Improving Service Quality Using Consumers' Complaints Data Mart which Effect on Financial Customer Satisfaction

Alaa Khalaf Hamoud[1],

Department of Computer Information System, University of Basrah, Iraq.

alaa.hamoud@uobasrah.edu.iq.

Hisham Noori Hussien[2]

Department of Computer Information System, University of Basrah, Iraq.

hisham1985130@gmail.com

Eman Talib Jasim [3]

Department of Computer Information System, University of Basrah, Iraq.

emantalib38@gmail.com

Arwa Akram Fadhil[4]

Department of Computer Information System, University of Basrah, Iraq. arwa.akram11@gmail.com

Zahraa Raad Ekal[5]

Department of Computer Information System, University of Basrah, Iraq. zahraa97alkabby@gmail.com

Abstract*-One of the best ways to enhance the performance of all companies and manage Customer Satisfaction is to get the consumers' complaints and analyze them in order to fix them. These complaints represent the consumers' behavior to the companies and how these company's response to them. Besides, customers' satisfaction is the main goal of all companies and this goal cannot achieve if they do not handle the customers' complaints. The paper represents a framework of complaint data mart construction where the source data are thousands of complaints about services and financial products of companies. The data mart represents the first step to implement an enterprise data warehouse (DW) to support strategic decisions. Reports are constructed to help analysts and decision-makers to support their decisions related to consumers' complaints and how to improve service quality. Two different categories of on-line analytical processing (OLAP) reports are used, offline and web OLAP reports. The two types of reports provide a deep view of the data and present the analysts with flexible charts that can be used in supporting strategic decisions. SQL Server Management Studio (SSMS), SQL Server Integration Services (SSIS), SQL Server Analysis Services (SSAS), SQL Server Reporting Services (SSRS) 2014 beside SQL Server Data Tools (SSDT) 2013 is used to build the data mart staging table, schema, cube, and OLAP reports. MS Excel Pivot table 2010 is used also to import the cube and build offline reports and implementing OLAP processes. This data mart can be utilized by consumers themselves besides decision-makers and analysts. The data mart can measure how the companies fix complaints issues and prevent them from occurring again and identify the factors that influence financial customers' satisfaction.

Keywords- Data Mart, Complaint, Service Quality, ETL, OLAP, Financial Customer Satisfaction.

I. INTRODUCTION

As an Information Technology (IT) administrator, when you work on any application that gathers data from different sources, from a different platform and want to analyze the information, the best model to provide such solution that supports strategic decisions is DW [1]. One of the most important concerns to organizations is improving service quality and ensuring long-term customer loyalty. Improving service quality and increasing customer satisfaction become a need for all organizations. The great challenge for all organizations in different industries is continuously presenting a high-quality service. The presented services involve invisible or intangible benefits to the customers, and thus the customers are rarely noticing the service quality. Normally, the customer does not notice the high-quality service and only be aware when service is failure and dissatisfaction [2].

There are many approaches used for enhancing service quality and handling customer complaints to provide a high-quality service in different domains such as car manufacturing [3], financial service [4], and internet services [5]. DW considered one of the best solutions for data analysts and decision-makers in strategic places. DW is a subject-oriented, non-volatile, time-variant, and integrated collection of data that used to support strategic decisions [6]. DW is a highly summarized collection of heterogeneous data sources that can be used to view the hidden patterns and analyze data related to the enterprise level. DW used to solve problems in many fields such as clinical path [7][8][9][10], invoices [11], information resources [12], and health service [13].

Datamart on the other side used to analyze data for single department and provide a summarized, de-normalized and shaped based on the requirements of the department. The other difference between DW and data mart is data sources age, in DW the data is long-term data (years) while data mart is a short-term data (months). Based on that, the decision made based on DW or data mart can determine the importance of that decision [6]. The implementation process of DW or data mart falls generally in two major approaches top-down and bottom-up [14].

In this paper, we will investigate many points such as:

- The possibility of using data mart to enhance service quality and handling customers' service by providing many choices for decision making
- How can data mart provide the decision makers with a short-term results of analyses that can be used in future decisions making?
- What is the best approach to implement data mart for handling customers' complaints?
- How can mining algorithms that can be implemented on customers' complaints data mart provide more detailed results?

The paper is arranged as follows: section (2) presents the related works to compliant systems and models that implemented to enhance customer service quality. Section (3) explains the model implementation roadmap starting from data collection to presenting reports. The final section (4) presents concluded points and future works.

Previous studies have intensively investigated financial customer satisfaction. They have used different models and variables to explain the satisfaction of customers in the financial environment. The majority of researchers have focused on the characteristic of the website and the quality of the information provided to customers [15]. However, the literature lacks studies that review the factors that influence financial customer satisfaction. This study reviews and integrates the literature to provide a comprehensive view of the factors that influence the online customer's satisfaction.

II. RELATED WORKS

Holger Hinrichs and Thomas Aden in [16] developed CLIQ (Data Cleaning with Intelligent Quality Management) project which is a system of quality management to perform data integration that fulfill the ISO 9001:2000 standard. CLIQ can handle the problem of integration steps in order to fulfill the user's needs with high quality. CLIQ enables the users to apply the quality management standards known from the manufacturing and service domains. The system is planned based on heterogeneous data sources to ensure analyzing different data and produce high-quality results. However, the designing approach is not clearly defined and the quality management evaluation is not implemented.

