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SURVEY

A Comprehensive State-of-the-Art Survey on Data Visualization Tools: Research Developments, Challenges and Future Domain Specific Visualization Framework

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ABSTRACT Data visualization is a powerful skill for the demonstration of meaningful data insights in an interactive and effective way. In this survey article, we collected 70 articles from last five years (2017-2022) to identify, classify, and investigate the various scopes, aspects and theories of data visualization. We also investigated the powerful applications of data visualization in various domains and fields such as visualization apps for health sector, Internet of things (IoTs), business dashboards, urban traffic management, smart buildings and environmental data visualization. However, after thorough investigation and classification, we conclude that, a comprehensive study is still missing about interactive, effective and efficient data visualization survey explaining basic current state-of-the-art best interactive visualization techniques, web-based tools and platforms, best performance theories, data structures and algorithms. In this survey article, we perform a thorough investigation to fill the gap on theoretical, analytical, statistical models and techniques for improving the performance of visualization. Current primary and domain specific future challenges are also reviewed, and related future research directions and opportunities are recommended.

INDEX TERMS Data visualization, interactive tools, effective techniques, web-based platform, collaborative visualization platform.

I. INTRODUCTION

Effective and interactive data visualizations are particularly significant across all formats. It converts abstract (raw) data into physical (actionable) data, such as shape, color, position, length, height, width etc, to present persuasive stories in a clear, logical, smart and plausible way. In this way, large numbers of data are analyzed promptly to make visualization efficient and interactive. The rows and columns of data are inadequate to create persuasive stories to appeal the audience. The aim should be to draw the visualization in a clear, smart and persuasive way to assist the decision makers to conclude the decisions with no time. Interactive visualizations can be useful even for non-professional customers to make graphs and charts to take significant decisions accordingly. With the advantages of people's natural affinity to interactive and influential visualization, it should be easy to see insights and hidden values choosing right visualization. With these benefits, data visualizations have been widely applied across all formats such as health sector, business sector, Urban sector, smart cities, smart buildings and so on. Before pondering motivation and contribution of this article, we first discuss a brief exposition of the data visualization articles in various domains in the last 5 years (2017-2022). **Figure. 1** shows the keywords cloud of the articles which have been investigated for this article. The size of the words describes the rate of recurrence which has been frequent during the visualization literature search. It can be seen that "Data", "Visualization",

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FIGURE 1. Keywords Cloud of Data Visualization related Published Papers (2017-2022).

''Interactive'' and ''Web-based'' are the most searched keywords during journals analysis process.

A. TAXONOMY OF DATA VISUALIZATION ARTICLES

The taxonomy of data visualization is laborious task. Since, several data visualization techniques, tools and platforms are available to generate effective and interactive visualization. However, in this survey, we classify data visualization with respect to various scopes and applications where advanced and interactive visualization techniques are still required to make better informed decisions. In the first stage, this survey collects 70 articles from last five years (2017-2022) to identify the various scopes, aspects and application of data visualization. We divide the 65 articles into 7 different scopes. We also classify these articles according to their domain research and approaches. The contribution of each article has been highlighted and cited in the **Table 1**. In this initial stage, this survey discusses the various aspects of 7 scopes. In **Scope-1**, the techniques to handling of various types of data, graphs, colours interaction and its integration are discussed. In **Scope-2**, the focus is on the data mining networks, environment and structure. In **Scope-3**, the role of decision-making techniques in data visualization is emphasised. In **Scope-4**, data visualization for big data and its emerging applications are analysed. **Scope-5** shares the visualization competencies in data security. In **Scope-6**, the key role of statistical analysis for visualization is explored. In the final **Scope-7**, various applications are reviewed to check the performance of visualization in specific domain. The contribution of each scope can be seen in the **Figure. 2** which explains the taxonomy of data visualization and classification of each scope using **Circular Packing** data visualization technique.

1) DATA VISUALIZATION ESSENTIALS

With the advancement of modern computers and algorithms, the scientific approaches to dealing with data and its visualization are evolving rapidly. The first scope covers the essentials of data of visualization. References [1], [2], [3], [4], [5], [6], and [7] summarized the essentials of data driven techniques to analyse the sampling methods to focus on important features for better and deeper understanding and to achieve better results of information visualization. Sarica *et al.* [5] used data driven technique to locate the better position for implementation of innovation which is also competitive data intelligence analytics. For better visualization, [3] employed machine learning algorithms. Machine learning models are used to forecast future visualization. To consider and cover all the features of information, [8], [9], [10], [11] proposed a knowledge-based visualization of information techniques. These techniques are developed to understand, interpret and demonstrate the pattern of existing visualization techniques and tools. They also share a complete guidance for interactive data visualization. References [12], [13], [14],and [15] mainly focused on spatial-temporal techniques and abstraction visualization. Descriptive visualization techniques and framework focused on several data observations, data points, units and highlight patterns and interpret the information. A descriptive framework can also provide a platform to evaluate the different categories of data visualizations [16].

References [17], [18], [19], [20], [21], [22], and [23] discussed the design of interactive data visualization. The construction of interactive graphs is a stark technique focusing on high level declarative features specifically on distributed data. For this, developers must have the expertise to handle the asynchronous data events for the construction of interactive visualization. Wu *et al.* [17] worked on two ideas; logical constraints and immutable distributed programming. Ono *et al.* [20] used three Jupyter Notebooks (matplotlib of callbacks, HTML and toolkits) for interactive visualization. This article [22] used feature oriented interactive visualization.

The tools in this review article [24] highlight the visualization tools which are used for collaborative visualization platforms and are very helpful for better decision making coordination. These papers [25], [26] summarized the implementation and advantages of collaborative visualization and application on multiple platforms. References [24], [25], [26], and [27] reviewed the various platforms to create an impactful collaborative foundation to produce interactive visualizations to improve and enhance the understanding of data insights.

References [28] and [29] reviewed the significant growth of ensemble visualization and highlighted the rising demand across multiple disciplines. They observed that ensemble visualization used the same facet and aggregation techniques for visualization. This survey [29] article covers ensemble visualization techniques and analytical tasks perspectives. It elaborates the surface and volume and emphasises the comparison and clustering techniques for analytical tasks in various visualization research opportunities. According to [30] scalability of visualization is incapable of discerning the issues between various datasets and plots. When the datasets change, the pattern of visualization is also changed and the issue of matching and mismatching generates. References [31], [32], [33], and [34] reviewed and proposed the methods to assess the multicriteria robustness evaluation and

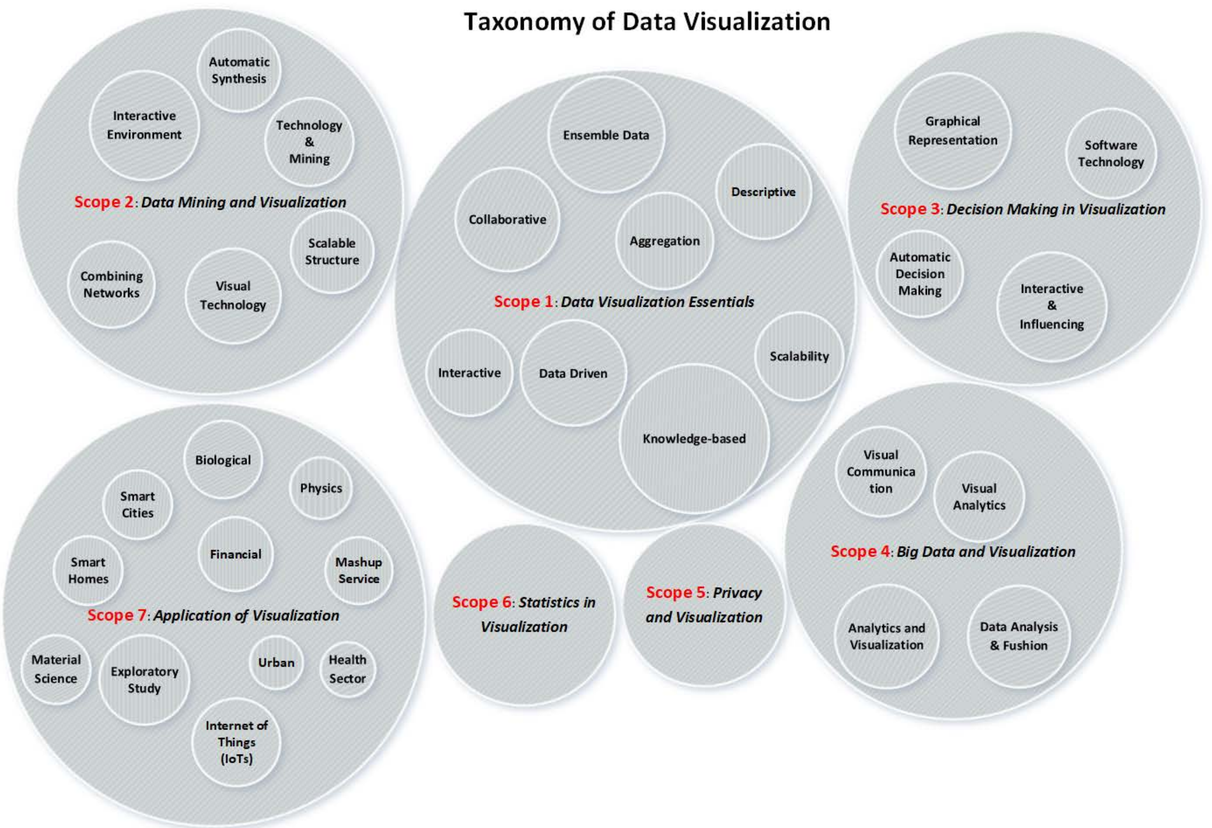

FIGURE 2. Taxonomy of Data Visualization.

impact of aggregation on the spatial and temporal distribution pattern of charts and maps.

