scientists to be aware of best practices in order to convey the story of their data in the most effective manner possible. This is due to the fact that figure making is frequently not instructed in a formal setting and figure standards are not widely enforced in the scientific community.

(Chen et al. 2020) studied Supporting Story Synthesis: Bridging the Gap between Visual Analytics and Storytelling For the most part, visual analytics is concerned with dealing with complicated data and employing sophisticated algorithmic, visual, and interactive techniques to support the analysis. There are times when it is necessary to explain the findings and outcomes of the study to an audience that does not have knowledge in visual analytics. In order to do this, the results of the study need to be displayed in a manner that is less complicated than what is generally utilized in visual analytics systems. Nevertheless, not only may analytical visualizations be too complicated for the audiences that are being targeted, but the information that needs to be presented may also be too complicated. The findings of the analysis could be comprised of a number of different components, each of which might entail a variety of different aspects. As a result, there is a gap on the way from acquiring analytical findings to conveying them, and inside this gap, there are two primary challenges: the complexity of the information and the complexity of the display. In order to solve this issue, we propose a general framework that connects the presentation of results with the analysis of data through the use of narrative synthesis. Within this framework, the analyst is responsible for generating and organising the contents of the story. We consider the findings as data structures, in contrast to prior studies, which represented the results of the analysis by storing the display states. As opposed to recording the history of analysis and enabling dual (that is, exploratory and communicative) usage of data displays, our primary focus is on choosing, compiling, and organising findings for further presentation. In the process of narrative synthesis, results are chosen, put together, and presented in meaningful layouts that take into consideration the structure of the material as well as the intrinsic features of its constituent parts. We present a methodology for the use of the suggested conceptual framework in the design of visual analytics systems. We also illustrate the generalizability of the technique by applying it to two different domains, namely social media and movement analysis.

(Nguyen, Jung, and Dang 2020) studied Revisiting Common Pitfalls in Graphical Representations Utilizing a Case-based Learning Approach The process of combining art and science in order to tell tales through graphical representations of data is known as data visualisation. When varied challenges, applications, needs, and design goals are taken into consideration, it is difficult to merge these two components to their maximum potential. In contrast to the scientific component, which necessitates the creation of images that are not only visually beautiful but also simple to interpret for consumers, the art component needs the creation of accurate representations of a substantial quantity of input data. In the absence of the scientific component, visualisation is unable to fulfil its function of producing accurate representations of the real data, which ultimately results in incorrect perception, interpretation, and decision-making. It is possible that the situation would be much more dire if the viewers were purposely misled by the production of inaccurate visual representations. Using a case-based learning method, this study that is still in the process of being written focuses on the misinformation that may be found in graphical representations. A survey is conducted, and the instances of erroneous data visualisation are projected onto essential units of visual communication. These units include size, value, form, size, and location. Furthermore, the purpose of this work is to establish fundamental ideas for the creation of more effective visualizations, as well as to assist viewers in comprehending the fundamental reasons for the abuse.

(Metze 2020) studied Visualization in environmental policy and planning: a systematic review and research agenda . When it comes to environmental policy and planning, visualizations are becoming an increasingly significant tool. They have a significant influence on how we understand environmental issues, the solutions to those issues, and whether or not we regard policies to be legitimate. works on visualisation in environmental policy and planning have been conducted for twenty years, and this study presents a systematic review that draws together such works. This review have proven visualization; environment; that visualization plays a role in data-communication, effects decision making, planning; public public perception, public engagement, and knowledge cocreation. On the basis of the systematic review, three research lines have been created with the objective of better taking into account the problems posed by a worldwide and engaged public that is formed around environmental and planning concerns through the use of the internet and social media. We are able to accomplish this by (1) moving beyond a knowledge deficit model, (2) paying more attention to the material dimensions of visualizations and their role in opening up spaces for cocreation, and (3) including the study of found images because these images contain information on public sentiment and are a form of public accountability.

(Wang et al. 2020) studied Cheat Sheets for Data Visualization Techniques In this study, the notion of cheat sheets for data visualisation approaches is presented. Cheat sheets are a collection of succinct graphical explanations and textual annotations that are influenced by infographics, data comics, and cheat sheets in other fields. The purpose of cheat sheets is to fulfil the growing need for easily available content that assists a broad audience in comprehending data visualisation techniques, including their application, the fallacies associated with them, and other related topics. The iterative design process that we have carried out with practitioners, teachers, and students of data science and visualisation has resulted in the creation of six different types of cheat sheets (anatomy, construction, visual patterns, pitfalls, false-friends, and well-known relatives) for six different types of visualisation, as well as formats for presentation. These are evaluated by a qualitative user survey that was conducted with eleven people. The results of this study suggest that our cheat sheets are both readable and helpful.

(Dimara et al. 2020) studied What is Interaction for Data Visualization? Despite the fact that interaction is an essential component of data visualisation, the meaning of the term interaction in the context of visualisation is vague and difficult to understand. The absence of a consensus on a definition is the source of this misunderstanding, according to our argument. In order to address this issue, we begin by putting together a comprehensive perspective on the interaction that takes place within the visualisation community. This perspective incorporates viewpoints from the fields of information visualisation, visual analytics, and scientific visualisation, as well as the contributions of both senior and young visualisation researchers. When we have a better understanding of this perspective, we will investigate the definition of interaction within the realm of human-computer interaction (HCI). Through the process of identifying similarities and contrasts between the perspectives of interaction in HCI and visualisation, we are able to construct a definition of interaction that is applicable to visualisation studies. The purpose of our definition is to serve as a tool for thinking and to promote interface design methods that are more innovative and daring. We think that by gaining a deeper knowledge of what interaction in visualisation is and what it can be, we will be able to improve the quality of interaction in visualisation systems and give individuals who use them more agency.

(Bibri 2021) studied Data-driven smart sustainable cities of the future: An evidence synthesis approach to a comprehensive state-of-the-art literature review In light of the recent paradigm shift in science and technology brought about by big data science and analytics, sustainable cities are now undergoing dramatic transformations that have never been seen before. The rising need to address the challenges that are associated with sustainable cities as fundamentally complex systems in terms of their future development planning, operational management, fragmented design strategies, and technological solutions is the driving force behind these significant developments. That is to say, sustainable cities are increasingly embracing and leveraging what smart cities have to offer in terms of big data technologies and their novel applications. This is being done in an effort to effectively deal with the complexities that they inherently embody, as well as to monitor, evaluate, and improve their performance with regard to sustainability. This is being done under the umbrella of what has been referred to as data-driven smart sustainable cities.

This new field is a big gap in and of itself, since it is still in its infancy, and the purpose of this article is to fill it together with the question of how much the integration of sustainable urbanism and smart urbanism is addressed, as well as what paths and shapes it takes. This article presents a comprehensive state-of-the-art literature assessment of the rapidly developing topic of data-driven smart sustainable cities. It does so by employing an evidence synthesis technique that is convincing. The findings of this study provide more evidence that big data technology will bring about fundamental and permanent changes to sustainable urbanism. These changes will bring about new and innovative approaches to monitoring, comprehending, analyzing, planning, and managing sustainable cities. When it comes to increasing and maintaining the contribution of sustainable cities to the aims of sustainability in the face of urbanisation, it is shown that the evolving development planning methods and operational management mechanisms that are enabled by data-driven technologies are of significant relevance. What smart urbanism entails and how it operates, on the other hand, raises a number of important questions. One of these questions is whether the policy and governance of data-driven smart sustainable cities of the future will become excessively technocentric and technocratic, respectively. Additionally, this question is relevant with regard to other aspects of social and environmental sustainability. When it comes to obtaining the outcomes that are wanted in terms of sustainability, it is equally necessary to address these significant current challenges. The purpose of this study and criticism of the current work on the prevalent and emerging paradigms of urbanism is to provide a helpful reference for academics and practitioners, as well as the essential material to educate them of the most recent advancements in the rapidly developing area of data-driven smart sustainable cities. In addition, the purpose of this study is to shed light on the growing adoption and uptake of big data technologies in sustainable urbanism. The study aims to assist policymakers and planners in evaluating the benefits and drawbacks of smart urbanism when it comes to implementing sustainable urban transformations in the era of big data. Additionally, the study aims to stimulate prospective research and further critical debates on the subject matter.

(Nguyen, Jung, and Gupta 2021) studied Examining data visualization pitfalls in scientific publications" The process of combining art and science in order to tell tales through graphical representations of data is known as data visualisation. When varied challenges, applications, needs, and design goals are taken into consideration, it is difficult to merge these two components to their maximum potential. While the art component demands the creation of images that are visually appealing and can be readily comprehended by users, the scientific component necessitates the creation of correct representations of a substantial quantity of input data. In the absence of the scientific component, visualisation is unable to fulfil its function of producing accurate representations of the real data, which ultimately results in incorrect perception, interpretation, and decision-making. It is possible that the situation might be much more dire if the viewers were purposely led astray by the production of inaccurate visual representations. In order to overcome the numerous errors that are associated with graphical representations, the primary objective of this study is to identify and comprehend the fundamental reasons that misinformation is prevalent in graphical representations. We examined the examples of misleading data visualisation that were found in the scientific papers that were gathered from indexing databases. After that, we projected these examples onto the fundamental units of visual communication, which include colour, shape, size, and spatial orientation. In addition, a text mining approach was utilized in order to derive useful insights from the typical difficulties associated with visualisation design. In order to determine whether or not there is a distinction in the proportions of frequent mistakes that occur in relation to colour, shape, size, and spatial orientation, the Cochran's Q test and the McNemar's test were each carried out. According to the research, the pie chart is the graphical representation that is utilized the most inappropriately, and the size of the pie chart is the most important factor. In addition, it was shown that there were statistically significant changes in the proportion of mistakes that occurred in relation to colour, shape, size, and spatial orientation.

(Wanzer et al. 2021) studied "The Role of Titles in Enhancing Data Visualization Dana" Within the communities of data visualisation and assessment, there is a widespread recommendation to make use of titles in order to communicate the message or the takeaway from the visualisation. The purpose of this study was to evaluate that proposal by investigating the ways in which informative or generic names influence the visual efficiency, aesthetics, believability, and perceived efficacy of a visualisation. The hypothetical programme that was investigated was also taken into consideration. In addition, the study investigated the impact that simple or complicated graphs, as well as having positive, negative, or mixed findings (also known as the valence of the results), had on the outcomes. Participants were randomly allocated to one of twelve conditions, which represented a between-subjects research with the following dimensions: two (graph: simple or complicated) times two (title: generic or informative) times three (valence: positive, negative, indifferent). The findings suggested that informative titles took less mental effort and were regarded to be more visually beautiful; nevertheless, they did not contribute to better correctness, credibility, or perceived efficacy in any other way. In addition, there was no correlation between the titles and either the type of graph or the valence of the findings. In spite of the fact that the findings indicate that it is potentially beneficial to think about using an informative title in data visualizations since such titles might lessen the amount of mental work required by the viewer, it is important to keep in mind the objective of the visualisation. Taking into account the objective of the visualisation can be a determining factor in determining the type of graph and title that will be most effective in serving the goals for which it was designed. Taking everything into consideration, this indicates that recommendations for data visualisation that have an effect on assessment reporting procedures have to be investigated more thoroughly through study.

(Wang et al. 2022) studied "A Survey on ML4VIS: Applying Machine Learning Advances to Data Visualization" Researchers have adapted machine learning (ML) approaches to visualizations in order to obtain better design, development, and assessment of visualizations. Many of these techniques were inspired by the tremendous success of machine learning (ML). The field of study known as ML4VIS has been receiving an increasing amount of interest from researchers over the past several years. It is necessary to have a systematic understanding of the integration of ML4VIS in order to properly adapt machine learning techniques for visualisation systems. Within the scope of this work, we conduct a comprehensive analysis of 88 ML4VIS research with the objective of providing answers to two compelling questions: "what visualisation processes can be assisted by ML?" as well as "what methods of machine learning can be utilized to alleviate visualization issues?" Data Processing4VIS, Data-VIS Mapping, Insight Communication, Style Imitation, VIS Interaction, VIS Reading, and User Profiling are the seven primary processes that are shown by this study as being able to profit from the use of machine learning techniques. An ML4VIS pipeline is comprised of seven processes that are connected to pre-existing visualisation theoretical models. The purpose of this pipeline is to shed light on the function that machine learning-assisted visualisation plays in general visualizations. In the meanwhile, major learning tasks in machine learning are being mapped onto the seven processes in order to link the capabilities of machine learning with the requirements of visualisation. Within the framework of the ML4VIS pipeline and the ML-VIS mapping, a discussion is held on the current practices and potential future prospects for ML4VIS. Despite the fact that further research projects are still required in the field of ML4VIS, we are hopeful that this study will serve as a foundation for further investigation.

(Lo et al. 2022) studied “Misinformed by Visualization: What Do We Learn From Misinformative Visualizations? To effectively convince an audience, data visualisation is an effective tool. A visualisation, on the other hand, has the potential to be deceptive or even deceitful if it is executed in an incompetent or malicious manner. In addition to providing additional support, visualizations contribute to the propagation of disinformation on the internet. Over the course of many years, the community of visualisation researchers has been aware of visualizations that misinform the audience. These visualizations are typically connected with the phrases lie and deceptive. Nevertheless, these conversations have chosen to concentrate on only a few specific examples. We open-coded more than one thousand real-world visualizations that have been identified as misleading in order to gain a better understanding of the landscape of misleading visualizations. As a result of these instances, we were able to identify seventy-four different sorts of problems and develop a taxonomy of deceptive components in visualizations. We discovered four paths that the research community might take in order to broaden the conversation on misleading visualizations.

These are as follows: (1) informal fallacies in visualizations; (2) leveraging norms and data literacy; (3) deceptive tactics in unusual charts; and (4) comprehending the designers' issue. This study establishes the framework for various research directions, particularly with regard to understanding, detecting, and preventing that which is being investigated.

(Korkut and Surer 2022) studied Visualization in virtual reality: a systematic review Over the course of the last several years, the importance of rapidly expanding virtual reality (VR) technology and methods has increased, and both academics and practitioners have been looking for effective visualizations in VR. Therefore, the use of gaming technology has been the primary focus up to this point. Studies on visualisation have not yet established a uniform baseline over the era of transition from two-dimensional visualizations to immersive ones, despite the increased interest and discussion in the field. The purpose of the study that is being provided is to provide a comprehensive literature review that describes the current state of research as well as the trends that are expected to emerge in the future regarding visualisation in virtual reality. Empirical and theoretical works of visualisation serve as the foundation for the research framework. A connection with visualisation background and theory, evaluation and design considerations for virtual reality visualisation, and empirical research are the three characteristics that we use to characterize the pieces of literature that we have studied. The results from this systematic review suggest that: (1) There are only a few studies that focus on creating standard guidelines for virtual reality, and each study individually provides a framework or employs previous studies on traditional 2D visualizations; (2) With the myriad of advantages provided for visualisation and virtual reality, most of the studies prefer to use game engines; (3) Although game engines are extensively used, they are not convenient for critical scientific studies; and The purpose of this systematic review is to contribute to the existing body of literature by providing a more accurate depiction of the evolving contexts, various aspects, and the interdependencies between them.

(Wang et al. 2022) studied Applying Machine Learning Advances to Data Visualization: A Survey on ML4VIS —Researchers have adapted machine learning (ML) approaches to visualizations in order to obtain better design, development, and assessment of visualizations. Many of these techniques were inspired by the tremendous success of machine learning (ML). The field of study known as ML4VIS has been receiving an increasing amount of interest from researchers over the past several years. It is necessary to have a systematic understanding of the integration of ML4VIS in order to properly adapt machine learning techniques for visualisation systems. In this work, we conduct a comprehensive assessment of 85 ML4VIS studies with the intention of answering two questions that served as the impetus for our research: what visualisation processes can be assisted by ML? as well as what methods of machine learning can be utilized to alleviate visualization issues? VIS-driven Data Processing, Data Presentation, Insight Communication, Style Imitation, VIS Interaction, and VIS Perception are the six primary stages in which the application of machine learning methods might be beneficial to visualizations, as revealed by this survey. An ML4VIS pipeline is comprised of six processes that are connected to pre-existing visualisation theoretical models. The purpose of this pipeline is to shed light on the function that machine learning-assisted visualisation plays in general visualizations. Simultaneously, the six processes are mapped into the primary learning tasks in machine learning in order to link the capabilities of machine learning with the requirements of visualisation. Within the framework of the ML4VIS pipeline and the ML-VIS mapping, a discussion is held on the current practices and potential future prospects for ML4VIS. Even though there is still a need for more research in the field of ML4VIS, we think that this article has the potential to serve as a foundation for further investigation. You may access an interactive web-based browser version of this poll by going to https://ml4vis.github.io.

(Weiskopf 2022) studied Uncertainty Visualization: Concepts, Methods, and Applications in Biological Data Visualization The purpose of this work is to offer an overview of uncertainty visualisation in general, as well as particular examples of applications in the field of bioinformatics. Starting from a processing and interaction pipeline of visualisation, components are discussed that are relevant for handling and visualizing uncertainty introduced with the original data and at later stages in the pipeline, which shows the importance of making the stages of the pipeline aware of uncertainty and allowing them to propagate uncertainty. A distinction is made between explicit and implicit representations of distributions, as well as various techniques of displaying summary statistics, mixed or hybrid visualizations, and other visual representations of uncertainty. We explain concepts and approaches for visual mappings of uncertainty. Illustrations of the fundamental ideas are provided for a number of different cases of graph visualisation under uncertainty. In the final section of this review article, the implications for the visualisation of biological data and the routes that future research should take are discussed.

(Park et al. 2022) studied Impact of data visualization on decision-making and its implications for public health practice: a systematic literature review Tools that aid in the visualisation of data have the ability to provide public health professionals with assistance in making decisions. The purpose of this study is to provide a concise summary of the scientific research and evidence concerning data visualisation and its influence on decision-making behavior, which is influenced by cognitive processes such as comprehension, attitude, or perception. An electronic literature search was carried out with the assistance of six different databases, which included evaluations of reference lists. Pre-defined search phrases were derived from the study questions that were asked. In the end, sixteen different research were incorporated into the study. From the findings of this research, it was discovered that data visualisation interventions had an effect on attitude, perception, and decision-making in comparison to controls. These links between the treatments and the results appear to be explained by mediating variables such as perceived trustworthiness and quality, knowledge particular to the area, fundamental views that are held in common by social groupings, and political opinions. Visualisation looks to provide benefits, including the ability to increase the amount of information that is presented and the reduction of the cognitive and intellectual burden that is associated with interpreting information for the purpose of decision-making. Nevertheless, there is a lack of awareness about data visualisation interventions that are relevant to the decision-making process of public health leaders, and there is little advice regarding the comprehension of a participant's individual features and activities. Depending on the control of confounding factors on attitude, perception, and decision-making, the evidence from this review shows that beneficial benefits of data visualisation can be detected. This is contingent upon the control of these aspects.

(Karande, Gallagher, and Han 2022) studied A Strategic Approach to Machine Learning for Material Science: How to Tackle Real-World Challenges and Avoid Pitfalls Piyush The use of machine learning (ML) has spread across all areas of research, including material science, as a result of its meteoric rise in popularity and success. There has been a rise in the amount of data collected in the field of material science as a result of the development of experimental procedures, which has encouraged material scientists to examine data-driven solutions to scientific challenges. Despite the fact that there is a growing number of resources accessible to get started with machine learning, there is a dearth of written material that discusses how to navigate the space of decisions that need to be taken in order to execute a reliable and trustworthy machine learning solution. As a result of a dearth of such resources, researchers are forced to sift through a plethora of articles and papers in an effort to identify the most effective method for addressing their issue. In the process, they may also find themselves falling victim to mistakes in a real-world scenario. This work seeks to function as a guide for researchers who wish to strategically approach an ML solution to their problem through the application of domain expertise and systematic evaluation of the primary parts of an ML pipeline. We focus on four parts of the ML pipeline: (1) issue formulation, (2) data curation, (3) feature representation and model selection, and (4) model generalizability and real-world performance. In each case, we discuss the space of decisions, provide examples from scientific literature, and illustrate how different choices can affect the outcome through a case study of predicting compressive strength of uniaxially pressed molecular solid, 2,4,6-triamino-1,3,5-trinitrobenzene (TATB) samples. Using a similar technique of critical thinking together with thorough assessment and diagnostics, researchers may be guaranteed of the dependability of predictions from their ML models

(Mantri et al. 2023) studied How Do Viewers Synthesize Conflicting Information from Data Visualizations? The accumulation of discoveries that either expand upon, contradict, contextualize, or rectify earlier results serves as the basis for the development of scientific knowledge. These incremental discoveries are frequently communicated to laypeople by scientists and journalists through the use of visualizations and text (for example, the beneficial and negative impacts of coffee use). As a consequence of this, readers are required to incorporate data that is both different and contradictory from a variety of sources in order to form judgements or make conclusions. However, the fundamental process that is responsible for accumulating information from a number of different visualizations is still not fully understood. To fill this knowledge gap, we carried out a series of four experiments with a total sample size of 1166 people. In each of these studies, participants were asked to synthesize empirical information from a pair of line charts that were given in sequential order. Our first experiment consisted of administering a baseline condition, which consisted of charts that depicted no particular setting in which the subjects held no strong beliefs. In Experiment 2, we incorporated real-world events into our visualizations, and in Experiment 3, we added supporting text descriptions that were comparable to those found in online news stories or blog posts. This was done in order to measure the generalizability of our findings. In each of the three tests, we changed the relative direction of the line slopes within the chart pairings as well as the size of those slopes. When the two charts displayed connections in the opposite direction (for example, one positive slope and one negative slope), we discovered that participants had a tendency to place a greater amount of importance on the positive slope between the two charts. When the two charts represented connections in the same direction (for example, both positive), the participants had a tendency to give greater weight to the slope that was less difficult to climb. The purpose of these studies is to characterize the synthesis behaviours of the participants based on the link between the information that they watched, to add to theories that define the cognitive mechanisms that are underpinning information synthesis, and to describe the design implications for data storytelling.

(Bhaskar et al. 2023) studied A Literature Review of the Effects of Air Pollution on COVID-19 Health Outcomes Worldwide: Statistical Challenges and Data Visualization In a number of studies and reviews that have been subjected to peer review, the association between exposure to air pollution and the spread and severity of COVID-19 has been investigated. On the other hand, the majority of the evaluations that are now available on this subject do not make a full presentation of the statistical issues that are connected with this field, they do not provide comprehensive guidance for researchers in the future, and they only examine the results of a very limited number of studies. During our examination of 139 studies, we found that 127 of them revealed a statistically significant positive connection between air pollution and unfavourable COVID-19 health outcomes. In this section, we provide a summary of the evidence, discuss the difficulties associated with statistical analysis, and offer suggestions for further research. We also propose an open-source data visualization tool that summarises these studies and allows the research community to submit evidence when new research papers are released. This tool was developed in order to summarize the 139 articles that contain data from geographical places all over the world.

(Bako et al. 2023) studied Understanding how Designers Find and Use Data Visualization The usage of examples is beneficial for the purpose of generating ideas and making the execution of visualisation design easier. Nevertheless, there is a lack of comprehension about the manner in which visualization designers utilise instances and the ways in which computational tools may help activities of this nature. A contribution that we provide in this work is an exploratory analysis of the approaches that are currently being used to incorporate visualisation examples. A total of fifteen university students and fifteen professional designers participated in semi-structured interviews that we conducted. The two primary design tasks that are the focus of our investigation are the search for examples and the use of examples. We describe the tactics and tools that have been noticed for carrying out these tasks, as well as the primary problems that are preventing designers from completing their workflows at the moment. In addition, we find themes that are not limited to either of these two activities. These themes include design fixation, curation procedures, and criteria for judging the value of examples. As a result of our findings, we address the implications for visualisation design and writing tools, and we indicate important topics for further research.

