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*Original Article*

# Visual Intelligence Framework for Business Analytics Using SQL Server and Dashboards

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***Abstract****: A framework of Visual Intelligence of Business Analytics is put forward, the SQL Server and Power BI are utilized to automate generation of dashboards depending on the characteristics of dataset. The framework fully incorporates all business intelligence pipeline facilities, such as ETL, star-schema modelling, and flat-table creation, to enable highly scalable and structured analysis. The visualization assignment is presented in a rule-based manner, which suggests using one of the following visual types Card, Pie, Bar, or Line depending on the size of data sets according to previously determined thresholds ($t_1$ and $t_2$). In this paper, the framework is used on the sales data leading to the production of two dashboard variants PLLCC and PBLCC, each comprising different chart arrangements. A quantitative analysis, based on a visual utility measure, shows that Variant 2 (PBLCC) is better than Variant 1 (PLLCC) with a measure of 1.94 against 1.54, indicating its higher performance in visualising medium-sized data. The dashboards provide multidimensional data and information about revenue patterns, product-level measurements, and seasonal patterns, which are in line with the perceptual cognition principles. The paper illuminates the applicative potential of a SQL-driven visual mapping process in boosting decision-making and storytelling. Automation of visual advice and workflow configuration of BI solutions, the framework presents an effective solution in practical workflow conditions to provide an adaptive, resilient, and interactive dashboard business intelligence solution.*

***Keywords****: Business Intelligence, SQL Server, ETL, Dashboard, Visualization, Power BI, Data Analytics.*

## I. INTRODUCTION

The business world of today is data-driven, necessitating an increasing number of companies to rely on intelligent systems that can convert transactional data to actionable information[1]. There is an increasing popularity of Business Intelligence (BI) solutions, which combine powerful data processing with intuitive visualizations due to the necessity of faster, interactive, and easier-to-work-with analytical tools[2]. To create an all-out solution of successful business analytics, this paper introduces a Visual Intelligence Framework, which is specifically designed to mingle dynamic dashboards with the SQL Server-based data processing technique.

The framework initially develops a conventional BI pipeline to retrieve transactional information on enterprise apps such as ERP, CRM, and POS. The ETL process involves cleaning the data, normalizing it and mapping it into a star schema structure of SQL Server[3][4]. Flattening of the schema yields the deformalized datasets that can be visualized by SQL JOIN operations. This preparation needed to support interactive dashboards that can deliver real-time insights.

The visualization recommendation is one of the primary innovations of the framework as it employs the size of the dataset to identify the most suitable types of charts, including cards, pie charts, bar graphs, and line charts[5]. This is done according to previously set threshold parameters, which ensure the visual forms adopted are readable and within the untrained cognitive capacity of the business users. The framework overhauls the traditional BI dashboard to dynamic analytical tool by adding intelligence into the visualization phase.

The methodology was proven by a sales data set that covered transactions between 2009 and 2020. Several dashboard designs (including PLLCC and PBLCC) have been created and evaluated based on a performance equation to determine the effectiveness of each display organization, as well as subsets of analysis[6]. These results indicate that the dashboards designed on this framework offer more decision-making support, enhanced clarity, and improved performance interpretation.

In the end, this study includes a scalable, modular and SQL-based visual intelligence architecture. It allows corporations to develop dashboards, which not only have technical soundness but also match the goals of business communication and human visual ability[7]. Providing a reliable path toward smarter, data-driven business decisions, the framework is agnostic across sectors and fits effortlessly in any existing SQL Server infrastructures

### A. Aim & Contributions of the Study

This study aims to develop an intelligent, SQL-driven visual analytics framework that automates the selection and assignment of dashboard visualizations based on dataset characteristics. By integrating ETL processes, schema design, and visualization logic, the framework enhances data interpretation and supports effective business decision-making through adaptive, user-centric dashboards. The key contributions are discussed below:

- Introduced a rule-based visual assignment function using dataset size thresholds ($t_1$, $t_2$) to automatically recommend chart types: Card, Pie, Bar, and Line.
- Developed a complete BI pipeline using SQL Server, including ETL, star schema modelling, and flat-table generation for dashboard input.
- Designed and implemented two visual dashboard variants (PLLCC and PBLCC) with real business KPIs and performed quantitative evaluation using a decision-support function.
- Validated the effectiveness of the PBLCC variant, which achieved a higher utility score, demonstrating its suitability for visualizing mid-sized data and enhancing dashboard-driven insights.

