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A Survey on Business Intelligence Solutions in Banking Industry and Big Data Applications

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Abstract

Nowadays, the economic and social nature of contemporary business organizations chiefly banks binds them to face with the sheer volume of data and information and the key to commercial success in this area is the proper use of data for making better, faster and flawless decisions. To achieve this goal organizations requires strong and effective tools to enable them in automating task analysis, decision-making, strategy formulation and risk prediction to prevent bankruptcy and fraud .Business Intelligence is a set of skills, technologies and application systems used to collect, store, analyze and create effective access to the task to help organizations better understand the business context and make accurate decision timely and respond quickly toward inflation, rate fluctuations and the market price. In this paper we review recent literature in the search for trends in business intelligence applications for the banking industry and its challenges and finally some articles that comprise this special issue are introduced and characterized in terms of business intelligence research framework.

Keywords: *Big Data, Business Intelligence, Risk Prediction, Bank Industry*

1. Introduction

Banking industry and financial services maintaining and improving are duo to having a safe transaction environment as Banking has become a prolific industry for innovation concerning information systems and technologies, in regard to including, some sort of interaction with digital technologies in human aspects of activity, which results in increasing production of data that can be interpreted and explored as digital traces of human behavior. So having authority on new technologies such as business intelligence is supposed as an inevitable requirement. Business intelligence (BI) is defined as an umbrella term that includes architectures, tools, databases, applications and methodologies with the goal of analyzing data in order to support decisions of business managers [77, 30]. The opportunities associated with data and analysis in different organizations have helped generate significant interest in BI, which is often referred to as the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions [48, 107]. In addition to the underlying data processing and analytical technologies, BI includes business-centric practices and methodologies that can be applied to various high-impact applications such as e-commerce, market intelligence, e-government, healthcare, and security. By business intelligence implementation, the information gap existing between senior executives and middle managers and even end users will be lost and the information is acquired by

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managers at any level in any moment with high quality and also specialist and analysts can improve their activities with low cost facilities and find better results [6, 24, 79, 43, 123]. In fact, business intelligence is based on a simple goal: «improves performance by creating the appropriate platform for decision making in organization» as the managers have comprehensive view towards enterprise data, trustworthy decisions are made [4]. Business intelligence, doesn't supposed as a product or as a system, but preferably as a new approach based on desired architecture comprising a set of analytic applications which invoke analytical and operational databases on commercial and industrial decision making intervals. Business intelligence applications, utilizing in the banking industry are named as follows:

- Marketing
- Risk management
- Fraud Detection
- Success prediction
- Folio port management
- Securities exchanges
- Customer retention/churn prediction
- Anti-money laundering
- Basel-based business intelligence building set

Employing business intelligence and taking advantages of its beneficial applications creates suitable platforms for incremental investments in the field of information technology [52, 72]. This article is organized as follows. first introduces the main concepts related with both banking and BI domains, next presents other references of literature analyses then pose the methods used for analyzing the literature, thenceforth, the results are discussed, following, conclusions are summarized.

2. Literature Review

All The business intelligence subject is defined as gathering, processing and analysis of a large amount of data from the internal and external system resources with intelligent tools to achieve organizational objectives and adopt immediate decisions when it is necessary and also refers to a smart kind of business management for improving technology and related applications in data access & data analysis field in order to help companies to make suitable trading decisions. The first step in understanding the business intelligence is recognizing the organizational intelligence, which consists of two parts, organizational intelligence as a process and organizational intelligence as a product. Enterprise intelligence is validating the enterprise capabilities in decision making in ordinary & anomalous conditions.

Efficient business intelligence as a tool to improve the decision making process in any organization will be helpful although in the past business intelligence has only been supposed profitably for private companies but recently it is adopted in public institutions too. Business intelligence as a tool used to design and manage the life cycle of the system accompanied with the effective support of the smart decisions. Using theoretical perspectives of commercial intelligence in any large organization should be prospective, though relatively political issues which lead in different management style and diverse expectations sometimes result in unforeseen consequences. Business intelligence is considered as the balm for weak organizations in the business sphere, however, intelligence in fact is a tool that can be profitable in the business affairs also business intelligence success in any organization is affected by review of the estimated successful behavior that its awareness can be so effective and efficient for business decisions and enhance its success rate smartly. Over two past decades, the organizations attitude towards their staff is severely changed in so far as the staff become main stream operator and financial partners, thus not only managers should get leadership skills, but also the employees should also learn some ways leading to self-guidance as the employee's empowerment refers to enterprise power & duty delegation hierarchy from higher to lower organizational category. All issues in financial services are engaged with money industry. The impact of the global financial crisis and credit scoring applications on bank managers for surviving and even exceling in today's turbulent business environment bind them to have a continuous focus on challenging problems and exploiting opportunities which demands a need for computerized support of managerial decision making thus the urgent need of decision support and business intelligence systems is felt .In this type of business, business intelligence applications focus on the financial operations instead of commercial ones. Generally, the business intelligence usage valuates the financial services and also can plays effective rule in tracking the abuse of financial assets which includes spoof discovering and cheat tracing.