Jing-Wei Liu [17] proposed a model based on a company database of customer interactions to analyze the behaviors of consumers to get an accurate customer classification. The goal of this model is to make validity and feasibility test in order to provide enterprises with better strategies of marketing besides the project management office (PMO) processes for their customers. Model implementation started by classifying Chinese text using text mining and fuzzy semantics for the PMO. The model implementation went through many steps, the first one is analyzing unstructured data content in order to convert the important information of textual shape and compile them to get keywords index. The next step, a decision, and classification algorithm and the Gfuzzy algorithm used for categorizing textual data by three factors: minimum, maximum, and moderate impact. In the last step, an effective strategy of marketing used to target the best service mode, growth models, and customer combinations. However, the DW construction process did not explain and clarified.

Bart Larivie`re, Dirk Van den Poel [4] analyzed the impact of handling the post- customers complaints on the future behavior after problem recovery. Since the dependent variable is determined by two binary values for duration indicator and for classification is either buy or not buy so they used techniques based on survival analysis. The main goal of the work is to get a better view and understanding of the period of customer complaints and to measure the impact of handling of complaints on the behavior of the customers over time. The technique of survival analysis is used to track the customers' behavior after solving the problem. The dataset holds complaints of 2326 customers. They found that complaints should be handled during investment which can affect the customers' behavior. However, the dataset considered small comparing with these used to build DW and data mart. Besides, they used five variables to measure and analyze the customers' behavior which can be considered few.

Sheng-Tun Li, Li-Yen Shue, and Shu-Fen Lee [5] developed a CRM system for internet service providers ISP company in Taiwan to manage the existing customers and measure the customer's satisfaction to increase the customers. The system measures customers' behavior based on pricing and services. The traffic data of IP addresses were used in a CRM system based on a semantic approach cross-industry standard process for data mining (CRISP-DM) methodology to explore the customers' usage of the network. The customer's usage analysis can help in determining the times and patterns of heavy usage. The management allowed to contact the maintenance or services to provide the cares or even products for the customers. However, the system model measured the customers' usage of the internet during all days and for all hours but the data is not covered many cities to find it the results remain same, besides the results of the analysis will be affected if the data takes many ISPs.

The table (1) discussed the results of ten researches and the dependent and indecent variables.

TABLE 1 LITERATURE REVIEW RESULTS OF VARIABLES RELATED TO CUSTOMER'S SATISFACTION.

No	**Citation**	**Dependent variable**	**Indecent variable**	**Result**
1	[18]	Financial customer satisfaction	information quality, system quality, service quality, product quality, delivery quality and perceived price	Information quality, system quality, service quality, product quality, delivery quality, and perceived price are significantly influence online customer satisfaction. *Additionally,* delivery quality followed by product quality was the most significant respectively.
2	[19]	Financial satisfaction	Navigability Playfulness Information quality Trust Personalization Responsiveness	This study is conceptual and it suggests that the six dimension of service quality can be used by other to determine the weakness of their services quality to enhance online customer satisfaction.
3	[20]	Customer satisfaction Intention to complain	- Distributive justice - Procedural justice - Interactional justice - Expectation - confirmation - Perceived usefulness - Trust	All the independent variables have significant influence on customer satisfaction except procedural justice. In addition, customer satisfaction influences negatively the intention to complain.
4	[21]	Customer satisfaction Customer loyalty	Web site design Ease of use Reliability Customer service	Web design, ease of use, reliability, and customer service influences the customer satisfaction significantly positively. The dimensions of ease of use and reliability influence the customer loyalty significantly positively. The dimensions of web design and customer service influence customer loyalty indirectly by customer satisfaction. The customer satisfaction significantly affects the customer loyalty
5	[22]	Financial customer satisfaction	information quality, web site design, merchandise attributes, transaction capability, security/privacy, payment, delivery, and customer service response time	Information quality, web site design, merchandise attributes, transaction capability, security/privacy, payment, delivery, and customer service – are strongly predictive of online shopping customer satisfaction,
6	[23]	Financial customer satisfaction Financial customer loyalty	Information quality website design product variation transaction ability response security/privacy payment system delivery customer service	Findings indicated that information quality, security (privacy), payment system, delivery, and customer service have significant influence on customer loyalty mediated by customer satisfaction. Transaction ability and response have no significant effect to both customer satisfaction and customer loyalty. Whereas web design and product variation only have a direct significant effect to customer loyalty.
7	[24]	Customer satisfaction	Perceived seeds process Service value Perceived ease of use Perceived control Interactivity	Findings indicate that as the electronic service delivery system process improves, a customer's perception of the website's ease of use increases, leading to increased service value and perceived control over the process, which increases customer satisfaction.
8	[25]	Financial customer satisfaction	Technology factors	Findings of the study indicated that convenience,

			Security features Website ease of use User friendly website Privacy Shopping factors Convenience Trustworthiness of information Ease of payment Time saving More online information Lower price Value for money Product factors Variety Type of product Well-known brands Logistic factors Delivery performance Delivery service	delivery, and time saving were viewed by customers as the most important reasons for buying online, while branding was viewed as the least important factor.
9	[26]	Disconfirmation Products Design functionality Service toward customers Overall satisfaction	System usability and effective marketing financial transactions and trust communication customer and sales support	The study was exploratory to develop new model of disconfirmation dimension
10	[27]	Customer satisfaction Customer e-loyalty	Technology acceptance factor website service quality specific holding cost	Findings indicated that customer e-satisfaction directly influence customer e-loyalty. technology acceptance factors directly influence customer e-satisfaction and e-loyalty; third, website service quality positively influence customer e-satisfaction and e-loyalty; and specific holdup cost can positively influence customer e-loyalty, but cannot positively influence customer e-satisfaction.

