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Data Visualization Technologies in Customer Relationship Management: A Methodological Review

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Abstract: Data visualization is integral to customer relationship management (CRM), facilitating comprehension, interpretation, and presentation of customer data effectively. It aids in under-standing customer interactions, identifying behavioral trends, and informing business decisions. This paper conducts an extensive literature review synthesizing insights from 22 carefully chosen journal articles, categorizing them into data visualization management stages: collection, preprocessing, storage, processing, analysis, and visualization. Various tools, techniques, and processes identified in the literature offer a comprehensive view of current methodologies and technologies. Beginning with data collection from diverse sources, including databases and surveys, the process progresses to preprocessing, involving techniques such as data normalization and cleansing. Storage emphasizes data confidentiality and integrity, utilizing encryption and digital watermarking. Real-time manipulation occurs through an Extract-Transform-Load process in data warehousing. Python and R are prominent tools for data analysis, employing techniques like data mining and opinion mining. In data visualization, real-time multidimensional analysis software and 3D methods cater to terminal devices, enhancing data comprehension through spatial relationships. Future research avenues include exploring real-world applications, advanced predictive analytics, interactive visualization techniques, integrating WiFi sensors, tag cloud diagrams, and leveraging business intelligence in data visualization technologies. Such endeavors promise to advance CRM practices and deepen insights into customer behavior.

Keywords: Data Visualization, Visualization, Customer Satisfaction, Customer Relationship Management, CRM

1. INTRODUCTION

Nowadays, as complex data sets continue to grow, effective data visualization has become key for businesses to manage and make sense of the vast pool of data. Such visualizations, essentially designed graphics, show data to allow one to gain insights, enhance understanding and allow for the identification of patterns, trends, or anomalies more quickly, fostering engaging discussions [1], [2], [3], [4], [5], [6]. Serving dual purpose in human information processing and decision-making, data visualization aims to offer a visually interactive way to present data, and to provide methods for data analysis, pattern discovery, and derivation of actionable insights for informed decision-making [2], [3], [7], [8]. In fact, data visualization, as a unique communication method, finds application in various domains, including the creation of organizational dashboards and reports for swift information assimilation. The business community identifies a number of key factors for their effective use, including prioritizing efficient, accurate, aesthetically appealing, and adaptability [3], [9], [10]. Some organizations differ in their approach to these tools, some develop their own software systems, while others opt for existing packages, ranging from open source to commercial offerings. Notable among these are programs like Tableau, Infogram, ChartBlocks, Datawrapper, Google Charts, QlikView, and SAS Visual Analytics. However, the adoption and implementation of these techniques face challenges, including cultural resistance, decision-makers' conscious and unconscious bias, and technology acceptance issues. Additionally, architectural concerns such as proximity measures, overlapping interests, rendering resolutions, and the scaling of axes,

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colors, and parameter weights present significant hurdles [3], [8]. One of the most significant human-related barriers found is the organizational resistance to change when it comes to adopting new and potentially unfamiliar visualization types [9]. Despite the advancement in data visualization technologies, there is still a lack of understanding how organizations can effectively adopt and integrate these tools for evaluating their datasets.

Adopting and integrating recent data visualization are crucial for maintaining and enhancing customer relationships as they are among the major considerations that businesses make. Customer Relationship Management (CRM) is the practice aimed at developing and sustaining profitable customer engagements and connections by delivering superior customer value and satisfaction, thereby improving business relationships with customers [2], [12], [13], [14]. CRM is integral to organizations as it addresses their customers interactions, business processes, and technology [15]. One of the key features of CRM is its ability to visualize a vast data collection to identify patterns, assisting business organizations in decision-making. In view of this, the strategic implementation of data visualization process, tools and technologies is essential in strategic decision-making processes, which are fundamental for the ongoing development and nurturing of customer engagements. This visualization is typically classified into three broad categories; information visualization, scientific visualization, and software visualization. Each category plays a unique role in the interpretation and utilization of complex and vast datasets within the realm of CRM.