### B. Organization of the paper

The paper is organized into five sections. Section I introduces the concept of visual intelligence for business analytics. Section II presents an existing literature on BI dashboards, SQL integration, and visualization frameworks. Section III details the methodology including ETL, star schema modelling, and dashboard generation. Section IV provides experimental analysis with visualization assignments and dashboard evaluation. Finally, Section V concludes the study, and potential future improvements.

## II. LITERATURE REVIEW

This section, Table I, presents previous research on business analytics, SQL-based dashboards, and BI frameworks, emphasising data integration, visualisation tools, curriculum alignment, and automated visual recommendation for decision-making.

Maruf et al. (2022) emphasize how better curriculum design, more experiential learning, and tighter ties to real-world data settings are needed to provide aspiring analysts the tools they need for contemporary analytical employment. The technical, pedagogical, and strategic aspects of SQL and Excel are critically examined in this review, which lays the groundwork for further study and curriculum development in analytical practice and education[8].

Himami et al. (2021) discuss using the Kimball technique in the design and development of a data warehouse. Using Microsoft SQL Server Integration Service and SQL Server Management Studio, the data warehouse schema is produced. A web-based application and Microsoft Power BI are used to create a dashboard that shows the data warehouse's analytical findings. The production environment of PT Bio Farma appears to be steady based on the dashboard display, which means that it does not affect the quality of the output. The data is input into an online application, and following testing, the application's viability is 84%[9].

Ashok et al. (2020) concentrate on providing information that helps customers choose the best product at a lower cost by comparing prices among several brands, retailers, and items. This includes, but is not limited to, helpful business indicators that allow company owners to assess the state of their enterprise. Using ETL procedures to extract, transform, and load data from several sources to create a centralized single source of information. After being ingested, integrated, and carefully selected, the data may be utilized for analytics to produce insightful information that improves the decision-making process[10].

Bagam (2019) explains data visualisation as one of the key components of business intelligence (BI), where business stakeholders can comprehend complex data and utilise it as inputs to make data-driven choices. Tableau, Power BI, QlikView, Google Data Studio, and D3.js are the six applications that were utilised for the evaluation. Usability, data processing, customization, integration, pricing, and support capabilities were all compared.[11].

Boulila et al. (2018) are eager to assist with higher education decision-making. When applied to academic matters, BI ideas can significantly enhance the process. The purpose of this study is to describe a BI solution that assists Taibah University's academic issues. May benefit from a suite of analytical tools that assist decision-making for various user types (students, teachers, administrators, and decision makers) by using business intelligence (BI). The three primary tasks of the suggested BI solution are (1) gathering data from various sources using the three operations (Extract, Transform, and Load); (2) putting forward a multifaceted solution that explains the academic procedures; and (3) visualizing the outcomes through a series of dashboards and reports. The SQL Server Data Tools are used for experiments[12].

Ananthanarayanan et al. (2018) explain DataVizard technology, which automatically suggests the best visual representation for the structured result to reduce this overhead. Specifically take into account two situations: the first is when a structured query, like SQL, has to be visualized, and the second is when a data table with a brief description attached has been obtained (e.g. tables from the Web). Demonstrate Data Vizard's ability to provide highly accurate visual presentation recommendations using a corpus of real-world database queries (and their outcomes) and several statistics tables that were scraped from the Internet. In addition, provide the findings of a user poll carried out to find out how users felt about the appropriateness of the charts compared to the data's plain text captions[13].