III. 3. MODEL

The data mart is constructed using the data from the consumer financial protection bureau [28]. The complaints are collected across all USA states and hold all the consumers' complaints about products, accounts, credit cards, loans for students or vehicles, money transfer, debt collection, and many other services for three years. The form to submit the complaint is updated to receive many options related to the product such as sub-product, issues, and sub-issue, time besides many language improvement. The search form provides many facilities based on text matching to find the complaints and check if it is solved or not.

The consumer complaints data mart takes its information from the Consumer Complaints Database. The database contains 18 columns with 65,499 records in it. The data stored is describing a user complaint about a specific product or service. It contains the source of the complaint, the date of submission, and the company the complaint was sent to for response. It helps improve the financial marketplace. The database columns include different and rich information. For example, the actions were taken by the company in response to the complaint, such as, whether the company's response was timely and how the company responded. If the consumer opts to share his personal information or not, the consumer's description of what happened. Companies also have the option to select a public response.

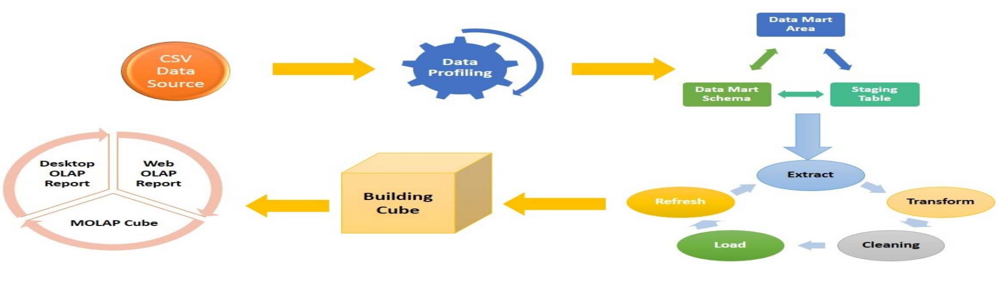

FIGURE 1. ROADMAP OF CONSTRUCTING COMPLAINT DATA MART.

A. Data Profiling and Data Preprocessing

The architecture of model implementation passed through many stages: data preprocessing, data profiling, preparing staging area, ETL implementing, building a cube, and construction reports, see figure (1). Data preprocessing includes many operations from data analysis to data profiling. Data preprocessing may hold some transformation processes in order to prepare data in the data staging area. The storage area of data mart includes data preprocessing area (staging table) that holds all the extracted data in order to perform transformation and loading processes. The preprocessing data analysis process which called data profiling is a fundamental process of data examination and assessment of data consistency, data quality, and integrity. The results of data profiling can be analyzed for better data mart implementation. Data profiling concentrates on attributes of individual columns data source where a complete summary that describe the uniqueness, data types, null ratio, and domain ranges of all columns are listed. Data profiling is a very important step in the DW and data mart constructing where the data source quality and all related informative statistics are shown. Dimension and fact tables can be clearly determined by using data profiling. The proposed keys for being primary keys, null ration in each column, mean and standard deviation, the minimum and maximum value can be determined in data profiling. Data profiling tool is available in SSDT where all results can be presented graphically for ease of use and understandability.

B. ETL Process

Implementing the ETL task takes to 70% of overall DW and data mart construction time and cost. Many tasks are involved which can be used to manipulate data to get integrated and cleaned data. These tasks (not limited to) are [29]:

1. Data extraction: include reading and understanding data that come from different sources. The data extraction includes also copying the required parts of data from data sources into the staging table. The data extraction process takes a great part of the time of overall ETL tasks.

2. Data cleaning: the process of detecting errors and correcting them when possible. Data cleaning involves handling missing values, correcting data conflicts, ensuring data integrity, and reducing noise [30].

3. Data transformation: involves a series of actions of transforming data into meaningful and valid formulas [31].

4. Load: the process of loading data mart tables with cleaned integrated data.

5. Refresh: the last step in ETL, where the data updates required over time. These updates need to be transferred from data sources into data mart repository [32].