3. Business Intelligence solutions

In this section some business intelligence solutions consist of architecture and implementations approaches in banking industry are reviewed and discussed and its advantages and disadvantages are also mentioned.

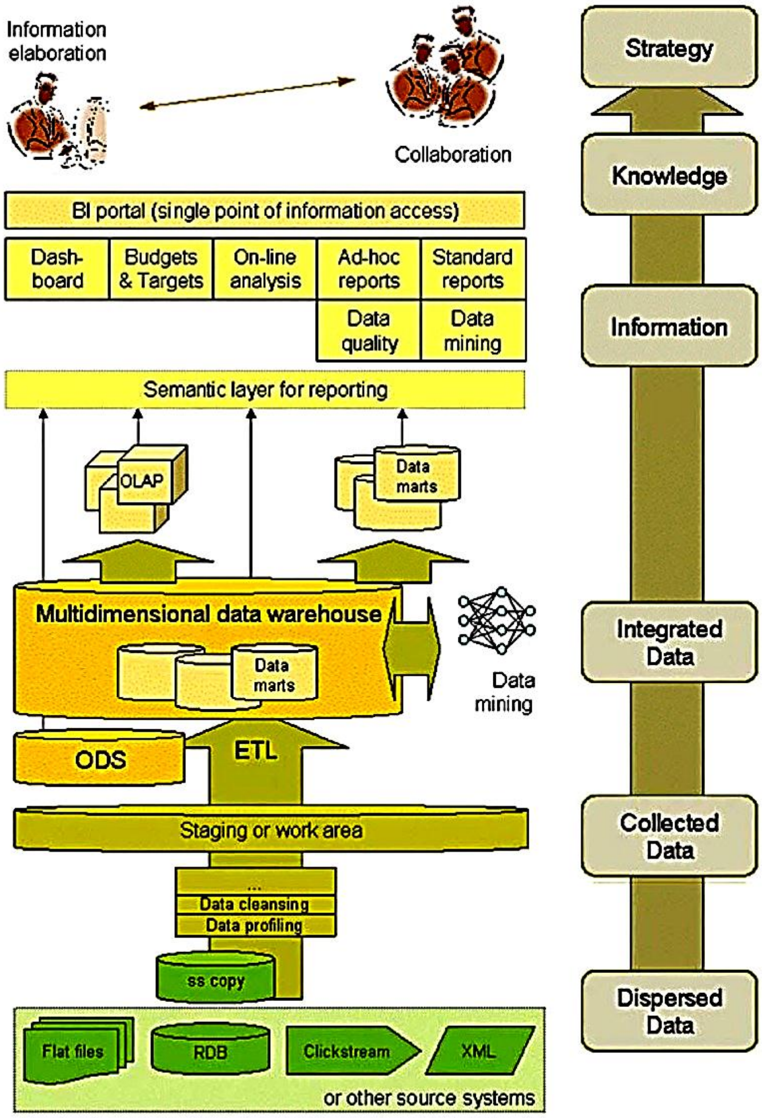

Figure 1: Components of a BI solution [8]

Banking domains, such as credit evaluation, branches performance, e-banking, customer segmentation and retention, are excellent fields for a wide variety of BI concepts and techniques which could be implemented by data mining(DM), text mining(TM), web mining(WB), data warehouses, decision support systems (DSS)schemes, cloud computing and also data virtualization. In following we review the most significant schemes used in articles respectively [2].