As a result, there has been an increase in scholarly publication focusing on the implementation of visualization technologies across a wide array of business sectors and industries. However, despite the increase, there remains a scarcity of research on the specific implementation of visualization that is particularly used in CRM. Thus, this paper examined various data visualization technologies, encompassing a range of platforms, tools, techniques and processes dedicated to generating visual data representation. Specifically, a key issue identified is the absence of standardization in existing studies that explore data visualization related to CRM, such as in areas like customer segmentation or predictive analysis. To fully leverage the advantages of these techniques, it is essential to understand how they fit into and enhance overall CRM strategy and system [18], [19]. Thus, there is an evident need for a more comprehensive review and synthesis of the existing literature to better understand data visualization technologies employed in CRM and how different industries utilize them to enhance their operations. Moreover, the implementation of the visualization technologies may face several challenges, including reluctance among developers to take the time to become acquainted with data visualization and do not consider it worthwhile, as well as the feeling of apprehension about transitioning from old systems to newer technologies despite them being more efficient and accurate [15], [16]. Additionally, the use of CRM may require more leadership direction, an understanding of leveraging the tools and technologies effectively and an assessment of the efficiency improvements in comparison to the expense of deploying the software [1]. Addressing these challenges is critical and, with careful planning, the adoption of visualization technologies in organizations can be greatly facilitated.

Therefore, building on the identified need for understanding the broader context of data visualization research within CRM, this paper aims to provide a comprehensive review of related literature on the different methods for integrating data visualization technologies. This review aims not only to offer valuable insights into current methodologies that can be utilized within management systems, but also to propose recommendations for future research directions to bridge the identified gaps in the existing literature. Also, this paper intends to highlight the practical application for a range of professionals, including developer, data visualization implementers, technology providers, CRM implementers, CRM managers and Information Systems researchers. By providing a detailed synthesis of existing studies, this paper can enrich the current body of knowledge, focusing on the use of data visualization in CRM.

2. MATERIALS AND METHODS

2.1. Literature Profiling

Nowadays, as complex data sets continue to grow, effective data visualization has become key for businesses to manage and make sense of the vast pool of data. Such visualizations, essentially designed graphics, show data to allow one to gain insights, enhance understanding and allow for the identification of patterns, trends, or anomalies more quickly, fostering engaging discussions [1], [2], [3], [4], [5], [6]. Serving dual purpose in human information processing and decision-making, data visualization aims to offer a visually interactive way to present data, and to provide methods for data analysis, pattern discovery, and derivation of actionable insights for informed decision-making [2], [3], [7], [8]. In fact, data visualization, as a unique communication method, finds application in various domains, including the creation of organizational dashboards and reports for swift information assimilation. The business community identifies a number of key factors for their effective use, including prioritizing efficient, accurate, aesthetically appealing, and adaptability [3], [9], [10]. Some organizations differ in their approach to these tools, some develop their own software systems, while others opt for existing packages, ranging from open source to commercial offerings. Notable among these are programs like Tableau, Infogram, ChartBlocks, Datawrapper, Google Charts, QlikView, and SAS Visual Analytics. However, the adoption and implementation of these techniques face challenges, including cultural resistance, decision-makers' conscious and unconscious bias, and technology acceptance issues. Additionally, architectural concerns such as proximity measures, overlapping interests, rendering resolutions, and the scaling of axes, colors, and parameter weights present significant hurdles [3], [8]. One of the most significant human-related barriers found is the organizational resistance to change when it comes to adopting new and potentially unfamiliar visualization types [9]. Despite the advancement in data visualization technologies, there is still a lack of understanding how organizations can effectively adopt and integrate these tools for evaluating their datasets.

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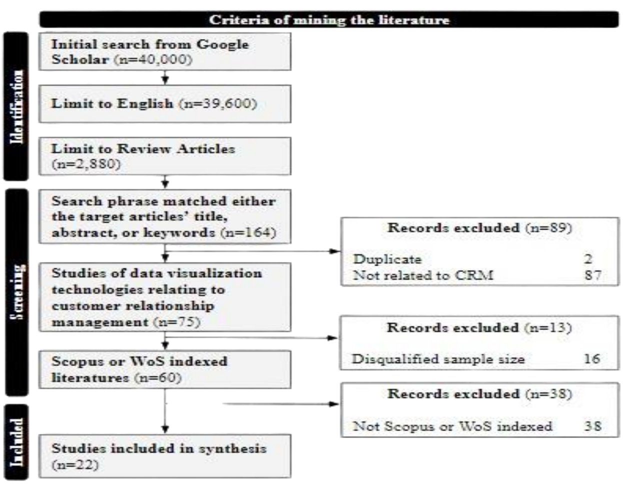

Figure 1. PRISMA Flowchart

After finalizing the sample size, a detailed profiling of the selected journal articles was conducted to understand their content and context. Each article was thoroughly scrutinized and tallied to come up with a profile, which included analyzing publication details, methodologies, publication year, country of origin, and authors' backgrounds. In addition, the SCImago Journal Rank was referenced to verify the reliability of the journals, providing further insights into their subject areas and categories.