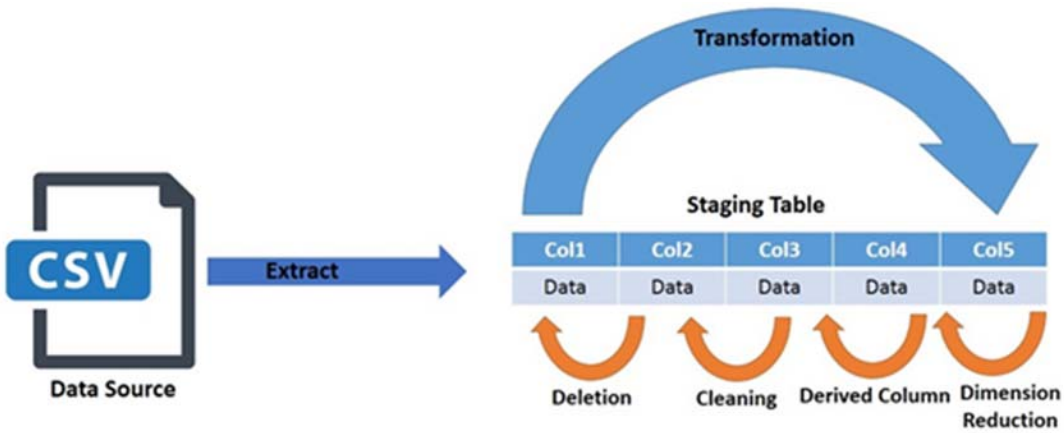

FIGURE 2. ETL FOR COMPLAINT DATA MART

The staging area represents the intermediate area between the data source and the data mart storage area [33]. This area holds the data temporarily in order to process it and loading it in dimension tables of the data mart. There are many operations executed in this area such as data archiving, data preprocessing, data extraction and cleaning, data conversion, indexing and loading, data quality ensuring, and dimension updating. The three major processes extraction, transform, and load (ETL) are performed in this area to produce the data mart. When OLAP queries perform, the dimension tables should be prepared and set to answer and provide all the intended results. The staging table holds all the data that should be manipulated. Data manipulation includes processes such as cleaning, enrichment, transformation, and deletion, see figure (2). The data types and values should be look-alike the data types of dimension tables.

In order to process data of complaint customer service, the data have been extracted from Comma Separated Value (CSV) file and load to the database in SQL Server Express Edition 2014. The source of data is freely available where the data published for research purposes. The dataset consists of consumers' complaints records about services and financial products of companies. SQL Server DBMS 2014 used to store data source, staging table and all dimensions and fact tables of the data mart. The staging table contains all the columns of all dimensions and fact tables.

The staging table is created to hold all the results of the processes such as data Conversion where all the columns in the database (nvarchar) were converted to suitable data types. Data profiling results where dataset is analyzed before making any further steps. After analyzing the data, dimensions were created to be able to answer all the queries in the future. Each dimension have a primary key that is represented in an auto incremental column. Many operations are performed for the data mart staging table such as:

- Primary Keys were added to the staging table.

- Derived columns received date column was divided into multiple columns (Day, DayOfWeek, Holiday, Quarter, Year)

- Replace NULL values with a suitable value based on the column data type.

To perform OLAP query, there are many types of OLAP environments form web OLAP to offline and multidimensional OLAP (MOLAP). It is very important to configure the OLAP query in the decision-making area to provide a fast response analysis for all dimensions. The reports in the decision-making area should be accessible by stakeholders (analysts, senior decision-makers, and service quality managers). There are three important factors that make the OLAP response so fast: dimension tables, fact table measurements, and concept hierarchy in the dimension table.

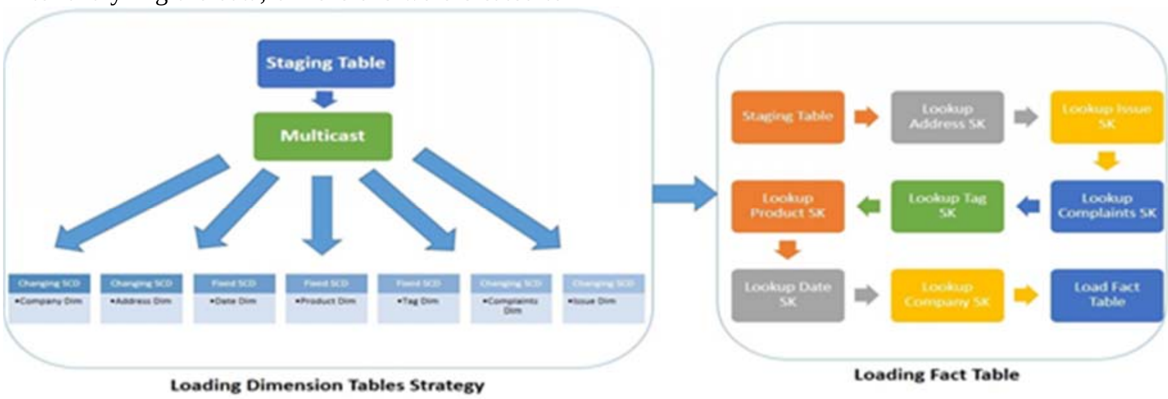

FIGURE 3. DIMENSIONS LOADING STRATEGY

The first two steps of ETL (extraction and transform) are performed in the staging area and specifically on the staging table by implementing the SSIS package. The extraction process does not involve a column selection process only but also involves the columns testing to check if they are fulfilling the data mart goals. The load stage is performed by two steps: loading dimension tables and then loading the fact table. Figure (3) shows the loading steps of data mart tables. The loading process of loading dimension tables includes loading seven dimension tables where the loading process of all tables is performed at the same time. The multicast tool is used in this task where it allows us to make a copy-like staging table in order to spread the same data for all dimension tables. Slowly changing dimension (SCD) task is used to load data from the staging table to the dimension table where there are two types of SCD performed (changing and fixed). Date, Product, and Tag are loaded using fixed SCD while other dimensions are loaded using changing SCD. The major difference between changing and the fixed attribute is the fixed SCD does not detect the changing in the staging table after loading the data into dimension tables while changing SCD detects the new changings in the dimension table.