2) DATA MINING AND VISUALIZATION

Data mining for visualization is a novel technique for mining of enormous datasets. Due to the advancement of technologies, every move of life is being recorded. Data has been generated in all fields of life [38]. The main task is to find and explore the beneficial information from the captured data. This is not a simple job inside massive data. This article [35] introduced the features of huge data and data mining technologies and highlighted the advantages and disadvantages of data mining techniques in terms of visualization. Bavishi *et al.* [36] introduced a novel approach of automatic synthesis visualization to use data mining techniques with best function and create better visualizations for customer. In the [39] authors developed data mining visualization environment aiming to design, investigate and assessment of visualization results. Researchers also evaluated the visualization challenges in the perspective of human computer interaction. In this article [40] integration of scalable methods and techniques proposed for data mining, data visualization and workflow for micro-task. These techniques created intelligent system that supported and assisted each other in visualization decision making and facilitation.

3) DECISION MAKING IN VISUALIZATION

Data visualization is used to visualize not only the charts, graphs and maps but insights. Therefore, data visualization is a significant method to deal with the hidden information of large datasets. Visualization helps researchers, scientists and industrialists to understand data, identify the expected risks and mitigate them proactively with valuable results. It is crucial for improving the decision making of the researchers, businessman and industrialists etc. Scope 3 highlights multiple techniques and models from top researchers and data scientists for enhancing decision making techniques and approaches of big data analytics and effective presentation and visualization of data. This research article [41] worked on new domain of visualization, uncertainty and decision making for interactive visualization. The actual work was to interpret the datasets and exploit the insight to assess effective decision making. It also helped to limit the uncertainty in visualizations. Kim *et al.* [42] proposed a visualization supporting tool to support decision making in visualization and implement interactive visualization for users. Design guidelines were also developed to evaluate the visualization to support domain experts. In this article [43] researchers worked on various methods to design an automatic decision making for visualization of quantitative tasks data. Automatic decision making is an evolving approach in big data problems

TABLE 1. Taxonomy of Data Visualization.

Scope	Classification	Topic	Years (2017-2022)	Cite
Scope 1: Data Visualization Essentials	Data Driven	Visualization of data driven Stories	2021	[1]
		Big data driven visual communication and visualization	2021	[2]
		Data driven mining and visualization	2019	[3]
		Driven data multivariate sampling and visualization	2019	[4]
		Data driven network and visualization	2019	[5]
		Resource flexing and data driven visualization	2018	[6]
		Data driven spatial temporal information and Visualization	2017	[7]
	Knowledge-based	Graph knowledge-based approach for visualization	2022	[8]
		Knowledge-based visualization and sentiment analysis	2021	[9]
		Visual analysis of knowledge-based network mapping	2021	[10]
		Knowledge-based information abstraction and interactive visualization	2020	[11]
	Descriptive	Descriptive study on large data analytics and visualization	2020	[12]
		Descriptive measures of spatial scale of data visualization	2018	[13]
		Descriptive attribute-based visualization	2018	[14]
		Descriptive platform for temporal data visualizations	2017	[15]
		Descriptive framework for visualizations of energy series data	2018	[16]
	Interactive	Interactive visualization here and now	2022	[17]
		Interactive network visualization	2022	[18]
		Interactive visualization images by neural networks	2021	[19]
		Interactive data visualization framework using Jupyter	2021	[20]
		Interactive visualizations of cognitive maps	2021	[21]
		Interactive visualization for feature	2021	[22]
		Interactive visualization fact or fiction?	2020	[23]
	Collaborative	Collaborative techniques for visualization	2021	[24]
		Collaborative web-based visualization for searching	2021	[25]
		Collaborative interactions and visualizations	2021	[26]
		A collaborative web-based platform for exploration of data visualization	2020	[27]
	Ensemble Data	Ensemble Data Exploration and Visualization	2021	[28]
		Ensemble visual analysis and visualization	2019	[29]
	Scalability	Effectiveness and scalability for data visualization	2020	[30]
	Aggregation	Visualization of different levels maps at aggregation	2022	[31]
		Exploring the impacts of aggregation on visualization	2020	[32]
		Disaggregation–aggregation data visualization approaches	2020	[33]
		Visualization and aggregation of three-dimensional spatial data	2018	[34]
Scope 2: Data Mining and Visualization	Visualization Technology	Research on visualization technology	2021	[35]
	Automatic Visualization	Automatic synthesis in visualization	2021	[36]
	Combining Networks	Combining network in visualization	2020	[37]
	Technology Mining	Data Mining Technology on Visualization	2020	[38]
	Interactive Environment	Interactive environment and visualization	2018	[39]
	Scalable Structure	Scalable ideation and data visualization	2017	[40]
Scope 3: Decision Making in Visualization	Graphical Representation	Uncertainty in decision making and visualization	2021	[41]
	Software Technology	Decision making in software technology and visualization	2021	[42]
	Automatic	Automated decision-making in visualization	2020	[43]
	Interactive and Influencing	Decision-making in interactive data and information visualization	2019	[44]
Scope 4: Big Data and Visualization	Data Analysis and Fushion	Information visualization of big data analysis and fusion	2021	[45]
	Visual Communication	Big data driven visual communication and visualization	2021	[46]
	Analytics and Visualization	Big data analytics and visualization	2020	[47]
	Visual Analytics	Big data visualization and analytics	2020	[48]
Scope 5: Privacy and Visualization	Privacy	Privacy awareness for exploring visualizations	2021	[49]
		Multilayer security for attack prevention	2020	[50]
		Reflection of privacy preserving on data visualization	2020	[51]
		Privacy preserving technique for visual query	2020	[52]
		Security model for visualization of internet of things data	2019	[53]
		Visual interface for privacy preserving	2018	[54]
		Collaborative learning methods for privacy	2017	[55]
Scope 6: Statistics in Visualization	Statistical	Visualizations and statistical methods	2021	[56]
		Statistical data and visualization	2021	[57]
		Statistical charts analysis using data visualization	2019	[58]
		Visualization challenge in statistical data	2017	[59]
Scope 7: Applications of Visualization	Urban	Visualization in Urban Management	2022	[60]
	Biological	Interactive visualization for biological data	2022	[61]
	Health Sector	Designing of health apps using data visualization	2021	[62]
	Material Science	Data visualization for material database	2020	[63]
	Physics	Visualization of performance data of a geophysics	2020	[64]
	Internet of Things	Data visualization and internet of things (IoTs)	2020	[65]
	Smart Homes	Cross-Domain Data for Smart Homes	2017	[66]
	Smart Cities	Visualization model of big data, network and graphic for smart cities	2019	[67]
	Financial	Financial data visualization modeling	2019	[68]
	Exploratory Study	Exploratory study of internet of things and data visualization	2018	[69]
	Mashup service	Mashup service of internet of things and visualization	2017	[70]

and helps to monitor and interpret quantitative data insights. Perdana *et al.* [44] proposed a decision-making model for interactive data and visualization. This model is capable to share the meaningful insights for interactive visualization and support to work on maximum features for better data visualization.

4) BIG DATA AND VISUALIZATION

Transforming big data into interactive and effective visualization needs expertise, skills and great attention from various data scientists and researchers. Scope 4 reviews the influence of researchers on big data environments and data visualization. In the article [45] the authors explored the techniques to exploit the big data, in terms of data fusion and data visualization using various charts and maps. Researchers worked on algorithms to propose visualization maps for complex networks of data. This [46] study provided a comprehensive analysis on big data, visual communication and visualization models. This work optimised the traditional technology and shared the analysis of the visual design of heterogeneous multidomain data. This research work [47] utilized the big data and created a web-based platform to visualise the results of energy consumption in terms of graphs, charts and maps. This work designed a dashboard to visualise the consumption. Authors [48] worked on the challenges that emerged with big data in terms of visualization. They mentioned that big data could be noisy, dynamic and heterogeneous to deal with for visualization.

5) PRIVACY AND VISUALIZATION

Data visualization is a useful tool for the interpretation and analysis of features, structure, and relationships among various variables. Therefore, privacy issues and the risk of data concealing could occur in tabular data. Scope 5 argues on the concept of privacy of visualization. This scope has limited literature work to discuss privacy issues of visualization. In the work [49], researchers investigated the application of visualization and implemented the two scenarios to assess the privacy of visualization. They summarised that it is still needed to explore the ideas on visualization privacy for emerging technologies [50], [53]. This paper [51] discussed the privacy preservation of sensitive information and key role of data visualization in privacy awareness for digital communications. It also investigated the relationship between information provision policies and privacy measurement parameters. Chen *et al.* [52] introduced federated learning technique for the encryption of visual features in local data modules and executed two approaches; query and prediction based federated learning. Wang *et al.* [54] proposed 'Graph-Protector' which guides users for the privacy preservation of visual interface and supports several visualization privacy schemes. For the better control of privacy, [55] proposed a compressive privacy preserving technique which compresses the information in a collaborative learning manner to process information in a securer mode.