Kumar and Belwal (2017) offer a productive Nobel solution to these issues by emphasizing the creation of a Performance Dashboard. By combining data mining, data visualization, and business intelligence technologies, the proposed method offers an ideal way to examine business trends, growth, profit margins, employee performance, customer satisfaction, areas for business improvement, and more. This performance dashboard presents the data by analyzing the business behaviour from the beginning of the organization[14]

***Table 1 : Summary of Comparative Analysis of Business Analytics using SQL & Dashboards***

| Reference | Objective | Methodology | Key Findings | Advantages | Limitations & Future Work |
|---|---|---|---|---|---|
| Maruf et al. (2022) | Improve curriculum design for analytics education | Evaluation of the strategic, educational, and technical applications of Excel and SQL | Emphasizes hands-on learning and conformity to real-world settings. | Builds foundation for curriculum development | Requires broader empirical validation across diverse educational contexts |
| Himami et al. (2021) | Construct a data warehouse for production monitoring | Kimball method, SQL Server, Power BI dashboards, Web app | Dashboard shows stable production at PT Bio Farma; 84% application feasibility | Integrates DW design with visualization for business decisions | Limited scalability and detailed performance metrics not discussed |
| Ashok et al. (2020) | Deliver pricing insights and business health metrics | ETL pipeline for data integration and centralized storage | Enables analytics for consumer and business decision-making | Real-time data insight and integration across sources | No performance comparison across tools or scalability discussion |
| Bagam (2019) | Compare BI visualization tools | Evaluation of six tools across usability, data handling, etc. | Visual tools are crucial for decision-making by stakeholders | Offers comparative tool evaluation | Does not test tools in real organizational settings |
| Boulila et al. (2018) | Support academic decision-making using BI | ETL process, multidimensional modelling, SQL Server Data Tools, dashboards | BI enhances academic affairs at Taibah University | Supports diverse user groups (students to administrators) | Case-specific, lacks generalization to other universities |
| Ananthanarayanan et al. (2018) | Recommend effective data visualizations automatically | DataVizard system; tested on SQL results & web tables | High accuracy in recommending suitable visualizations | Reduces overhead in manual chart selection | Limited scope in terms of data complexity and domain diversity |
| Kumar and Belwal (2017) | Analyze business KPIs via performance dashboard | Integration of BI, data mining, visualization | Dashboards reveal trends, profits, satisfaction, improvements | Holistic business monitoring through visualization | May need updated toolsets and scalability for real-time data |

## III. METHODOLOGY

The proposed methodology adopts a structured Business Intelligence (BI) pipeline designed to transform raw transactional data into actionable insights through intelligent visual dashboards. This end-to-end pipeline includes five core stages: data collection, ETL processing, schema modelling and flattening, visualization assignment, and dashboard design. The framework was validated using a sales dataset that tracked transactions between the year 2009 and 2020. It comprises principal business measures Items Sold, Items Cost as well as time elements Year, Quarter, Month and Date. This data is very sensitive and is similar to the typical performance monitoring and decision-making data in retail business. First transactional data is obtained through operational enterprise systems including ERP, CRM and POS. Data is transformed using an ETL (Extract transform load) process that cleans up, standardizes and arranges data into a structured star schema within the SQL server. The star schema is then denormalized into a flattened data set via SQL JOIN operators to support ad hoc querying and graphical display of the business information along with associated dimensional data.

It then uses a rule-based visualization assignment function that is assigned to the dataset subsets to the most suitable choice of graphs, Card, Pie, Bar, or Line depending on their size. The classification of the dataset as small, medium, and large is done based on threshold parameters $t_1$ and $t_2$ to ensure an accurate visual construct and cognitive interpretability. Lastly, the chosen data charts displayed on a dashboard interface with the help of Microsoft Power BI. The process makes sure that the final dashboards are both analytically deep and visually clear to create quick insights and enable rational decision-making. Combining SQL-based data preparation and smart visual design, the methodology produces a scalable and flexible approach to today's business analytics.

### A. Data Collection

The traditional Business Intelligence (BI) pipeline was used to collect the data for this study. Raw transaction data is first pulled out of the various systems of operations, followed by transformation and organization of data into analytical frameworks and subsequently loaded into data warehouses to support further visualization. To streamline decision-making, this pipeline follows standard BI requirements and ensures that data is ready to perform descriptive and predictive analytics.