Table 1: Summary of BI Advantages [116]

Business Aspect	Business Intelligence Advantage	Benefits
Competitive Advantage	• Market Research • Risk management • Manufacturing Optimization	• Finding Elements of Market Dominance • Bankruptcy Prediction, Better Investments • Better Material Usage, Shipments, Scheduling
Customer Relationship Management	• Costumers Targeting • Pricing Discrimination • Market Baskets • Customers Satisfaction	• Target Specific customers with the right products • Dynamic pricing • Better Marketing and Advertisements • Find the reasons and the costs of switching, chum, and satisfactory levels
Logistic and Supply Chain Management	• Production Managements • Scheduling Supply Chain • Dynamic Reactions • Forecasting	• Prevent overproduction and underproduction • Help dynamically manage the supplies during their move through the chain • React immediately to changes to help sustain supply • Forecast the demand for production
Anomalies and Fraud Detection	• Fraud Detection • Anomaly Detection	• Help find fraudulence transactions, fraudsters, hackers, and possible counterfeiting • Find what data to leave out, why such anomalies happened, and avoid considering them

4. BI implementations with mining tools

The Information and Communication Technologies revolution brought a digital world with huge amounts of available data. The information and communication technologies revolution provided us with convenience and ease of access to information, mobile communications and even possible contribution to this amount of information. Enterprises use mining technologies to search vast amounts of data for vital insight and knowledge .Mining tools comprises data mining, text mining, and web mining are used to find hidden knowledge in large databases or the Internet. Mining tools are automated software tools used to achieve business intelligence by finding hidden relations, and predicting future events from vast amounts of data. This uncovered knowledge helps in gaining completive advantages, better customers' relationships, and even fraud detection.

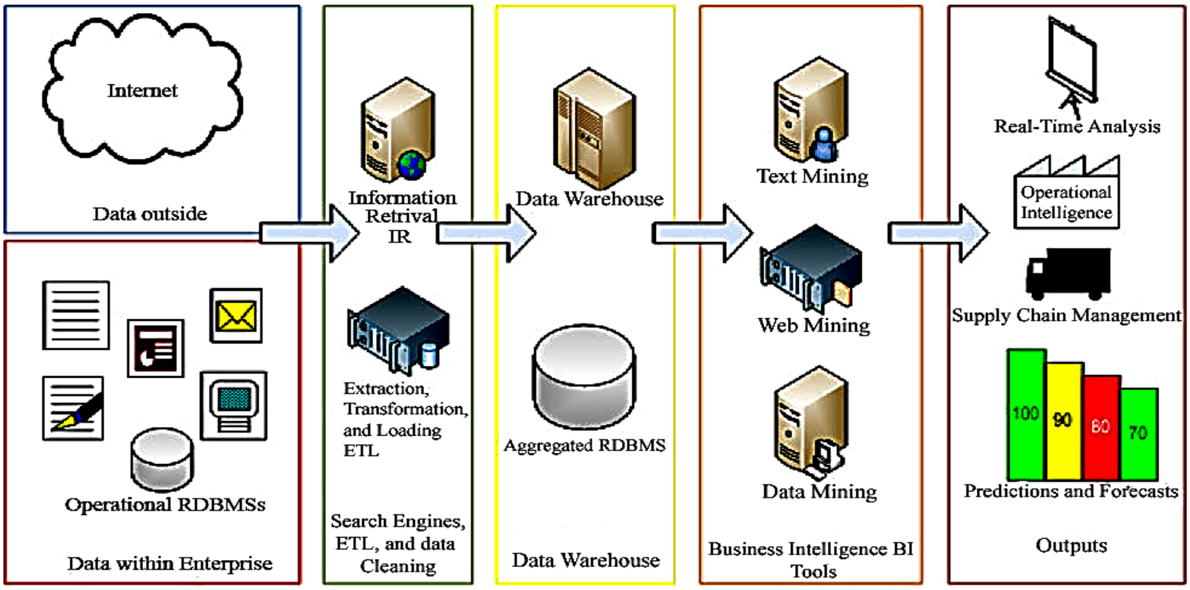

Figure 2: Data Transforming into Business Intelligence [116]

Data Mining (DM) which is defined as the process of analyzing large database, usually data warehouses or internet, used to discover new information, hidden patterns and behaviors. It's an automated process of analyzing huge amounts of data to discover hidden traits, patterns and to predict future trends and forecast possible opportunities. In [116] a data mining approach for risk management in banking industry is proposed. In [75] the IT risk in an organization was assessed through an intelligent system benefiting from fuzzy analysis and certainty factors. Risk management can be defined as the process of identification, analysis and either the acceptance or mitigation of uncertainty in investment decision making which is highly applicable in banking industry which is about managing uncertainty related to a threat and consists of financial risk management(comprise market risk, credit risk, operational risk, and liquidity risk), security risk management(includes political risks, reputational risks, bioengineering risks, and disaster risks), and enterprise resource risk management.