6) STATISTICS IN VISUALIZATION

Statistical modeling is a mathematical technique of using statistical theories in data analysis. Statistical theories can play a vital role to mapping between statistical data and visualization of univariant, bivariant and multivariant datasets. Multiple algorithms have been developed for recommending effective and interactive charts, graphs and maps using statistical models and theories. Several algorithms have also been proposed to highlight the errors and their solutions for data analysis using statistical techniques. Scope 6 studies the contribution of statistical models in data visualization. Patil [56] used statistics to generate charts avoiding possible errors. Statistical models increased the reproducibility of interactive visualization. Statistical models are very significant for the effective and interactive visualization of big data. Multiple statistical algorithms have been discussed and proposed for interactive visualization. Statistical algorithms introduced z-axis for better and more interactive visualization. Statistics is also very helpful to generate more interactive shapes, charts and graphs [56], [57], [58], [59].

7) APPLICATIONS OF VISUALIZATION

Scope 7 investigates the powerful application of data visualization in various domains and fields. Data visualization techniques were used and analysed for urban traffic, emissions, and air quality data. A dashboard design generates effective and interactive visualization for all public and private roads, and traffic signals. The information from sensors used to generate effective visualization for Urban Traffic Monitoring [60]. Verschaffelt *et al.* [61] discussed JavaScript visualization library to create effective and interactive visualization. In this article, four types of visualizations are used for the visualization of biological data; Heatmap, Sunburst, Treeview and Treemap. Wang and Wang [62] explored the developed applications (apps) on data visualization for health sector. These apps provided an effective presentation, worked for interactive design methodology and developed trends analysis for a better understanding of visualization. Data visualization for the health department is very substantial to predict, examine and manage the patient data. Visualization plays essential role to build up the health service mechanism and system. In [63] a web-based application is discussed to visualise similar characteristics of materials and their online search. This application showed best results for correct and effective visualization using multidimensional data. This application shared the correct information of groups of metals and the origin of metals using visualization. This article [64] used performance and interactive visualization and five metrics to explore load imbalance for geophysics. It is substantial work to visualise the imbalances of loads during uneven conditions. Iram *et al.* [66] explored the inter-dependencies of cross domain data for the visualization of context aware data for smart homes. Chen *et al.* [67] worked on the data visualization of urban planning, construction, operation, and management. Data visualization for smart cities worked for whole life cycle presentation to investigate, explore and establish a thorough platform for analysis. It has reviewed the various types of data inputs, multiple graphs techniques, and colour combination. Internet of Things (IoTs) is a system of interconnected networks aiming to collect, share and exchange data between sensors to the Internet for further processing. Wireless sensors network is an essential component of the IoT and mobile agents have been identified as an efficient technique for data collection from sensors [71], [72]. However, the challenge is to select a suitable mapping technique in which the data generated by sensors can be visualized effectively and efficiently. The mapping between IoTs data and visualization depends upon the data dimensions and spatio-temporal aspects of the data. The direct visualization of IoTs data requires machine learning algorithms to overcome the issue of mapping. It discusses the contribution on visualization tools, techniques and platforms for the Internet of Things (IoTs). Protopsaltis *et al.* [65] focuses on developing efficient and effective data collection and visualization techniques. It also explores different techniques to make visualization descriptive, interactive and collaborative. It has explored the effectiveness of scalability and aggregation in of visualization.

B. MOTIVATION AND NEED OF THIS SURVEY

After reviewing the existing visualization articles, which can be seen in **Table 1** on various scopes, it has been found that a comprehensive study is still missing that can be valuable (i) to measure and highlight the best tools, techniques, and platforms (ii) to learn about best visualization algorithms and data structures enhancing the performance of visualization and (iii) to support in better understanding of web-based data visualization. To meet the requirement of the state-of-the-art survey, the following sections need thorough investigations.

1) TECHNIQUES FOR ENHANCING THE PERFORMANCE OF VISUALIZATION

The performance of visualization should be effective and scalable covering the basic components such as data manipulation and data mapping. Efficient visualization depends upon the various approaches such as integrated, interactive, automatic, and collaborative etc.

a: APPROXIMATE VISUALIZATION

With the increasing amount of data, the traditional models are not suitable to provide fast, efficient and interactive visualization. This visualization technique covers the gap between huge data and interactive presentation. This technique speeds up the process and enhances the performance of visualization.

b: PROGRESSIVE VISUALIZATION

This visualization technique works for hierarchical structure and aggregation of data. This is very efficient for various zones of spatial and temporal values and used to support exploration of user-based visualization. This is very effective to increasing the performance of visualization resolutions (zoom in & out).

c: RECOMMENDATION VISUALIZATION

In data visualization, it is highly desirable to work and involve every step of information. This technique works on the challenge to enhance the performance of visualization using automatic visualization recommendation systems and this solution plays an important role for better understanding of data insights.

2) ALGORITHMS AND DATA STRUCTURE FOR BETTER UNDERSTANDING OF DATA VISUALIZATION

a: GRAPH VISUAL ANALYSIS

Graph visual analysis is the visual representation of network data such as nodes and edges and it stores the pattern of information in the form of graph. It is an essential representation of data dealing with complex structure of information. It is significant algorithm which assists the data scientists making forecasting visual analysis effective and interactive.

b: BUBBLE SORT VISUAL ANALYSIS

Bubble sort visual analysis works on the idea sorting algorithm. This algorithm compares the adjacent pairs elements and analyse the positions before visualization. For wrong sequence of adjacent elements, this algorithm helps in swapping the positions of variable for better understanding of data visualization.

c: LINK LIST VISUAL ANALYSIS

Link list visual analysis works on a group of nodes (vertices) which make an orders (sequences). In this algorithm, each node is consisted of information and is connected to another node of sequence. For effective and interactive visualization variations such nodes (vertices) and orders (sequences) are employed as a data structure.

d: TREE TRAVERSAL VISUAL ANALYSIS

Tree traversal visual analysis works in the form of graph traverse. This algorithm is employed in each vertex (node) in the data structure (tree) for better understanding of data visualization. For checking the process of each node, this algorithm is classified into depth first search and breadth first search operations.

C. CONTRIBUTION OF THIS SURVEY

Our survey paper differs in several aspects. Therefore, the contribution of this survey article is summarised as follows.

- A comprehensive study has been reviewed on several data visualization scopes and classifications to emphasize the importance of this survey.
- State-of-the-art tools, techniques, and platforms are presented in this survey to measure, highlight, and achieve the best and most interactive visualization.
- A thorough investigation on theoretical, analytical, and data structural models and techniques is presented for better understanding and improving the performance of data visualization.
- Current primary and domain specific future challenges are reviewed, and related future research directions and opportunities are also recommended in this paper.

The structure of this article is presented in **Figure 3** and drafted as follows. Section 2 reviews the state-of-the-art tools, techniques, and platforms of data visualization. Section 3 investigates the theoretical, analytical, and statistical models and techniques. Section 4 highlights major domain specific data visualization challenges. Furthermore, related future directions and opportunities are also recommended in this section. Section 5 concludes this survey.

II. PRELIMINARIES OF DATA VISUALIZATION

Data visualization has been extensively used for data processing to generate an efficient, effective and interactive graphs, charts, and maps. In this section, we review and examine the existing state-of-the-art data visualization techniques, tools and better-performed platforms for efficient, interactive and

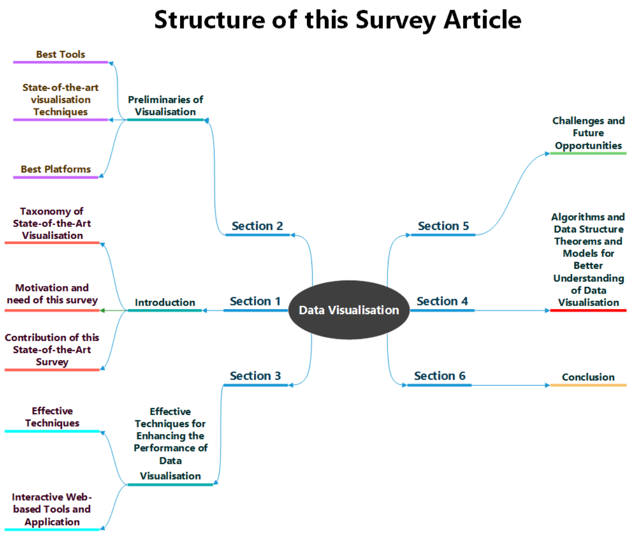

FIGURE 3. **Structure of the Article.**

effective data visualization. Firstly, we start by giving a discussion on the techniques and related effective chart, graph and map types. Secondly, we review the most commonly used tools focusing on the top three programming languages in particular Python, R and JavaScript. Lastly, we explore and present interactive data visualization platforms, which have been extensively used for interactive data visualization in academia and industries. Several contributions have already been made in the scientific society from these prospective platforms.