*a) Source Systems*

In real-life business intelligence conditions, systems like Point-of-Sale (POS), Customer Relationship Management (CRM), and Enterprise Resource Planning (ERP) frequently become the key sources of transactional information[15]. Such platforms bring forth critical business data such as financial transactions, customer profiles, and product sales. Although the BI architecture of the study itself is platform-agnostic, these systems are considered good examples of operational data sources that become feeds into SQL Server-based pipelines to be used by downstream analytics and dashboard visualization

*b) Extract-Transform-Load (ETL) Process*

The ETL process is needed to convert raw data into usable format. The first thing is extraction of data out of various source systems[16]. After that, it transforms, including cleaning, normalization, and mapping into a star schema. Analysis and querying are made easier by this structure. As seen in Figures 1 and 2, the converted data is then loaded into Data Marts (DM) or Data Warehouses (DW), allowing for structured storage for effective dashboard visualizations and analytical processes.

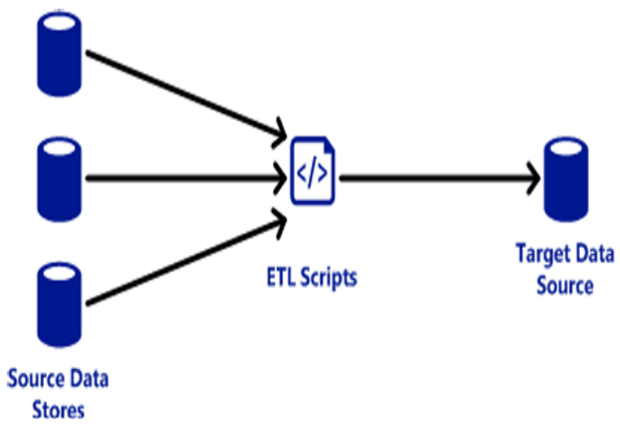


***Figure 1 : ETL Scripts General Use-Case***

The ETL procedure in a business intelligence pipeline is depicted in Figure 1. For analysis and dashboard visualization, data is loaded into a target data source, like a data warehouse or data mart, after being extracted from several source data stores and transformed (cleaning, aggregating, formatting) using ETL scripts.

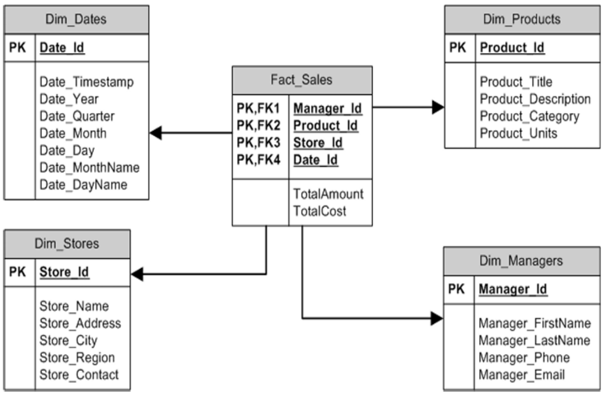


***Figure 2 : Sample Star Schema Data Warehouse Design***

Figure 2 illustrates a star schema data warehouse design. The central Fact_Sales table contains foreign keys referencing four-dimensional tables Dates, Products, Stores, and Managers. It stores measurable data (TotalAmount, TotalCost), while dimension tables provide contextual business details used for querying, analysis, and visualizations in Business Intelligence systems.

*c) Dataset Description*

A sales dataset covering transactions from 2009 to 2020 was used to validate the proposed framework. It included key performance measures such as Items Sold and Items Cost, along with time-based attributes like Date, Year, Quarter, and Month. The dataset was structured using a star schema model and transformed into a flat structure using SQL queries for visualization mapping and dashboard generation.

**B. Dataset Preparation**

To simplify the visualization process, the data is initially organized with the help of the star schema and is later converted into a flat structure. This is a procedure that involves SQL JOIN operations between the central fact table and its related dimension tables. A combination of descriptive dimension attributes and business measures is used to form a de-normalized one[17]. This structure enhances the usefulness of the dataset as it makes it optimal for use in filtering, projection, and analytical tasks required to visualise dashboards. After the flat dataset is ready, analytical subsets are obtained to be used in visualization assignment.