2.2. Analysis of CRM Data Visualization Methods

The analysis of methodologies of the 22 journal articles involved categorizing them into five sub processes of data visualization. This framework is a tool used to evaluate the effectiveness of different methods, with the following subprocesses: (1) data collection, (2) data preprocessing, (3) data storage, (4) data processing and analysis, and (5) data graphing [24], [25]. As shown in Figure 2, the categorization framework assists in documenting each step to ensure comprehensive and accurate information reporting. The methodologies gathered, using the Journal Approach Matrix, are considered as tools, techniques, and processes, each essential for analyzing the subprocesses. In other words, these three perspectives were used to analyze each subprocess, which is a critical step towards effective data representation and interpretation. The initial step, data collection, serves as the foundation upon which the entire visualization process is built. As emphasized by [26], the quality of visualization outcomes is inherently dependent on the precision and relevance of the raw data. However, raw data, often existing in domain-specific formats, is challenging to work with directly [27]. This leads to the subsequent subprocess, data preprocessing, which involves meticulously cleaning and formatting of data to ensure its suitability for further analysis. This stage not only maintains data integrity but also preserves its inherent characteristics [26]. Concurrently, data storage plays a crucial role. It entails managing and organizing data in a scalable manner that aligns with the requirements of various data-reliant applications [28].

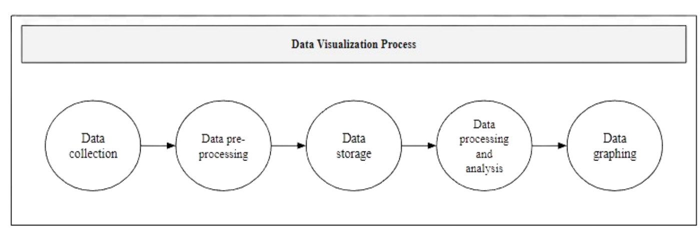

Figure 2. Data Visualization Process

Next, the processed data enters the phase of data processing and analysis, marking the fourth subprocess. This phase, as identified by [29], delves into understanding the impact of data processing and analysis techniques on the overall effectiveness of the system and involves visualization transformation, where data is refined from analytical abstractions to visualization abstractions or graphical representations. The final phase, data graphing takes center stage as the fifth subprocess. It involves the selection of appropriate visualization modes and chart types, promoting the creation of innovative graphs, and upholding visual continuity for efficient data processing. This subprocess is enhanced by view transformations, adjusting aspects like position, rotation, and scaling [27]. In essence, these subprocesses are interconnected, whereby each subprocess is dependent on the accuracy and efficiency of the preceding ones. From data collection to graphing, each phase contributes to the overall process, culminating in the synthesis of insights and understanding. Without accurate data collection, subsequent phases like preprocessing, storage, and analysis would be compromised, highlighting the synergistic nature of these subprocesses.

A combination of inductive and deductive qualitative coding was used to identify the themes within the identified studies which involved the depth examination of the data, assigning specific codes to each piece of information [19]. The codes facilitated the grouping of similar pieces of information, allowing the identification of patterns and themes in the data. Once the coding was completed, more detailed data analysis was carried out, connecting themes across the selected journal articles and drawing key conclusions. Qualitative coding is an important part of any review, as it allows researchers to gain deeper insights into their data and draw meaningful conclusions from the data. The review evaluated the various aspects of data visualization technologies, including tools, techniques and process encompassing data collection, preprocessing, storage, analysis and visualization following approaches utilized and recommended in previous studies.

2.3. Research Gap Analysis

This paper applied qualitative coding to organize and categorize the conclusions and recommendations of the 22 selected journal articles into themes. The categories were then used to construct initial codes, which included keywords commonly addressed in each article's conclusion and recommendations. The codes were then validated and finalized by careful and rigorous evaluation of the studies, confirming that they accurately reflected critical information and details concerning data visualization in CRM. Following an exhaustive synthesis of the selected literature, research gaps related to data visualization were identified. These gaps were then aligned with the problem statement and objectives of this paper, highlighting any significant gaps in the literature. Some of the gaps related to over reliance on theoretical models, an apparent lack of open-source platform/program, and insufficient evaluation of tools, techniques, methods and processes used in data visualization.