A. STATE-OF-THE-ART VISUALIZATION TECHNIQUES

This section discusses a brief summary of interactive data visualization techniques, tools and platforms [73]. Primarily, we divide data visualization techniques into seven (7) various groups to understand the interactive functionalities of data insights and visualize them effectively. We group them into data distribution, data correlation, data ranking, data evolution, data maps and data flow. This is demonstrated in **Figure 4**. We also classify each group according to their visualization types such as line, graph, area, plot, map, bubble, network, radial and parallel coordinates. In **Group-1**, various data points allow visualization distribution techniques which explore the relationship between various numeric variables in various perspective. In **Group-2**, the different data visualization correlation techniques are reviewed to handling the correlation of various types of data, graphs, colours interaction, visualization and its integration. In **Group-3**, the focus is on the data visualization ranking structure, various interactive environment, and visual network mining. In **Group-4**, the various data points, entities, and links are represented in a hierarchical structure to explain the relationship among nodes, edges and links as a part of a whole in data visualization. In **Group-5**, the area of data line, charts, and graphs represent the evolution of data visualization for one or numerous numeric variables to visualize the pattern over intervals of data insights. In **Group-6**, the data points are displayed to extract the specific useful information to have effective and interactive graphical map visualization. In **Group-7**, each variable is displayed as a flow or links among numerous variables and entities. The size of the visualization significance is proportional to the data linking or flow. These are the state-of-the-art and most significant visualization techniques, which have been extensively used in academia, industries, and in business corporations.

B. BEST VISUALIZATION TOOLS

Data visualization tools are useful in the advancement of data analysis and visualization. Most of the data visualization tools have effective visualization libraries that require less code to perform analysis, and to manipulate the entities of datasets. Visualization tools are used to transform the data into effective and interactive visual lines, charts, graphs, and maps and allow generating rich attractive graphics in the browser locally. These tools help to explore various univariate, bivariate and multivariate visualization methods. They also provide web-based user interfaces to facilitate interactive visualization. In this survey article, we discuss the top three programming languages (Python, R, JavaScript) and their libraries for effective and interactive data visualization which can be seen in the **Figure 5**. Therefore, our first goal of discussing interactive data visualization tools is to make easy for researchers, scientist, engineers and business analysts to understand and comprehend which language and library can create interactive and effective visual graphics for the exploratory, empirical and investigative data analysis and visualization. The second goal is to explore and present tools and related libraries that could effectively be used for generating complex and intuitive charts and plots for categorical and numerical data. In the **Table 2**, we have explored and presented the strength and effectiveness of various libraries in top three programming languages (Python, R, JavaScript) for providing better understanding of their functionalities that can provide effective, efficient and interactive visualization techniques.

C. TOP VISUALIZATION PLATFORMS

There are several data visualization platforms available today. But among them, we consider the state-of-the-art data visualization platforms on the following features: i) open-source, ii) easy to learn iii) powerful and customisable iv) require less code v) support web services vi) variety of chart, graphs, maps vii) upgrade continuously viii) higher numbers of users ix) multiple data import options and x) support dynamic data and visualization. Based on these features and characteristics, the researchers, scientist, engineers and business analysts could easily choose a platform that is more suitable according to their case studies to perform better, interactive and effective data visualization. We use **Circular Packing** visualization technique, that is presented in **Figure 6** to discuss the strengths and weakness of top data visualization platforms.

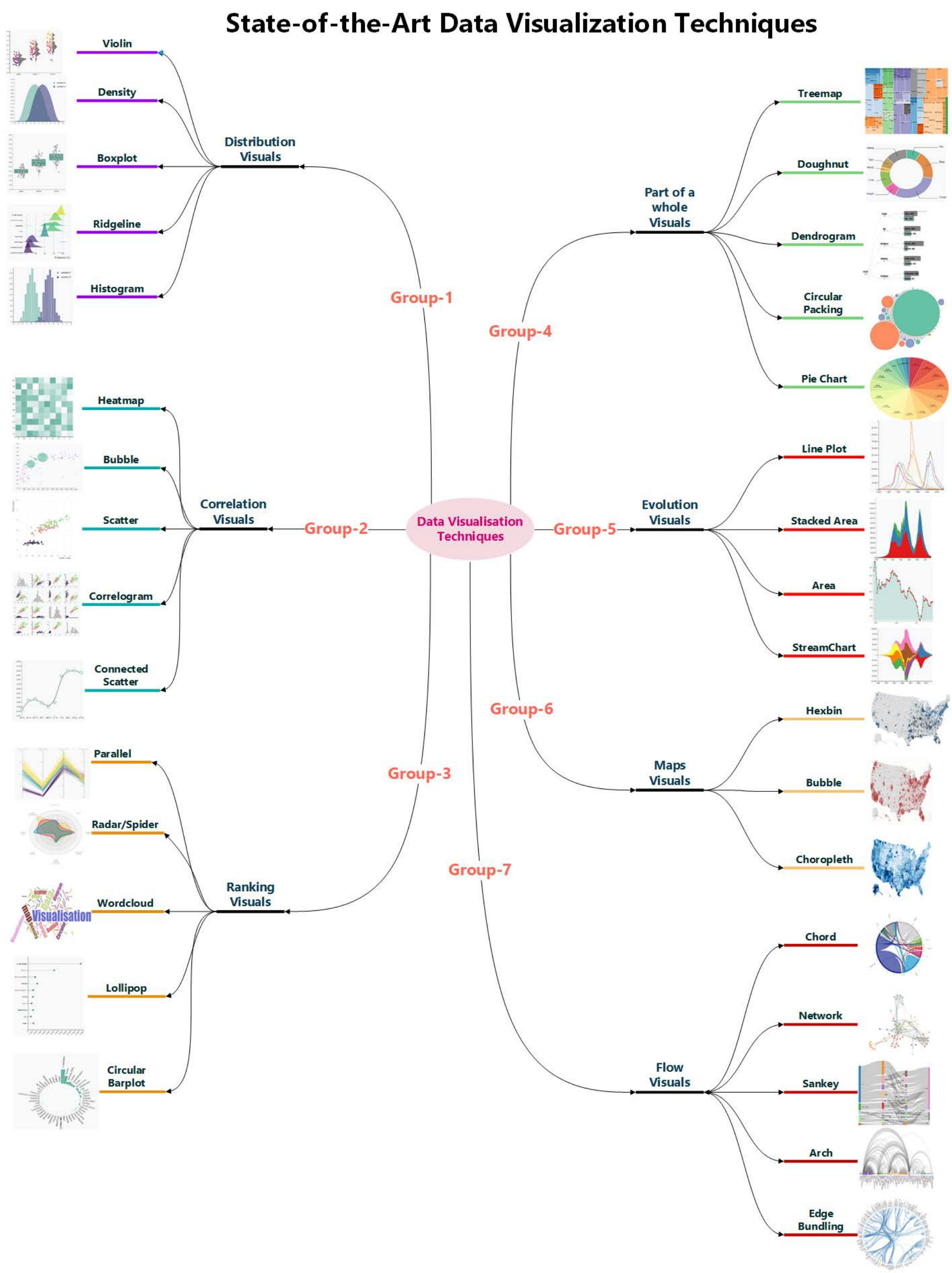

FIGURE 4. State-of-the-Art Data Visualization Techniques.

Table 3 is also helpful selecting the best platform form for future work.

III. EFFECTIVE TECHNIQUES FOR ENHANCING THE PERFORMANCE OF DATA VISUALIZATION

A. APPROXIMATE VISUAL ANALYSIS

Visual study and analysis of high dimensional information is still a challenging task. Direct visual analysis works well for few metrics such as scatterplot and parallel coordinate. However, this technique is not effective for high dimensional dataset. Indirect visual analysis is capable to work and provide better performance on the high dimensionality challenges. Aggregation queries is also crucial class for the sequence of columns values. The main issues are to manage selective arbitrary predicates and to offer thorough error guarantees without keeping the huge samples size. The effective way to provide speedy answers to aggregation queries, [97] proposed measure biased sampling scheme. They also proposed a solution for random samples aggregation. Similarly, they conducted experiments on real as well as synthetic datasets. In [98] interactive visual system developed to inspect the approximation level and analysis of

TABLE 2. Visualization Libraries in R, Python, JavaScript.