(Lavanya et al. 2023) studied A Comprehensive Review of Data Visualization Tools: Features, Strengths, and Weaknesses" Processing, interpreting, and sharing data have all been significantly improved by the introduction of data visualisation technologies. As the quantity of data that is available continues to grow, it has become increasingly vital to show the data in a manner that is not only simply intelligible but also visually beautiful. As a consequence of this, data visualisation tools have become indispensable for the processes of data analysis and decision-making in a variety of sectors, including engineering, business, healthcare, and the social sciences. The purpose of this review article is to offer an overview of the many data visualisation tools that are now accessible, including their advantages and disadvantages, as well as their characteristics. In the first step of this process, we will discuss the notion of data visualisation and the significance of its role in the process of data analysis. Following that, we will present a concise history of data visualisation, focusing on its development over time, beginning with static charts and progressing to interactive and dynamic visualizations. Bar charts, line graphs, scatter plots, heat maps, tree maps, and network diagrams are some of the data visualisation tools that are accessible. Following that, we cover the tools that are available. We give examples of when and how each style of visualisation may be used to effectively show and understand data. These examples are provided for each type of visualisation. Next, we take a look at the capabilities and features of some of the most popular data visualisation tools, including Tableau, Power BI, Google Data Studio, D3.js, and Python libraries such as Matplotlib, Seaborn, and Plotly. We explore the advantages and disadvantages of each tool, as well as present examples of applications that are applicable in the real world. We also emphasise the significance of selecting the appropriate visualisation tool by taking into consideration the type of data, the audience, and the aim of the visualisation. We also go over the best practices for developing good data visualizations, such as selecting the appropriate colour palette, designing for accessibility, and avoiding the typical errors that are encountered. We conclude by discussing upcoming advances and trends in the field of data visualisation. Some examples of these developments include the use of augmented and virtual reality for data visualisation, as well as the incorporation of machine learning and artificial intelligence into visualisation tools. In conclusion, the process of data analysis has evolved to the point where data visualisation tools have become an indispensable component. Presented in this review article is an overview of the data visualisation tools that are now available, including their features, strengths, and shortcomings. Researchers and analysts are able to effectively display and interpret data when they have a thorough awareness of the strengths and limits of various visualisation tools. This ultimately results in improved decision-making and an increased level of insight.

(Clarinval and Dumas 2024) studied "Intra-City Traffic Data Visualization: A Systematic Literature Review" There are well-known mobility challenges that are caused by the growing number of people living in urban areas. These issues include pollution and roadways that are often crowded. These problems, in addition to having a significant influence on the environment, have a detrimental impact on the quality of life of the nation's population. The development of new technologies has made it possible to collect enormous volumes of data concerning traffic, which can then be analysed to identify problems with mobility and provide potential solutions. As a means of extracting the most useful information from this traffic data, information visualisation is becoming an increasingly popular tool. In this work, we provide the systematic literature analysis we did to examine the existing research in intra-city traffic data visualization. We have created a selection of 146 relevant works, which we have analysed in depth from numerous viewpoints, including the data that was utilized, the domain difficulties, the visualisation techniques and interaction, and the end-user that we are aiming for. This selection was made in accordance with a well established and stringent process. We were able to discover typical behaviours such as the most utilized visualization approaches and the challenges treated the most often. We were able to discover previously unexplored study paths and make suggestions for new lines of inquiry as a result of this. Specifically, we saw that there was a lack of attention for user studies and a lack of visualizations that enabled individuals to participate in the process of contemplating issues linked to mobility.

(De Souza Alencar et al., 2019) studied Visualization Methods for Educational Timetabling Problems concluded that, and This research conducts a Systematic "Literature Review (SRL) on the use of cutting-edge Information Visualization (IV) techniques to solve the Educational

Timetabling Problem (Ed-TTP). The goal here is to demonstrate how IV can improve how people understand the interconnected parts of a schedule for a school or institution. We also look at the ways in which interactive IVs have been suggested to aid in the development and enhancement of scheduling solutions, especially in cases where scheduling conflicts provide a significant challenge.

(Park et al., 2022) studied Impact of data visualization on decision-making and its implications for public health practice concluded that Data visualization tools may help public health professionals make better decisions. Informed by cognitive processes like comprehension, attitude, or perception, this review outlines the research and evidence around data visualization and its effect on decision-making behavior. Six databases were consulted in an electronic literature search, and reference lists were also examined. The search criteria were established in advance in response to the research questions. The final meta-analysis includes data from sixteen research. This review indicated that compared to controls, data visualization interventions had a significant effect on changes in attitude, perception, and decision-making". Perceived trustworthiness and quality, domain-specific knowledge, fundamental ideas shared by social groupings, and political opinions all seem to mediate the links between treatments and outcomes.

(Isenberg et al., 2013) studied A Systematic Review on the Practice of Evaluating Visualization concluded that, and We provide a review of the current climate and historical evolution of evaluation procedures as stated in papers presented at the IEEE Visualization conference. Through a methodical analysis of the features and aims of the evaluations that have been provided, we want to engage in meta-reflection regarding assessment in our community. We used and expanded upon a previously established coding technique to undertake a systematic review of 10 years' worth of assessments in the published publications. Our analysis reveals the most popular assessment objectives, how they have changed over time, and how they compare to those of the IEEE Information Visualization conference". For the most part, we discovered that assessments focused on measuring the quality of output photos and the efficacy of algorithms were the most common.

(Landvoigt & Cardoso, 2017) studied Analysis about publications on Facebook pages: finding of important characteristics discovered, and Learning analytics has great potential for transforming classroom instruction. Learner awareness tools, which give learners with up-to-date information on their learning status, are one method in which this line of inquiry may lead to positive change for students. Interactions like this often happen in the midst of continuous learning activities (like when students are enrolled in a course or even in the present). In this piece, “we examine open learner models, a significant subset of learner awareness tools (OLMs). An Open Learner Model ...provides access to the machine's model of the learner as a powerful tool for facilitating learning.

(Schneider et al., 2017) studied A Conceptual Model of The Economics of Visualization In Diagnostics and Surgery discovered that certain games may be more effective media for providing health therapies than others, and implementation for gamification is a crucial component. We will discuss the constraints and provide recommendations on how to proceed to prevent repeating the same mistakes in the future. The modern technology utilized in healthcare for evaluation and monitoring, together with the increasing use of digital platforms (e.g., smartphones, tablets, and laptops), provide ideal conditions for the development of gamification (e.g., ePRO, online questionnaires, wearable devices). While it is clear that current e-Health apps increase engagement in the short term via the use of extrinsic incentives, the potential of gamification over the long term has not yet been investigated. Existing ideas in psychology and game design should be examined for potential solutions.

(Samuel et al., 2019) studied A Systematic Review of Current Trends in Web Content Mining discovered that some of the least-explored areas of online content mining include knowledge in web documents, relevance rating of websites, and so on (WCM). Few efforts have been made to study WCM, and those that have focused on the techniques employed and the challenges answered did not go into sufficient detail. This is in contrast to the generic data mining tools used for knowledge discovery in web. Existing efforts to examine the literature on WCM fail to show which issues have received insufficient attention and which application domain receives the greatest attention. The purpose of this assessment was to provide a semi-structured, all-encompassing summary of the current state of WCM practices, issues, and proposed remedies. To compile this extensive literature evaluation, 57 sources were consulted, spanning the years 1999-2018. These sources included journals, conference proceedings, and workshop reports. The results show that despite the progress that has been made in WCM, many difficulties still need to be solved, including updating dynamic content, effective content extraction, reducing noise blocks, etc. Furthermore, most proposed solutions to the difficulties still" have their own limits, making this field of research fruitful for further study. Data caching for a dynamic website.

2.4 Research Studies & Key FocusAreas

Author/Year	Key Aspects	Methodology Approach	Summary of finding
Van Wijk (1991)	Spot Noise Texture Synthesis	Developed a new method called YprMnoise	Demonstrated that spot noise provides local control and is suitable for creating textures on curved surfaces.
Erickson (1993)	Artificial Realities for Data Visualization	Conceptual analysis	Discussed the power of visualization in enhancing understanding and the sensory engagement in viewing data.
Van Wijk (1991)	Research Challenges in Geovisualization	Outline of a research agenda	Presented an integration of visualization techniques across multiple disciplines for geospatial data.

Nielson (2002)	Data Visualization: The State of the Art	Review of occlusion and visibility culling techniques	Highlighted the shift from software-based to hardware-assisted techniques due to the advancement in OpenGL.
Flowers (2005)	Auditory Graphing	Review and reflection on auditory graphing	Identified challenges in auditory graphing due to limitations in understanding auditory perception and attention.
Broadhurst & Kell (2006)	Statistical Strategies in Metabolomics	Analysis of common pitfalls in metabolomics	Emphasized the risk of false discoveries and proposed solutions including enhanced study design and validation techniques.
Bresciani & Eppler (2008)	The Risks of Visualization	Analysis through literature review, interviews, and focus groups	Categorized the risks of visualization into social, cognitive, and emotional, offering strategies to mitigate these risks.

Carpendale (2008)	Evaluating Information Visualizations	Advocacy for empirical research	Emphasized the importance of empirical research in information visualization to validate research and encourage the use of diverse evaluative methodologies.
Munzner (2008)	Process and Pitfalls in Writing Information Visualization Research Papers	Historical model of research process	Provided guidance on avoiding common pitfalls in the writing and submission of information visualization research papers.
Wang, Yu, and Ma (2008)	Importance-Driven Time-Varying Data Visualization	Analytical approach using conditional entropy	Introduced a relevance-driven strategy for visualizing time-varying volume data to highlight significant features using importance curves.

Bresciani and Eppler (2008)	The Perils of Visualization	Literature review, interviews, focus groups	Identified and categorized the social, cognitive, and emotional risks associated with visualization from both user and creator perspectives.
Zuur, Ieno, and Elphick (2010)	Protocol for Data Exploration to Avoid Common Statistical Problems	Protocol development	Presented a protocol for data exploration to address common statistical issues in ecology and provided guidelines to manage data analysis challenges.
Kelleher and Wagener (2011)	Effective Data Visualization in Scientific Publications	Survey of visualization literature	Compiled ten guidelines for enhancing data visualization in scientific publications to improve communication and understanding of data.

Bertini, Tatu, and Keim (2011)	Quality Metrics in High-Dimensional Data Visualization	Systematization of strategies using quality measures	Proposed a systematization of visual exploration techniques in high-dimensional data visualization and assessed the efficacy of different quality metrics.
Brodlie, Osorio, and Lopes (2012)	Uncertainty in Data Visualization	Review within a reference model framework	Discussed methods for visualizing uncertainty, differentiating between the visualization of uncertainty and the uncertainty of visualization methods. Highlighted challenges in visualizing uncertainty due to dimensional constraints.

Sousa Santos and Dias (2013)	Evaluation in Visualization	User-centered design approach and systematic evaluation	Emphasized the importance of systematic evaluation in visualization, recommending multiple phases of assessment to ensure effectiveness and user understanding.
Isenberg et al. (2013)	Evaluating Visualization Practices	Systematic review based on coding schemes from prior research	Analyzed evaluation techniques in visualization, showing a shift towards user performance and feedback assessments. Highlighted the need for better formalization of domain-specific practices and reasoning assessments.

Shahin, Liang, and Babar (2014)	Software Architecture Visualization Techniques	Systematic literature review (SLR) using the EBSE methodology	Categorized software architecture visualization techniques into graph-based, notation-based, matrix-based, and metaphor-based categories. Pointed out the need for more objective evaluation methods and industrial surveys to assess the application and challenges of visualization techniques in practice.

2.5 Summary

This article presents a comprehensive analysis of the existing literature on the difficulties and hazards that are inherent in data visualization strategies. The purpose of this chapter is to establish data visualization as an essential instrument at the intersection of data science and communication. Although it is effective for the development of insights and the dissemination of information, it is also laden with a multitude of dangers that have the potential to undermine its effectiveness and overall integrity. The chapter provides a nuanced understanding of the numerous challenges that are involved in the process of creating, interpreting, and consuming visualizations by synthesising insights from theoretical frameworks, empirical studies, and practical applications. This is accomplished through a meticulous examination of scholarly works that span a variety of fields.As a result of these studies, it is clear that the problems associated with visualization are many and may be fairly subtle. These pitfalls include design defects such as improper scale or deceptive chart types, as well as perceptual mistakes and cognitive biases for example. These errors have a substantial impact on the interpretation of data and have the potential to result in misunderstandings, as well as judgments that are based on inaccurate representations of the data. The chapter also covers the need of doing an in-depth analysis of visualization methods and provides insights on successfully navigating these issues. It places an emphasis on the necessity of using visualization techniques with vigilance in order to maintain the integrity of the information that is being communicated. article serves as a basic element in comprehending the complex terrain of data visualization problems, underlining the significance of a cautious and educated deployment of visualization approaches to reduce possible risks in data-driven decision-making and communication.an analysis of the complexity involved in the interpretation of visual data, including the identification of important areas where mistakes often occur and the proposal of strategies to overcome these concerns. It places an emphasis on the relevance of matching visual design with the cognitive capacities of users in order to improve understanding and decrease the likelihood of an incorrect interpretation. The chapter places a special emphasis on the need of visualizations to accommodate a wide range of audiences. It emphasizes the importance of adapting the degree of complexity and interaction to different levels of knowledge and cultural settings in order to guarantee clear and efficient communication across all audiences.Additionally, the paper highlights the dynamic nature of data visualization, which is characterized by the ongoing development of new tools and technologies that provide new possibilities and problems throughout the process. It is imperative that continued study be conducted to investigate how these breakthroughs might be used to enhance visualization processes and steer clear of new dangers that may arise as a result of improvements in technology. For example, the expansion of interactive and real-time data visualizations necessitates the development of unique methodologies in order to preserve accuracy and dependability without compromising the level of insight.This chapter makes a significant contribution to a more comprehensive knowledge of the crucial part that meticulous and purposeful visualization plays in the process of information interpretation and distribution by means of its methodical investigation.

CHAPTER III
METHODOLOGY

3.1 Overview of the Research Problem

The choice that a researcher will make about the technique of research that they will choose is impacted by a variety of different elements. The viewpoint of the researcher who is conducting the study, the nature of the subject matter that is being researched, the present state of scientific research and ideas, and the context in which the relevance of the problem is formed are all examples of these types of factors. When attempting to validate a hypothesis or investigate the elements that impact a result, a quantitative approach is often the most effective strategy to apply. When these data were taken into consideration, a quantitative approach was proposed as a potential technique of inquiry. (Steele, J., & Iliinsky, N. 2010)

3.2 Operationalization of Theoretical Constructs

The courageous data explorer, you are about to embark on a dangerous voyage across the treacherous realms of data visualization dangers. You go deep into the dungeons of study, armed with your reliable sword of critical analysis, and you are prepared to unearth the concealed dangers and mysteries that are hiding there.

Gameplay Mechanics:

- It is important to investigate many locations, each of which represents a separate category of data visualization errors (for example, charts that are deceptive or scale that is not suitable).
- It is possible to come against adversaries in the shape of misleading visualizations and inaccurate data representations.
- Participate in fights by examining and criticizing the visuals, making use of your talents in interpretation and assessment.
- Utilize power-ups such as "Data Literacy Potion" and "Statistical Accuracy Amulet" to enhance your analytical capabilities and improve your overall performance.
- Engage in the process of solving puzzles and riddles that put your knowledge of fundamental principles in data visualization theory to the test.
- The collection of artifacts and relics that provide insights into the most successful methods and tactics for data transmission should be undertaken.

Character Development:

- Your adventurer may be personalized by adding traits such as "Analytical Insight," "Visualization Mastery," and "Critical Thinking."
- The completion of missions and the successful completion of tasks will allow you to level up your character, which will unlock new powers and approaches for data analysis.
- In order to overcome the challenges that are associated with data visualization, it is important to form alliances with other data explorers and share information and tactics with them.

Quest Progression:

- Experience the thrill of embarking on journeys that will test your ability to apply operationalized frameworks to real-life circumstances inside the gaming world.
- Take advantage of opportunities to earn prizes and recognition for your ability to successfully apply theory in practice and accomplish significant results.
- Put your grasp of operationalized structures and your ability to execute them to the test by facing challenges and opponents.

3.3 Research Purpose and Questions

It is in the middle of the labyrinthine complexity of data visualization that our noble purpose is unfolding in this vast adventure. Clarity is often clouded by the shadows of distortion and ambiguity. The objective of our organization is twofold: first, to shed light on the obscure areas of visual data transmission; second, to equip fellow explorers with the knowledge and foresight that are required to traverse the perilous terrain of visualization traps with self-assurance and accuracy. We start on this journey with a persistent dedication to unearthing the many layers of difficulties and possibilities that are inherent in the visualization of information. As guardians of truth in the domain of data, we are committed to this endeavor. The goal of our research is to shed light on the routes to clarity and comprehension in the wide terrain of visual data representation by means of painstaking investigation and academic rigor. This will allow us to untangle the tangled web of typical mistakes that entangle both rookie explorers and seasoned researchers alike. Our search is motivated by a strong feeling of responsibility to the pursuit of knowledge and enlightenment. We are aware of the significant influence that efficient data transmission has on the process of decision-making, the resolution of problems, and the advancement of society. We want to go beyond simple observation and analysis by digging into the intricacies of data visualization issues. Instead, we would like to take on the role of proactive stewardship in our pursuit of truth and openness in the sharing of information.

We hope that by undertaking this laudable work, we will be able to establish a new paradigm of data literacy and empowerment. In this paradigm, every explorer will be equipped with the skills and insights that are required to differentiate between truth and deceit among the many kinds of visible data. By deciphering the secrets of misrepresentation and distortion, we are laying the groundwork for a future in which clarity and truth are the most important things. This will help to cultivate a culture of informed decision-making and intellectual integrity in the field of data analysis and interpretation.

In the interest of achieving our mission, we make a solemn promise to preserve the greatest standards of scholarship and honesty, guided by an unwavering dedication to the quest of the truth and the sharing of information. The lofty values of discovery, enlightenment, and the constant search of clarity in the face of the intricacies of visual data representation are what propel us forward as we march out into the unknown with unshakable resolution and unrelenting determination.As the guardians of truth in the realm of data visualization, our mission is crystal clear: to shed light on the way forward in the midst of the shadows of ambiguity and misrepresentation, and to equip all those who are brave enough to venture into the realm of visualized data with the knowledge and foresight that is required to navigate its dangers with the courage and conviction that is required.

Research Questions:

1. What are the most common pitfalls encountered in data visualization across various domains and applications?
2. How do different types of data visualization techniques contribute to the emergence of specific pitfalls?
3. What cognitive biases and perceptual distortions contribute to the misinterpretation of visualized data?
4. How do factors such as audience demographics and context influence the susceptibility to data visualization pitfalls?

5. What strategies and best practices can be employed to mitigate the risks associated with common data visualization pitfalls?
6. How do advancements in technology and design impact the prevalence and nature of data visualization pitfalls over time?

3.4 Research Design

It is possible that the design of the study, which makes use of a technique known as data gathering, measurement, and analysis, would be able to assist in answering research questions and achieving research objectives. When it comes to doing research, there is no one predetermined set of best practices that can be adhered to. This is because every single researcher is different. Since the two research projects employ the same approach, it is impossible to discriminate between them since there is no means to differentiate between them. In light of this, there is no need to discriminate between the two of them. The scope of this study included doing research on both primary and secondary sources of information during the course of the investigation. S. M. Kosslyn's work from 2006 The design of our quest is methodically built in our academic expedition. It combines scientific rigor and multidisciplinary teamwork in order to successfully traverse the complex maze of data visualization problems. This design serves as our compass, directing us with clarity and purpose through the intricacies of data visualization.In the beginning of our adventure, we will do a thorough assessment of the existing literature, which will cover a wide range of fields including information visualization, cognitive psychology, and graphic design. Through this foundational inquiry, we are able to get a better knowledge of the fundamental ideas and theories that are pertinent to the difficulties associated with data visualization, so providing the platform for our empirical studies.

In order to establish a conceptual framework that elucidates the theoretical components that drive visualization problems, we draw upon the insights that we have gained from the literature. Our efforts to conduct empirical research are shaped by this framework, which acts as a compass throughout the process of designing and carrying out our study.

The technique that we use is a mixed-methods approach, which combines qualitative investigation with quantitative research in order to get a comprehensive knowledge of the challenges that are associated with visualization. Comparatively, qualitative approaches include interviews, focus groups, and expert reviews, while quantitative methods include the systematic classification and analysis of visuals. In order to ensure that our dataset is both comprehensive and reflective of the actual world, we gather a wide variety of visualizations from scholarly literature, media sources, and apps that are used in the real world. In addition, focused interviews and surveys provide detailed perspectives on the potential and problems that are associated with data visualization. It is via meticulous analysis and synthesis that we are able to extract the most important insights and trends, so shedding light on the fundamental aspects that contribute to visualization mistakes. For the purpose of ensuring the validity and reliability of our results, we put them through validation methods, which include peer review and comments from experts.

3.5 Area and Sample

Area: Multimodal data visualization: Investigating the potential pitfalls and benefits of using multiple visual and non-visual modalities (such as audio, haptic feedback, and text) to represent complex data.

Sample Size: 50-100 studies

3.6 Participant Selection

The process of selecting participants is an essential component of our trip as we embark on our academic mission to discover the secrets behind the dangers associated with data visualization. For the purpose of enhancing our investigation and contributing to the overall comprehension of visualization difficulties, we are looking for people who have a wide range of viewpoints, areas of knowledge, and experiences. This is analogous to putting together a group of different explorers.

Inclusion Criteria:

- We cast a broad net, looking for participants from a variety of fields and backgrounds that are important to data visualization. These fields include, but are not limited to, academic institutions, private businesses, government agencies, and organizations that are not-for-profit.
- Individuals who interact with visualized data in their respective disciplines, such as researchers, practitioners, educators, designers, analysts, and decision-makers, may be considered participants.

Expertise and Experience:

- Individuals that have skill and experience in data visualization, including the ability to develop, analyze, and critique representations, are given priority in our hiring process.
- It is possible for participants to possess a wide variety of skills and abilities, ranging from theoretical understanding of cognitive psychology and design principles to technical competency in visualization tools and methods.

Diversity and Representation:

- We are conscious of the significance of diversity and representation in the process by which we choose participants, and we make every effort to make sure that persons from underrepresented groups and communities that are marginalized are included.
- Our objective is to form a varied group of individuals that is representative of the wide range of viewpoints and experiences that are present within the larger community of data visualization practitioners and academics.

3.7 Data Collection Procedures

To answer important questions and analyze the results, we use data collection as a technique of systematizing the process of obtaining and measuring information. This allows us to evaluate the outcomes. Surveys are a common strategy that is used when it comes to the collection of information from very big populations. There are two primary components that constitute a survey: a question and a response to the question by the respondents.

- ➢ Questions
- ➢ Responses

We will create the questions for ***Data visualization pitfalls: a systematic review*** The collected data is kept in an orderly database.

3.8 Data Collection Methods

The systematic collection of data and the subsequent measurement and assessment of that data are two of the most prevalent techniques to data acquisition; however, there are a number of alternative methods that may be used. The purpose is to obtain data that is accurate and true, and this objective is independent of the technique that is utilized. The gathering of evidence of the highest possible quality should be the ultimate objective of any activity that includes the collecting of data. This evidence may then be utilized in a full data analysis to offer answers to the research questions that have been posed. Cleveland, W. S., and R. McGill's 1984 publication

Primary Data

The major instrument that was used in the analysis of the data was a questionnaire. In the area of the survey that is devoted to questions, there is a logical progression of questions. In order to gather information on the topic, a questionnaire was developed.. ***Data visualization pitfalls: a systematic review***

Secondary Data

In addition to providing researchers with access to larger and more accurate data sets than they would be able to get on their own, the use of secondary data analysis has the potential to save researchers a significant amount of time and effort that would otherwise be spent on the process of data collection on their own.

It is possible to get secondary data from a number of sources, such as:

1. Internet, journals, the media, and research papers are all examples of sources of information which may be accessed online.
2. A wide range of additional things, including academic results, libraries, and institutional observations, are also included in this category.

In order to completely capture prior changes and/or discoveries, social and economic change experts look for secondary data. This is because a new survey cannot catch all of the available information. Some examples of secondary sources of knowledge that may be obtained on the internet are books and journal articles. (Chambers, J. M., Cleveland, W. S., Kleiner, B., & Tukey, P. A. 1983)

3.9 Data Analysis

There are several steps involved in the process of analyzing and interpreting data. The process starts with a review of the data and concludes with a suggestion for action. A vast number of corporate, scientific, and social science fields are included in the scope of data analysis, which covers a wide variety of procedures and approaches related to data analysis.

As per the findings of the study, a whole component is dismantled and put through its paces in isolation. Data analysis is the act of transforming raw data into information that may be used for decision-making on a more meaningful level. The gathering and examination of data is done in order to provide answers to questions, assumptions, or notions.

Data Analysis Techniques

Survey System includes most commonly used survey statistics that includes following techniques:

1. Percents
2. Medians
3. Means
4. Standard Deviations
5. Standard Errors
6. Chi-squares
7. Differences between Proportions
8. *t*-tests

3.10 Research Design Limitations

In the course of our academic endeavor to solve the secrets surrounding the dangers of data visualization, it is very necessary to acknowledge the limitations that dictate the course of our search. It is necessary for us to navigate within the limits that impact the design of our study, despite the fact that our strategy has been meticulously constructed.