3. RESULTS

3.1. Literature Profiling Results

The earliest research publications related to data visualization found in the sample literature were from 1996, with fewer than two publications per year until 2014. Since then, there has been significant growth in the number of publications on data visualization, as illustrated in Figure 3. This could be due to the continual growth in the amount of digital data accrued from various sources, driving the need for businesses to use innovative data management and reporting methods. The emerging data sources emphasize the demand for varied and dynamic visualization types and techniques in the field of visual analytics to generate insights [11].

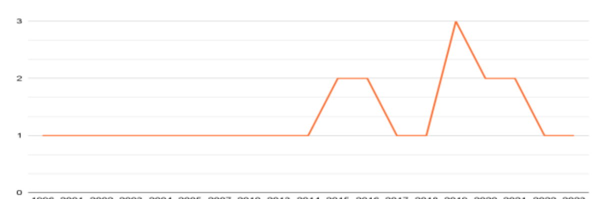

Figure 3. Publication Per Year

Despite the growth of big data and the apparent critical role of data visualization technologies in CRM software, the research in this area remains limited. Table 1 shows the number of articles per country, with the United States ranking as the most investigated country in the selected literature sample with seven journal articles (31.82%) out of 22. This could be attributed to the fact that the USA is more advanced in innovation and technology, including data visualization, compared to any other country. The United Kingdom follows in the next rank with three journal articles (13.64%), and both China and Japan with two journal articles each (9.09%). Other countries represented with one publication each including Greece, Jordan, Italy, Australia, South Korea, Malaysia, Hong Kong/China, and Malaysia/Indonesia, collectively contribute eight journal articles (36.36%) to the literature sample.

Table 1. The Research settings of the prior studies

Item	Pre-2010	2011-2013	2014-2016	2017-2019	2020-2023	Total
Methods–						
Qualitative	2	1	2	2	2	9
Quantitative	2		2	2	4	10
Qualitative and Case Study	2			1		3
Countries–						
The USA	3		2	1	1	7
The UK	1	1		1		3
China					2	2
Japan			1		1	2
Greece			1			1
Jordan				1		1
Italy					1	1
Australia				1		1
South Korea	1					1
Malaysia				1		1
Cross-country*	1				1	2

Prior studies have identified 24 various areas of expertise among researchers, with each research article featuring up to three different areas of expertise. Notably, three research experts are mentioned in at least two research articles [17], [24]. Figure 4 shows that there are three prominent areas of expertise, including Informatics, Art and Design, and Computer Science and Engineering, with the highest concentration being 4 researchers from 3 different journal articles [17], [30], [31]. The findings from the analysis also highlighted the prominence of Informatics, Marketing, and Computer Science and Engineering as key areas of expertise in these studies [17], [30], [31], [32], [33], [34].

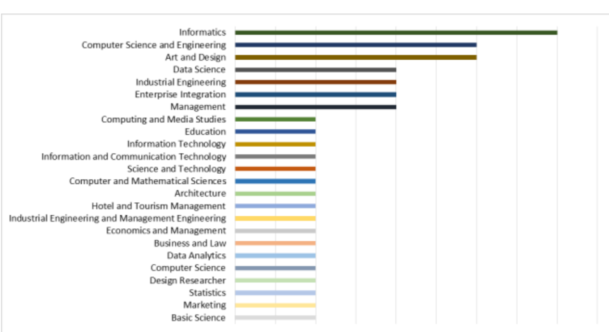

Figure 4. Research Areas of Expertise

The journal articles were categorized according to their subject area and category. There are a total of 38 subject areas. As depicted in Figure 5, Computer Science emerged as the most represented subject with 17 papers (44.74%), followed by Engineering with six papers (15.79%). Business, Management, and Accounting ranked third with four papers (10.53%). The remaining (28.95%) were distributed among Decision Sciences (three papers, 7.89%), Mathematics (three papers, 7.89%), Physics and Astronomy (two papers, 5.26%), Economics (two papers, 5.26%), and Social Sciences (one paper, 2.63%). The majority of articles fell under the area of Computer Science (17 papers) [6], [17], [24], [25], [32], [33], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], of which two were from IEEE Transactions on Visualization and Computer Graphics [33], [38]. Moreover, the categories of Computer Vision and Pattern Recognition, Computer Networks and Communications, and Computer Science, each feature the most papers (5 papers in each category) [6], [17], [24], [35], [43], [44], primarily falling under the broader Computer Science category, as shown in Figure 6.