Tools	Libraries	Strength	Cite
JavaScript	D3.js	can be used without plugin.	[73]
		can manipulate HTML, SVG etc.	
		open-source library.	
	Recharts	is light to create interactive graphs, charts and maps.	[74]
		easy to use.	
		can control SVG elements.	
		can work under D3 hood.	
	Victory	can create basic charts for customization and labels for different datasets.	[75]
		easy to use and intuitive.	
		Graphs and charts can easily be modified.	
	React-vis	simple and interactive graph visualization library.	[76]
		can create interactive bar charts, maps, area, graphs etc.	
		API is relatively simple.	
		Flexible and light for creating animations.	
	Chart.js	lightweight and responsive	[77]
		can use HTML5 elements.	
		can easily combine various datasets and create interactively charts and graphs.	
	Echarts	excellent for the Web.	[78]
		can work with big datasets.	
		can support Canvas rendering and SVG.	
	TradingVue.js	simple and easy for trading.	[79]
		reactive and responsive for trading matters.	
		can create interactive charts and graphs with customizable fonts and colors.	
Python	Matplotlib	can create static, interactive, and animated visualizations.	[80]
		can control customization of charts.	
	Seaborn	can create statistical data visualization.	[81]
		suitable for exploring data.	
		can deal with univariate and bivariate distributions.	
		can visualize numerical and categorical variables.	
		can automatic plotting and estimation using regression model.	
		can create complex visualizations like multi-plot grids.	
	Bokeh	can create interactive charts and graph.	[82]
		can create interactive web dashboards.	
	Plotly	can deal with convenient functions.	[83]
		can add and use customizations.	
		can create 3D visualization.	
	missingno	can visualize the missing values and information.	[84]
		can create heatmaps and dendrograms to display correlations between missing values.	
	Folium	can create map visualizations.	[85]
		can manipulate and plot interactive leaflet map and choropleth visualizations.	
R	ggplot2	popular library used grammar of graphics.	[86]
		works on graphics language for generating interactive charts and plots.	
		can visualize both univariate and multivariate variable and entities of numerical and categorical data.	
	ggvis	can create interactive graphics for charts and plots locally.	[87]
		can leverage the infrastructure of interactive graphics.	
		can build interactive graphics for empirical, exploratory and investigative data analysis.	
	Plotly	open-source for creating interactive web-based graphs.	[88]
		can create interactive, and effective charts, plots and graphs.	
		can create, and distribute graphs, charts and maps online as well as offline.	
	VIMGUI	can visualize the imputation of univariate, bivariate, and multivariate graphs and plots.	[89]
		allow graphical user interface to implement chart and plot methods.	
	VIM	can visualize missing and/or imputed values.	[90]
		can use for exploring analyzing the data for missing and/or imputed values.	

high dimensional data for visualization. They investigated the interactive visual modification within high dimensional data without compromising the visual quality and analysis. They also highlighted that how their interactive visual system is beneficial for the real-world problems and is very supportive for the analysis of high dimensional information. Alabi and Wu [99] worked on the challenge to link visual interactivity and data volumes. They investigated the sample-based model for approximate query processing. It was explored to build approximate solution for interactive visualization. In the model, the algorithm was used to employ on linear and non-linear functions to observe the correctness and approximate answers of query approximation automatically.

Optimistic approximate queries visualization proposed in [100]. This method used to detect and investigate the approximate errors and results in an interactive way. The focus in this research work was to enhance the speed and interactivity for exploratory visual analysis. They developed a tool ''Pangloss'' which was used for multi and high dimensional datasets. They used sample-based model for the study of interactive visualization. Agarwal *et al.* [101] worked on the accuracy of ''exploratory queries'' for high dimensional

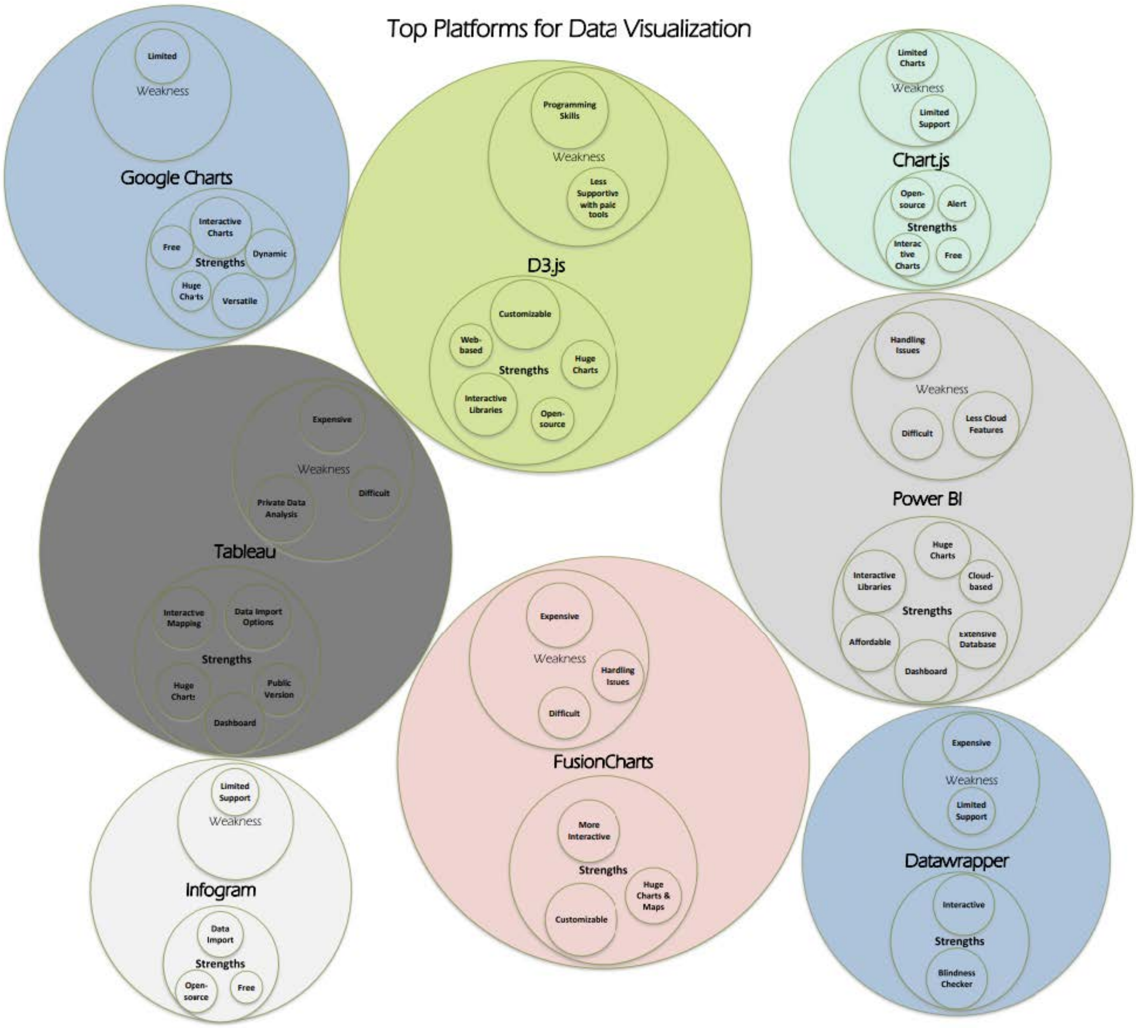

FIGURE 6. Best Platforms for Visualization.

data. In this research work, authors worked on the algorithm to diagnose the techniques that used for the error bars can sometimes be inaccurate operations. They developed a technique that can be used to validate the runtime errors for various procedure. They worked on the multiple optimization techniques for the diagnosis of the error bars and ensuring the interactivity of complete query visualization. In the end of this research article, they developed an end-to-end model using sampling for the approximation of query processing.

B. RECOMMENDATION VISUAL ANALYSIS

Recommendation system is very effective and interactive for visual analysis. Multiple recommendation systems have been developed and proposed for interactive, effective and efficient data visualization. The objective behind these recommendation systems is to uncover the hidden meanings and values of data automatically. Multiple algorithms have been proposed for recommending effective and interactive charts, graphs and maps. Several recommendation algorithms have also been proposed to highlight the errors and their solutions using statistical techniques. Zeng *et al.* [102] proposed a framework that is efficient to compare the visual algorithms recommendations for empirical and theoretical data visualization. The proposed framework works for the central connecting system to create effective recommendation for interactive visualization. The algorithm of this framework listed the best space for effective visualization and ranked the best space by comparing and approximating. The framework has three components. First is network for effective visualization, second is algorithm for recommendation system and the third one is prediction for the ranking and approximation of visualization that will be listed.

Chakrabarti *et al.* [103] proposed "rule-based" recommendation system for data visualization. In this paper, authors developed "knowledge-based" rule for effective and impartial data visualization. The proposed recommendation system used the characteristics such as user feedback and intended tasks for interactive visualization. Therefore, the article summarized its contribution into following categories; a) Data classification taxonomy for visual analysis b) Taxonomy of

TABLE 3. Best Platforms for Visualization.