3.11 Scope and Generalizability:

- Our expansive reach may result in a loss of depth, which will restrict the extent to which we are able to investigate certain elements of visualization errors.
- Due to the fact that the findings may be contingent on the environment in which they were obtained, it is possible that they may not generalize across all fields.

3.12 Sampling and Participant Bias:

- In spite of our best efforts, it is possible that biases exist owing to the demographics and opinions of the people who participated in our study.
- Participant self-selection has the potential to result in a skewed sample, which will have an effect on the degree to which our results are representative.

3.13 Data Quality and Reliability:

- Because the quality of the visualizations that we have gathered might vary in terms of their correctness and completeness, the credibility of our analysis is contingent on this.
- The validity of our findings may be compromised if the data we use are either insufficient or inconsistent.

3.14 Methodological Constraints:

- Despite the fact that our procedures are carefully selected, they are not without their inherent limits.
- It is possible that the depth or breadth of our research may be limited due to limitations in resources or time, which would have an effect on the reliability of our results.

CHAPTER IV

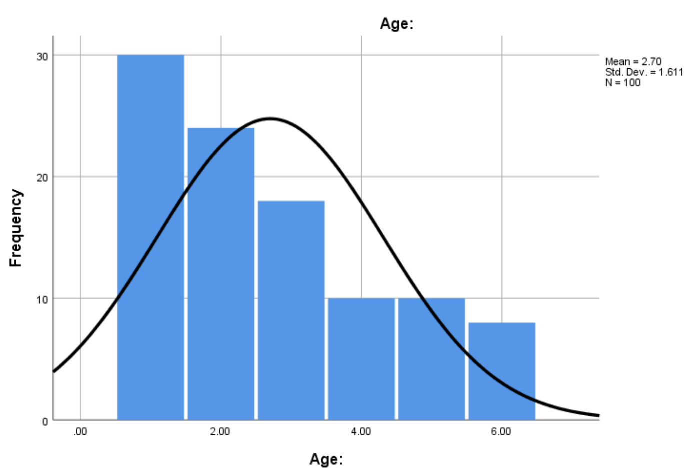
DATA ANALYSIS

Data analysis is the process of inspecting, cleaning, transforming, and modelling data in order to discover useful information, draw conclusions, and support decision-making. It involves a wide range of techniques and methods to explore and analyze data, including statistical analysis, data visualization, and machine learning. The main goals of data analysis are to identify patterns and trends, make predictions, and generate insights that can inform decisions and drive action. It involves using data to answer specific questions, uncovering relationships and dependencies, and testing hypotheses. Effective data analysis requires a combination of technical skills, domain expertise, and critical thinking. It involves working with large and complex datasets, choosing the right tools and techniques for the job, and communicating findings clearly and effectively.

Table 1

Age:					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Under 18 years old	30	30.0	30.0	30.0
	18-25 years old	24	24.0	24.0	54.0
	26-36 years old	18	18.0	18.0	72.0
	37-47 years old	10	10.0	10.0	82.0
	48-58 years old	10	10.0	10.0	92.0
	59 +years old	8	8.0	8.0	100.0
	Total	100	100.0	100.0	

Graph 1

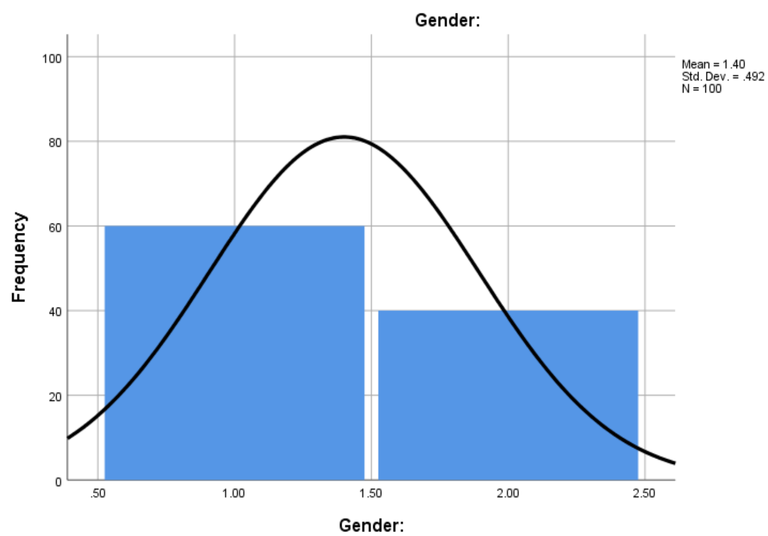


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Age:" 30(30%) respondents responded Under 18 years old, 24(24%) respondents responded 18-25 years old, 18(18%) respondents responded 26-36 years old and 10(10%) respondents responded 37-47 years old and 10(10%) respondents responded 48-58 years old.

Table 2

Gender:					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	60	60.0	60.0	60.0
	Male	40	40.0	40.0	100.0
	Total	100	100.0	100.0	

Graph 2

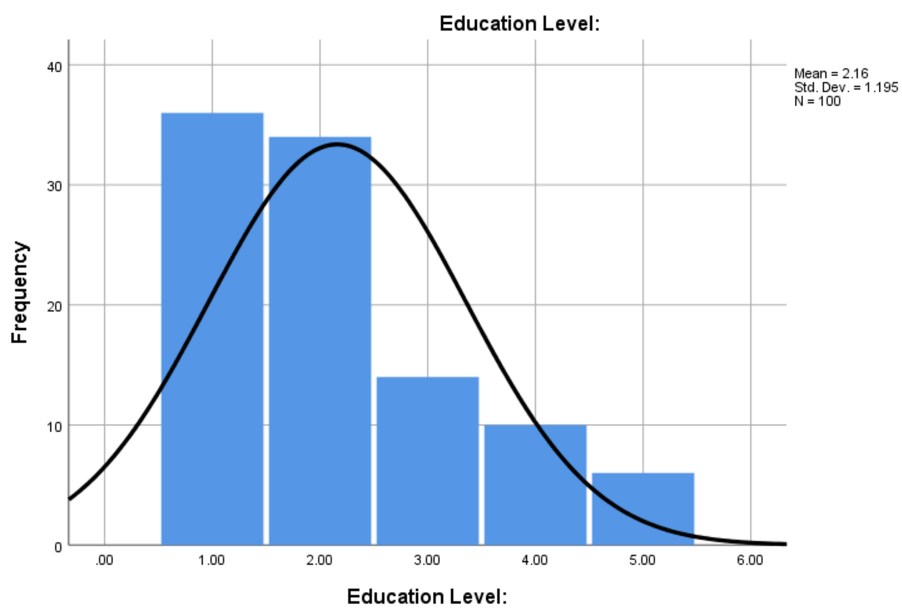


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Gender:" and 60(60%) respondents responded as Female, whereas 40(40%) respondents responded as Male

Table 3

Education Level:					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than high school	36	36.0	36.0	36.0
	High school diploma or equivalent	34	34.0	34.0	70.0
	Some college, no degree	14	14.0	14.0	84.0
	Associate degree	10	10.0	10.0	94.0
	Other (please specify)	6	6.0	6.0	100.0
	Total	100	100.0	100.0	

Graph 3

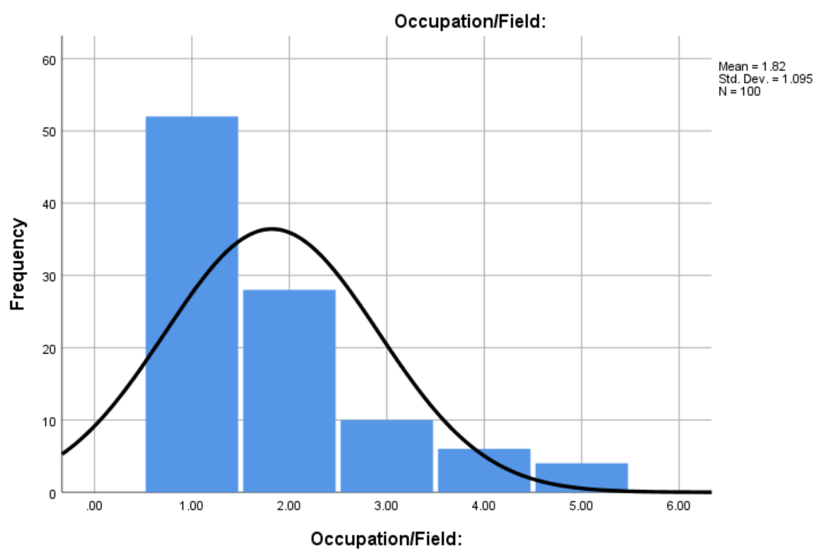


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Education Level:" 36(36%) respondents responded Less than high school, 34(34%) respondents responded High school diploma or equivalent, 14(14%) respondents responded Some college, no degree and 10(10%) respondents responded Associate degree and 6(6%) respondents responded Other (please specify).

Table 4

Occupation/Field:					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Business/Finance	52	52.0	52.0	52.0
	Healthcare/Medicine	28	28.0	28.0	80.0
	Education/Research	10	10.0	10.0	90.0
	Government/Nonprofit	6	6.0	6.0	96.0
	Other (please specify)	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 4

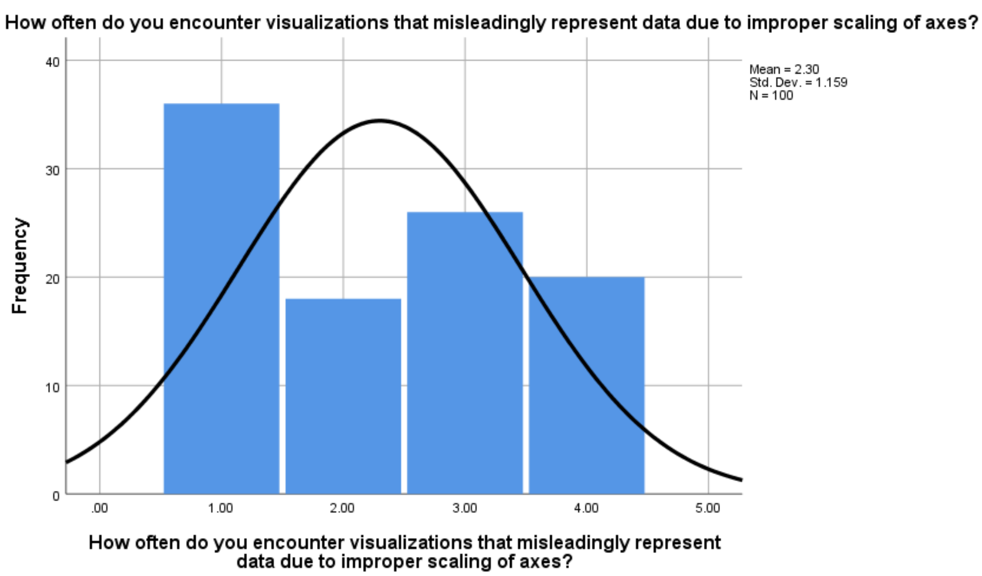


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Occupation/Field:" 52(52%) respondents responded Business/Finance, 28(28%) respondents responded Healthcare/Medicine, 10(10%) respondents responded Education/Research and 6(6%) respondents responded Government/Nonprofit and 4(4%) respondents responded Other (please specify).

Table 5

How often do you encounter visualizations that misleadingly represent data due to improper scaling of axes?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very often	36	36.0	36.0	36.0
	Occasionally	18	18.0	18.0	54.0
	Rarely	26	26.0	26.0	80.0
	Never	20	20.0	20.0	100.0
	Total	100	100.0	100.0	

Graph 5

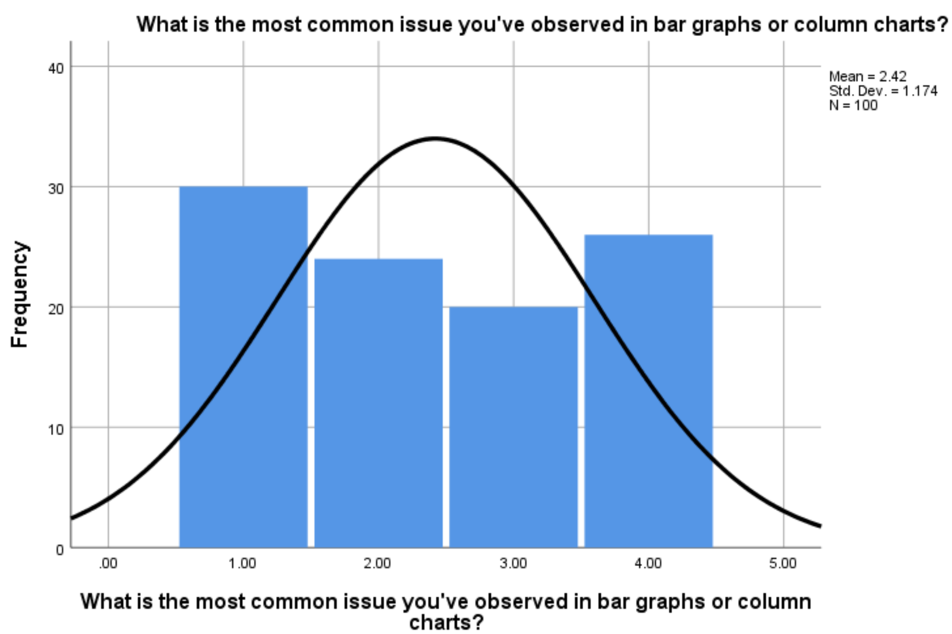


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "How often do you encounter visualizations that misleadingly represent data due to improper scaling of axes?" 36(36%) respondents responded Very often, 18(18%) respondents responded Occasionally and 26(26%) respondents responded Rarely where as 20(20%) respondents responded Never.

Table 6

What is the most common issue you've observed in bar graphs or column charts?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Truncated axes that exaggerate differences	30	30.0	30.0	30.0
	Inconsistent intervals on the axis	24	24.0	24.0	54.0
	Overlapping bars that obscure data	20	20.0	20.0	74.0
	Using 3D effects that distort perception	26	26.0	26.0	100.0
	Total	100	100.0	100.0	

Graph 6

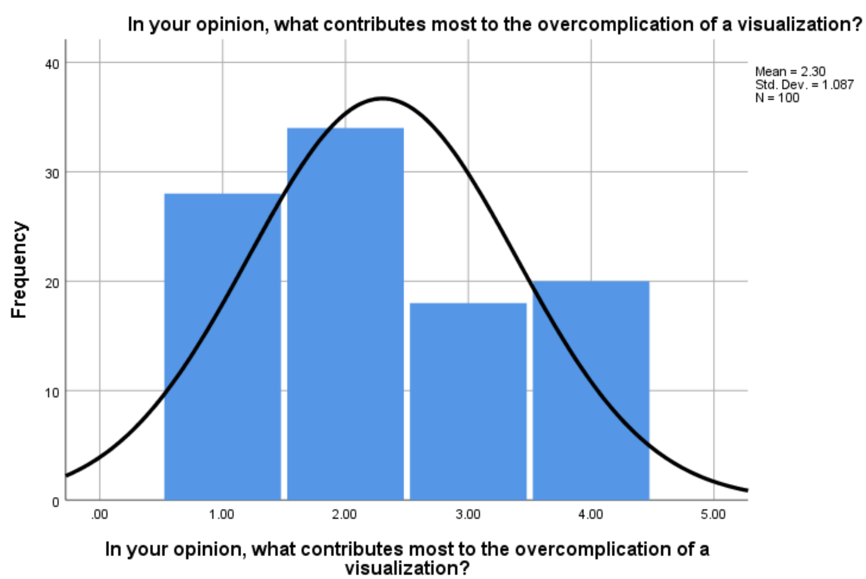


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "What is the most common issue you've observed in bar graphs or column charts?" 30(30%) respondents responded Truncated axes that exaggerate differences, 24(24%) respondents responded Inconsistent intervals on the axis and 20(20%) respondents responded Overlapping bars that obscure data where as 26(26%) respondents responded Using 3D effects that distort perception.

Table 7

In your opinion, what contributes most to the overcomplication of a visualization?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Too many data points	28	28.0	28.0	28.0
	Excessive use of colors and patterns	34	34.0	34.0	62.0
	Incorporating too many variables in a single chart	18	18.0	18.0	80.0
	All of the above	20	20.0	20.0	100.0
	Total	100	100.0	100.0	

Graph 7

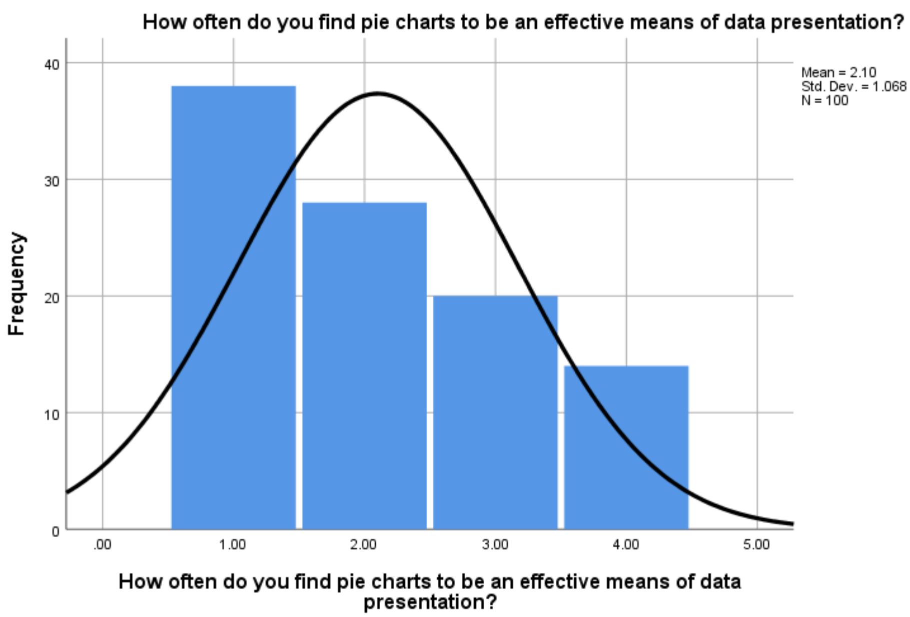


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about " In your opinion, what contributes most to the overcomplication of a visualization?" 28(28%) respondents responded Too many data points, 34(34%) respondents responded Excessive use of colors and patterns and 18(18%) respondents responded Incorporating too many variables in a single chart where as 20(20%) respondents responded All of the above.

Table 8

How often do you find pie charts to be an effective means of data presentation?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very often	38	38.0	38.0	38.0
	Occasionally	28	28.0	28.0	66.0
	Rarely	20	20.0	20.0	86.0
	Never	14	14.0	14.0	100.0
	Total	100	100.0	100.0	

Graph 8

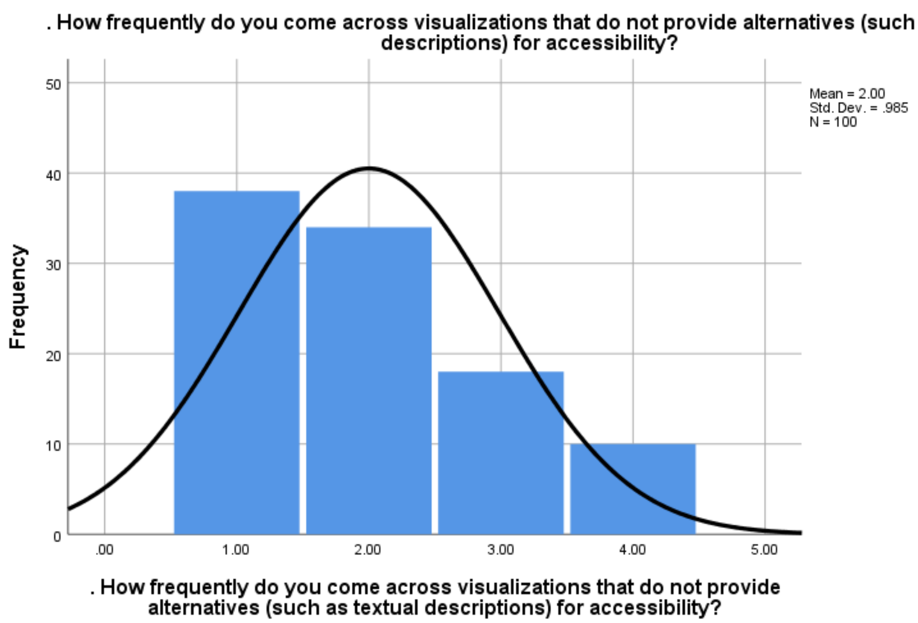


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "How often do you find pie charts to be an effective means of data presentation?" 38(38%) respondents responded Very often, 28(28%) respondents responded Occasionally and 20(20%) respondents responded Rarely where as 14(14%) respondents responded Never.

Table 9

. How frequently do you come across visualizations that do not provide alternatives (such as textual descriptions) for accessibility?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very often	38	38.0	38.0	38.0
	Occasionally	34	34.0	34.0	72.0
	Rarely	18	18.0	18.0	90.0
	Never	10	10.0	10.0	100.0
	Total	100	100.0	100.0	

Graph 9

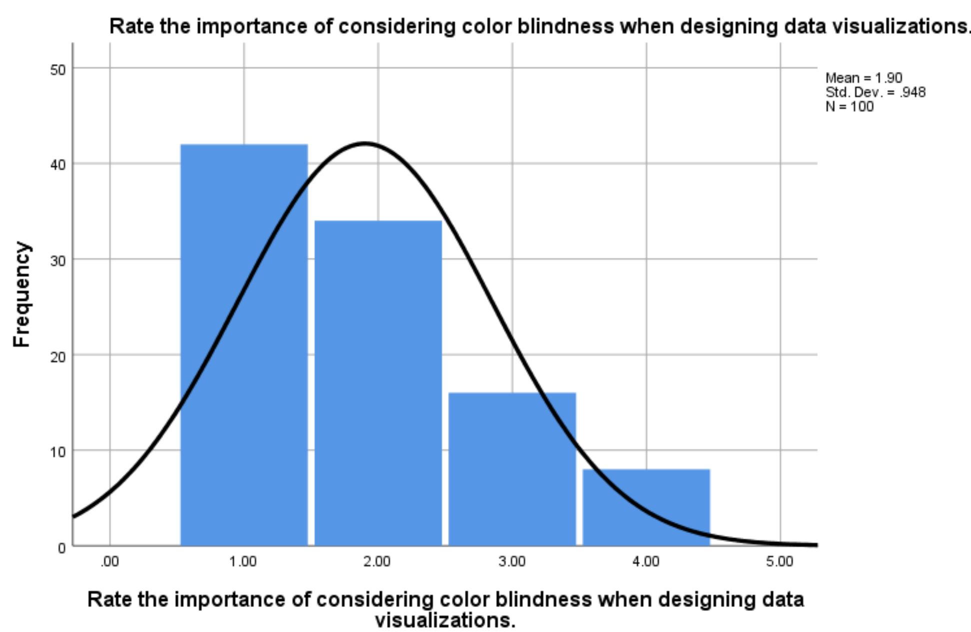


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about ". How frequently do you come across visualizations that do not provide alternatives (such as textual descriptions) for accessibility?" 38(38%) respondents responded Very often, 34(34%) respondents responded Occasionally and 18(18%) respondents responded Rarely where as 10(10%) respondents responded Never.

Table 10

Rate the importance of considering color blindness when designing data visualizations.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very important	42	42.0	42.0	42.0
	Somewhat important	34	34.0	34.0	76.0
	Not very important	16	16.0	16.0	92.0
	Unimportant	8	8.0	8.0	100.0
	Total	100	100.0	100.0	

Graph 10

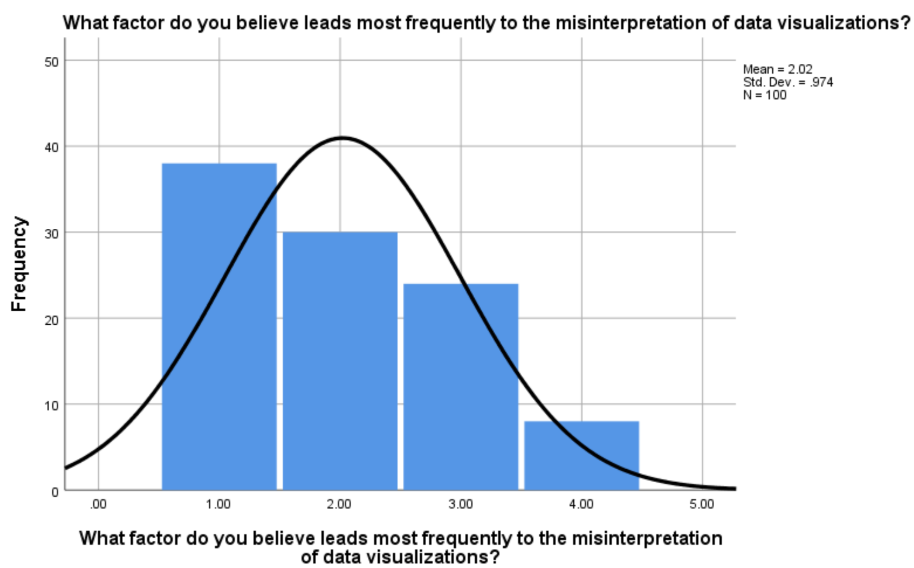


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Rate the importance of considering color blindness when designing data visualizations." 42(42%) respondents responded Very important, 34(34%) respondents responded Somewhat important and 16(16%) respondents responded Not very important where as 8(8%) respondents responded Unimportant.