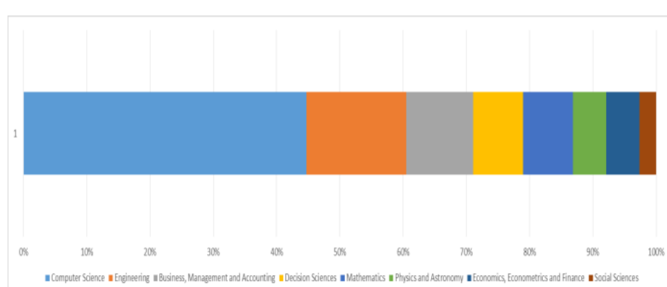

Figure 5. Journal Subject Area

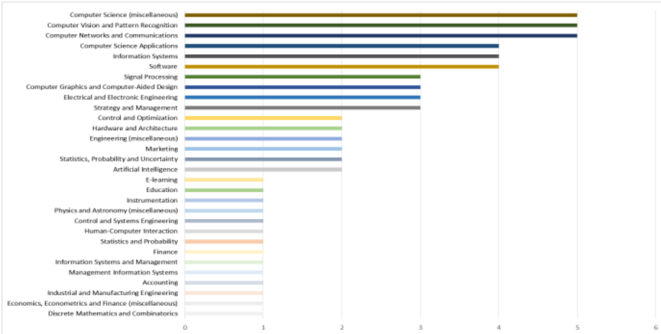

Figure 6. Journal Category

the studies, they focused on data sources of the visualization systems, identifying sources such as [24], [25], [33], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [46], [48], [49] analysts, web server logs, facilities, WiFi-enabled devices and RFID, printed service reports, emails, messages, and chat sessions from social network interactions for gaining insights into the performance of a system. These sources ranged from operational data in spreadsheets, databases, and text files from servers. Facilities can provide rich information on customer databases, survey databases, transaction databases, customer contact centers, customer surveys, and voice of the customer (VOC) databases. WiFi-enabled devices and RFID were used to collect data. Printed service reports, emails, messages, and chat sessions from social network services can also provide valuable insights into customer behavior. This allows for quick and accessible data from multiple sources for more comprehensive analysis and insights into system performance and customer behavior.

Table 2. Data Collection Tool

Data sources	**Journal ID**
computer programs	**8** [25], [35], [36], [37], [39], [40], [42], [43]
archival records	**3** [24], [41], [48]
surveys	**2** [33], [42]
observations	**1** [38]
hardware	**1** [44]

3.2. Methodology Analysis

The literature synthesis aimed to identify the tools, techniques, and processes used in data visualization, while also enabling a better understanding of the published journal articles. The 22 qualified articles underwent a detailed synthesized and coding to identify important characteristics of the studies. This was followed by an analysis and interpretation of results. Summaries of findings in each subprocess are described in the subsequent sections.

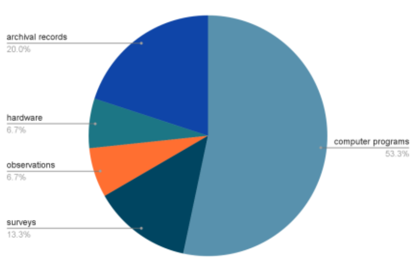

Figure 7. Data Collection Tools, Techniques, or Processes

Data collection, as the initial process in data visualization, involves gathering data from various sources such as databases, surveys, and other sources [25], [39], [46], [47] as shown in Figure 7. 16 out of 22 studies discussed the data collection process of their data visualization system, and upon synthesizing

DATA PROCESSING

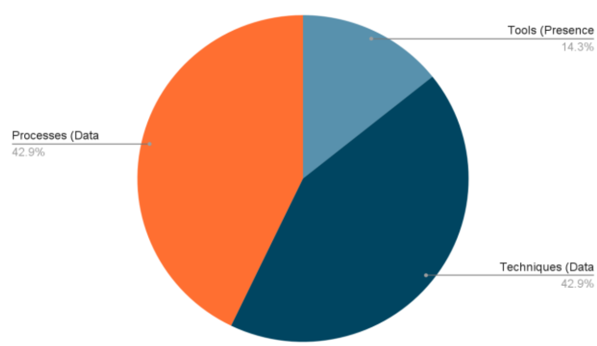

Figure 8. Data preprocessing tools, techniques, or processes

Table 3. Data Preprocessing tools, techniques, or processes

Data pre-processing	**Journal ID**
Tools	
Presence Zones server	**1** [43]
Techniques	
Data normalization	**1** [24]
Oversampling (SMOTE)	**1** [35]
Factor analysis	**1** [42]
Processes	
Data parser	**1** [45]
Data cleanser	**1** [45]
Adding additional fields	**1** [41]