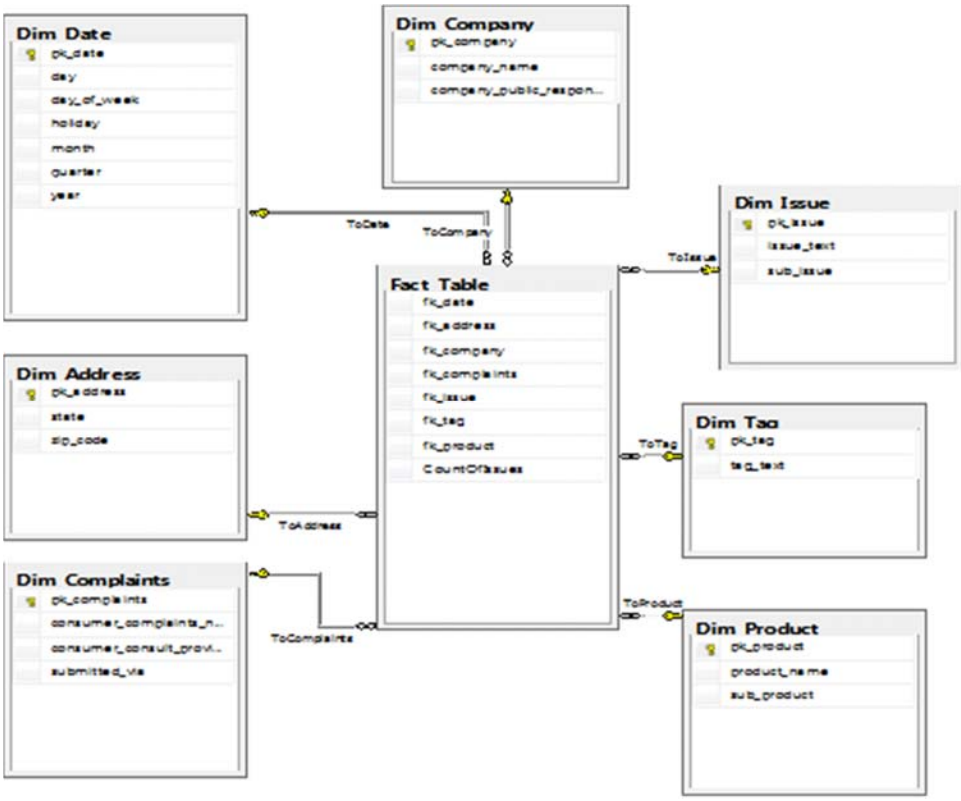

FIGURE 4. COMPLAINTS DATA MAR SCHEMA

The schema of a complaint data mart as shown in figure (4) is constructed by the SSMS 2014 tool where all tables are built. Complaint data mart schema consists of seven dimensions (Product, Tag, Issue, Complaint, Address, Date, and Company) connected to the fact table. The fact table consists of one measurement (countOfIssues) and seven concatenating keys to dimension tables. The measurement key is a calculated function overall dimension tables that returns the number of complaint issue after applying complex OLAP query. The key point behind the fast response of the OLAP query is using dimension tables that hold the hierarchy concept. This concept almost constructs dimension like an address that permits OLAP operations easily. There are many advantages for using star schema [34] such as the fast response of OLAP query, processing the changes of dimensions with time, allow many hierarchies for dimensions, and easy and simple schema to build and understand.

C. Building Cube

Building a cube is required to construct a platform for analysts to get their answers for all questions in OLAP queries. The answers are shown in a chart form or a table form. SSAS 2014 is used to implement the cube of Complaint data mart which consists of dimension tables with a hierarchy that confirms the goal. The multidimensional cube is the base of performing OLAP queries. The multidimensional cube is used due to its advantages such as high performance and fast response [8][35]. Figure (5) shows the flexibility of implementing OLAP queries using SSAS to show the results as a table. The analyst can easily drag the dimension column or dimension hierarchy with measurement to present the result in a very fast way. The figure shows the number of complaints in California (CA) state according to a quarter of the year where the third quarter has the most number of complaints along all years 2242 complaints while the first quarter with 2193 complaints and fourth quarter with 2184 complaints. The second quarter takes the lowest number of complaints with 1357.

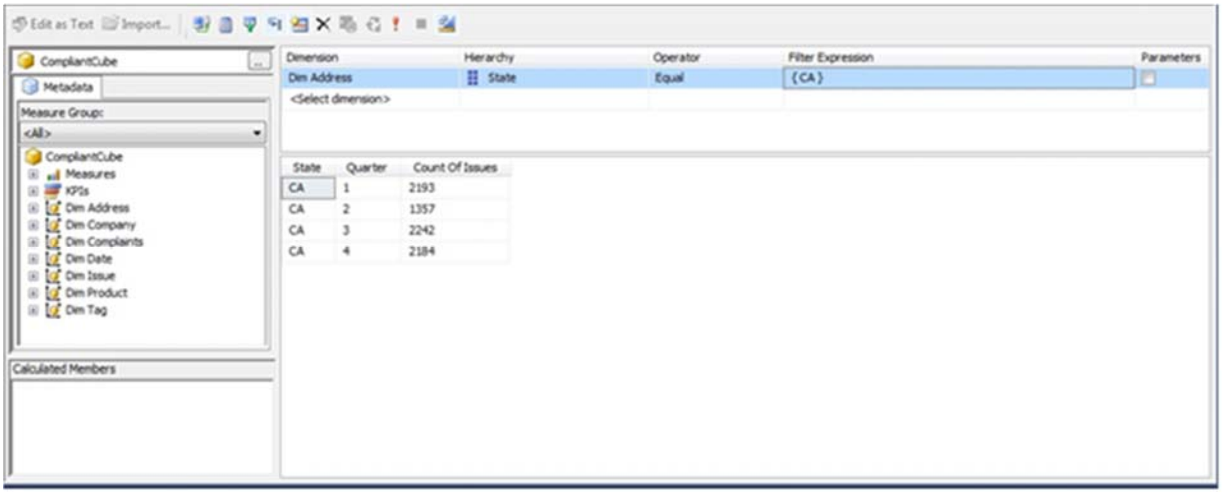

FIGURE 5. COMPLAINTS' NUMBER IN CA

Figure (6) show the number of complaints according to the month where the result is shown as a table. The first month has the highest number of complaints among all month with 6307 issues. This table can provide the analysts and decision-makers a brief view of the overall performance of all companies and improve the performance of all companies by satisfying the consumers. The importance of performing OLAP queries using SSAS projects is to investigate the results and get very fast results to check if these results can help the decision-makers or not. The other advantage of SSAS cube is to check the data mart or DW implementation standards and find if they are satisfied or not. In the next reports, this result will be clarified by a chart to show the complaints according to months.