Table 11

What factor do you believe leads most frequently to the misinterpretation of data visualizations?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of contextual information	38	38.0	38.0	38.0
	Ambiguous legends or keys	30	30.0	30.0	68.0
	Inappropriate choice of visualization type	24	24.0	24.0	92.0
	Misleading axis labels or titles	8	8.0	8.0	100.0
	Total	100	100.0	100.0	

Graph 11

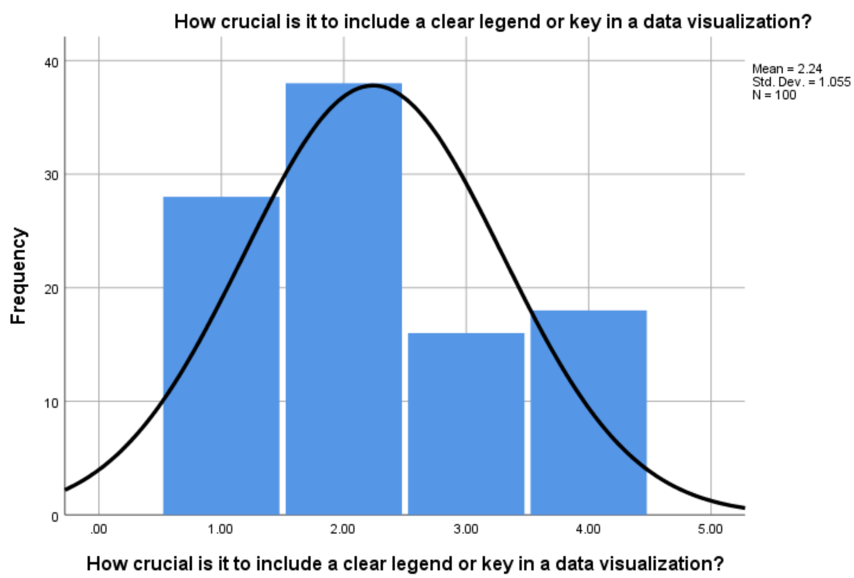


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "What factor do you believe leads most frequently to the misinterpretation of data visualizations?" 38(38%) respondents responded Lack of contextual information, 30(30%) respondents responded Ambiguous legends or keys and 24(24%) respondents responded Inappropriate choice of visualization type where as 8(8%) respondents responded Misleading axis labels or titles.

Table 12

How crucial is it to include a clear legend or key in a data visualization?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very crucial	28	28.0	28.0	28.0
	Somewhat crucial	38	38.0	38.0	66.0
	Not very crucial	16	16.0	16.0	82.0
	Not crucial at all	18	18.0	18.0	100.0
	Total	100	100.0	100.0	

Graph 12

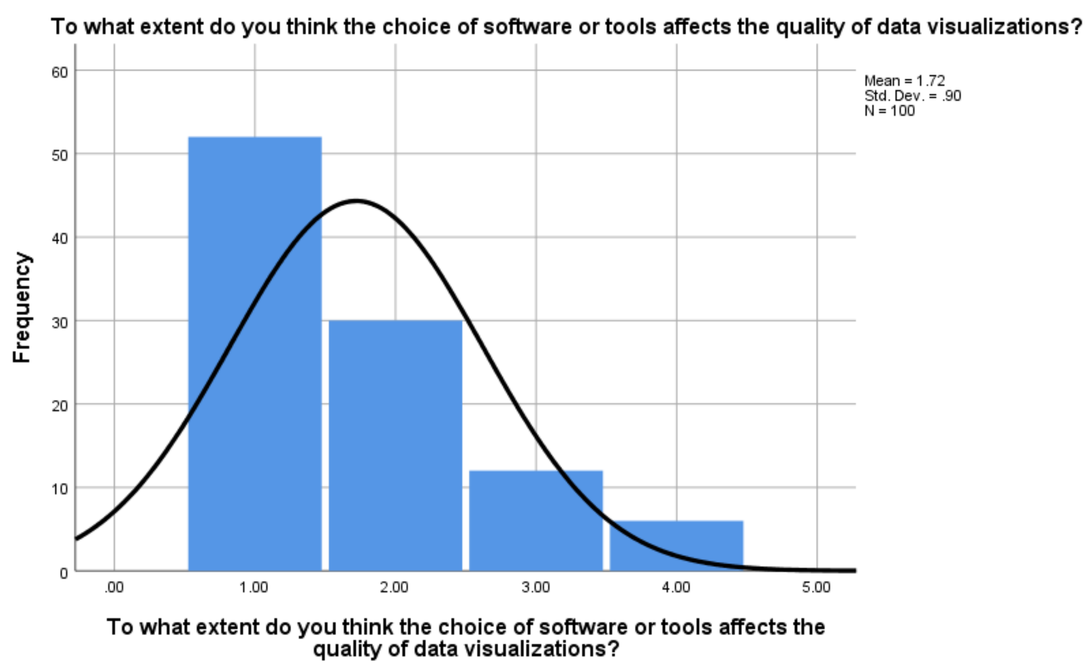


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "How crucial is it to include a clear legend or key in a data visualization?" 28(28%) respondents responded Very crucial, 38(38%) respondents responded Somewhat crucial and 16(16%) respondents responded Not very crucial where as 18(18%) respondents responded Not crucial at all.

Table 13

To what extent do you think the choice of software or tools affects the quality of data visualizations?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Significantly	52	52.0	52.0	52.0
	Moderately	30	30.0	30.0	82.0
	Slightly	12	12.0	12.0	94.0
	Not at all	6	6.0	6.0	100.0
	Total	100	100.0	100.0	

Graph 13

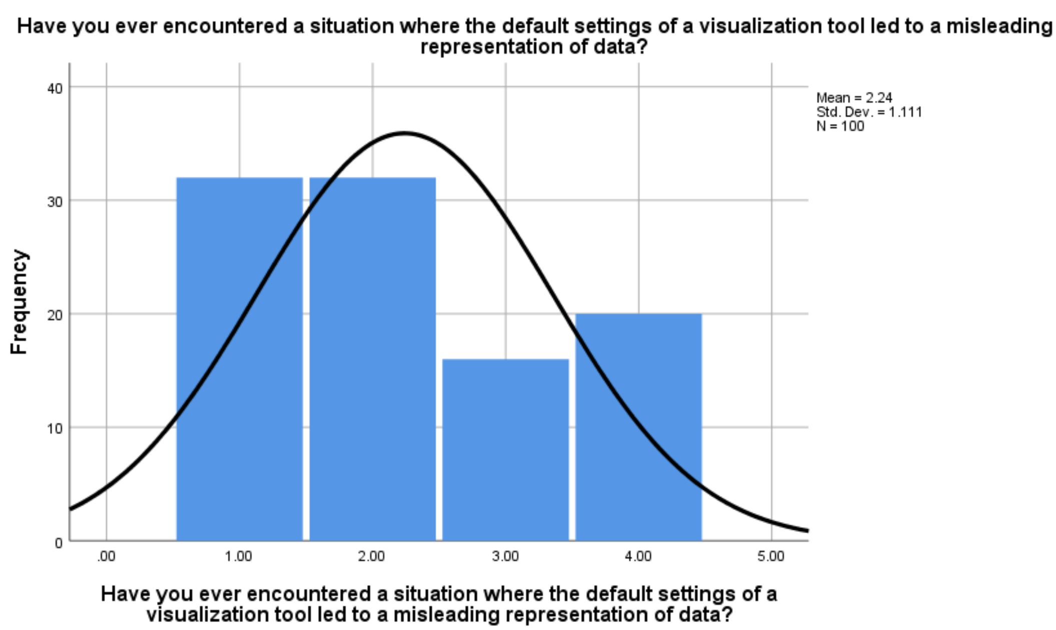


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "To what extent do you think the choice of software or tools affects the quality of data visualizations?" 52(52%) respondents responded Significantly, 30(30%) respondents responded Moderately and 12(12%) respondents responded Slightly where as 6(6%) respondents responded Not at all.

Table 14

Have you ever encountered a situation where the default settings of a visualization tool led to a misleading representation of data?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes, frequently	32	32.0	32.0	32.0
	Yes, but rarely	32	32.0	32.0	64.0
	No, but I see how it could happen	16	16.0	16.0	80.0
	No, never	20	20.0	20.0	100.0
	Total	100	100.0	100.0	

Graph 14

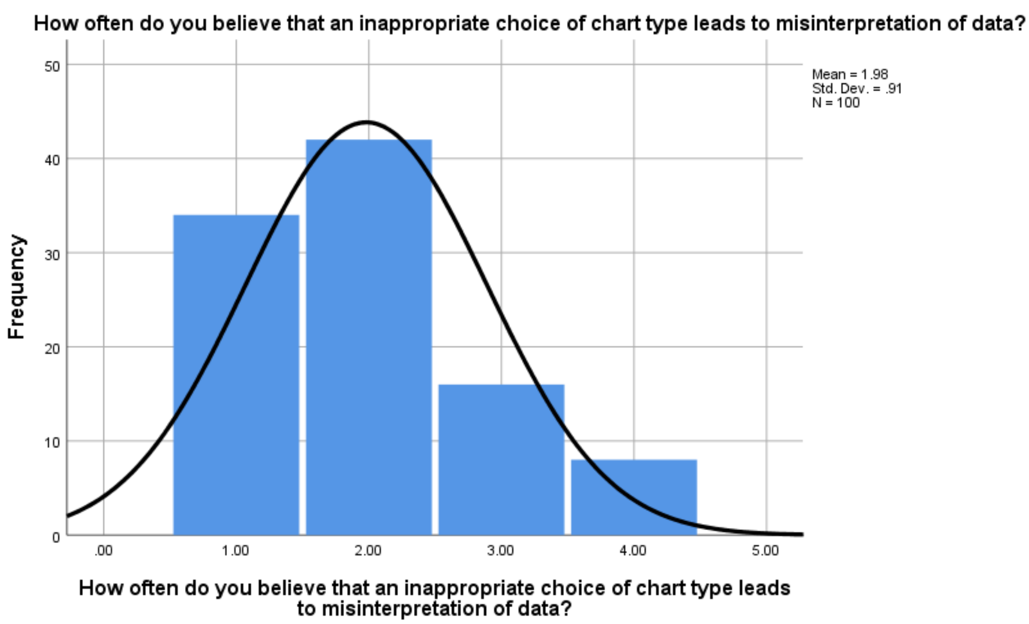


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Have you ever encountered a situation where the default settings of a visualization tool led to a misleading representation of data?" 32(32%) respondents responded Yes, frequently, 32(32%) respondents responded Yes, but rarely and 16(16%) respondents responded No, but I see how it could happen where as 20(20%) respondents responded No, never.

Table 15

How often do you believe that an inappropriate choice of chart type leads to misinterpretation of data?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very often	34	34.0	34.0	34.0
	Occasionally	42	42.0	42.0	76.0
	Rarely	16	16.0	16.0	92.0
	Never	8	8.0	8.0	100.0
	Total	100	100.0	100.0	

Graph 15

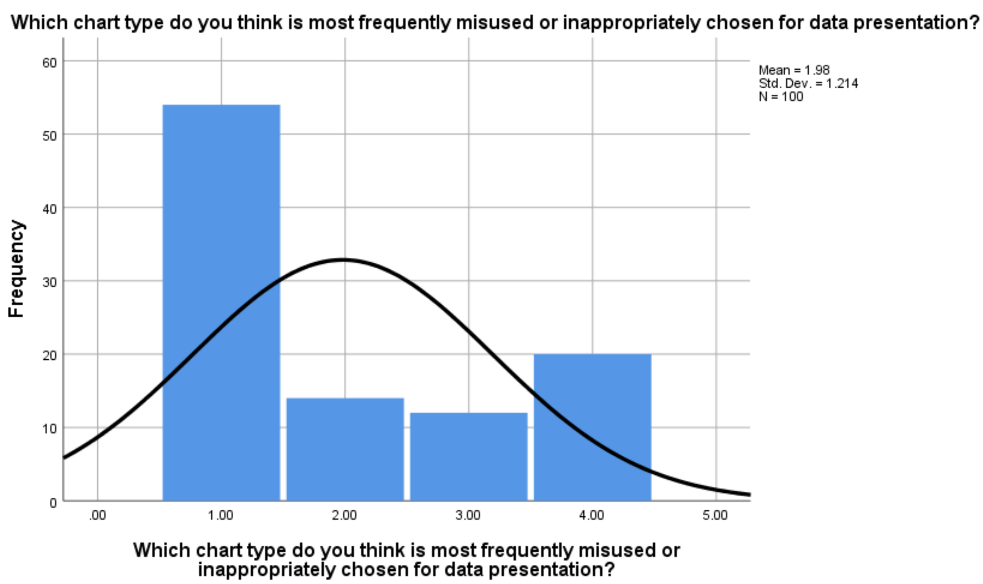


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "How often do you believe that an inappropriate choice of chart type leads to misinterpretation of data?" 34(34%) respondents responded Very often, 42(42%) respondents responded Occasionally and 16(16%) respondents responded Rarely where as 8(8%) respondents responded Never.

Table 16

Which chart type do you think is most frequently misused or inappropriately chosen for data presentation?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Pie charts	54	54.0	54.0	54.0
	Bar charts	14	14.0	14.0	68.0
	Line graphs	12	12.0	12.0	80.0
	Scatter plots	20	20.0	20.0	100.0
	Total	100	100.0	100.0	

Graph 16

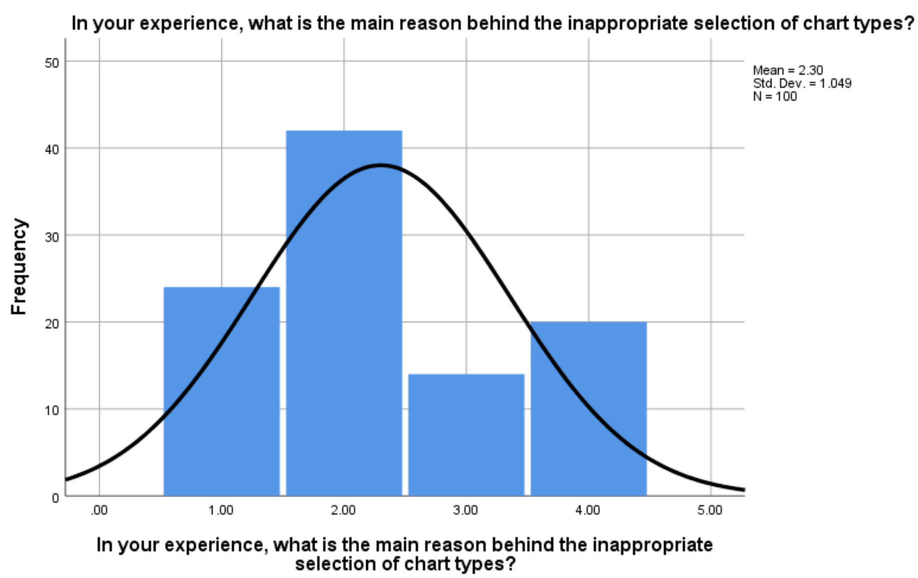


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Which chart type do you think is most frequently misused or inappropriately chosen for data presentation?" 54(54%) respondents responded Pie charts, 14(14%) respondents responded Bar charts and 12(12%) respondents responded Line graphs where as 20(20%) respondents responded Scatter plots.

Table 17

In your experience, what is the main reason behind the inappropriate selection of chart types?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of understanding of the data	24	24.0	24.0	24.0
	Insufficient knowledge of different chart types and their uses	42	42.0	42.0	66.0
	Trying to make the data appear more favorable or dramatic	14	14.0	14.0	80.0
	Software defaults or limitations	20	20.0	20.0	100.0
	Total	100	100.0	100.0	

Graph 17

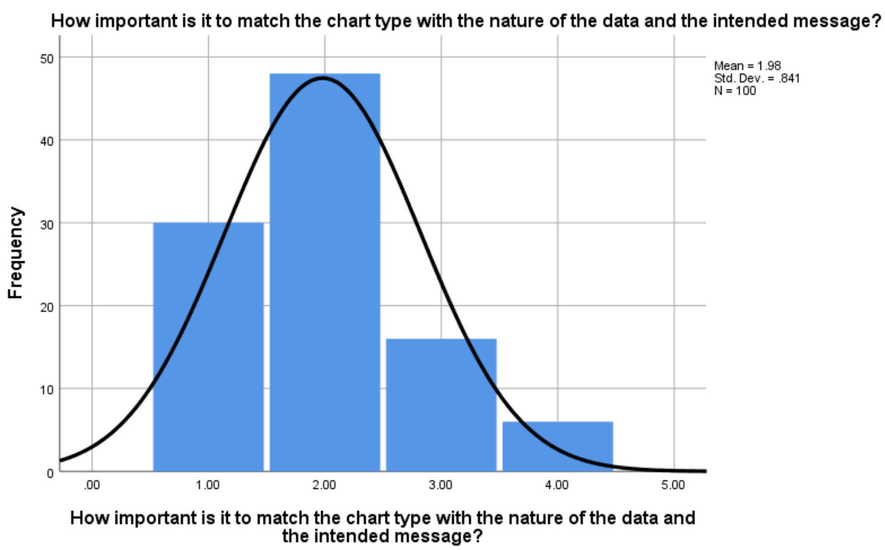


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "In your experience, what is the main reason behind the inappropriate selection of chart types?" 24(24%) respondents responded Lack of understanding of the data, 42(42%) respondents responded Insufficient knowledge of different chart types and their uses and 14(14%) respondents responded Trying to make the data appear more favorable or dramatic where as 20(20%) respondents responded Software defaults or limitations.

Table 18

How important is it to match the chart type with the nature of the data and the intended message?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Extremely important	30	30.0	30.0	30.0
	Very important	48	48.0	48.0	78.0
	Somewhat important	16	16.0	16.0	94.0
	Not important	6	6.0	6.0	100.0
	Total	100	100.0	100.0	

Graph 18

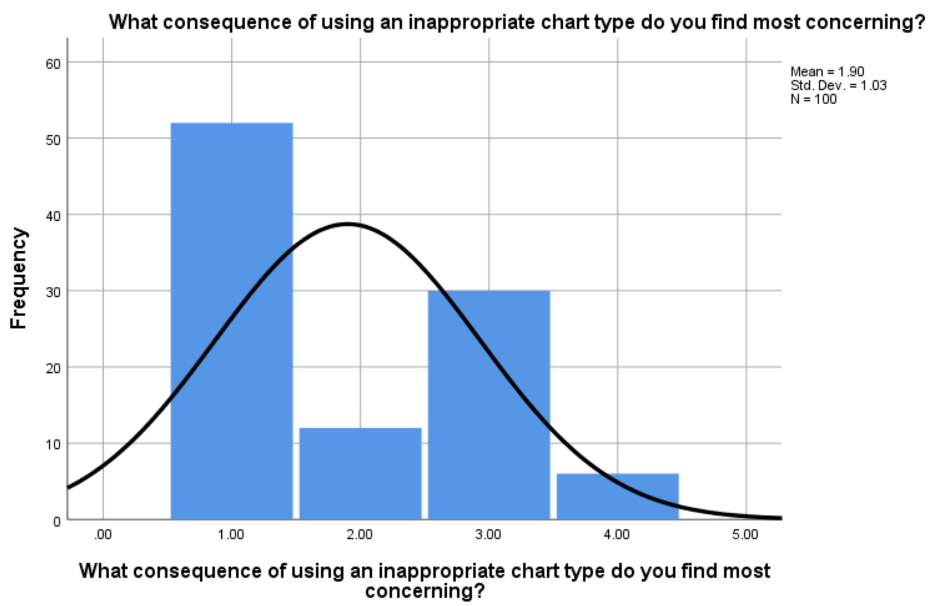


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "How important is it to match the chart type with the nature of the data and the intended message?" 30(30%) respondents responded Extremely important, 48(48%) respondents responded Very important and 16(16%) respondents responded Somewhat important where as 6(6%) respondents responded Not important.

Table 19

What consequence of using an inappropriate chart type do you find most concerning?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Misleading the audience	52	52.0	52.0	52.0
	Oversimplifying complex data	12	12.0	12.0	64.0
	Overcomplicating simple data	30	30.0	30.0	94.0
	Obscuring key insights or patterns	6	6.0	6.0	100.0
	Total	100	100.0	100.0	

Graph 19

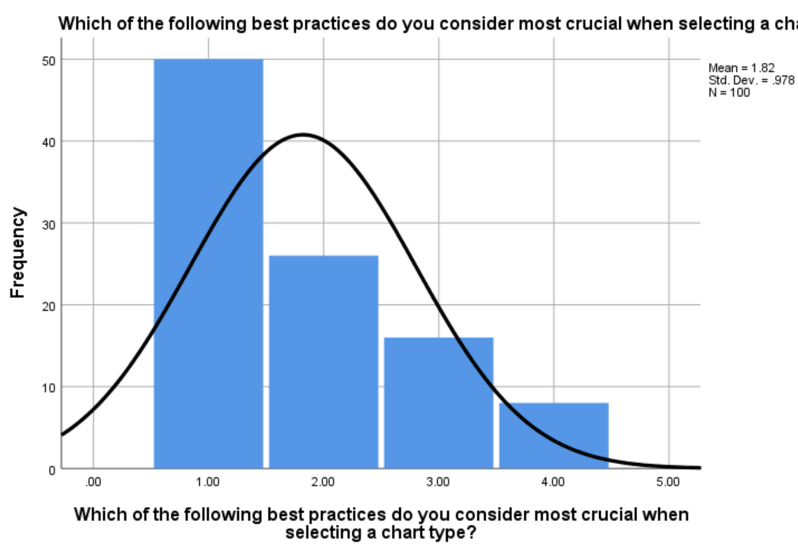


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "What consequence of using an inappropriate chart type do you find most concerning?" 52(52%) respondents responded Misleading the audience, 12(12%) respondents responded Oversimplifying complex data and 30(30%) respondents responded Overcomplicating simple data where as 6(6%) respondents responded Obscuring key insights or patterns.

Table 20

Which of the following best practices do you consider most crucial when selecting a chart type?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Understanding the audience's familiarity with different chart types	50	50.0	50.0	50.0
	Aligning the chart type with the key message or insight to be communicated	26	26.0	26.0	76.0
	Considering the data's scale and distribution	16	16.0	16.0	92.0
	Testing the visualization with a subset of the audience for clarity and interpretation	8	8.0	8.0	100.0
	Total	100	100.0	100.0	

Graph 20

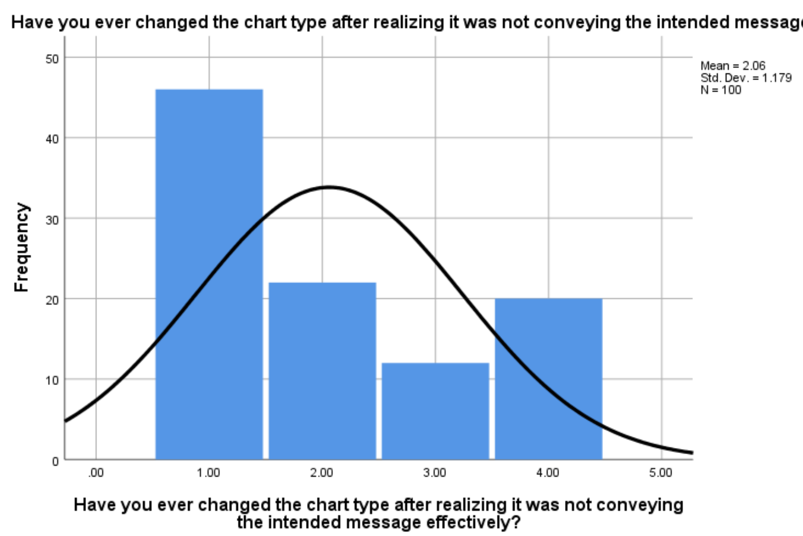


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Which of the following best practices do you consider most crucial when selecting a chart type?" 50(50%) respondents responded Understanding the audience's familiarity with different chart types, 26(26%) respondents responded Aligning the chart type with the key message or insight to be communicated and 16(16%) respondents responded Considering the data's scale and distribution where as 8(8%) respondents responded Testing the visualization with a subset of the audience for clarity and interpretation.