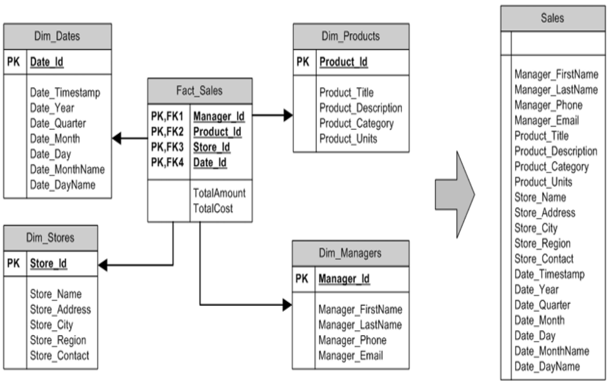


***Figure 3 : Sample Flat Structure Derived from A Star Schema***

Figure 3 illustrates the change of a star schema. Attributes of dimension tables are joined with fact table using SQL JOIN operations. The resulting denormalized dataset, shown on the right, integrates all relevant measures and descriptive attributes, enabling efficient filtering, projection, and visualization for BI dashboards.

**C. Data Analysis**

The star schema is converted into a flat dataset through SQL JOIN operations, analytical subsets are generated using SQL queries[18]. These subsets enable focused exploration of business measures such as sales and revenue across different time dimensions. Each resulting dataset is evaluated to determine the most appropriate visualization based on its size.

Flat datasets are analyzed using the following function in Equation (1):

$$Visualization(DS) = \begin{cases} Card & if\,|DS| = 1 \\ Pie & if\ 2 \leq |DS| \leq t_1 \\ Bar & if\ t_1 + 1 \leq |DS| \leq t_2 \\ Line & if\ |DS| > t_2 \end{cases} \quad (1)$$

Where, $|DS|$ is the dataset size. The thresholds used are $t_1$ = 4 – 6 and $t_2 = 10 - 15$, Based on established visualization guidelines. Figures 4 and 5 illustrate the analysis pipeline and mapping of attributes to chart axes.

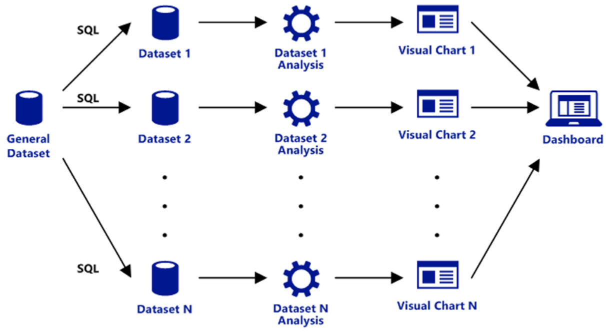


***Figure 4 : Generic Data Pipeline for the Proposed Approach***

The dataset analysis pipeline, as shown in Figure 4, queries a flat dataset using SQL to generate multiple analytical subsets. Each subset undergoes analysis to determine the appropriate visualization type (e.g., pie, bar, line, card). The resulting charts are then assembled into a final dashboard for effective business intelligence visualization.

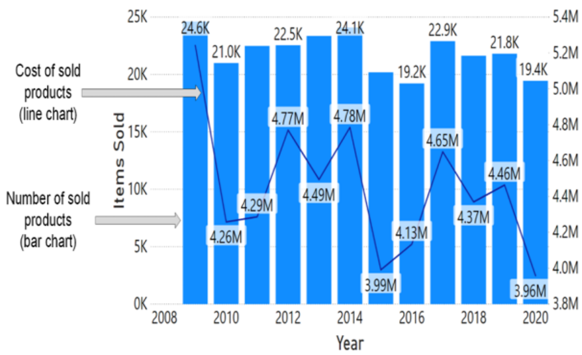


***Figure 5 : Example of Dataset Mapping to the Visual Chart Axes***

This visualizes sales data using a combo chart as shown in Figure 5. The bar chart represents the number of sold products annually, while the line chart overlays the cost of sold products. This dual-axis visualization enables comparison of quantity and revenue trends over time, as recommended in the dataset analysis and dashboard design methodology.