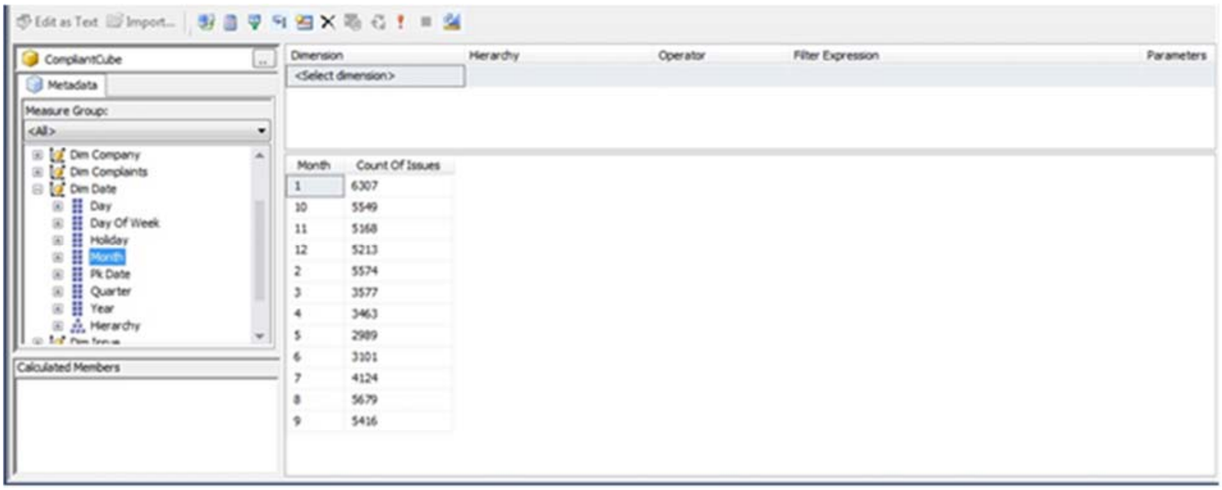

FIGURE 6. COMPLAINTS' NUMBER ACCORDING TO MONTHS

D. Reports

OLAP technology is used with DW and data mart to get fast accurate answers for any OLAP query [6]. OLAP can process the fact table and dimensions and roll back if any error occurs. OLAP cube is a basic component of a data mart model that stores complex calculations and security settings which can be integrated with data mining algorithms and tools [36][37]. The relational OLAP (ROLAP) system is built on the top of the relational DBMS. There are three different categories of OLAP systems [38]:

• MOLAP: refers to multidimensional OLAP where the OLAP server is built by a multidimensional database where all indexes are stored and retrieved.

• ROLAP: the ROLAP server sends OLAP query parameters and receives the answers from the relational database. One of the ROLAP types is desktop OLAP (DOLAP) where the analyst has the ability to perform OLAP queries using DOLAP software or a pre-created multidimensional database.

• HOLAP: refers to hybrid OLAP where it is a combination of MOLAP and ROLAP strength features.

There are also web OLAP where all OLAP query calculations are performed and accessed from web browsers. In our model, three types of OLAP queries are performed (SSAS cube view, online reports using SSRS, and offline reports by using MS Excel pivot table).

1. Web OLAP

One of the most effective tools to view OLAP reports is a web OLAP report where the analyst can view the OLAP cube remotely through a web browser. Web OLAP can be considered as a merging result of OLAP with the world wide web (WWW). The easiness of web OLAP, availability, and easiness make the web OLAP the best choice for analysts. Besides, web OLAP is a client-server technology that almost doesn't need any deployment efforts. Figure (7) shows the overall complaints according to the month where the first month has a large number of complaints with more than 6000 complaints. The fifth month has the lowest number of complaints with 2300 complaints.

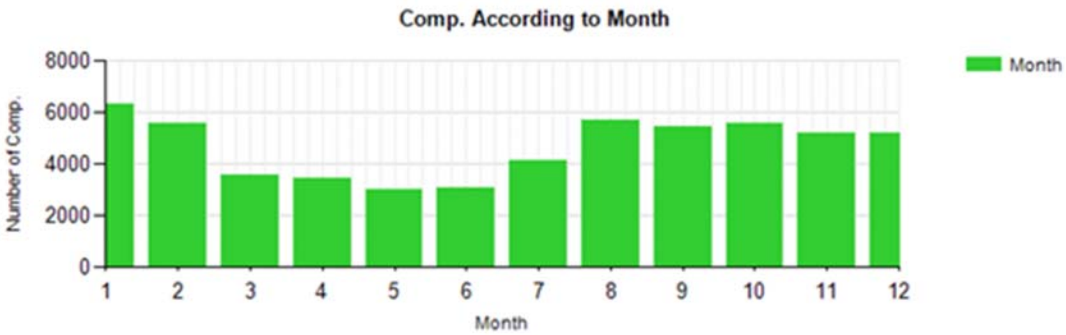

FIGURE 7. COMPLAINTS NUMBER ACCORDING TO MONTH.