Table 21

Have you ever changed the chart type after realizing it was not conveying the intended message effectively?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes, frequently	46	46.0	46.0	46.0
	Yes, occasionally	22	22.0	22.0	68.0
	Rarely	12	12.0	12.0	80.0
	never	20	20.0	20.0	100.0
	Total	100	100.0	100.0	

Graph 21

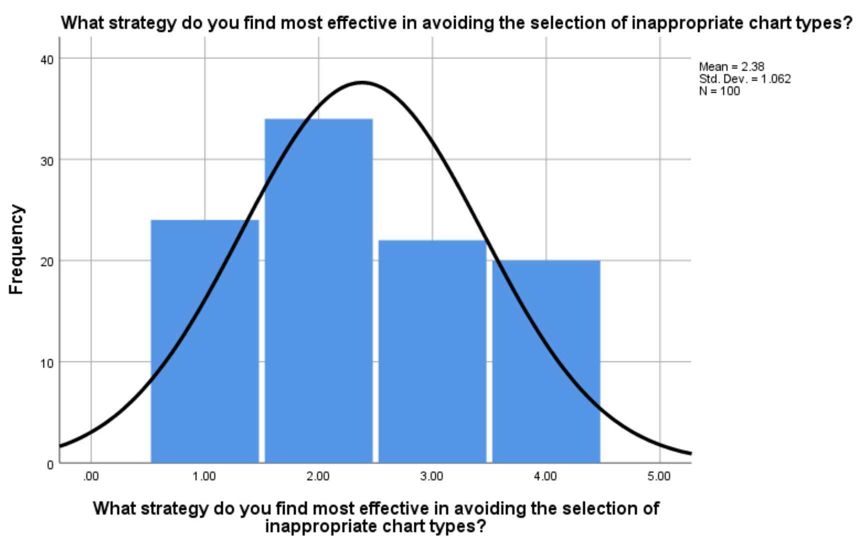


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Have you ever changed the chart type after realizing it was not conveying the intended message effectively?" 46(46%) respondents responded Yes, frequently, 22(22%) respondents responded Yes, occasionally and 12(12%) respondents responded Rarely where as 20(20%) respondents responded never.

Table 22

What strategy do you find most effective in avoiding the selection of inappropriate chart types?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Regularly reviewing best practices in data visualization	24	24.0	24.0	24.0
	Consulting with peers or experts during the design phase	34	34.0	34.0	58.0
	Using software with guidance or recommendations for chart types	22	22.0	22.0	80.0
	Conducting user testing or feedback sessions on preliminary designs	20	20.0	20.0	100.0
	Total	100	100.0	100.0	

Graph 22

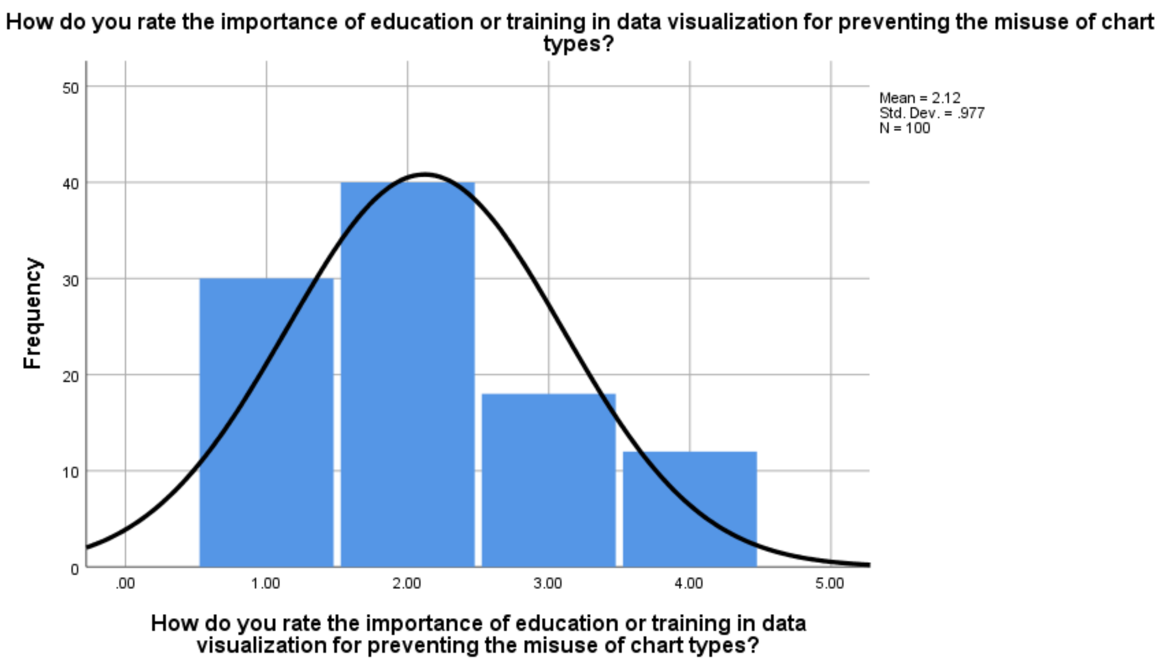


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "What strategy do you find most effective in avoiding the selection of inappropriate chart types?" 24(24%) respondents responded Regularly reviewing best practices in data visualization, 34(34%) respondents responded Consulting with peers or experts during the design phase and 22(22%) respondents responded Using software with guidance or recommendations for chart types where as 20(20%) respondents responded Conducting user testing or feedback sessions on preliminary designs.

Table 23

How do you rate the importance of education or training in data visualization for preventing the misuse of chart types?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Extremely important	30	30.0	30.0	30.0
	Important	40	40.0	40.0	70.0
	Somewhat important	18	18.0	18.0	88.0
	Not important	12	12.0	12.0	100.0
	Total	100	100.0	100.0	

Graph 23

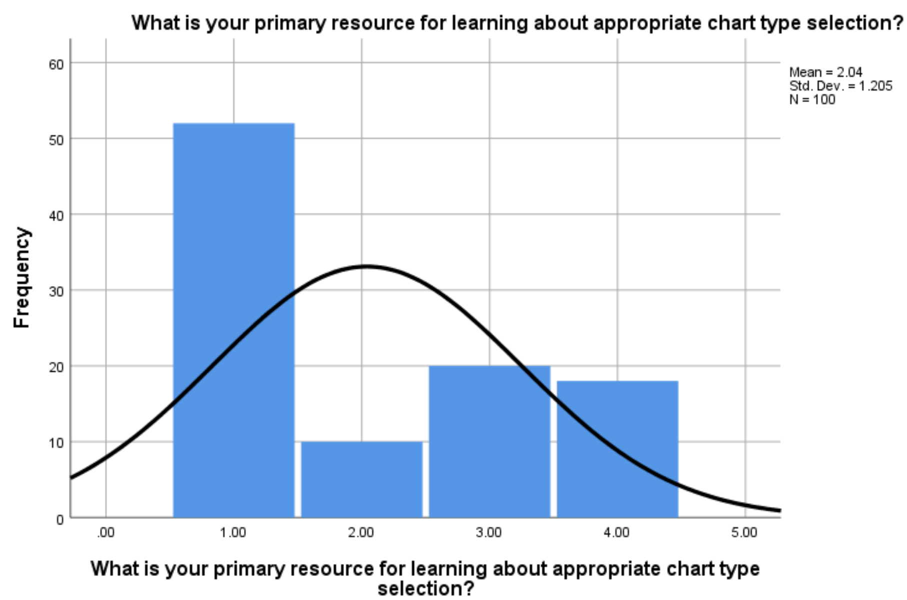


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "How do you rate the importance of education or training in data visualization for preventing the misuse of chart types?" 30(30%) respondents responded Extremely important, 40(40%) respondents responded Important and 18(18%) respondents responded Somewhat important where as 12(12%) respondents responded Not important.

Table 24

What is your primary resource for learning about appropriate chart type selection?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Books or academic publications on data visualization	52	52.0	52.0	52.0
	Online tutorials and courses	10	10.0	10.0	62.0
	Blogs and articles by data visualization experts	20	20.0	20.0	82.0
	Trial and error with different visualization tools	18	18.0	18.0	100.0
	Total	100	100.0	100.0	

Graph 24

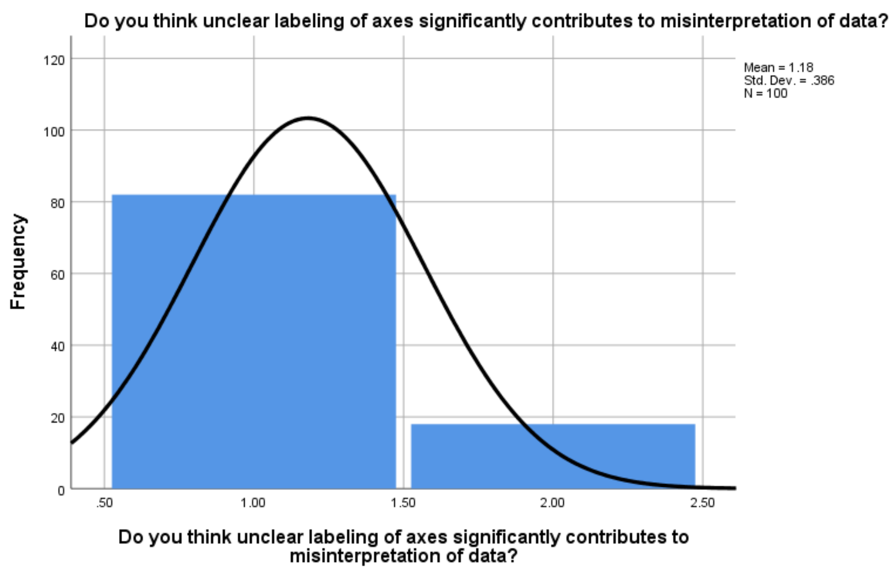


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "What is your primary resource for learning about appropriate chart type selection?" 52(52%) respondents responded Books or academic publications on data visualization, 10(10%) respondents responded Online tutorials and courses and 20(20%) respondents responded Blogs and articles by data visualization experts where as 18(18%) respondents responded Trial and error with different visualization tools.

Table 25

Do you think unclear labeling of axes significantly contributes to misinterpretation of data?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	82	82.0	82.0	82.0
	No	18	18.0	18.0	100.0
	Total	100	100.0	100.0	

Graph 25

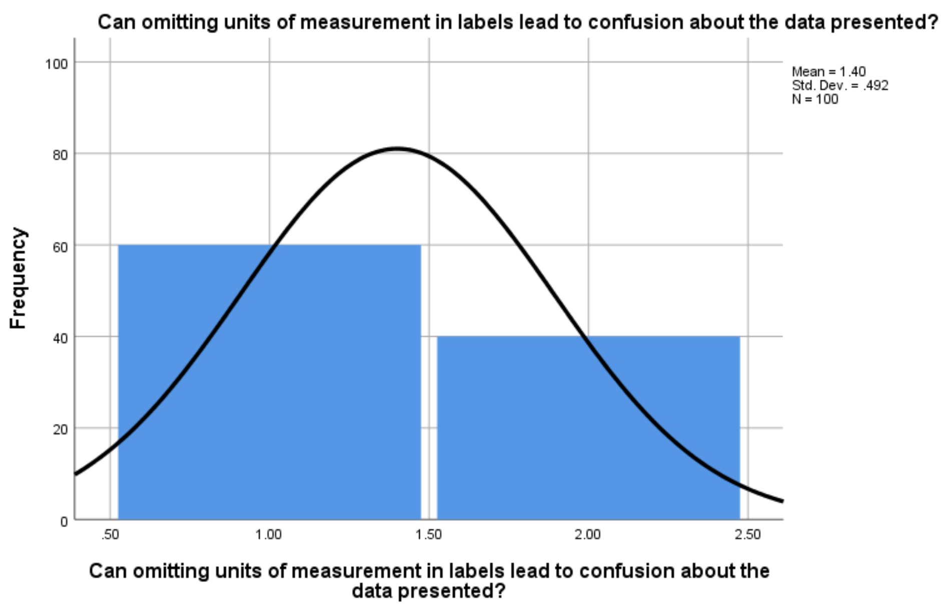


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Do you think unclear labeling of axes significantly contributes to misinterpretation of data?" and 82(82%) respondents responded as Yes, whereas 18(18%) respondents responded as No

Table 26

Can omitting units of measurement in labels lead to confusion about the data presented?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	60	60.0	60.0	60.0
	No	40	40.0	40.0	100.0
	Total	100	100.0	100.0	

Graph 26

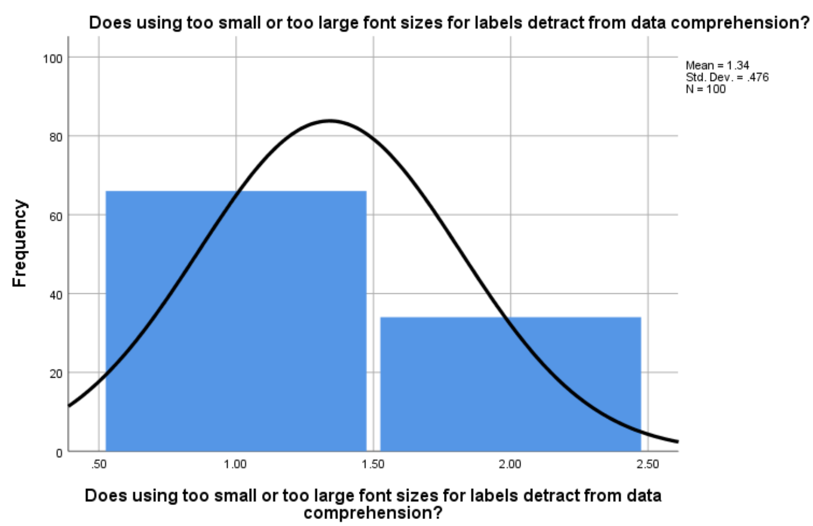


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Can omitting units of measurement in labels lead to confusion about the data presented?" and 60(60%) respondents responded as Yes, whereas 40(40%) respondents responded as No

Table 27

Does using too small or too large font sizes for labels detract from data comprehension?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	66	66.0	66.0	66.0
	No	34	34.0	34.0	100.0
	Total	100	100.0	100.0	

Graph 27

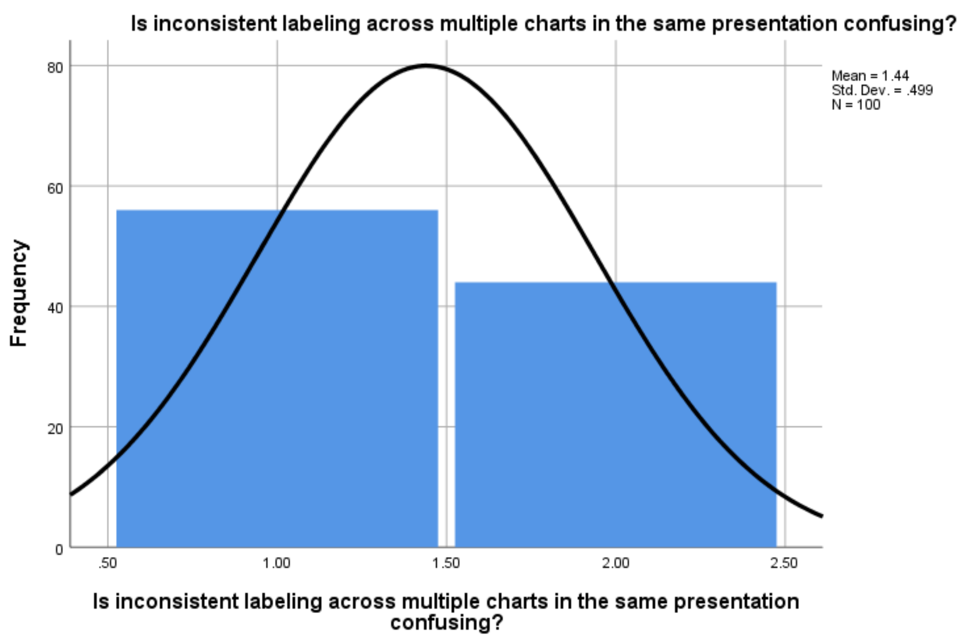


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Does using too small or too large font sizes for labels detract from data comprehension?" and 66(66%) respondents responded as Yes, whereas 34(34%) respondents responded as No

Table 28

Is inconsistent labeling across multiple charts in the same presentation confusing?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	56	56.0	56.0	56.0
	No	44	44.0	44.0	100.0
	Total	100	100.0	100.0	

Graph 28

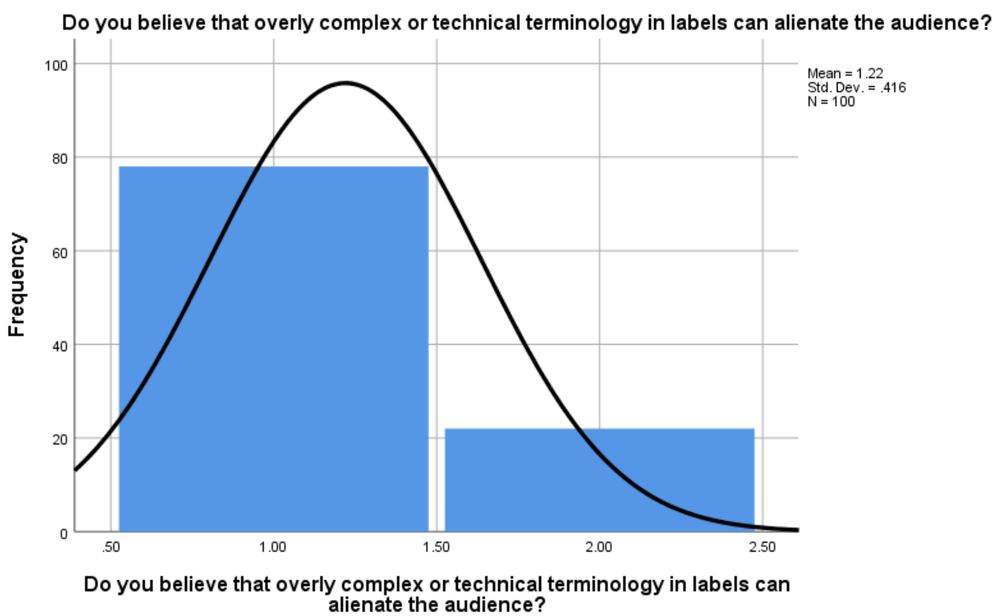


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Is inconsistent labeling across multiple charts in the same presentation confusing?" and 56(56%) respondents responded as Yes, whereas 44(44%) respondents responded as No

Table 29

Do you believe that overly complex or technical terminology in labels can alienate the audience?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	78	78.0	78.0	78.0
	No	22	22.0	22.0	100.0
	Total	100	100.0	100.0	

Graph 29

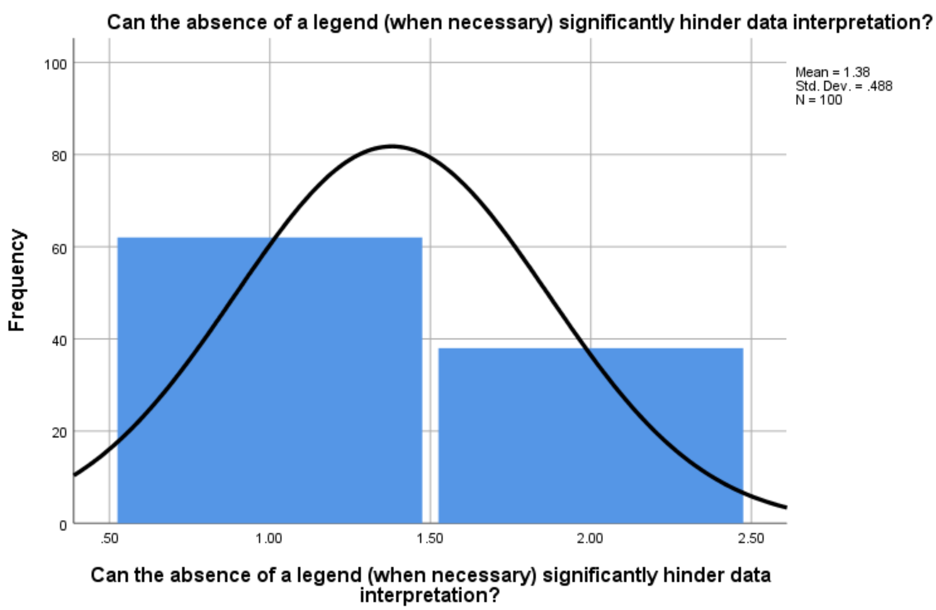


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Do you believe that overly complex or technical terminology in labels can alienate the audience?" and 78(78%) respondents responded as Yes, whereas 22(22%) respondents responded as No

Table 30

Can the absence of a legend (when necessary) significantly hinder data interpretation?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	62	62.0	62.0	62.0
	No	38	38.0	38.0	100.0
	Total	100	100.0	100.0	

Graph 30

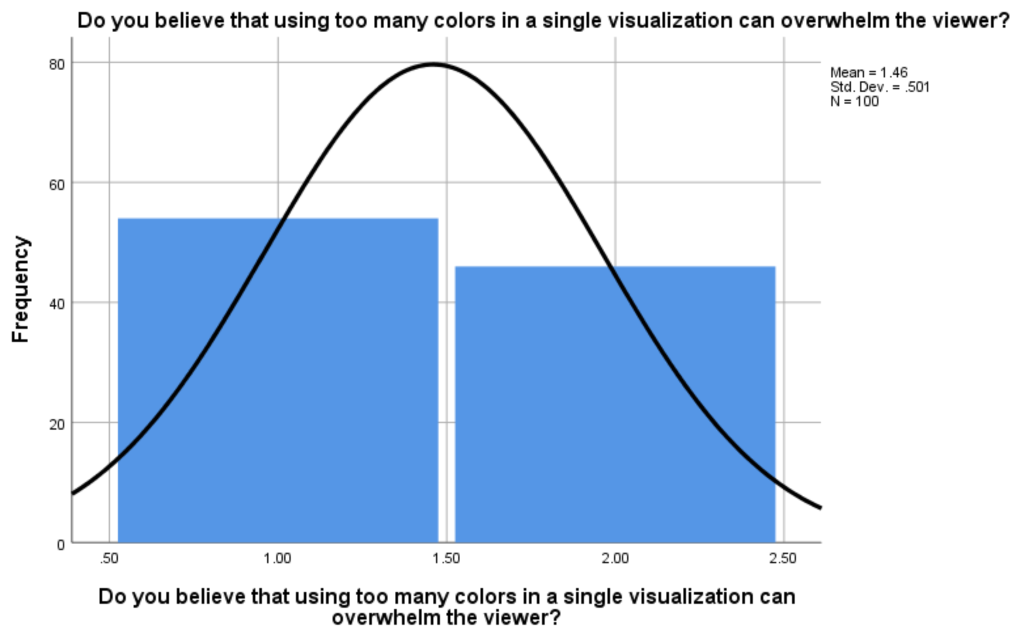


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Can the absence of a legend (when necessary) significantly hinder data interpretation?" and 62(62%) respondents responded as Yes, whereas 38(38%) respondents responded as No

Table 31

Do you believe that using too many colors in a single visualization can overwhelm the viewer?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	54	54.0	54.0	54.0
	No	46	46.0	46.0	100.0
	Total	100	100.0	100.0	