**D. Dashboard Design Process**

This procedure describes a methodical way to create dashboards for business intelligence. It involves transforming star schema data into flat structures, preparing analytic subsets using SQL[19], and determining appropriate visualizations using dataset size thresholds as shown in Figure 6. Choosing and positioning charts that best aid in data interpretation and decision-making is the aim.

*a) Schema Flattening*

SQL is used to join the fact and dimension tables in the star schema, resulting in a flat structure. To facilitate querying and analysis for visual representation on dashboards, this guarantees a single table with all required attributes and measures[20].

*b) Subset Preparation*

SQL selection, projection, and aggregation operations are used to create subsets of the flat dataset. The formation of these subsets, on which visualization is based, presents important views of the data, like the revenue every three months or the sales of items each month.

*c) Threshold Evaluation*

Each of the subsets is tested on its size and checked against pre-set thresholds ($t_1$ and $t_2$)[21]. This helps in determining the most appropriate visualization pie, bar, line, or card to use in the display of the dataset on the dashboard appropriately and successfully.

*d) Visualization Recommendation*

There is a specific algorithm employed to suggest the appropriate visualization depending on the size of the data. The pie charts are recommended when the dataset is small, bar charts are recommended when the dataset is medium, line charts when the dataset is large, and cards are the most suitable to render the single-value dataset to obtain instant understanding.

*e) Dashboard Assembly*

The visually perceived information is translated into charts that are placed on the dashboard following the selection of the chart types. The layout takes into consideration the readability and clarity that could be easily identified by the users to identify the trends, comparisons, or some metrics that are relevant to their business decision making needs.

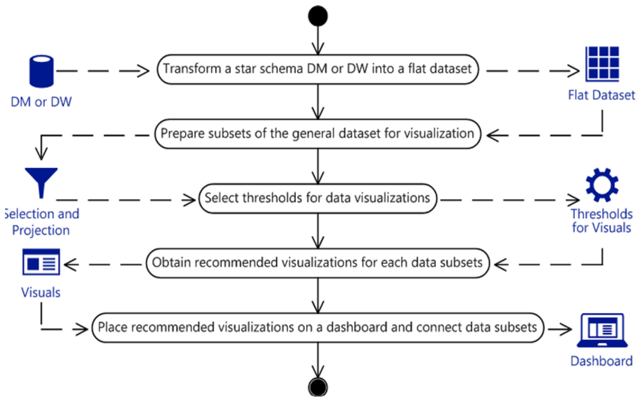


***Figure 6 : Dashboard Design Process Diagram***

The dashboard design process is shown in Figure 6. It starts by converting a star schema to flat data and preparation of data subsets. Visualization types are chosen and thresholds, and based on them the visualization types suggested to every subset. Lastly, the selected images are displayed on a dashboard and connected with related datasets.

## IV. RESULT ANALYSIS AND DISCUSSION

The research was conducted in an experimental setting with the help of SQL Server 2019 and Microsoft Power BI on a Windows 10 professional computer with 64-bit architecture, Intel Core i5 processor with 12 GB of RAM. The framework had a set of ETL pipelines and a star schema model to process a sales dataset into flat, ready-to-analyse datasets. The recommendations on visualization were created using the threshold of dataset size and reflected the following four types of charts: Card, Pie, Bar, and Line. Two forms of dashboards were tested PLLCC and PBLCC. The results reveal that Variant 2 (PBLCC) is superior to Variant 1 in visual effectiveness, indicating that it is more suitable for visualising a mid-sized dataset.

### A. Visualization Assignment Results

In this section, the recommendations for visualization of the five analytical datasets created based on the sales dataset are provided. All the datasets were considered about their size and twelve combinations of the data were considered where $t_1 \in \{4,5,6\}$ and $t_2 \in \{10,11,12,15\}$. Based on the visualisation purpose explained above, the datasets were assigned to a combination of four kinds of charts, Card, Pie, Bar, or Line.

The recommendation results are summarized in Table II. Only two distinct combinations of visualizations were produced:

- PLLCC: Pie, Line, Line, Card, Card
- PBLCC: Pie, Bar, Line, Card, Card

This demonstrates the consistency and flexibility of the approach across varying dataset volumes. The visual assignments align well with human-perception principles, assigning bar charts to mid-sized data and line charts to larger datasets.