The figure (8) lists the complaints number classified by month to show the details of complaints in each quarter. The quarter four has a large number of complaints 15930 with 28.3%. Likewise, the number of complaints in the first quarter is 15458 with 27.5% while the third quarter takes 15219 with 27.1%. The second quarter take the lowest number of complaints with 9553 with 17.1%.

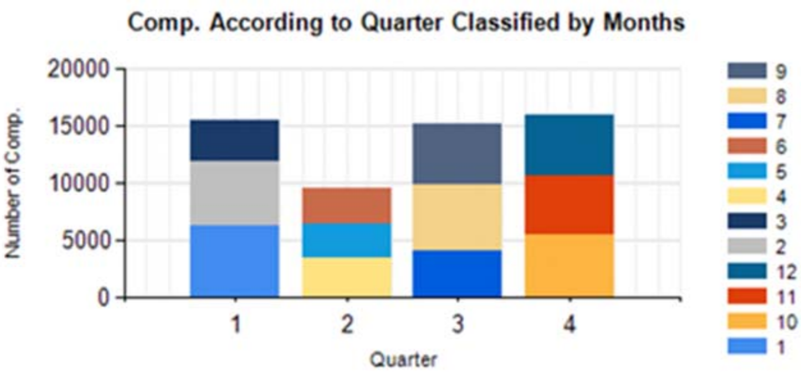

FIGURE 8. COMPLAINT NUMBER ACCORDING TO DETAILED QUARTERS.

2. Offline OLAP

The second category of OLAP reports is offline OLAP reports. This category is implemented using the MS Excel Pivot table where the complaint cube imported from the SSAS server to perform all the OLAP operations. Pivot table provides the analyst with an easy platform to implement all OLAP operations such as (roll-up, drill down, slice and dice). The results of OLAP queries can be presented using different chart styles such as pie, tabular, columnar, and many other styles.

The figure (9) shows the complaints according to the day of the week. The figure shows a detailed number of complaints where the first day of the week takes the lowest number of complaints with 2334 while the fourth day takes the highest number of complaints with 10797 complaints. The second day takes 9402 where the third day takes 10397 complaints. The fifth day takes 10594 while the sixth day takes 9325 complaints. It can be clearly observed that the days 2 to 6 takes the highest number of complaints while the first and seventh days takes the lowest number of complaints.

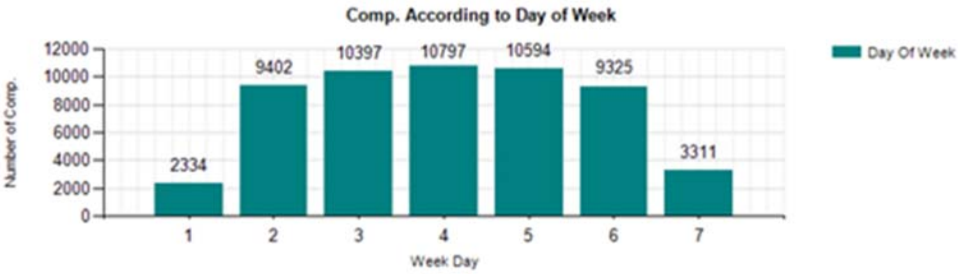

FIGURE 9. COMPLAINT NUMBER ACCORDING TO DAY OF WEEK.

Sometimes, it is very helpful to show the complaint issue that takes the highest number of complaints. Among 102 complaint issues, loan modification, collection, and foreclosure with 8285. The complaint issue incorrect information takes the second-highest number of complaints with 7544 where the loan servicing and payment takes 5746. The other complaints are listed in the figure.

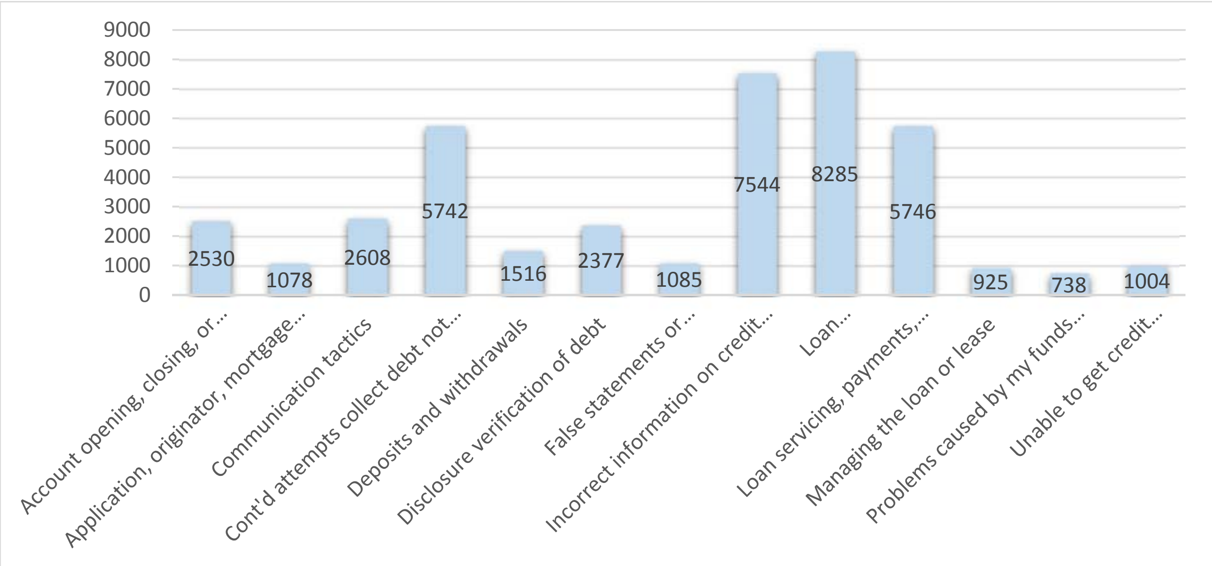

FIGURE 10. COMPLAINT ISSUES.