Toolkits Platforms	Strengths	Weakness	Cite
D3.js	Powerful and customizable. Open-source library and works without any plugin. Requires very less code. Focus on web standards. Numerous types of charts.	Demands programming knowledge. Difficult to learn.	[73]
Power BI	Availability of cloud service. Offers a dashboard single view. Can integrate with Microsoft basic tools. Can get learning tutorials. Large numbers of users. Upgrades tools continuously. Open options for database connectivity.	Not easy to learn. Difficult for large data. Cloud service lacks important visualization features.	[91]
Tableau	Multiple visualization imports options. Available visualization mapping. Free version is public. Available learning material.	Paid versions are high-priced. Free version doesn't support privacy.	[92]
Infogram	Has free version with basic visualization features. Provides editor tool drag and drop preferences. Supports additional data visualization imports.	Supports less built-in data sources for visualization.	[93]
Google Charts	Creates online interactive visualization. Supports dynamic data with results on HTML5 and SVG. Includes variety of chart visualizations. Supports dynamic data.	Includes limited services and support.	[94]
FusionCharts	Supports dynamic visualization features. Includes variety of chart and map visualizations. Integrates multiple programming languages and frameworks.	Is costly. Overloads simple visualizations.	[95]
Datawrapper	Supports data visualization of newsroom. Supports a tool to check color blindness.	Limited options for data sources.	[96]
Chart.js	Free and open source. Supports variety of chart and maps. Alerts and responsive. compatible for cross-browser results.	Has limited visualization options. Includes limited services and support.	[77]

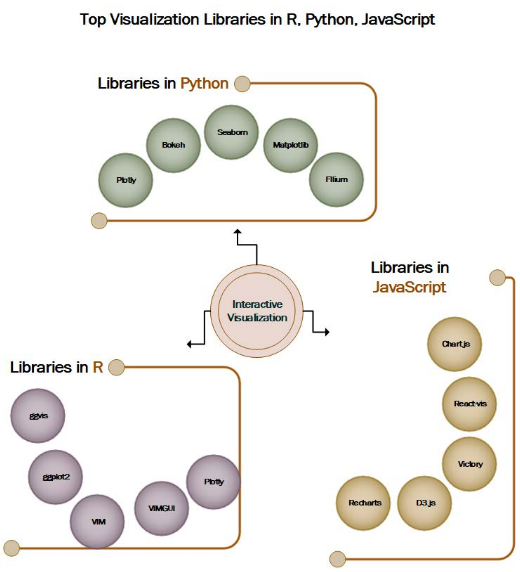

FIGURE 5. Top Visualization Libraries in R, Python, JavaScript.

mapping visual structures c) Draft rules for "knowledge-based" rule. Maruta and Kato [104] proposed a recommender system for the visual analysis of tabular data. This system was capable to predict the interactive visualization of bar charts, line, pie, networks etc. The proposed system used the statistical algorithms to visualize the intent features as well as data columns. Authors also proposed a model that was used to classify and find the essential graph columns along important parts of the targeted visualization using headers. They used neural algorithms in the model to achieve better visualization results for columns and targeted data.

Qian *et al.* [105] focused on the issue of personalized visual recommendation and developed a learning framework to provide a best solution. Explicitly, the focus was on individual user visual interactions for effective visualization. The developed framework can learn from associated visualizations from various user's experiences, although, the visualizations are generated from several datasets. Zhu *et al.* [106] is a survey article on an automatic visual and infographic recommendations. This article reviewed automatic recommendation systems and classified the visual system into the following visualizations categories such as annotation, graph, network, graph-network and storytelling. The current challenges and their future direction are also reviewed.

C. PROGRESSIVE VISUAL ANALYSIS

Investigating large volume of data requires speedy feedback from the specialist to the system. When the data becomes huge and complex, it is very difficult to analyse, and computation can no longer be finished in a required time. Therefore, the process of information investigation is severely impeded. In this scenario, a new paradigm is significant and appropriate that brings the latency level low performing

TABLE 4. Effective Techniques for Enhancing the Performance of Data Visualization.

Technique	Contribution	Evaluation	Cite
Approximate Visual Analysis	Uniform & measure-biased sampling.	proposed measure biased sampling scheme. They also proposed a solution for random samples aggregation. Similarly, they conducted experiments on real as well as synthetic datasets.	[97]
	Visual modification within high dimensional data.	They investigated the interactive visual modification within high dimensional data without compromising the visual quality and analysis.	[98]
	Explored approximate query processing model with linking visual interactivity and data volumes.	Authors worked on the challenge to link visual interactivity and data volumes. They investigated the sample-based model for approximate query processing.	[99]
	Developed a tool to increase the speed and interactivity for exploratory visual analysis.	The focus in this research work was to enhance the speed and interactivity for exploratory visual analysis. They developed a tool "Pangloss" which was used for multi and high dimensional datasets.	[100]
	Developed a technique used to validate the runtime errors.	They developed a technique that can be used to validate the runtime errors for various procedure. They worked on the multiple optimization techniques for diagnosis the error bars and ensuring the interactivity of complete query.	[101]
Recommendation Visual Analysis	Developed a framework to contextualize broad range of recommendation algorithms for visualization.	proposed a framework that is efficient to compare the visual algorithms recommendations for empirical and theoretical data visualization. The proposed framework works for the central connecting system to create effective recommendation for interactive visualization.	[102]
	Developed a knowledge-based visualization recommendation engine, that supports a huge number of visual analysis techniques.	proposed "rule-based" recommendation system for data visualization. In this paper, authors developed "knowledge-based" rule for effective and impartial data visualization.	[103]
	Developed method to predict the most appropriate visualization type based on statistical features.	proposed a recommender system for the visual analysis of tabular data. This system was capable to predict the interactive visualization of bar charts, line, pie, networks etc. The proposed system used the statistical algorithms to visualize the intent features as well as data columns.	[104]
	Developed a personalized recommendation system for past visualization interactions.	focused on the issue of personalized visual recommendation and developed a learning framework to provide a best solution. Explicitly, the focus was on individual user visual interactions for effective visualization.	[105]
	Classified automatic tool for visual recommendations into a set of various application such as network-graph and storytelling visualization.	proposed an automatic visual and infographic recommendations. This article reviewed automatic recommendation systems and classified the visual system into the following visualizations categories such as annotation, graph, network, graph-network and storytelling.	[106]
Progressive Visual Analysis	Developed a technique for multiresolution and decomposition of density map protecting the comparative data densities and outliers.	introduced "pyramid-based" sampling technique. The goal of this work was to facilitate progressive visualization. This proposed technique used to carry progressive visual analysis deal with high dimensional data in pieces and updated the scatterplot with visible and effective changes.	[107]
	developed a progressive visual model for visual representation of a data structure, with enabled user interactions.	developed a model for progressive visual analysis. The key objective of progressive visualization is an abstraction on various elements for constructing an effective visualization using constant response and interactions for computational driving.	[108]
	Developed a progressive visualizations technique for exploratory settings to interact with user behaviour for instantaneous visual analysis.	proposed three visual conditions which are progressive, instantaneous and blocking. They analysed that the p erformance and presentation were equally well and effective with either progressive or instantaneous visual analysis.	[109]
	Worked on progressive computation for visual analysis performing computations in a progressive way.	a new paradigm is appropriate that brings the latency level low performing computations in a progressive way.	[110]

computations in a progressive way [110]. Chen *et al.* [107] introduced "pyramid-based" sampling technique. The goal of this work was to facilitate progressive visualization. This work proposed technique used to carry progressive visual analysis deal with high dimensional data in pieces and updated the scatterplots with visible and effective changes. Ventocilla and Riveiro [108] developed a model for progressive visual analysis. The key objective of progressive visualization is an abstraction on various elements for constructing an effective visualization using constant response and interactions for computational driving. Zgraggen *et al.* [109] explored the impact of progressive visual analysis in empirical settings. This article proposed three visual conditions which are progressive, instantaneous and blocking. They analysed that the performance and presentation were equally well and effective with either progressive or instantaneous visual analysis. The contributions from this article are; a) progressive visual analysis outperforms blocking visualization in user activity metric and b) progressive visual analysis is similar to instantaneous visualization in many metrics. Therefore, progressive visual analysis is sustainable solution to attain scalability in exploration systems.

our aim for this section is to explore the techniques which are significant to improve the performance of data visualization. Because Visual study and analysis of high dimensional information are still needed to be investigated to meet the challenges of data scalability, aggregation and dimensionalities. In **Figure 7**, we have investigated the data visualization relation among approximate, recommendation and progressive visual analysis. We also discuss various research work for the effective techniques in **Table 5** for better performance of data visualization. In **Table 5**, we discuss the contribution and performance evaluation of each technique. Therefore, this table is helpful to provide better understanding of state-of-the-art techniques for future data visualization.