Graph 31

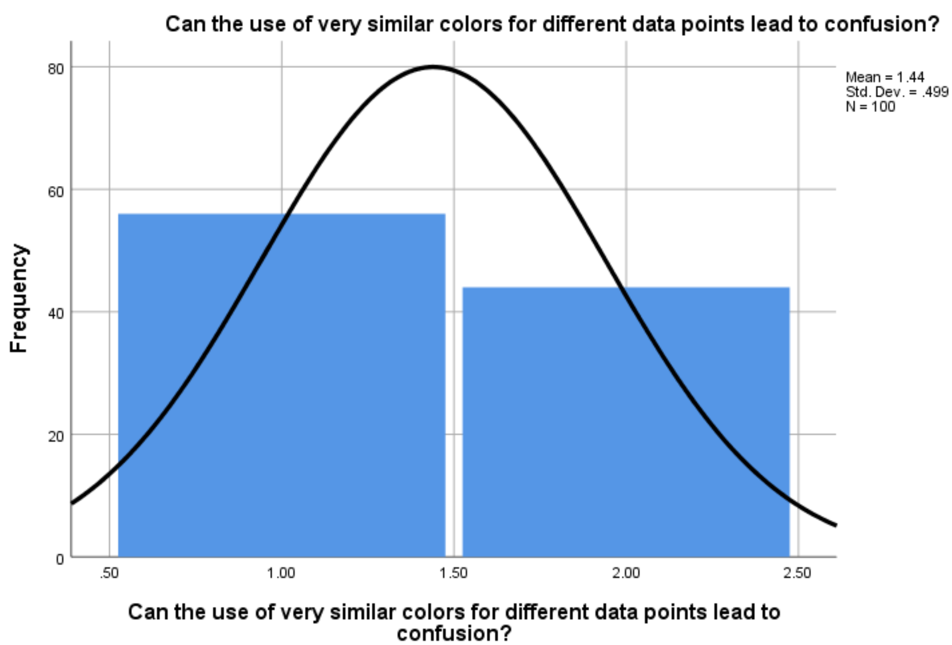


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Do you believe that using too many colors in a single visualization can overwhelm the viewer?" and 54(54%) respondents responded as Yes, whereas 46(46%) respondents responded as No

Table 32

Can the use of very similar colors for different data points lead to confusion?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	56	56.0	56.0	56.0
	No	44	44.0	44.0	100.0
	Total	100	100.0	100.0	

Graph 32

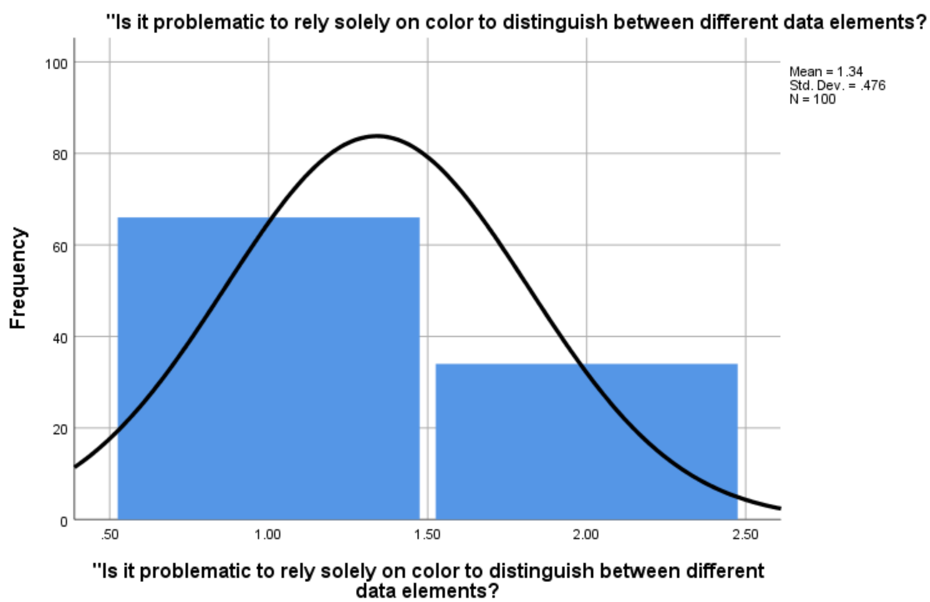


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Can the use of very similar colors for different data points lead to confusion?" and 56(56%) respondents responded as Yes, whereas 44(44%) respondents responded as No

Table 33

"Is it problematic to rely solely on color to distinguish between different data elements?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	66	66.0	66.0	66.0
	No	34	34.0	34.0	100.0
	Total	100	100.0	100.0	

Graph 33

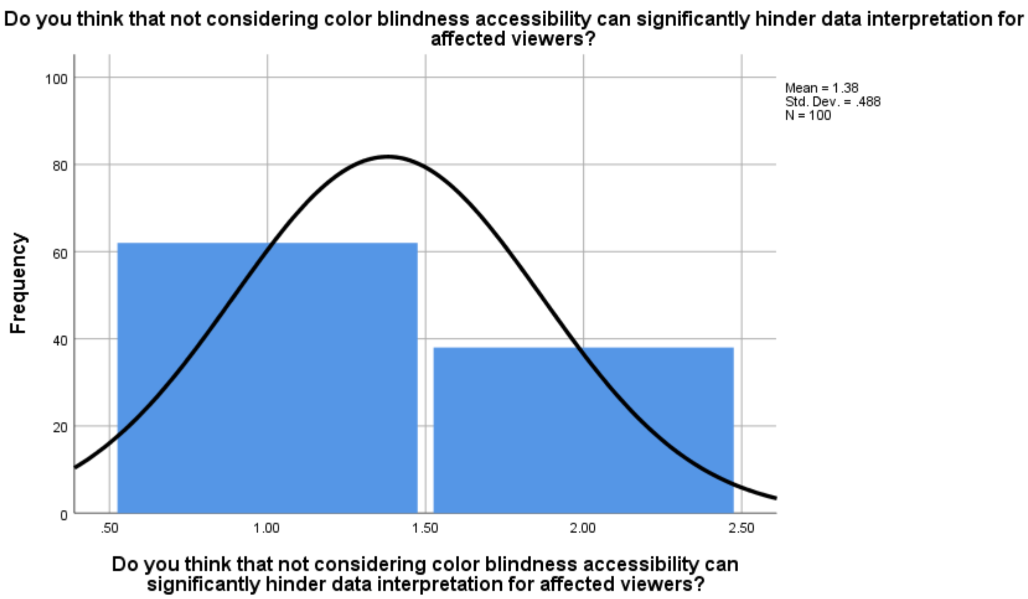


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about ""Is it problematic to rely solely on color to distinguish between different data elements?" and 66(66%) respondents responded as Yes, whereas 34(34%) respondents responded as No

Table 34

Do you think that not considering color blindness accessibility can significantly hinder data interpretation for affected viewers?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	62	62.0	62.0	62.0
	No	38	38.0	38.0	100.0
	Total	100	100.0	100.0	

Graph 34

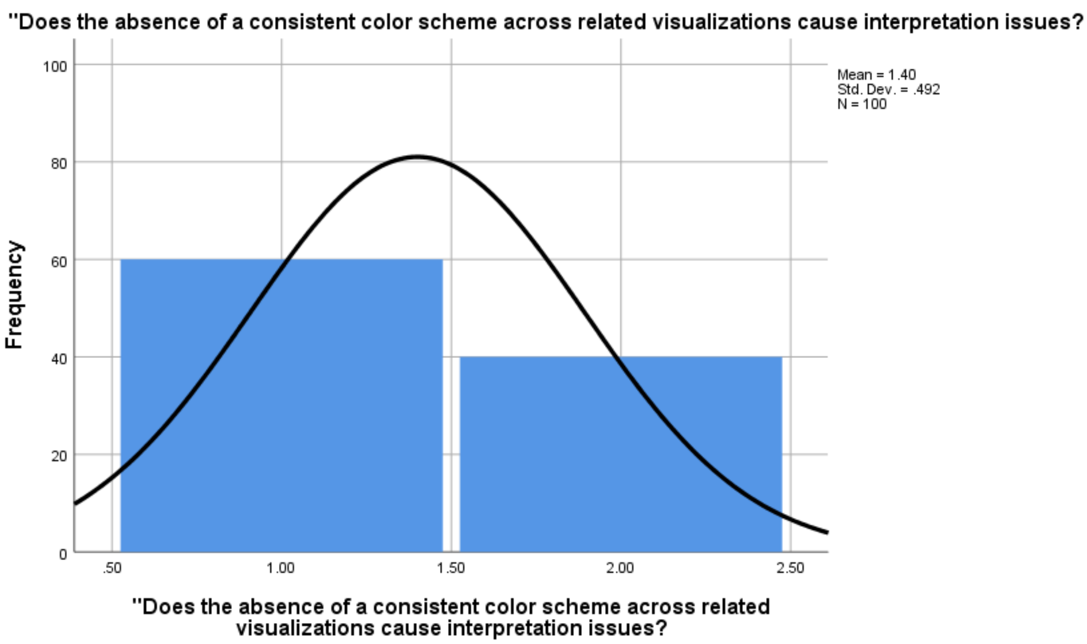


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Do you think that not considering color blindness accessibility can significantly hinder data interpretation for affected viewers?" and 62(62%) respondents responded as Yes, whereas 38(38%) respondents responded as No

Table 35

"Does the absence of a consistent color scheme across related visualizations cause interpretation issues?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	60	60.0	60.0	60.0
	No	40	40.0	40.0	100.0
	Total	100	100.0	100.0	

Graph 35

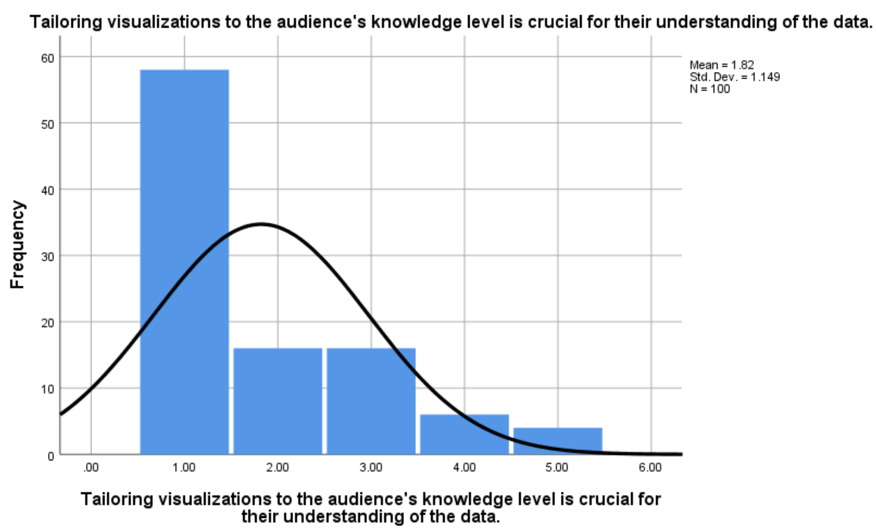


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about ""Does the absence of a consistent color scheme across related visualizations cause interpretation issues?" and 60(60%) respondents responded as Yes, whereas 40(40%) respondents responded as No

Table 36

Tailoring visualizations to the audience's knowledge level is crucial for their understanding of the data.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	58	58.0	58.0	58.0
	Agree	16	16.0	16.0	74.0
	Neutral	16	16.0	16.0	90.0
	Disagree	6	6.0	6.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 36

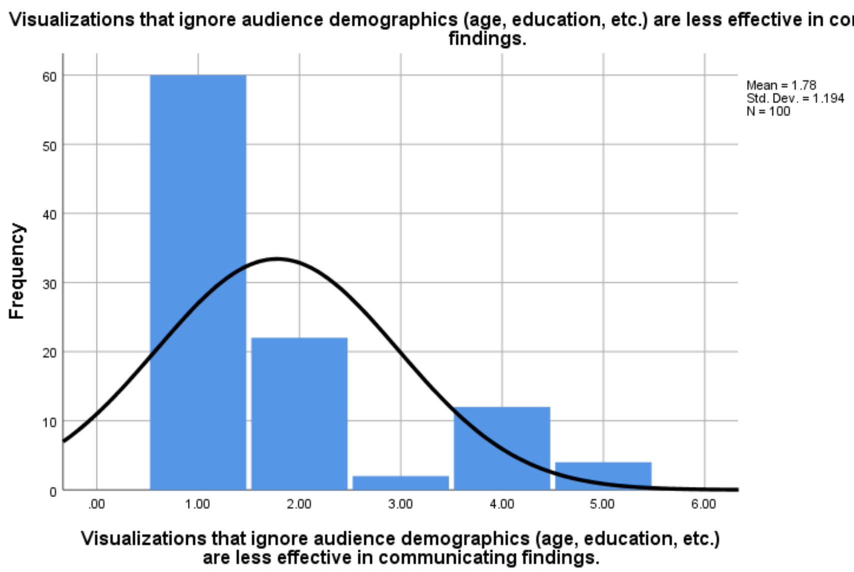


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Tailoring visualizations to the audience's knowledge level is crucial for their understanding of the data." 58(58%) respondents responded Strongly Agree, 16(16%) respondents responded Agree, 16(16%) respondents responded Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

Table 37

Visualizations that ignore audience demographics (age, education, etc.) are less effective in communicating findings.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	60	60.0	60.0	60.0
	Agree	22	22.0	22.0	82.0
	Neutral	2	2.0	2.0	84.0
	Disagree	12	12.0	12.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 37

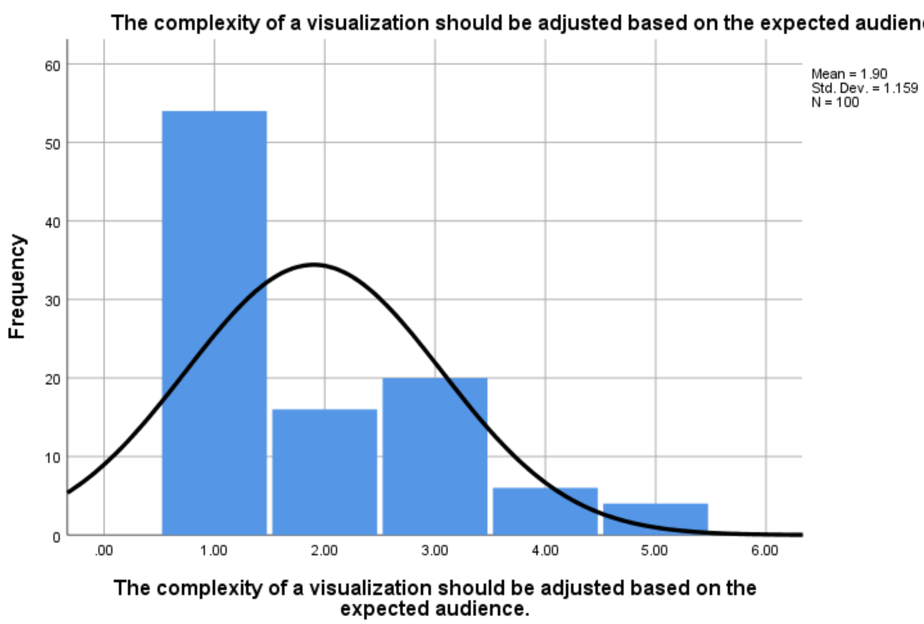


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Visualizations that ignore audience demographics (age, education, etc.) are less effective in communicating findings." 60(60%) respondents responded Strongly Agree, 22(22%) respondents responded Agree, 2(2%) respondents responded Neutral and 12(12%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

Table 38

The complexity of a visualization should be adjusted based on the expected audience.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	54	54.0	54.0	54.0
	Agree	16	16.0	16.0	70.0
	Neutral	20	20.0	20.0	90.0
	Disagree	6	6.0	6.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 38

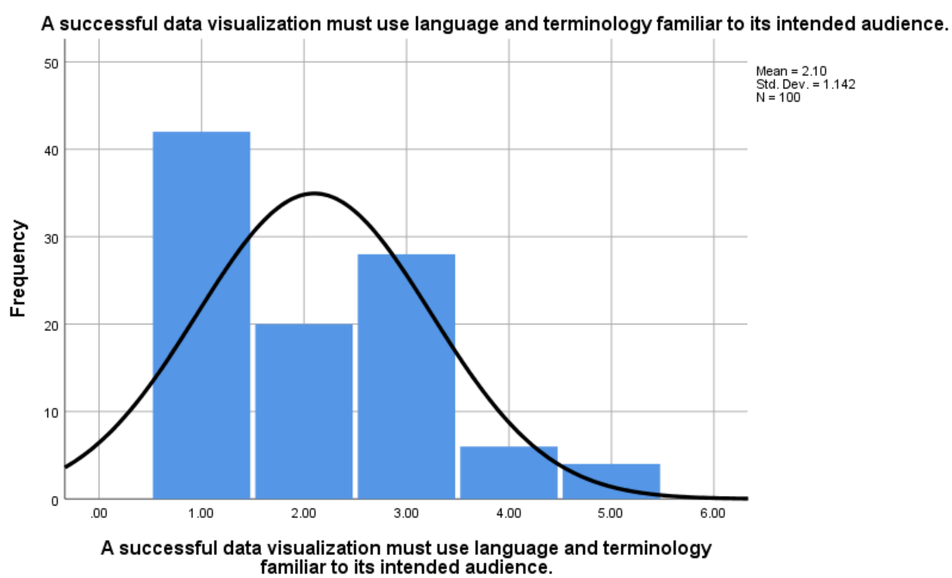


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "The complexity of a visualization should be adjusted based on the expected audience." 54(54%) respondents responded Strongly Agree, 16(16%) respondents responded Agree, 20(20%) respondents responded Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

Table 39

A successful data visualization must use language and terminology familiar to its intended audience.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	42	42.0	42.0	42.0
	Agree	20	20.0	20.0	62.0
	Neutral	28	28.0	28.0	90.0
	Disagree	6	6.0	6.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 39

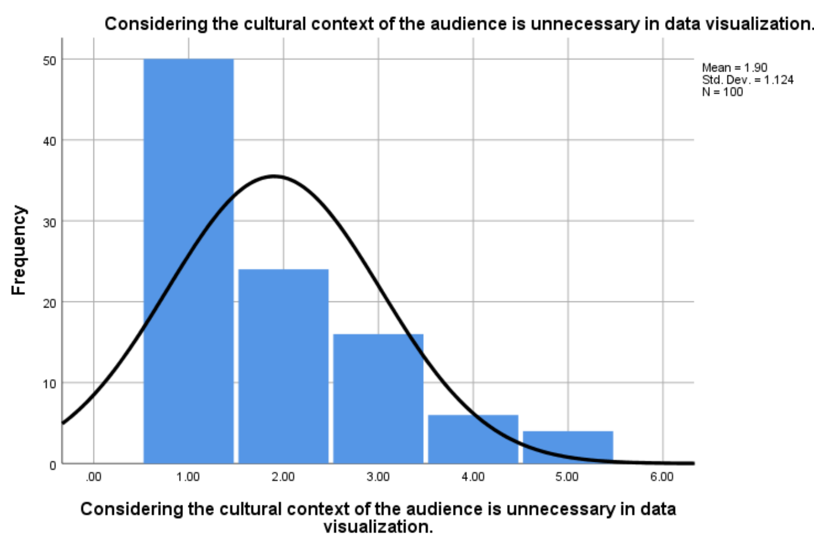


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "A successful data visualization must use language and terminology familiar to its intended audience." 42(42%) respondents responded Strongly Agree, 20(20%) respondents responded Agree, 28(28%) respondents responded Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

Table 40

Considering the cultural context of the audience is unnecessary in data visualization.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	50	50.0	50.0	50.0
	Agree	24	24.0	24.0	74.0
	Neutral	16	16.0	16.0	90.0
	Disagree	6	6.0	6.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 40

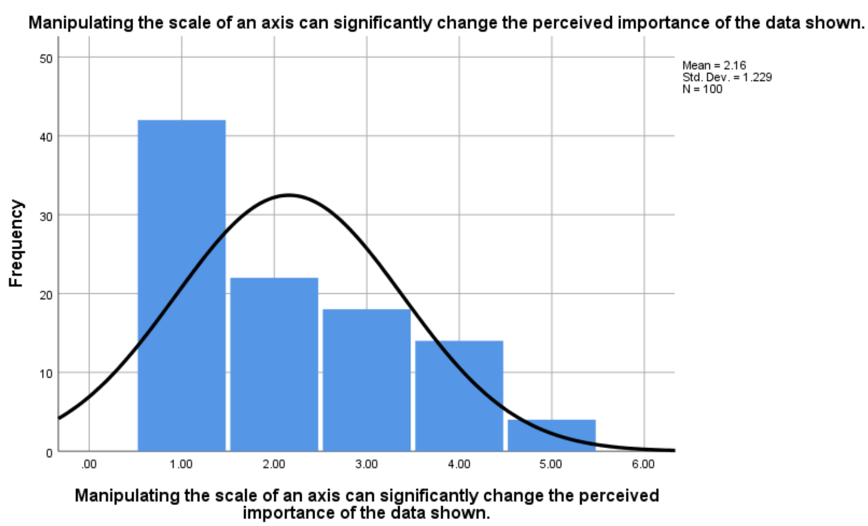


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Considering the cultural context of the audience is unnecessary in data visualization." 50(50%) respondents responded Strongly Agree, 24(24%) respondents responded Agree, 16(16%) respondents responded Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

Table 41

Manipulating the scale of an axis can significantly change the perceived importance of the data shown.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	42	42.0	42.0	42.0
	Agree	22	22.0	22.0	64.0
	Neutral	18	18.0	18.0	82.0
	Disagree	14	14.0	14.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 41

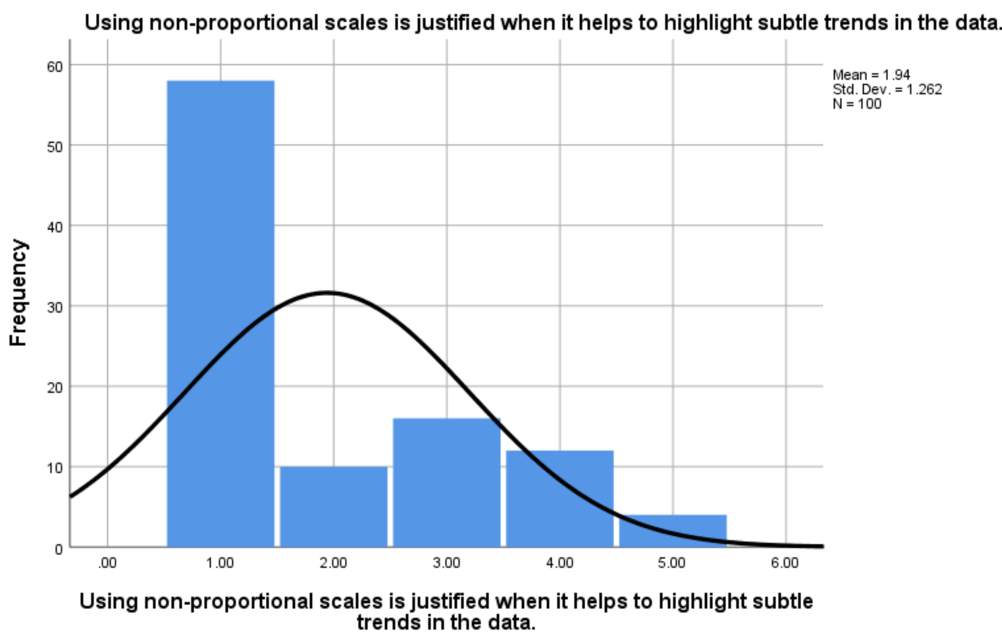


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Manipulating the scale of an axis can significantly change the perceived importance of the data shown." 42(42%) respondents responded Strongly Agree, 22(22%) respondents responded Agree, 18(18%) respondents responded Neutral and 14(14%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

Table 42

Using non-proportional scales is justified when it helps to highlight subtle trends in the data.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	58	58.0	58.0	58.0
	Agree	10	10.0	10.0	68.0
	Neutral	16	16.0	16.0	84.0
	Disagree	12	12.0	12.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 42

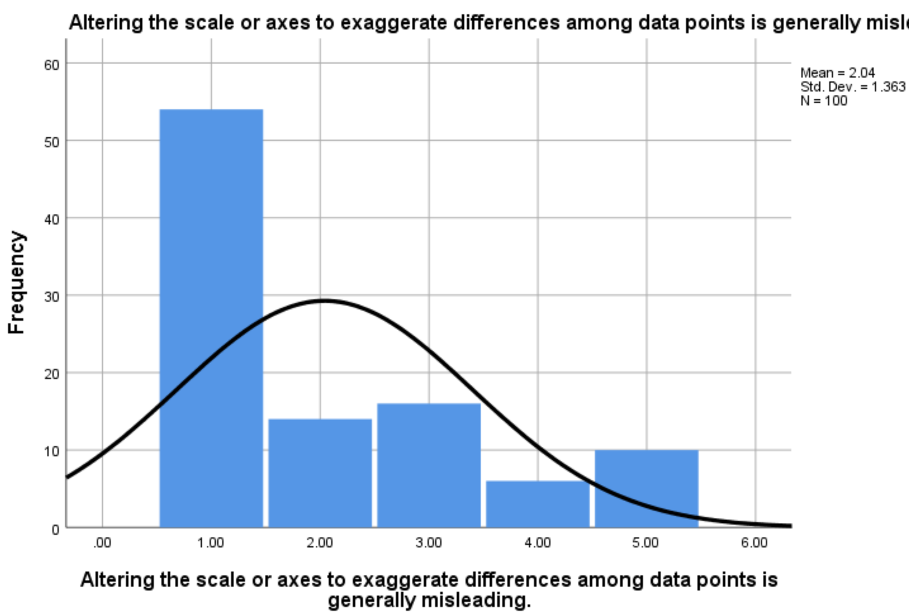


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Using non-proportional scales is justified when it helps to highlight subtle trends in the data." 58(58%) respondents responded Strongly Agree, 10(10%) respondents responded Agree, 16(16%) respondents responded Neutral and 12(12%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

Table 43

Altering the scale or axes to exaggerate differences among data points is generally misleading.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	54	54.0	54.0	54.0
	Agree	14	14.0	14.0	68.0
	Neutral	16	16.0	16.0	84.0
	Disagree	6	6.0	6.0	90.0
	Strongly Disagree	10	10.0	10.0	100.0
	Total	100	100.0	100.0	

Graph 43

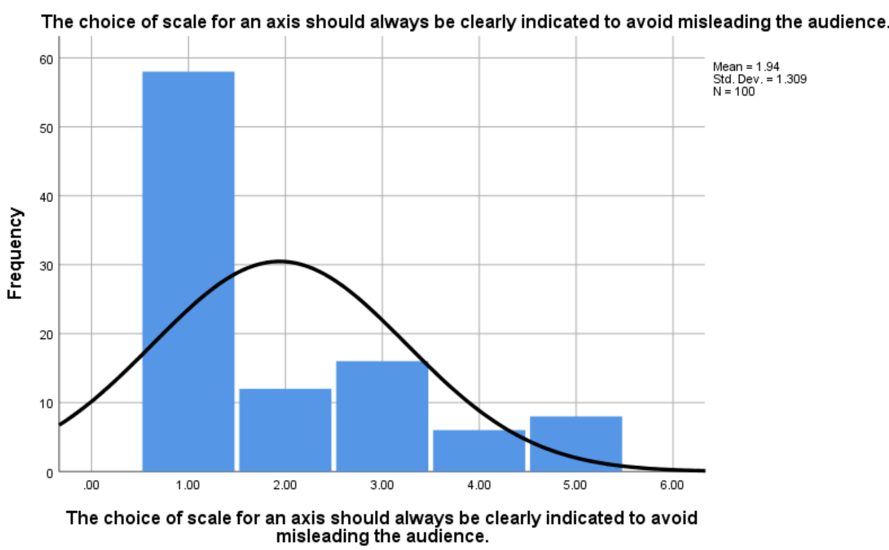


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Altering the scale or axes to exaggerate differences among data points is generally misleading." 54(54%) respondents responded Strongly Agree, 14(14%) respondents responded Agree, 16(16%) respondents responded Neutral and 6(6%) respondents responded Disagree and 10(10%) respondents responded Strongly Disagree.