The next figure (11) shows the complaints according to states where some states are excluded since they had the minimum number of complaints. The states with the maximum number of complaints are California 8000 complaints, Florida 5300 complaints, New York 3700 complaints, and Texas 4700 complaints. From this figure, the decision-makers should make the strategic decisions to find the reasons behind the complaints and try to quickly response them in order to eliminate them or at least reduce them.

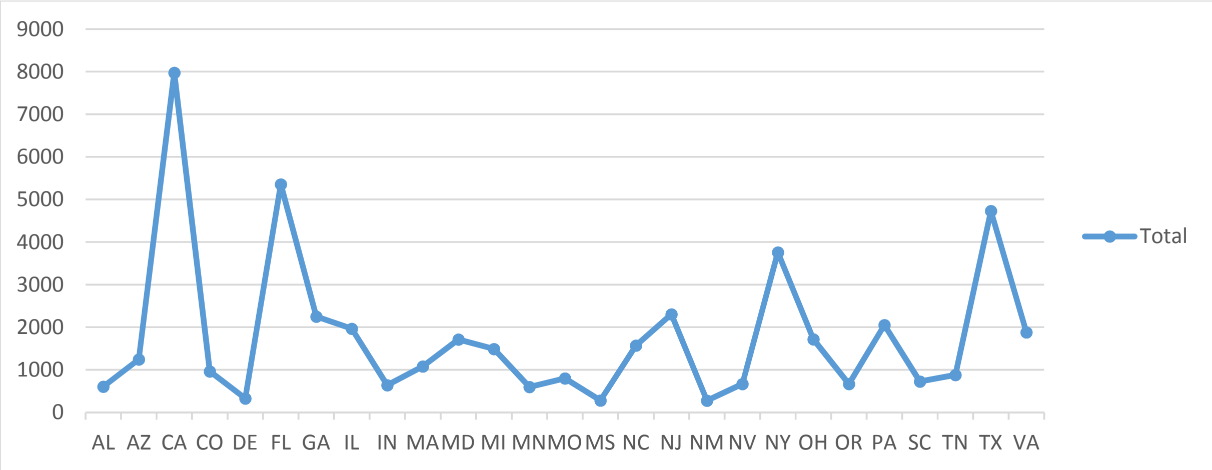

FIGURE 11. COMPLAINT ACCORDING TO STATES.

This category of reports can help the analysts and decision-makers to get very fast and customized results. The analysts can easily select the dimension and determine the chart style to get a deep view about the general performance of the companies for all states.

IV. CONCLUSION AND FUTURE WORKS

The paper presents a roadmap to construct a compliant data mart to support decisions related to customer's service quality. Although the source of the data provides a platform to submit and retrieve the complaint's status, the model of implementing data mart can be considered as an addition where the analysts can present the results from different perspectives. The analysts and decision-makers can present the results based on the cubic data form where the data are constructed based on multidimensional form.

The design approach used for data mart implementation is bottom-up for many reasons such as fast implementation and delivery process, providing a standalone application that can be used to measure success factors of DW, and getting the analysis results and reports for the department data before implementing the organizational DW. SSMS is used to store the data of data mart in data mart tables (fact and dimensions). SSIS is used to implement ETL stages while SSAS is used to create a complaint cube to perform all OLAP queries. SSRS finally is used to construct web OLAP reports. All the processes of SSIS, SSAS, and SSRS are performed through the SSDT project.

The multidimensional cube is constructed based on the fact table and seven dimension tables. The dimensions represent the candidate queries that can be performed to answer all questions as an OLAP query. There are two types of implemented OLAP report, offline and web OLAP reports. The major difference between them is the way of access where the web OLAP can be accessed remotely while offline OLAP can be used locally. The reports vary from listing the complaints number according to date, address, company, issue, or even state. The reports can help all stakeholders and decision-makers to select the dimensions and get customized reports. Offline OLAP reports provide flexibility to select chart type and determine measurement and dimensions and perform different OLAP operations.

The data mart gives the analysts and decision-makers the ability to investigate the importance of enterprise DW and how can it affect the decision making on the strategic decisions. The best way to improve service quality is to provide a high level of quality of services and fast response to consumers' dissatisfaction. It is also better to provide the consumers with a platform that educates them and gives them a top view of all companies' performance. Handling customers' complaints can improve the future behavior of customers and enhance service quality. The proposed future work is implementing a mobile application to get notifications when the number of complaints of specific issues or for a specific company, month, or state exceeds the previous number of complaints. In this case, it will be very helpful to implement key performance indicators (KPI) for each case to measure the performance of companies and consumer satisfaction.

Trust factor and the reputation of the financial seller are important factors. However, studies in this field are few. It is recommended that future work investigate the influence of trust and reputation on the financial customer satisfaction. Traditional or offline customer satisfaction has linked the satisfaction to the quality. However, online customer satisfaction differs in term of the service. Thus, an investigation of the influence of service quality.

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