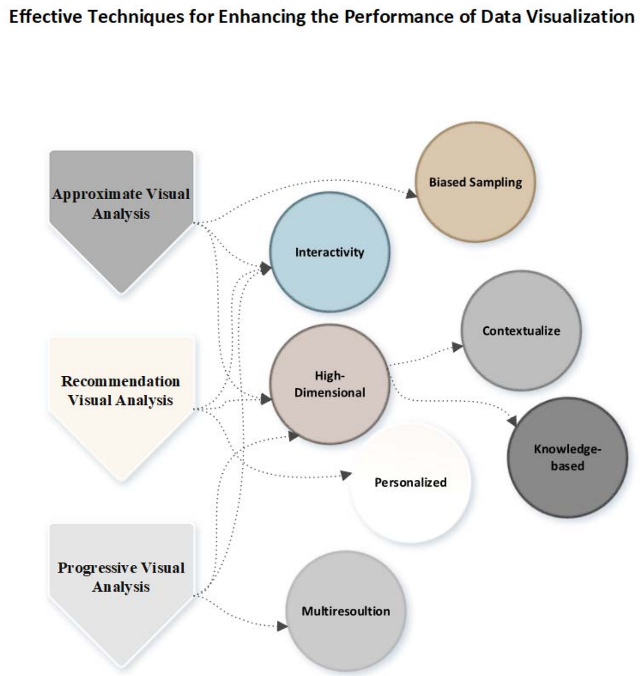

FIGURE 7. **Effective Techniques for Enhancing the Performance of Data Visualization.**

IV. ALGORITHMS AND DATA STRUCTURE FOR BETTER UNDERSTANDING OF DATA VISUALIZATION

A. GRAPH VISUAL ANALYSIS

Graph supports predefined visual analysis. Graph structures are very useful to visualize data in various domain problems. A graph can connect the objects in visualization called vertices and build relationships between objects to make visualization more effective called edges [111]. The operations of graph algorithms work for visualization are Depth First Search (DFS) and Breadth First Search (BFS) algorithm. BFS algorithm is used queuing for efficient ordering the nodes for effective visualization. DFS algorithm employs stack visualization for better explanation in order to make visualization more interactive. While working on the graph visualization with selected algorithm, the nodes must be demonstrated in a correct order during visual analysis.

B. BUBBLE SORT VISUAL ANALYSIS

Bubble sort supports predefined and interactive visual analysis. The predefined visual analysis works on the algorithm where arrays are generated randomly. These randomly generated arrays operate dynamically for visual analysis [112]. This visual analysis algorithm runs the multiple sorting algorithms such as merge sorting, selection sorting etc. This algorithm is useful for the following visualization: front end, implementation, design and assessment etc [113]. The steps in bubble sort visual analysis are operated dynamically that allow user to use custom entries to generate interactive visualization [114].

C. LINK LIST VISUAL ANALYSIS

The linked list supports both interactive and predefined visual analysis. The operations for interactive and predefined visual analysis are insert, append, prepend and remove but in the linked list append and prepend are not effective operations for interactive visualization. The aptness of append and prepend in link list are conditional on the pointer operations [115].

D. TREE TRAVERSAL VISUAL ANALYSIS

Tree traversal supports predefined visual analysis. The operations for predefined visual analysis are preorder, inorder and postorder. In this algorithm the visualization shares the similar relation and structure. Therefore, it is easy to understand this tree traversal algorithm for visual analysis [116]. According to [84] tree traversal algorithm is recursive, and an effective visualization of stack can be generated.

E. STACK VISUAL ANALYSIS

Stack supports both interactive and predefined visual analysis. The operations for the stack visual analysis are push and pop. Data structure of stack visual analysis uses stack, indexed array and pointer. The first operation is push to add new value in the stack and second operation pop uses to retrieve the value for interactive visualization [117].

V. INTERACTIVE WEB-BASED TOOLS AND APPLICATION

In the previous sections, we have already discussed and explored various data visualization tools, techniques, libraries, and platforms. However, in this section, we explore the latest web-based data visualization tools in various applications. These web-based tools deal with the huge and complex datasets quickly and easily to generate interactive visualization. These tools are recently published and easily available and accessible online. Colantoni *et al.* [119] provided a web-based edge-computing solution to handle data of spectral images with visualization interaction using Edge Computing, Spectral Reflectance Images, Hierarchical Transformation of the Information. Jin *et al.* [120] trained and implemented machine learning algorithms on datasets of Operational Taxonomic Unit (OTU) to identify and investigate key groups of taxonomic and its composition using numerical metadata by applying linear regression or a deep-neural network, Data Normalization, and User Configurable Parameters. Rodríguez *et al.* [121] developed a web-based platform for convenient histograms and contact maps display and analysis using parser module, contact map formats. Sherlock *et al.* [122] developed a platform for exploration and investigation of interactive and context-aware datasets using the client–server model of ‘‘Discrete Global Grid System’’. Qin *et al.* [123] developed an effective and interactive web-based tool for 3D visualization applications. Qin *et al.* [123] developed a web-based interactive visualizations platform for instant and convenient analysis, comparisons, and generalization. Lu *et al.* [124] developed

TABLE 5. Data Structures and Algorithms for Better Understanding of Data Visualization.

Categorization	Supported Visualization	Operations	Evaluation	Citation
Graph visual analysis	Predefined	Depth first search, Breadth first search	Standard	[111]
Bubble sort visual analysis	Predefined, Interactive	selection sort, merge sort	Standard	[112], [113], [114]
Link list visual analysis	Predefined, Interactive	Insert, Remove, Append, Prepend	Not standard	[115]
Tree traversal visual analysis	Predefined	Preorder, Postorder, Inorder	Standard	[116], [118]
Stack visual analysis	Predefined, Interactive	Push, Pop, Top	Standard	[117]

web-based real-time interactive and effective 3D weather data visualization platform using "WebGIS" technology [125]. Built an open-source interactive JavaScript platform based on WebGL for quick graph visualization large datasets using graph and layout algorithms, node connections and link. Wang *et al.* [126] developed a G6 platform for flexible usability of high template graph visualization with the implementation of graph instance, data flow, graph element, graph interaction, event graph listening, graph state style, graph interaction mode, graph layout, graph analysis algorithm and graph plugin. Bimonte *et al.* [127] developed a geovisualization platform for an effective pivot tables and map visualization using geovisualization, dimensions order, nested data spatial levels, and demo scenario. Kupssinskü *et al.* [128] developed a platform to visualize the spectra. Saska *et al.* [129] developed an open-source JavaScript library for complex datasets to visualize the features of complex networks [130]. Developed a tool for scientist and non-scientist to tackle the complexity of data through 5D multivariant data visual analytics with graph controls, data controls, and download/upload data. Nagel *et al.* [131] developed a web-based tool for exploration and investigation of sensors data about spatial and temporal dimensions. We also discussed the contributions and challenges of these web-based tools in **Table 6**.

VI. CHALLENGES AND FUTURE OPPORTUNITIES

In this section, we outline several challenges in data visualization that still need proficient expertise through advance approaches.

A. CHALLENGES

1) SCALABILITY

Scalability is a traditional challenge in visual analysis. In modern day issues, experts need to monitor, understand and visualize important information and changes in the data. The challenge is to distinguish variations in data when data changes between visualizations. Significant approaches and algorithms can be used to investigate and explore the behaviour of datasets. Therefore, data visualization shows scalability issues during planning and designing [132], [133]. It is still required to work on corresponding data variations and rendering visualization scalability issues.

2) VISUAL ANALYSIS OF SPATIO-TEMPORAL DATA

A dataset consists of a series of time variations and positions aiming at the interpretation and visualization of information pattern to recipients. Despite the current progressive resources, visual analysis seeks to improve and enhance the strategies of understanding the fundamental infrastructure of spatio-temporal data analysis. A mathematical and/or statistical approach is required to deal with modern day datasets relations and correlations algorithms. This approach will also be expected to combine distinct datasets to create an interactive and user-friendly experience and practices for spatio-temporal data [134], [135].

3) AUTOMATIC VISUAL ANALYSIS

One of the key challenges is to develop automatic data visualization techniques which assures automatic effective and interactive visualization regardless of the size and complexity of the data. Similarly, the technique facilitates to explore and investigate the interesting insights of the datasets automatically and should be able to monitor these insights uninterruptedly. Automatic visual analysis can help to solve the issues of visualization aware data searching, cleaning, integration and visualization [136], [137], [138].

4) VISUAL ANALYSIS OF DATABASE

Databases are a crucial part of the public and private sectors. Databases build special operators for optimization and effective visualization. Thus, multiple operators support to visualize huge volume datasets. Special operators assist collaborative visualization for multiple consumers using multiple smart devices at the same times. Hence, efficient and interactive visual analysis for databases is also a key challenge in modern days applications. An efficient technique is imperative to enhance the performance of visualization [139], [140].

5) FEDERATED VISUAL ANALYSIS

Privacy preservation of visual analysis is overlooked since long. Nevertheless, it is a key challenge for collaborative and promising data visualization across numerous sectors. The idea behind federated visual analysis is to reformulate the learning data framework to visual federated services. It encompasses the encrypted externalizations of translated visual aspects of datasets. There are three approaches for privacy preservation of visual analysis that have been reported. They are query-based federated visual analysis, prediction-based and multi-agent-based federated visual analysis. An efficient approach is yet to be developed for the usefulness, practicality and robustness of visual analysis [141], [142].

TABLE 6. Web-based Data Visualization Tools.