Table 44

The choice of scale for an axis should always be clearly indicated to avoid misleading the audience.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	58	58.0	58.0	58.0
	Agree	12	12.0	12.0	70.0
	Neutral	16	16.0	16.0	86.0
	Disagree	6	6.0	6.0	92.0
	Strongly Disagree	8	8.0	8.0	100.0
	Total	100	100.0	100.0	

Graph 44

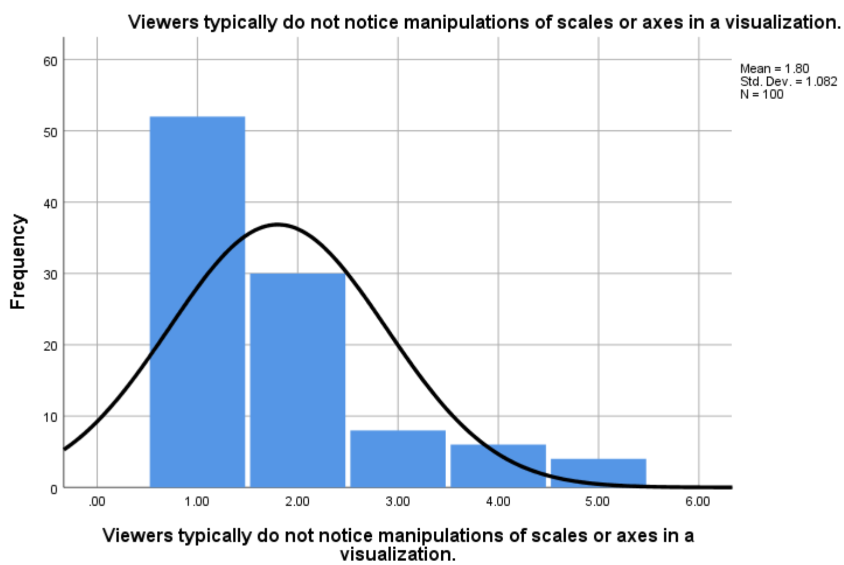


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "The choice of scale for an axis should always be clearly indicated to avoid misleading the audience." 58(58%) respondents responded Strongly Agree, 12(12%) respondents responded Agree, 16(16%) respondents responded Neutral and 6(6%) respondents responded Disagree and 8(8%) respondents responded Strongly Disagree.

Table 45

Viewers typically do not notice manipulations of scales or axes in a visualization.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	52	52.0	52.0	52.0
	Agree	30	30.0	30.0	82.0
	Neutral	8	8.0	8.0	90.0
	Disagree	6	6.0	6.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 45

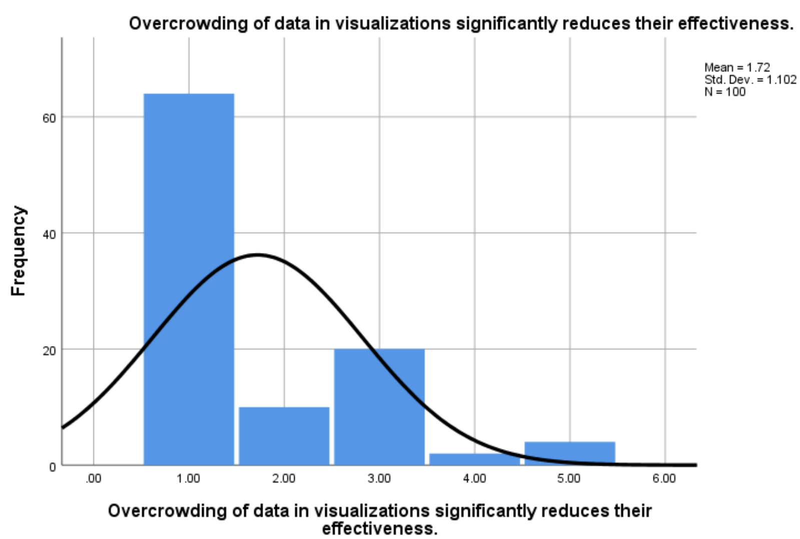


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Viewers typically do not notice manipulations of scales or axes in a visualization." 52(52%) respondents responded Strongly Agree, 30(30%) respondents responded Agree, 8(8%) respondents responded Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

Table 46

Overcrowding of data in visualizations significantly reduces their effectiveness.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	64	64.0	64.0	64.0
	Agree	10	10.0	10.0	74.0
	Neutral	20	20.0	20.0	94.0
	Disagree	2	2.0	2.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 46

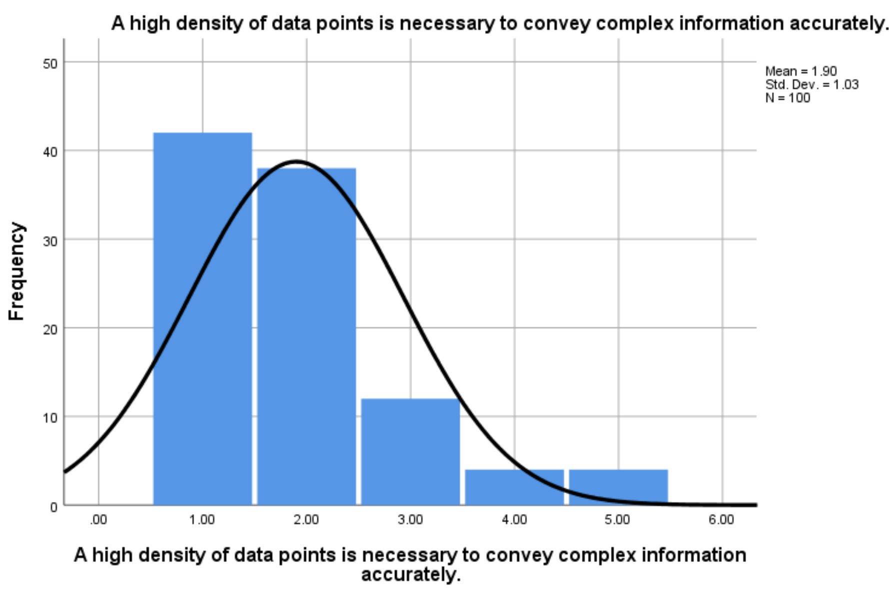


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "Overcrowding of data in visualizations significantly reduces their effectiveness." 64(64%) respondents responded Strongly Agree, 10(10%) respondents responded Agree, 20(20%) respondents responded Neutral and 2(2%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

Table 47

A high density of data points is necessary to convey complex information accurately.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	42	42.0	42.0	42.0
	Agree	38	38.0	38.0	80.0
	Neutral	12	12.0	12.0	92.0
	Disagree	4	4.0	4.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 47

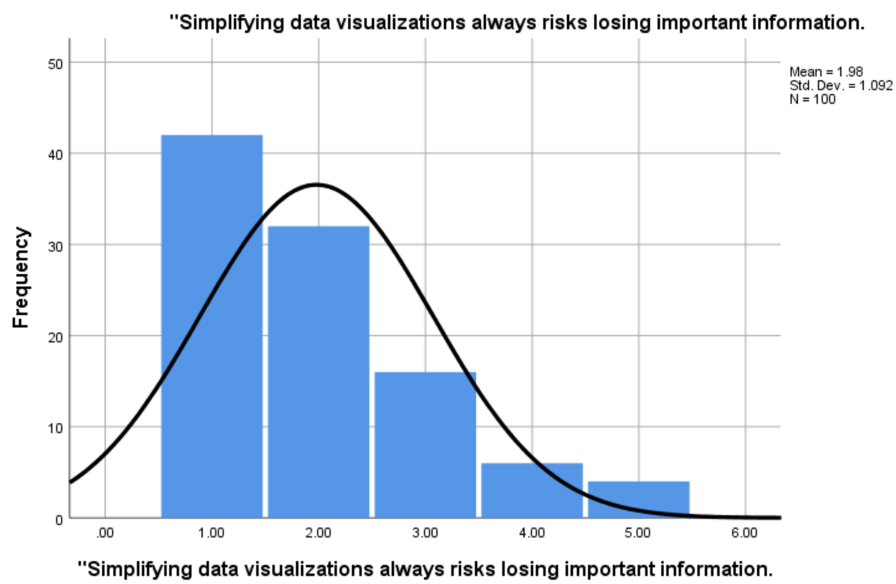


From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about "A high density of data points is necessary to convey complex information accurately." 42(42%) respondents responded Strongly Agree, 38(38%) respondents responded Agree, 12(12%) respondents responded Neutral and 4(4%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

Table 48

"Simplifying data visualizations always risks losing important information.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	42	42.0	42.0	42.0
	Agree	32	32.0	32.0	74.0
	Neutral	16	16.0	16.0	90.0
	Disagree	6	6.0	6.0	96.0
	Strongly Disagree	4	4.0	4.0	100.0
	Total	100	100.0	100.0	

Graph 48



From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about ""Simplifying data visualizations always risks losing important information." 42(42%) respondents responded Strongly Agree, 32(32%) respondents responded Agree, 16(16%) respondents responded Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

HYPOTHESIS TESTING

When we perform a one-way ANOVA for a single study, you obtain a single F-value. However, if we drew multiple random samples of the same size from the same population and performed the same one-way ANOVA, we would obtain many F-values and we could plot a distribution of all of them. This type of distribution is known as a sampling distribution.

Because the F-distribution assumes that the null hypothesis is true, we can place the F-value from our study in the F-distribution to determine how consistent our results are with the null hypothesis and to calculate probabilities.

The probability that we want to calculate is the probability of observing an F-statistic that is at least as high as the value that our study obtained. That probability allows us to determine how common or rare our F-value is under the assumption that the null hypothesis is true. If the probability is low enough, we can conclude that our data is inconsistent with the null hypothesis. The evidence in the sample data is strong enough to reject the null hypothesis for the entire population.

The F-value in an ANOVA is calculated as: variation between sample means / variation within the samples.

The higher the F-value in an ANOVA, the higher the variation between sample means relative to the variation within the samples.

The higher the F-value, the lower the corresponding p-value.

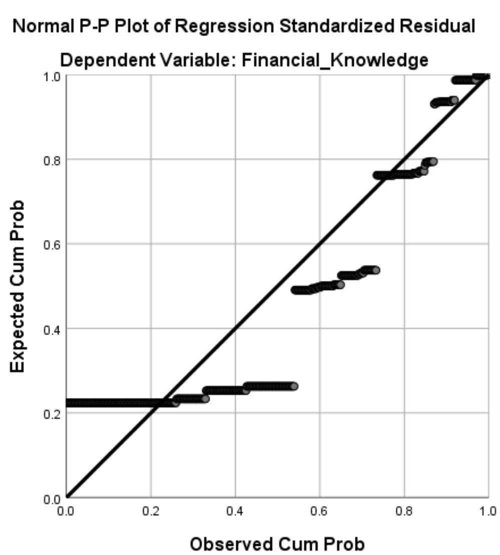
If the p-value is below a certain threshold (e.g. $\alpha = .05$), we can reject the null hypothesis of the ANOVA and conclude that there is a statistically significant difference between group means".

1. The use of inappropriate chart types leads to misinterpretation of data in data visualization.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	122.416	1	222.416	926.246	.000[b]
	Residual	32.409	528	.125		
	Total	129.825	529			

a. Dependent Variable: data visualization factors

b. Predictors: (Constant), data visualization Total



The F-value in an ANOVA is calculated as: variation between sample means / variation within the samples.

The higher the F-value in an ANOVA, the higher the variation between sample means relative to the variation within the samples.

The higher the F-value, the lower the corresponding p-value.

If the p-value is below a certain threshold (e.g. $\alpha = .05$), we can reject the null hypothesis of the ANOVA and conclude that there is a statistically significant difference between group means.

It means alternate hypothesis is accepted "The use of inappropriate chart types leads to misinterpretation of data in data visualization."

2. **Poor labelling practices in data visualization led to confusion and misinterpretation of data.**

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	52.110[a]	3	.000
Likelihood Ratio	82.358	3	.000
Linear-by-Linear Association	52.305	1	.000
N of Valid Cases	100		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 16.53.

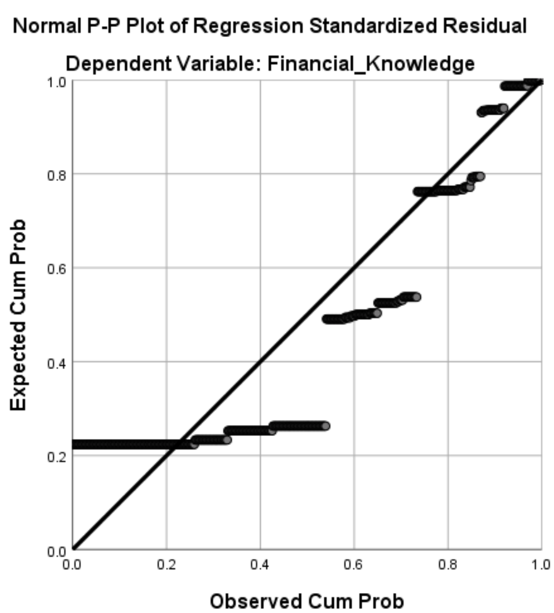
The Chi-Square tests indicate highly significant associations between the variables, with p-values of .000 for all tests. Therefore, none of the associations are rejected; they are all accepted as statistically significant.

3. Inadequate use of color in data visualization can hinder data interpretation and understanding

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	422.416	3	492.416	476.246	.000[b]
	Residual	47.409	498	.115		
	Total	459.825	499			

a. Dependent Variable: demographic factors

b. Predictors: (Constant), demographic factors Total



The F-value in an ANOVA is calculated as: variation between sample means / variation within the samples.

The higher the F-value in an ANOVA, the higher the variation between sample means relative to the variation within the samples.

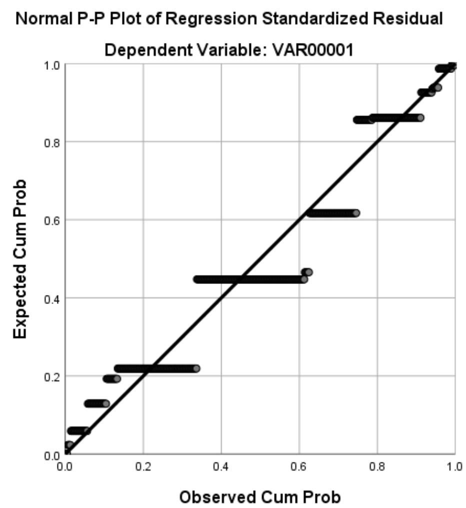
The higher the F-value, the lower the corresponding p-value.

If the p-value is below a certain threshold (e.g. $\alpha = .05$), we can reject the null hypothesis of the ANOVA and conclude that there is a statistically significant difference between group means.

It means alternate hypothesis is accepted **"**Inadequate use of color in data visualization can hinder data interpretation and understanding**."**

4. **Failure to consider the needs of the audience in data visualization results in ineffective communication of research findings.**

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	234.968	4	43.742	2459.754	.000[b]
	Residual	22.872	435	.052		
	Total	227.840	589			
a. Dependent Variable: ineffective communication						
b. Predictors: (Constant), ineffective communication total						



The F-value in an ANOVA is calculated as: variation between sample means / variation within the samples.

The higher the F-value in an ANOVA, the higher the variation between sample means relative to the variation within the samples.

The higher the F-value, the lower the corresponding p-value.

If the p-value is below a certain threshold (e.g. $\alpha = .05$), we can reject the null hypothesis of the ANOVA and conclude that there is a statistically significant difference between group means.

It means alternat hypothesis is accepted *Failure to consider the needs of the audience in data visualization results in ineffective communication of research findings*

5. Manipulation of scales or axes in data visualization can distort the data and mislead viewers.

Case Processing Summary						
	N	Percent	Mean	N	Mean	N
Gender: * A high density of data points is necessary to convey complex information accurately	100	100.0%	1.0057	350	1.0000	344
Gender: * Overcrowding of data in visualizations significantly reduces their effectiveness.	100	100.0%	2.0000	50	1.9286	56

6. Overcrowding of data in visualizations can make it difficult to read and interpret the data accurately.

Correlations

		The choice of scale for an axis should always be clearly indicated to avoid misleading the audience.	Altering the scale or axes to exaggerate differences among data points is generally misleading.	Using non-proportional scales is justified when it helps to highlight subtle trends in the data.
The choice of scale for an axis should always be clearly indicated to avoid misleading the audience.	Pearson Correlation	1	.784**	.874**
	Sig. (2-tailed)		.000	.000
	N	100	100	400
Altering the scale or axes to exaggerate differences among data points is generally misleading.	Pearson Correlation	.884**	1	.767**
	Sig. (2-tailed)	.000		.000
	N	100	100	100
Using non-proportional scales is justified when it helps to highlight subtle trends in the data.	Pearson Correlation	.874**	.967**	1
	Sig. (2-tailed)	.000	.000	
	N	100	100	100

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation coefficients provided indicate strong positive relationships between all pairs of variables, and all correlations are highly significant at the 0.01 level (2-tailed). Therefore, none of the correlations are rejected; they are all accepted as statistically significant.

CHAPTER 5

RESULT AND DISCUSSION & CONCLUSION

5.1 Discussion of Results

Data visualisation is an essential tool for communicating the insights that may be gleaned from complicated information. Nevertheless, despite its significance, there are a great number of traps that researchers and practitioners need to be aware of in order to avoid misinterpreting or misrepresenting the data. The purpose of this systematic study is to investigate and classify these potential problems in order to provide direction for the implementation of efficient data visualisation strategies. Inappropriate use of scaling, in which axes are modified in order to emphasise or lessen the apparent influence of the data, is a frequent mistake that may lead to undesirable results. According to Cairo (2016), this might result in a misunderstanding of the patterns or comparisons that are included within the data. Another potential issue is the practice of picking and selecting certain data points or time periods to provide support for a given story. According to Few (2009), this may lead to findings that are biassed and can also compromise the integrity of the visualisation being used. When a visualisation has an excessive number of data points, a phenomenon known as over-plotting takes place. This phenomenon makes it harder to identify distinct patterns or trends. According to Wickham (2009), this circumstance has the potential to obfuscate significant insights and impair the usefulness of the visualisation. The failure to give sufficient context or background information in a visualisation might result in misunderstandings due to the lack of context. There is a possibility that viewers will not comprehend the relevance of the data or how it is connected to the overarching subject matter (Healy & Moody, 2014).The visualisations that are produced as a consequence of ignoring the distribution of data points might be deceptive. Using a bar chart to display skewed data without first converting the data might, for instance, cause the viewer's impression of the distribution to be distorted (Tufte, 2001).When it comes to data visualisation, another potential issue is the improper use of colour. It is possible to make visualisations difficult to perceive by selecting colour schemes that are not suitable or by neglecting to take into consideration potential colour blindness (Brewer, 1994).It is possible for data visualisations to restrict exploration and make comprehension more difficult if they lack enough interaction. According to Kosara and Mackinlay (2013), the viewer's capacity to examine the data may be positively impacted by the presence of interactive components such as tooltips or filtering choices. For data visualization to be effective, it is necessary to pay close attention to possible traps that have the potential to distort or mislead the data that is being visualised. Creating visualisations that properly convey insights and promote data-driven decision-making is something that academics and practitioners may do by first gaining an awareness of these errors and then avoiding them.When data points or axes are incorrectly labelled, it may result in confusion or incorrect interpretation. According to Keller and Wagener (2011), it is essential to make certain that labels appropriately reflect the data that is being represented and that units of measurement are stated in a clear manner. In the absence of properly validating the correctness and integrity of the data before to visualisation, it is possible to arrive at conclusions that are either misleading or incorrect. Wickham and Grolemund (2017) state that in order to guarantee the dependability of the visualisations, it is essential to carry out activities that include the validation and cleansing of data.An excessive amount of visual features, such as gridlines, borders, or embellishments that are not essential, may cause the visualisation to become cluttered and divert viewers' attention away from the primary message. An improvement in clarity and understanding may be achieved by simplifying the design and eliminating any clutter that is not essential (Tufte, 1990). Choosing a chart type that is not suited for the data might make it more difficult to comprehend and can also lead to incorrect interpretation. It is of the utmost importance to choose the chart style that is most appropriate, as this will ensure that the data is correctly represented and will make accurate interpretation easier (Few, 2012).It is possible that persons with impairments will be unable to access and comprehend the visualisation if accessibility criteria are not taken into consideration. In order to ensure that visualisations are accessible to all users, including those who may have visual or cognitive disabilities, it is essential to design them in such a way that they are accessible. Creating trend lines without taking into account the statistical significance of the data or the chronological context might result in erroneous conclusions about the patterns that are present in the data. The validation of trends via the use of proper statistical tools and the provision of context for interpretation are both essential (Cleveland, 1993).The use of visual encodings that are unclear or unfamiliar might cause viewers to get confused and distort the message that the visualisation is trying to convey. It is of the utmost importance to make use of visual representations that are concise, easy to understand, and in accordance with preexisting standards (Munzner, 2014).When it comes to repeatability and transparency, the failure to provide enough documentation or metadata about the data that was utilized in a visualization may be particularly problematic. It is vital to document the data sources, processing methods, and any alterations that were made in order to guarantee the authenticity of the visualisation (Wilkinson et al., 2012).The process of drawing conclusions from a sample of data that is not typical of the whole might result in interpretations that are biassed or skewed. According to Kleinberg et al. (2015), it is essential to take into account the possibility of bias in the procedures used to collect data and to make certain that the samples used appropriately represent the community of interest.It is possible to mislead someone by purposefully or inadvertently altering the visual representation of data in order to highlight certain characteristics or communicate a specific message. When it comes to visualisations, it is very necessary to maintain integrity and honesty in order to prevent misrepresentation (McGrath, 2018).In the process of aggregating data without taking into account the proper degree of granularity, it is possible to hide key features and lead to misunderstandings. According to Korn and Shaffer (2015), it is essential to find suitable aggregation algorithms that not only maintain the integrity of the data but also properly portray the patterns that lie under the surface.The failure to conduct a comprehensive analysis of the data prior to the creation of visualisations may lead to omissions or the loss of valuable insights. The process of doing exploratory data analysis is very necessary in order to identify patterns, outliers, and correlations that may be used to guide the development of efficient visualisations (Tukey, 1977).It is possible to restrict the efficacy and expressiveness of visualisations by relying simply on the default parameters that are offered by visualisation tools. According to Mackinlay (1986), it is essential to personalise visualisations so that they are tailored to the particular qualities of the data as well as the requirements of the audience. In the process of drawing conclusions from visualisations, it is possible to lead to overconfidence if one ignores or minimises the uncertainty that exists in the data. As stated by Gelman et al. (2014), it is of the utmost importance to add indicators of uncertainty, such as confidence intervals or error bars, in order to effectively communicate the trustworthiness of the results. The failure to take into account cultural or contextual aspects during the design process of visualisations may lead to the misreading of specific audiences or the alienation of certain audiences. According to Wong (2010), it is essential to customise visualizations so that they are culturally sensitive and relevant to the audience that is being targeted.