Data preprocessing for data visualization, essential for preparing data analysis involves cleaning and formatting the data, was discussed in 12 studies [24], [32], [35], [36], [38], [40], [41], [42], [43], [45], [46], [49]. Two (2) out of 12 studies mentioned what they used in preprocessing, such as SQL and Java using java.util.Iterator [32], [45]. Six (6) out of 12 generally addressed preprocessing in a data visualization system, highlighting activities like extracting key indicators, dividing them into primary and secondary indicators, and splitting them into different dimensions for further analysis. The remaining six studies delved into more specific preprocessing methods. For example, 1 study discussed data normalization, a process of transforming data into a common format to allow for more accurate comparison and analysis in an operation [24]. Another study implemented oversampling methods like SMOTE (Synthetic Minority Over-sampling Technique) to ensure balanced data distribution with varying percentages [35]. Tools like data parsers and cleansers were also employed to examine features and remove irrelevant data from the dataset respectively [45]. Techniques such as factor analysis were used to reduce datasets with many variables [42]. Advanced algorithms were implemented in the Presence Zones server to enhance the quality and accuracy of raw data and overcome challenges related to that matter [43]. Additionally, some studies included additional fields for actual and required sequence numbers to improve the manageability of the data by eliminating periodicity [41].

DATA STORAGE

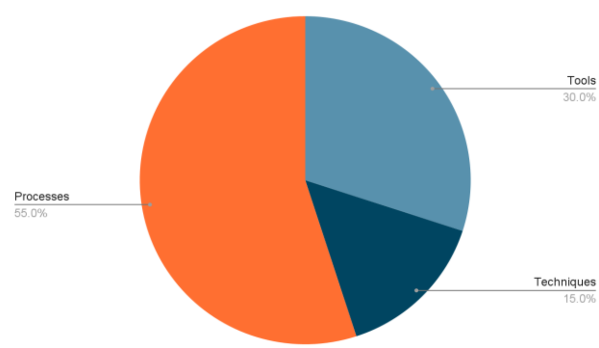

Figure 9. Data Storage Tools, techniques, or processes

Data Processing and Analysis

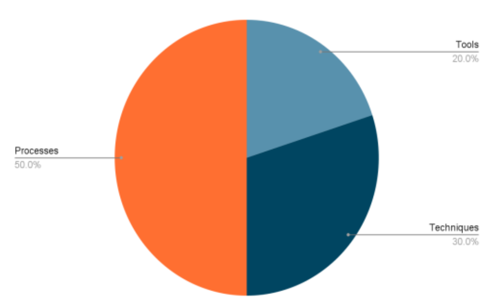

Figure 10. Data Processing and analysis tools, techniques or, processes

Table 4. Data Preprocessing tools, techniques, or processes

Data storage	**Journal ID**
Tools	
Storage Technologies	**3** [25], [40], [49]
Data Protection Technologies	**1** [25]
Database Management	**1** [42]
Data Integration	**1** [43]
Techniques	
Real-time Manipulation and Correlation	**1** [40]
Data Warehouse	**1** [43]
Log Case Complaint System	**1** [24]
Processes	
Importing Processed Data into Databases	**9** [32], [33], [37], [39], [41], [42], [45], [48], [49]
File Input Streams	**1** [45]
Caching Frequently Used Extracted Database Information	**1** [45]

Data processing and analysis, involving the examination of data to gain insights into patterns, trends, correlations, and other useful information, often employs statistical methods such as regression analysis or machine learning algorithms. This phase is critical for extracting meaningful information from data stored in a database. Eighteen (18) out of 22 studies discussed the data processing and analysis process [6], [24], [25], [32], [33], [36], [37], [38], [39], [40], [41], [42], [43], [46], [47], [48], [49], [50]. One (1) study highlighted a system that provides a unified interface for connecting to and querying any SQL RDBMS (Relational Database Management System) using ODBC (Open Database Connectivity) or JDBC (Java Database Connectivity) drivers [32]. Tools like Python and R language are used for analyzing the data, allowing users to identify patterns and trends, extract customer opinions, and perform statistical analysis [25]. Additionally, data mining techniques are employed to derive key factors or significant insights into customer characteristics and needs, while opinion mining techniques are utilized for gathering customer opinions from the stored data, with subjective logic managing the extracted opinions with different degrees of uncertainty [42]. Some studies have mentioned the use of an incremental big data processing system to either process the entirety of the data or refine it for further analysis [6].