Visualization recommendations for five datasets ($DS_1$–$DS_5$) based on varying dataset sizes ($|DS|$) and threshold values $t_1$ (for pie charts) and $t_2$ (for bar charts) as presented in Table II. For small datasets like $|DS_1| = 4$, pie charts (P) are consistently recommended across all thresholds. For moderate-sized data like $|DS_2| = 12$, the visualization varies: when $t_2 = 10$ or $11$, line charts (L) are suggested, while bar charts (B) are preferred when $t_2$ is 12 or more. Larger datasets like $|DS_3| = 481$ consistently yield line charts due to their suitability for trend analysis over many data points. For scalar values like $|DS_4|$ and $|DS_5| = 1$, cards (C) are universally appropriate as they convey single-value summaries effectively.

| DS | $t_1$ | 4 | 5 | 6 | 4 | 5 | 6 | 4 | 5 | 6 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $t_2$ | 10 | 10 | 10 | 11 | 11 | 11 | 12 | 12 | 12 | 15 | 15 | 15 |
| 1 | $\lvert DS_1 \rvert = 4$ | P | P | P | P | P | P | P | P | P | P | P | P |
| 2 | $\lvert DS_2 \rvert = 12$ | L | L | L | L | L | L | B | B | B | B | B | B |
| 3 | $\lvert DS_3 \rvert = 481$ | L | L | L | L | L | L | L | L | L | L | L | L |
| 4 | $\lvert DS_4 \rvert = 1$ | C | C | C | C | C | C | C | C | C | C | C | C |
| 5 | $\lvert DS_5 \rvert = 1$ | C | C | C | C | C | C | C | C | C | C | C | C |

***Table 2 : Recommended visualizations for each dataset across threshold combinations***

## B. Dashboard Design Evaluation

To compare the effectiveness of the two recommended visualization sets (PLLCC and PBLCC), a quantitative evaluation was performed using the following Equation (2):

$$Var_i = \sum_{j=1}^{v} \frac{w_j}{max_{k=1}^{v} w_k} \cdot \frac{d_j}{max_{k=1}^{v} d_k} \cdot x_j \qquad (2)$$

Where $x_j$ is the number of visuals of type j, $w_j$ is the prevalence of that visual type, $d_j$ j represents how well the visual supports decision-making, and v is the number of different visual types used.

The evaluation results show that Variant 2 (PBLCC) scored 1.94, outperforming Variant 1 (PLLCC), which scored 1.54. This indicates that bar charts are better suited for visualizing medium-sized datasets (e.g., 10–15 categories), making Variant 2 more effective for business insights.

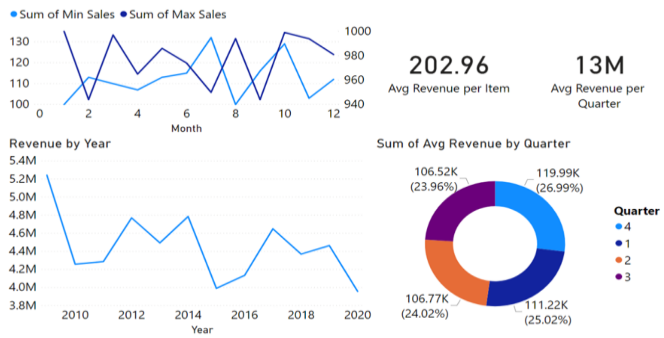


***Figure 7 : Sample Dashboard Design for the First Recommended Set of Visuals (Pllcc)***

The dashboard provides a comprehensive multi-angle sales analysis using SQL-driven visualization techniques from the proposed framework as shown in Figure 7. The top line chart compares the Sum of Minimum and Maximum Sales across months, showing values from 100 to 140 units and a maximum peak close to 1000. On the right, KPI cards display an Average Revenue per Item of 202.96 and Average Quarterly Revenue of 13M, offering quick insights. The line chart below shows revenue trends declining from 5.2M to 3.96M between 2009 and 2020.

The doughnut chart presents the average revenue per quarter, highlighting Quarter 2 with 119.99K (26.99%), followed closely by Quarter 3 with 111.22K (25.02%). This chart reveals seasonal revenue distribution, derived from denormalized SQL datasets, supporting the framework's goal of effective dashboard-based decision-making through intelligent visual design.