Topic (Target Visualization)	Technique/Methodology	Contribution	Challenges	Year	Cite
Web-based visualization of spectral images of vegetation	Edge Computing, Spectral Reflectance Images, Hierarchical Transformation of the Information	Provides web-based edge-computing the solution to handle data of spectral images with visualization interaction.	Issue of "Reflectance Factor Gradient" in tangent angle and false color.	2022	[119]
Interactive web-based visualization of microbiome data using machine learning (Mian)	Apply linear regression or a deep-neural network, Data Normalization, User Configurable Parameters	Train and implement machine learning algorithms on datasets of operational taxonomic unit (OTU) to identify and investigate key groups of taxonomic and its composition using numerical metadata.	Performance efficiency of large data. intuitively exploration and visualization of gene meta data.	2022	[120]
Web-based visualization of protein maps data (ConPlot)	Parser module, contact map formats	Provides a web-based platform for convenient histograms and contact maps display and analysis.	Diversity of multiple data sources. Display of multiple data tracks and patterns in images.	2021	[121]
Interactive web-based data styling using digital earth and multigrid	Client–server model of "Discrete Global Grid System"	Provides a platform for exploration and investigation of interactive and context-aware datasets.	to handle large-scale time-varying data. exploration and investigation of data-driven contents.	2021	[122]
Web-based visualization 3D framework for large-volume oceanic data	Explained multiple data layers for visualization of oceanic data	Developed an effective and interactive web-based tool for 3D visualization applications.	Issue of adoption of intermittent 3D data enhance the data analysis and 3D dynamic rendering functionalities	2021	[123]
Web-based data visualization for multidimensional data of astronomy	Data partitioning, filtering, and aggregations	Developed web-based interactive visualizations platform for instant and convenient analysis, comparisons, and generalization.	Issue of dimensionality and marginalization. Issue of multiple data sources integration.	2021	[124]
Web-based interactive visualization of large datasets of weather	Data parsing, Data layering, Data segmentation, Data transformation for 3D tiles, Coordinate transformation	Developed web-based real-time interactive and effective 3D weather data visualization platform using "WebGIS" technology.	Challenge of complex data patterns and structure for 3D. Challenge of dynamic visualization for meteorological datasets.	2021	[125]
Web-based visualization of graphs and networks (NetV.js).	Graph and layout algorithms, Node connections and link	Built an open-source interactive JavaScript platform based on WebGL for quick graph visualization large datasets.	Challenge of efficient and interactive large graph datasets. Challenge of heterogeneous graphs visualization.	2021	[126]
Web-based visualization library for graph (G6).	Graph instance, Data flow, Graph element, Graph interaction, Event graph listening, Graph state style, Graph interaction mode, Graph layout, Graph analysis algorithm, Graph plugin	Developed a G6 platform for flexible usability of high template graph visualization.	The following are the challenges; Element Customization, State Management, Interaction Modes, Graph Layout etc	2021	[127]
Web-based visualization tool for map queries (Map4OLAP).	Geovisualization, Dimensions order, Nested data spatial levels, System implementation, Demo scenario	Developed a geovisualization platform for an effective pivot tables and map visualization.	the order of dimensions nested spatial levels.	2021	[128]
Web-Based platform for Hyperspectral Data visualization (Vizspectraldata).	visualization, organization, and processing of spectral curves	Developed a platform to visualize the spectra.	Challenge of efficient and interactive datasets. Challenge of heterogeneous data visualization among peers.	2021	[129]
Web-based visualization of large networks (ccNetViz).	Core features, Animation features, Dynamic features	Developed an open-source JavaScript library for complex datasets to visualize the features of complex networks.	Challenge of nodes versatility, edge bundling, and canonical representation. Customization issue.	2020	[130]
Web-based interactive visualization of big data (Wiz).	Graph controls, Data controls, Download/upload data	Developed a tool for scientists and non-scientist to tackle the the complexity of data through 5D multivariant data visual analytics.	Challenge of investigating the relationships among complex datasets .	2020	[131]
Web-based visualization of uncertain spatio-temporal data (cpmViz).	PostgreSQL/PostGIS, node backend, REST interface, TypeScriptand, d3.js	Developed a web-based tool for exploration and investigation of sensors data about spatial a nd temporal dimensions.	Challenge of interactivity of complex datasets for spatial and temporal dimensions.	2019	[132]

6) COGNITIVE VISUAL ANALYSIS

Cognitive visualization deals with complexity and uncertainty in visualization. Cognitive visual analysis is useful for the alignment of theoretical and map framework and to enhance the performance of visualization in the data learning process. It can learn, develop the strange pattern of data and increase the interactivity of visualization. The visual cognitive modelling is still a challenge to work on observable data and to reconstruct the complex issues [143], [144], [145].

7) PROVENANCE VISUAL ANALYSIS

The extraction of contextual data for visualization with prominence reasoning is a key challenge. Extracting required information from datasets involve the approaches such as conceptualization, summarization, querying, comparisons and visualization. Several techniques have been proposed for provenance visual analysis. But it is still required to evaluate, summarize and compare the provenance data and discover related solutions [146], [147], [148].

8) BIG DATA VISUAL ANALYSIS

The challenges of big data visualization are still existed. They are directly linked with the volume, variety, velocity, veracity, scalability and interoperability of domain specific data. The big data needs more space and memory, hence requires a platform that could potentially store large datasets which is still a key challenge. For big data visualization, the designing of structures, working on multiscale variables and to visualize the whole pattern of information are still daunting tasks to perform. Multiple user datasets need special care to deal, and scalability is directly linked with the large datasets [149], [150], [151], [152], [153], [154], [155], [156].

9) INTERNET OF THINGS VISUAL ANALYSIS

The challenges of big data visualization are still existed and need to deal with the volume, variety, velocity, veracity, scalability and interoperability of domain specific data. The big data needs more space and memory, and it demands the platform that store large datasets which is still a key challenge. For big data visualization, the designing of structures, working on multiscale variables and to visualize the whole pattern of information are still daunting tasks to perform. Multiple user datasets need special care to deal, and scalability is directly linked with the large datasets [157], [158], [159], [160]

10) MACHINE LEARNING VISUAL ANALYSIS

The algorithms of machine learning have the ability to learn, adapt, analyse, and reason to create the best visualization. The integration of machine learning algorithms with visualization can strengthen the feature prediction and enhance the decision-making process of visualization [132], [155], [161], [162].

B. FUTURE WORK

1) CONCEPTUAL FRAMEWORK FOR VISUALIZATION OF SMART HOUSE DATA

For the purpose of good research work, a two Storey Smart House facility will be used as a test bed to learn, investigate, plan, and develop distributed algorithms for effective and efficient visualization and carry out new ideas for the application of data analytics and visualization for smart houses and buildings. This facility will also be used as a data collection hub for future research work. This research facility will be a wonderful opportunity for collaboration work among public and private sectors that will help us to learn and collaborate with professionals nationally and internationally. Smart sensors and technologies are installed and used for construction as well as to monitor and control the indoor environment and gadgets for smart houses and buildings. The purpose of our research work is to design and develop a web based real time visual analytics platform using data from Smart house Building. A visual platform will be used for visualizing the quality of the indoor environment to become more efficient and environmentally friendly. This platform will also be used to help in the construction of high-quality buildings. This is a good opportunity for us to focus and work on the issues and challenges that have been faced by various stakeholders like Government and Energy Providers, Smart Housing Agencies and Smart house Builders etc. This work is also a good opportunity for us to collaborate with various stakeholders to explore, highlight and work on the solutions they are looking for. In our research, we intend to tackle the challenges addressed in this area. Consequently, we propose an efficient real time visualization platform. **Figure 8** illustrates the conceptual framework of the proposed visualization platform. The conceptual framework consists of four (4) components including: 1) sensors layers, 2) gateway, 3) data storage and processing and 4) data visualization. In sensors layer, nodes will be deployed to sense data, while mobile agent will be used for efficient data collection from sensors [163], [164]. The mobile agent will introduce a dynamic itinerary planning mechanism [165], [166], [167] using intuitionistic fuzzy logic where ranking will be based on various use case scenarios. It will also avoid node failure during MA migration. Gateway will be used for sending data for further processing and storage before visualization. Finally, data will be visualized to the end user using a novel visualization technique.

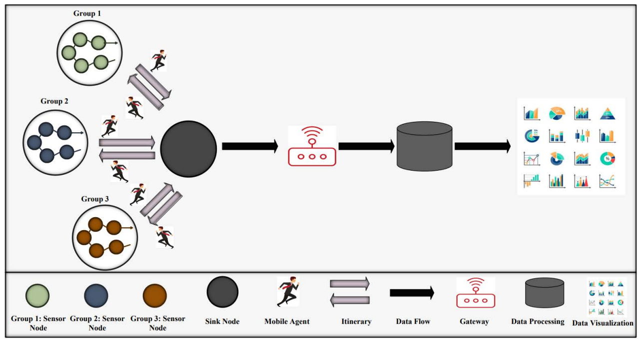

FIGURE 8. Conceptual framework for data visualization.

VII. CONCLUSION

With the thorough investigation of last five years data visualization articles at first, we concluded that a comprehensive study is still missing about interactive, effective and efficient data visualization tools, platforms, best performance theories, data structures and algorithms. We conducted a thorough investigation to fill the gap on theoretical, analytical, data structural models and techniques for improving the performance of visualization. The taxonomy of each visualization scope aimed to draw the visualization in a clear, smart and persuasive way to assist the decision makers to conclude the decisions with no time. Interactive visualizations can be useful even for non-professional customers to make graphs and charts significant to take decisions succinct. With the advantages of people's natural affinity to interactive and effective visualization, it is easy to produce insights and hidden values that are helpful to take better-informed decisions. With these benefits, data visualizations have been widely applied across all sectors.

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