Table 5. Data Processing and analysis tools, techniques, or processes

Data processing and analysis	Journal ID
Tools	
Database Connectivity (ODBC, JDBC)	**1** [32]
Programming Languages (Python, R Language)	**1** [25]
Techniques	
Data Mining	**1** [42]
Opinion Mining	**1** [33]
Subjective Logic Handling	**1** [33]
Processes	
Analyzing data to identify patterns and trends, extract customer opinions, and perform statistical analysis.	**3** [33], [39], [50]
Deriving key factors from customer characteristics and customer needs.	**1** [42]
Incremental big data processing system or data reduction system to process the entire data or clean it for further analysis.	**1** [6]

DATA GRAPHING

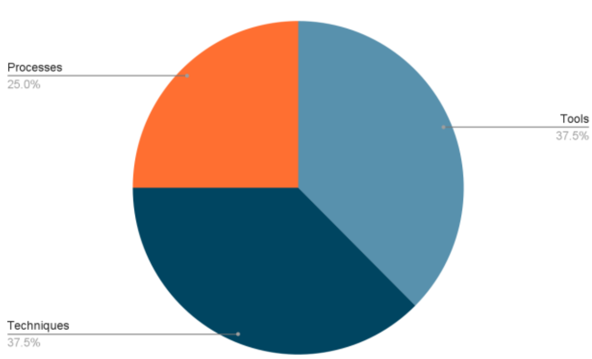

Figure 11 Data graphing tools, techniques, or processes

Data visualization involves creating visual representations of the data to enhance understanding and interpretation, often through creating charts, graphs, maps, or other visualization forms. All 22 studies in the sample discussed their approaches to data graphing process [6], [24], [25], [30], [32], [33], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [48], [49], [50]. One (1) of the studies focused on graphing software, which provides users with real-time, multidimensional data analysis capability, allowing for effective analysis of complex marketing, financial, statistical, and other data available today in a manner they claim is more effective than looking at numbers or charts/graphs [30]. Another study demonstrated the use of 3D visualization in real-time on terminal devices, transforming data into visual representation [36], based on choosing the correct chart type and adding graphs. This process includes clarifying data using spatial relationships, maintaining page integrity and organizing display charts according to established business indicators, and reflecting the distinction between the primary and secondary, improving delivery efficiency [46]. Innovative visualization techniques such as tree maps, violin plots, and interactive social media-based visualizations were used to communicate sustainability concepts to potential consumers [48]. A study discussed a system that enables real-time interactive visual data mining through a web browser with Java activation [40], while another emphasized the importance of an interactive dashboard for providing visually appealing graphical representation of the processed data [24]. Additionally, complex opinion data were analyzed using integrated visualization like scatterplot and radial visualization. These diverse methods underscore the importance of choosing the right visual tools to make complex data more accessible and comprehensive [33].

Table 6. Data Graphing tools, techniques, or processes

Data graphing	Journal ID
Tools	
Graphing Software	**4** [30], [32], [33], [37]
Web Browser with Java Activator	**1** [40]
Interactive Dashboard	**1** [24]
Techniques	
Hierarchical and Structural Visualizations Radial Visualization	**2** [33], [48]
Statistical Visualizations Violin Plots	**2** [33], [48]
3D Visualization	**1** [36]
Interactive Social Media-Based Visualizations	**1** [48]
Processes	
Real-Time Multidimensional Data Analysis	**1** [30]
Chart Selection and Design Choosing the Correct Chart Type	**1** [46]
Data Processing and Efficiency	**1** [46]
Spatial and Layout Considerations	**1** [46]

3.3. Research Gap Analysis

This section identified research gaps in the context of data visualization technologies within CRM, as revealed from the sample literature. While the previous sections have discussed aspects such as data collection, preprocessing, data storage, data processing and analysis, and data visualization, there is a noticeable lack in addressing the practical application of data visualization technologies and processes in CRM. Data visualization is an important tool for understanding customer behavior and trends and can pinpoint areas for improvement in customer service and growth opportunities. However, the studies appeared not to discuss how to effectively apply data visualization technologies in CRM. This includes crucial aspects like selecting the right data visualization tools, designing effective visualizations, and interpreting visualizations results. Without a comprehensive understanding of these topics could hinder organization in optimally leveraging data visualization technologies for CRM efforts. Moreover, the analysis of the studies highlighted certain limitations such as studies based on theoretical models tested through formulated examples that might not reflect real-world scenarios; the use of proprietary that are not widely accessible for public use, incomplete documentation for programming libraries; and data analysis techniques that require extensive resources and expertise, which may be beyond the capabilities of non-experts.