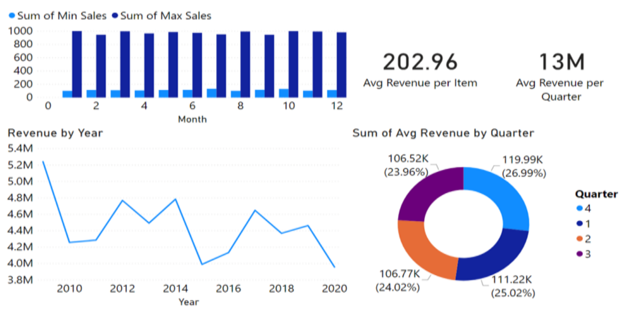


***Figure 8 : Sample Dashboard Design for the Second Recommended Set of Visuals (PBLCC)***

The dashboard visualizes critical revenue and sales trends derived from SQL-processed flat datasets following the proposed framework, as shown in Figure 8. The top bar chart compares the Sum of Min and Max Sales across 12 months, showing max sales consistently at around 1000 units, while min sales remain under 300 units. The KPI indicators reflect an Average Revenue per Item of 202.96 and a Quarterly Average Revenue of 13M, calculated through SQL aggregation and slicing operations. The line chart below tracks Revenue by Year, revealing a sharp peak at 5.2M in 2009, followed by fluctuating values and a drop to 3.96M in 2020.

The doughnut chart displays Average Revenue by Quarter, highlighting Quarter 1 with the highest share of 119.99K (26.99%), followed by Quarter 3 at 111.22K (25.02%). These values, aligned with time dimensions from the denormalized dataset, support dynamic visual recommendations and enhance decision-making through data-driven storytelling.

### C. Novelty and justification

The novelty of this study lies in its development of a unified Visual Intelligence Framework that seamlessly integrates SQL Server-based data management with automated visualization logic, addressing a key limitation in traditional BI systems manual and non-adaptive chart selection. The framework introduces a threshold-based visualization assignment mechanism that dynamically selects appropriate chart types (Card, Pie, Bar, Line) based on dataset volume, enhancing user interpretability and decision accuracy. It leverages ETL pipelines, star schema modelling, and rule-based mapping to automate end-to-end business analytics. This addresses a gap in research under the expanding need of intelligent, perception-aligned visual analytics justified by the increasing demand in this field because this solution allows visualization intelligence to be a direct part of the data pipeline. The quantitative analysis based on a decision-support function also proves its efficiency, as Variant 2 (PBLCC) had the highest score on the visual effectiveness, thus proving its real-life application, scale, and consistency.

## V. CONCLUSION AND FUTURE SCOPE

Data visualization is a key element in the process of Business Intelligence (BI) improvement because it aids in turning extensive data into practical information. Decision-making, finding trends, and streamlining operations can be done better when companies possess the necessary tools and strategies. But companies should consider issues like quality data and security, scalability and user adoption to fully exploit BI. The study gives visual intelligence model that combines SQL Server and automated dashboard design to improve business analytics. The approach, based on the principles of data-driven storytelling, uses the dataset-size thresholds to determine the correct chart type: Card, Pie, Bar, or Line so that it would be perceived and interpretable. The framework will involve the full ETL processing, designing a star schema, and producing dashboards in Power BI. Two variants of visualization were designed and tested, PLLCC and PBLCC, with a quantitative utility function. PBLCC has been proven effective with a score of 1.94 as compared to PLLCC indicating that it works in mid-sized data representation. This intelligent mapping of data to visuals not only streamlines dashboard creation but also improves decision-making. The study confirms the viability of integrating SQL querying, transformation, and visualization into a unified, automated pipeline.

Future work can enhance the framework by incorporating real-time data streaming and adaptive threshold tuning for dynamic datasets. Integration with natural language query interfaces and AI-based visualization recommendation engines may improve user interactivity. Expanding beyond sales data, the framework can be applied to sectors like healthcare, finance, and education. Further validation using large-scale, live enterprise databases will strengthen its applicability in practical business intelligence environments.

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