Visualization tools can be broadly categorized as standalone applications, web-based presentations, web-based development tools primarily composed of software libraries (APIs), or programming language modules (e.g., Python or Java modules). They can also be classified based on various criteria such as software type, visualization structure, operating system compatibility, licensing, scalability, extendibility, or release date. Caldarola and Rinaldi (2017) identified 36 software tools grouped into four categories: scientific visualization, data visualization, information visualization, and business intelligence tools. Certain tools like Microsoft Excel, Amazon Quicksight, and Microsoft Power BI offer database-related and GUI-based functionalities with a "direct manipulation" principle. Despite their widespread usage, these tools are not discussed further in this article as they are beyond its scope. While visualization construction tools are often criticized for limiting creativity due to their fixed properties, they are still preferred for their user-friendly interfaces that do not require programming skills. While visualization libraries aim to simplify complexity, they still demand a level of expertise. Beyond these libraries, development platforms and cross-platform tools spanning multiple domains have emerged to meet the demand for user-friendly and adaptable graphical systems. The quest for such systems traces back to Bertin's Semiology of Graphics (Bertin, 1983), which laid the foundation for formalizing graphing techniques. This formalization evolved into structural theories of graphics, bridging computer graphics with information visualization theories. Cleveland and McGill (1984) furthered this exploration by experimenting with retinal variables like position, color, and size.

Recent advancements build upon Wilkinson's (2012) theories, inspiring visualization interfaces like Lyra (Satyanarayan and Heer, 2014) and VegaLite (Satyanarayan et al., 2017), as well as grammar-based systems like Polaris (Stolte et al., 2002). These tools, including Lyra and iVisDesigner (Ren et al., 2014), facilitate the creation of custom visualizations based on modular concepts without coding. However, their support for visual forms and parameters remains limited. Building upon Wilkinson's grammar formalization, various visualization grammars, toolkits, and frameworks have emerged, categorized into low-level and high-level grammars. Low-level grammars such as D3 (Bostock et al., 2011), Vega (Satyanarayan et al., 2015), and Protovis (Bostock and Heer, 2009) offer fine-grained control for highly customized graphics. D3, especially popular for web development, allows detailed specification of data bindings to visual properties. High-level declarative grammars like Vega-Lite and ECharts (Li et al., 2018) prioritize exploratory visualization, encapsulating details for rapid visualization production.

Frameworks have been developed to abstract complexities, such as Prefuse (Heer et al., 2005), offering a collection of visualization tools similar to Java-based libraries. GPU-powered visualizations, like Stardust (Ren et al., 2017), leverage rendering performance improvements, providing user-friendly building blocks for both 2D and 3D visualizations. Addressing the gap between artists and expert coders, programmable IDEs like VisComposer (Mei et al., 2018) utilize tree-based visual structures akin to D3. Similarly, interactive systems like VisAct (Wu et al., 2020) offer high-level grammar for semantic actions, guiding users through a wide range of visual forms.Efforts in developing interactive toolkits for information visualization have predominantly focused on traditional 2D representations, limiting exploration in immersive 3D environments. However, recognizing the potential of 3D environments for immersive experiences, scientific visualization has driven the advancement of virtual reality (VR) systems. One widely utilized framework for scientific visualization is the Visualization Toolkit (VTK) (Hanwell et al., 2015), an extensive library facilitating data display and interaction. Integration of VTK with VR environments became feasible through OpenVR, an API supporting SteamVR by Valve, thereby ensuring compatibility with devices like Oculus Rift and HTC Vive.

Recent research has increasingly delved into immersive environments for non-spatial data. Despite its gaming-oriented design, the Unity game engine has emerged as a standard platform for developing immersive environments. Toolkits like IATK (Cordeil et al., 2019) and DXR (Sicat et al., 2019) have been tailored for building immersive data visualizations using the Unity engine. DXR employs a declarative framework inspired by Vega-Lite, offering interactive and extensible visualizations exportable to various platforms, including mixed reality (MR) devices like Microsoft HoloLens and VR headsets. Conversely, IATK's API, akin to D3, simplifies visualization construction through a grammar of graphics approach.Building upon previous applications such as ImAxes (Cordeil et al., 2017a) and FiberClay (Hurter et al., 2018), IATK facilitates visualization creation with three-dimensional axes, albeit lacking collaboration features. FiberClay, evaluated with air traffic controllers, visualizes large-scale spatial trajectory data in 3D, enabling query construction via selections of 3D beams. ImAxes, an open-source information visualization tool, implements interactive scatterplots, histograms, and parallel coordinates manipulable through reconfigurable axes using natural interactions.

5.2 Findings

- "From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Age: 30(30%) respondents responded Under 18 years old, 24(24%) respondents responded 18-25 years old, 18(18%) respondents responded 26-36 years old and 10(10%) respondents responded 37-47 years old and 10(10%) respondents responded 48-58 years old.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Gender: and 60(60%) respondents responded as Female, whereas 40(40%) respondents responded as Male
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Education Level: 36(36%) respondents responded Less than high school, 34(34%) respondents responded High school diploma or equivalent, 14(14%) respondents responded Some college, no degree and 10(10%) respondents responded Associate degree and 6(6%) respondents responded Other (please specify).
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Occupation/Field: 52(52%) respondents responded Business/Finance, 28(28%) respondents responded Healthcare/Medicine, 10(10%) respondents responded Education/Research and 6(6%) respondents responded Government/Nonprofit and 4(4%) respondents responded Other (please specify).
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about How often do you encounter visualizations that misleadingly represent data due to improper scaling of axes? 36(36%) respondents responded Very often, 18(18%) respondents responded Occasionally and 26(26%) respondents responded Rarely where as 20(20%) respondents responded Never.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about What is the most common issue you've observed in bar graphs or column charts? 30(30%) respondents responded Truncated axes that exaggerate differences, 24(24%) respondents responded Inconsistent

intervals on the axis and 20(20%) respondents responded Overlapping bars that obscure data where as 26(26%) respondents responded Using 3D effects that distort perception.

- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about In your opinion, what contributes most to the overcomplication of a visualization? 28(28%) respondents responded Too many data points, 34(34%) respondents responded Excessive use of colors and patterns and 18(18%) respondents responded Incorporating too many variables in a single chart where as 20(20%) respondents responded All of the above.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about How often do you find pie charts to be an effective means of data presentation? 38(38%) respondents responded Very often, 28(28%) respondents responded Occasionally and 20(20%) respondents responded Rarely where as 14(14%) respondents responded Never.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about . How frequently do you come across visualizations that do not provide alternatives (such as textual descriptions) for accessibility? 38(38%) respondents responded Very often, 34(34%) respondents responded Occasionally and 18(18%) respondents responded Rarely where as 10(10%) respondents responded Never.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Rate the importance of considering color blindness when designing data visualizations. 42(42%) respondents responded Very important, 34(34%) respondents responded Somewhat important and 16(16%) respondents responded Not very important where as 8(8%) respondents responded Unimportant.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about What factor do you believe leads most frequently to the misinterpretation of data visualizations? 38(38%) respondents responded Lack of contextual information, 30(30%) respondents responded Ambiguous legends or keys and 24(24%) respondents responded Inappropriate choice of visualization type where as 8(8%) respondents responded Misleading axis labels or titles.

- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about How crucial is it to include a clear legend or key in a data visualization? 28(28%) respondents responded Very crucial, 38(38%) respondents responded Somewhat crucial and 16(16%) respondents responded Not very crucial where as 18(18%) respondents responded Not crucial at all.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about To what extent do you think the choice of software or tools affects the quality of data visualizations? 52(52%) respondents responded Significantly, 30(30%) respondents responded Moderately and 12(12%) respondents responded Slightly where as 6(6%) respondents responded Not at all.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Have you ever encountered a situation where the default settings of a visualization tool led to a misleading representation of data? 32(32%) respondents responded Yes, frequently, 32(32%) respondents responded Yes, but rarely and 16(16%) respondents responded No, but I see how it could happen where as 20(20%) respondents responded No, never.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about How often do you believe that an inappropriate choice of chart type leads to misinterpretation of data? 34(34%) respondents responded Very often, 42(42%) respondents responded Occasionally and 16(16%) respondents responded Rarely where as 8(8%) respondents responded Never.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Which chart type do you think is most frequently misused or inappropriately chosen for data presentation? 54(54%) respondents responded Pie charts, 14(14%) respondents responded Bar charts and 12(12%) respondents responded Line graphs where as 20(20%) respondents responded Scatter plots.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about In your experience, what is the main reason behind the inappropriate selection of chart types? 24(24%) respondents responded Lack of understanding of the data, 42(42%) respondents responded Insufficient

knowledge of different chart types and their uses and 14(14%) respondents responded Trying to make the data appear more favorable or dramatic where as 20(20%) respondents responded Software defaults or limitations.

- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about How important is it to match the chart type with the nature of the data and the intended message? 30(30%) respondents responded Extremely important, 48(48%) respondents responded Very important and 16(16%) respondents responded Somewhat important where as 6(6%) respondents responded Not important.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about What consequence of using an inappropriate chart type do you find most concerning? 52(52%) respondents responded Misleading the audience, 12(12%) respondents responded Oversimplifying complex data and 30(30%) respondents responded Overcomplicating simple data where as 6(6%) respondents responded Obscuring key insights or patterns.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Which of the following best practices do you consider most crucial when selecting a chart type? 50(50%) respondents responded Understanding the audience's familiarity with different chart types, 26(26%) respondents responded Aligning the chart type with the key message or insight to be communicated and 16(16%) respondents responded Considering the data's scale and distribution where as 8(8%) respondents responded Testing the visualization with a subset of the audience for clarity and interpretation.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Have you ever changed the chart type after realizing it was not conveying the intended message effectively? 46(46%) respondents responded Yes, frequently, 22(22%) respondents responded Yes, occasionally and 12(12%) respondents responded Rarely where as 20(20%) respondents responded never.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about What strategy do you find

most effective in avoiding the selection of inappropriate chart types? 24(24%) respondents responded Regularly reviewing best practices in data visualization, 34(34%) respondents responded Consulting with peers or experts during the design phase and 22(22%) respondents responded Using software with guidance or recommendations for chart types where as 20(20%) respondents responded Conducting user testing or feedback sessions on preliminary designs.

- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about How do you rate the importance of education or training in data visualization for preventing the misuse of chart types? 30(30%) respondents responded Extremely important, 40(40%) respondents responded Important and 18(18%) respondents responded Somewhat important where as 12(12%) respondents responded Not important.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about What is your primary resource for learning about appropriate chart type selection? 52(52%) respondents responded Books or academic publications on data visualization, 10(10%) respondents responded Online tutorials and courses and 20(20%) respondents responded Blogs and articles by data visualization experts where as 18(18%) respondents responded Trial and error with different visualization tools.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Do you think unclear labeling of axes significantly contributes to misinterpretation of data? and 82(82%) respondents responded as Yes, whereas 18(18%) respondents responded as No
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Can omitting units of measurement in labels lead to confusion about the data presented? and 60(60%) respondents responded as Yes, whereas 40(40%) respondents responded as No
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Does using too small or too large font sizes for labels detract from data comprehension? and 66(66%) respondents responded as Yes, whereas 34(34%) respondents responded as No

- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Is inconsistent labeling across multiple charts in the same presentation confusing? and 56(56%) respondents responded as Yes, whereas 44(44%) respondents responded as No
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Do you believe that overly complex or technical terminology in labels can alienate the audience? and 78(78%) respondents responded as Yes, whereas 22(22%) respondents responded as No
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Can the absence of a legend (when necessary) significantly hinder data interpretation? and 62(62%) respondents responded as Yes, whereas 38(38%) respondents responded as No
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Do you believe that using too many colors in a single visualization can overwhelm the viewer? and 54(54%) respondents responded as Yes, whereas 46(46%) respondents responded as No
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Can the use of very similar colors for different data points lead to confusion? and 56(56%) respondents responded as Yes, whereas 44(44%) respondents responded as No
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Is it problematic to rely solely on color to distinguish between different data elements? and 66(66%) respondents responded as Yes, whereas 34(34%) respondents responded as No
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Do you think that not considering color blindness accessibility can significantly hinder data interpretation for affected viewers? and 62(62%) respondents responded as Yes, whereas 38(38%) respondents responded as No
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Does the absence of a

consistent color scheme across related visualizations cause interpretation issues? and 60(60%) respondents responded as Yes, whereas 40(40%) respondents responded as No\

- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Tailoring visualizations to the audience's knowledge level is crucial for their understanding of the data. 58(58%) respondents responded Strongly Agree, 16(16%) respondents responded Agree, 16(16%) respondents responded Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Visualizations that ignore audience demographics (age, education, etc.) are less effective in communicating findings. 60(60%) respondents responded Strongly Agree, 22(22%) respondents responded Agree, 2(2%) respondents responded Neutral and 12(12%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about The complexity of a visualization should be adjusted based on the expected audience. 54(54%) respondents responded Strongly Agree, 16(16%) respondents responded Agree, 20(20%) respondents responded Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about A successful data visualization must use language and terminology familiar to its intended audience. 42(42%) respondents responded Strongly Agree, 20(20%) respondents responded Agree, 28(28%) respondents responded Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Considering the cultural context of the audience is unnecessary in data visualization. 50(50%) respondents responded Strongly Agree, 24(24%) respondents responded Agree, 16(16%) respondents responded

Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Manipulating the scale of an axis can significantly change the perceived importance of the data shown. 42(42%) respondents responded Strongly Agree, 22(22%) respondents responded Agree, 18(18%) respondents responded Neutral and 14(14%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Using non-proportional scales is justified when it helps to highlight subtle trends in the data. 58(58%) respondents responded Strongly Agree, 10(10%) respondents responded Agree, 16(16%) respondents responded Neutral and 12(12%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Altering the scale or axes to exaggerate differences among data points is generally misleading. 54(54%) respondents responded Strongly Agree, 14(14%) respondents responded Agree, 16(16%) respondents responded Neutral and 6(6%) respondents responded Disagree and 10(10%) respondents responded Strongly Disagree.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about The choice of scale for an axis should always be clearly indicated to avoid misleading the audience. 58(58%) respondents responded Strongly Agree, 12(12%) respondents responded Agree, 16(16%) respondents responded Neutral and 6(6%) respondents responded Disagree and 8(8%) respondents responded Strongly Disagree.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Viewers typically do not notice manipulations of scales or axes in a visualization. 52(52%) respondents responded Strongly Agree, 30(30%) respondents responded Agree, 8(8%) respondents responded Neutral and

6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.

- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Overcrowding of data in visualizations significantly reduces their effectiveness. 64(64%) respondents responded Strongly Agree, 10(10%) respondents responded Agree, 20(20%) respondents responded Neutral and 2(2%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about A high density of data points is necessary to convey complex information accurately. 42(42%) respondents responded Strongly Agree, 38(38%) respondents responded Agree, 12(12%) respondents responded Neutral and 4(4%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree.
- From the analysis it was observed that of graph and table above, and they indicate the sample data which includes 100 respondents. It was discussed about Simplifying data visualizations always risks losing important information. 42(42%) respondents responded Strongly Agree, 32(32%) respondents responded Agree, 16(16%) respondents responded Neutral and 6(6%) respondents responded Disagree and 4(4%) respondents responded Strongly Disagree."

5.3 Conclusion

The visualization of data is a strong tool that can be used for storytelling and data communication. It makes it possible for diverse audiences to access and comprehend information that is otherwise difficult to comprehend. On the other hand, our research has brought to light a number of typical problems that have the potential to negatively impact the efficiency of visual data displays. Among them are problems such as deceptive scales, images that are too intricate, bad color choices, neglecting the demands of the audience, cherry-picking data, inconsistent visual signals, and a lack of contextual information.There are substantial repercussions that may result from these errors. Misinterpretations of data, poor decision-making, and a decline in the trustworthiness of the data source are all possible outcomes that might result from their presence. In order to ensure that their visual representations adhere to the values of clarity, accuracy, and fairness, it is essential for those who create data visualizations to be aware of the problems that they face and to make every effort to do so. In the future, research should continue to investigate novel approaches to avoiding these issues. This may be accomplished, for example, by developing new visualization tools and methodologies that place an emphasis on flexibility, user involvement, and ethical standards. In addition, fostering a more comprehensive comprehension of visualization literacy among the general audience has the potential to significantly improve the efficiency with which complicated data is communicated. When everything is said and done, the objective should be to cultivate a culture of critical engagement with visual data, one in which both producers and consumers are equipped with the skills required to critically examine and constructively utilize information. It is possible for the industry to advance toward more dependable and effective data communication methods if it first recognizes and then addresses the main difficulties that are associated with data visualization.

CHAPTER 6

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

"Data Visualization Pitfalls" is an in-depth examination of the typical faults and obstacles faced in data visualization, which is vital for strategic decision-making across a variety of sectors, including business analytics, scientific research, and public policy. The paper that was supplied contains this exploration. This chapter places a strong emphasis on the significance of detecting and comprehending these potential traps in order to ensure that visual data representations continue to preserve their integrity, clarity, and correctness. It methodically classifies typical mistakes, such as the incorrect interpretation of graphical characteristics and the introduction of biases throughout the process of data collection and presentation, and it emphasizes the enormous influence that these difficulties may have on the interpretation of data and the decision-making processes. Furthermore, the chapter stresses the importance of ethical visualization practices, advocating for the development of best practices and guidelines that enhance the transparency and usefulness of visualized data, thereby supporting informed decision-making and promoting greater trust in visualized insights. This article goes further into the ramifications of these data visualization errors, highlighting the substantial influence that they have on both academic research and practical implementations. This chapter serves as an important resource for practitioners working in the domains of data science, statistics, and information visualization. It does this by identifying and evaluating frequent mistakes and misunderstandings. Additionally, it provides insights into the constraints and problems that are connected with visual data representations. The development of more robust procedures and tools for data analysis and presentation is made possible by this comprehensive study, which not only improves our awareness of these potential problems but also offers a framework for their development. Furthermore, the results have practical ramifications across a variety of areas that are relied upon for making decisions based on data, such as the corporate world, the healthcare industry, the financial sector, and public policy. The purpose of this chapter is to enable professionals to critically examine and improve their data visualization techniques by increasing their understanding of possible pitfalls and the implications of those mistakes. This will eventually result in an improvement in the quality and dependability of insights that are generated from visual data. In addition, the study makes a contribution to the larger discourse that is taking place around data literacy and communication, which helps to promote a better informed and effective conveyance of information to a variety of audiences.

A culture that values critical inquiry, openness, and rigor is advocated for in this chapter by means of a comprehensive examination of various hazards that are inherent in the process of visualization. These hazards range from subtle choices such as color and scale to more overt issues such as cherry-picking data or omitting essential context. For the purpose of ensuring that visualized data continues to be an effective tool for creating insights, aiding decision-making, and furthering social development, this viewpoint is very necessary.The growing ecosystem of data visualization tools and platforms is also discussed in the systematic review. These tools and platforms, while providing accessibility to advanced data analysis capabilities, also add new degrees of complexity and danger. It is recommended in this chapter that practitioners have a solid understanding of the underlying concepts and possible risks associated with data visualization. This is done with the intention of preventing the dissemination of misleading narratives or the drawing of incorrect conclusions from visualized data. The purpose of this chapter is to provide practitioners with the information and tools required to efficiently traverse the complicated landscape of data visualization. This will be accomplished by integrating academic research, case studies, and the views of experts. Among them are the promotion of a greater knowledge of the cognitive and perceptual biases that influence interpretation, as well as the encouragement of the adoption of best practices that improve the accuracy, transparency, and ethical use of visual data.

It is imperative that practitioners stay up to date with the latest trends, technologies, and approaches in the field of data visualization as these technologies continue to develop and become increasingly integrated into a variety of disciplines. The ongoing education that is provided enables the refining of procedures and the mitigation of growing hazards that are connected with the use of new technologies and vast datasets that are challenging to understand.

A multidisciplinary approach to data visualization is also advocated for in this study. This method would include concepts from the fields of psychology, design theory, and information science into its framework. This method contributes to a deeper understanding of the ways in which visual information is viewed and understood, which has the potential to dramatically improve the efficiency of data visualizations. Practitioners are able to develop visual representations that are not only technically correct but also connect better with their target audiences if they include these various views. These representations that are more engaging and insightful may be created by practitioners.The chapter provides a fundamental basis for the advancement of best practices in data visualization, which is the systematic review that is introduced in the chapter. The need of taking a proactive approach to knowing and avoiding frequent hazards, cultivating a culture of integrity and ethical responsibility, and regularly engaging with the most recent advancements in the area is highlighted by this. Data visualization is a discipline that may continue to give substantial value by assisting decision-making processes and fostering a better understanding of complicated data across a variety of industries. This can be accomplished via collaborative initiatives such as these.

6.2 Implications

1. Misleading Scales

The use of non-standard or shortened scales on graphs may either understate or exaggerate trends, which is a potential pitfall. Implications: It is possible for viewers to incorrectly understand the severity or relevance of the facts, which may result in incorrect conclusions and judgments.

2. Overcomplicating Visuals

Confusion might arise when an audience is presented with a single visualization that has an excessive number of components, colors, or a combination of several sorts of data. The relevance of this is that complexity has the ability to hide the primary message, so diminishing the efficiency of the data exchange and maybe resulting in an excessive amount of information.

3. Poor Color Choices

Charts may be difficult to read if they are constructed using colors that are too similar to one another or that do not contrast properly. The implications of this include that it may result in accessibility problems, especially for those who have color vision abnormalities, and that it may also compromise the general readability of the depiction.

4. Ignoring Audience

The process of creating visualizations without taking into account the audience's degree of understanding or what they regard to be intuitive. Implications: If the visualization is not adapted to the audience for whom it is meant, it may fail to communicate effectively, which may result in disengagement or misunderstanding.

5. Cherry Picking Data

showing data in a selective manner that is supportive of a specific argument while disregarding data that is not supportive of the argument. The implications of this include that it may result in biased presentations and maybe unethical reporting, which will damage both credibility and trust.

6. Inconsistent Visual Cues

Applying distinct styles or measurements to data sets that are comparable in a number of different charts. The implications of this are that inconsistencies might cause confusion among the audience and make it difficult to appropriately compare data across several renderings.

7. Not Providing Context

Presenting statistics without providing adequate background information or writing that explains it. In the absence of context, viewers may be unable to comprehend the meaning or relevance of the facts, which may result in conclusions that are either shallow or erroneous.

6.3 Recommendations for Future Research

- **Adaptive Visualizations**
  Investigate the possibility of developing dynamic visualizations that may respond to the input or involvement of users in real time, so allowing the display to be customized to the specific degrees of understanding or interests of each particular user.
- **Visualization Literacy**
  Conduct research on the ways in which visualization literacy may be increased across a variety of demographics. This involves discussing the most effective methods for educating consumers on how to analyze and comprehend complicated visual data.

- **Augmented and Virtual Reality**

  Examine the ways in which augmented reality (AR) and virtual reality (VR) may be used in the process of data visualization. One possible avenue of investigation for this study is to investigate how immersive settings might improve one's comprehension of intricate data structures and linkages.

- **Automated Design Tools**

  It is important to develop and assess tools that can automate the construction of visualizations. These tools should follow to best practices in design and usability, and they should also enable users to easily customize their visualizations.

- **Cross-Cultural Visualizations**

  Investigate the potential impact that cultural variations have on the interpretation of visual data. It is possible that this will result in the creation of visuals that are more easily understood by everyone.

- **Ethical Visualization**

  It is important to pay attention to the ethics of visualization, which includes the ways in which data and designs might mislead, as well as the obligation of visualizers to avoid the abuse of information.

- **Impact of Color Psychology**

  Delve deeper into how color schemes affect the interpretation and emotional impact of data visualizations, which could improve the effectiveness of visual data communication.

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but also meaningful and insightful.

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