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Table 7. Common study limitations

Common Study Limitations	**Journal ID**
Lack of documentation of programming libraries	**16 [6], [24], [25], [30], [33], [35], [37], [38], [39], [41], [42], [44], [45], [46], [47], [50]**
Based on theoretical models	**7 [24], [37], [41], [42], [43], [48], [50]**
Requires a large number of resources and expertise	**6 [33], [37], [38], [41], [47], [50]**
Not an open-source platform/program	**2 [33], [37]**

Table 8. Data graphing tools, techniques, or processes

Future Research Recommendations	**Journal ID**
Application to real-world setup	**3** [30], [36], [40]
Exploring the use of advanced predictive analysis tools	**2** [6], [48]
Utilizing business intelligence	**1** [45]
Exploring the use of tag cloud diagrams	**1** [33]
Creativity techniques	**1** [38]
Investigating the use of 4-D rotations and matrix arrangements of conditional plots	**1** [50]

The paper has synthesized common recommendations from the sample studies to serve as a guide for future research. As depicted in Table 8, they emphasized the practical application of data visualization systems in a real-world setup, as well as expanding research into designing and use in different industries and contexts. This could entail using data visualization to analyze customer behavior or financial performance, identifying areas of improvement or growth opportunities. Further, the paper suggests exploring the use of technologies in data visualization, such as predictive analytics tools, 4-D rotations, matrix arrangements of conditional plots, interactive data visualizations, WiFi sensors, tag cloud diagrams, and the utilization of Business Intelligence (BI). This approach would enable future researchers, as well as business organizations to gain a more comprehensive understanding of their data and identify correlations and insights of different variables that may not have been apparent before.

Additionally, further research could look into the development of more effective visualization systems that are user-friendly and easily interpretable. It can contribute to the evolution and enhancement of data visualization methodologies, to facilitate better user comprehension and decision-making. Integrating modern technologies in data visualization can improve its practical applications and technical capabilities. This helps businesses tailor their systems to tackle specific issues, providing more accurate insights. By adopting this approach, companies can make better decisions and gain a broader understanding of relevant dynamics within their organizations [51].

4. CONCLUSION AND RECOMMENDATION

This literature review synthesizes 22 studies to explore how data visualization enhances customer relationship management (CRM). It reveals how data visualization aids in understanding customer needs and behavior, spotting trends, and formulating strategies. By leveraging data visualization technologies, businesses can unlock insights into their customers, informing effective engagement strategies and aligning with business objectives. Through qualitative coding, the review offers comprehensive methodologies for visualizing large data sets, addressing research gaps, and providing recommendations for future studies.

Following a systematic literature review adhering to PRISMA guidelines, the journals were profiled for content and quality, and this resulted in 22 final studies from Scopus as well as Web of Science Journals. To analyze the methodologies in data visualization employed by these studies, the structured framework was utilized encompassing five sub processes or categories: data collection, data preprocessing, data storage, data processing and analysis, and data graphing. Through the application of qualitative coding, this paper identified recurring themes across these five subprocesses. The initial thematic codes, generated from common words, were then validated and finalized to ensure they accurately represented the key information. This synthesized analysis not only provided insights into current practices and technologies related to data visualization, but also revealed significant gaps in the literature, which were aligned to the overarching problem statement and objectives of this paper. This reveals that research publication on data visualization began as early as 1996, but experienced minimal output until 2014. Subsequently, there was considerable growth in data visualization research, likely due to increasing volumes of digital data. In other words, the upsurge in data visualization research reflects the expanding digital data landscape, attracting a wide range of expertise, predominantly from the field of computer science and that the United States emerged as the leading contributor within this body of work, accounting for 31.82% out of 22 articles.

The process of data visualization research involves rigorous methodologies in data collection, preprocessing, and storage to manage increasing digital data volumes. Data collection gathers data from various sources, emphasizing diversity. Preprocessing cleans and formats data using techniques like normalization and factor analysis. Data storage employs encryption and digital watermarking for security, with ETL transferring data to warehouses. Python and R tools are used for data processing and analysis, employing techniques like data mining and opinion mining. Graphical representation utilizes specialized software for real-time, multidimensional analysis and 3D visualization. Despite comprehensive coverage, studies lack practical guidance on tool selection, visualization design, and result interpretation. Future research should explore how data visualization can enhance customer engagement, aid in targeted marketing campaigns, identify customer dissatisfaction points, and evaluate its impact on customer loyalty. This will lead to more intuitive and user-friendly visualizations.

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