The risk properties are known as uncertainty, dynamic interconnection, dependence and complexity which the first two ones have been widely recognized in inter-temporal models from the behavioral decision and behavioral economics areas and the last two ones are well studied in finance disciplines. The suitable techniques known in this area are early warning systems[19,53,118,99] (in macroeconomic models, insurance stochastic optimization, financial surveillance mechanisms, industrial applications, logistics risks identification in small to medium enterprises), neural networks-based risk systems [58, 119,45, 25,60] (in software reliability assessment, credit card validation, test mining application, financial risk trading), risk-based decision making [104, 111, 87, 65, 54, 85, 102, 67] (in loan-risk analysis, technology investments, political pluralism in commercial banks expansion, stakeholder investment, risk assessment), game-based risk systems[81, 124, 73, 71, 41] (industrial risk management, probabilistic risk analysis in the context of counterterrorism, vertical differentiation in online advertising, enterprise risk management), credit risk decisions [47, 105, 117, 18, 94] (in linear discriminant analysis, large banks credit worthiness, credit scoring, bank loan, risk avaricious investment) and enterprise risk management data mining [101, 57, 82, 103](in corporate finance, fraud detection, credit risk estimation, bankruptcy risk, risk chain supply, economic downturns), agent-based risk management[40, 17, 21, 66, 74, 10] (in bankruptcy risks modeling, chain risk management, economic downturns, critical financial markets, self-emerging networks) and engineering risk analysis based on optimization tools[1, 16, 95, 61] (in mechanical systems, real options analysis, maintaining risky systems).In [42] a customer churn prediction method considering data mining constraint to provide comprehensible models for non-experts is proposed.

Most business is taking the customer retention issue seriously. Customer churn prediction models are a kind of tool that helps marketing planners to sense the churning before it actually happens. Most work on customer churn analysis aims at inducing an accurate churner classification model. Besides high predictive accuracy of the model comprehensibility is also an important issue as pointed out in recent work on churn prediction [89, 110, 108]. The model representation should be in a form that is easy to understand by most users, not just the experts. Prediction models are conventionally built by the systematic process using statistical methods such as regression analysis. Since the emergence of new technology such as data mining, more and more business analysts have paid attention to this new technology. In this method induction results of delivery model are considered as association rules set and a frame work for incorporating induced model to the decision support system.

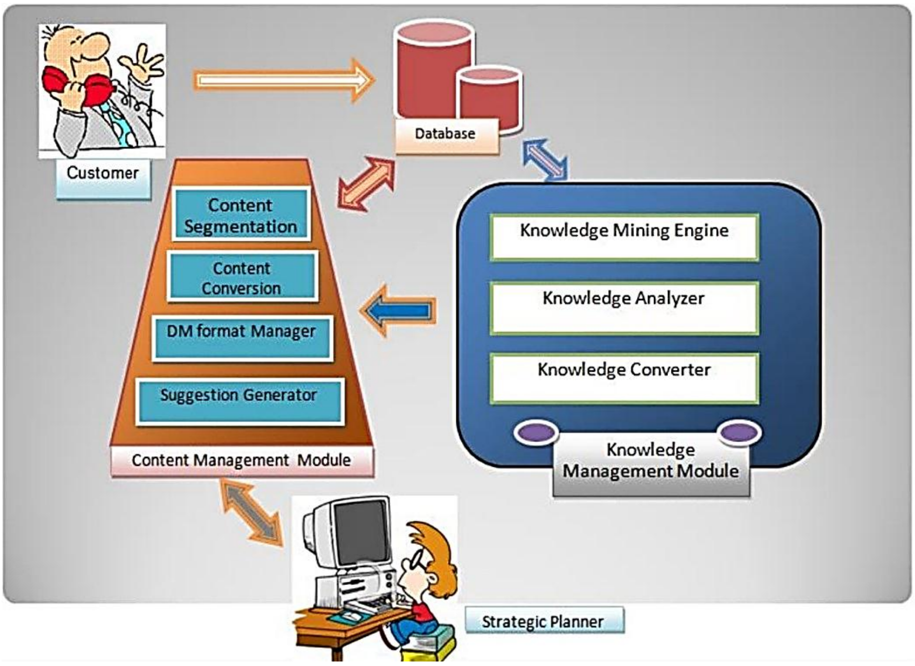

Figure 3: The pattern analysis framework to induce knowledge for supporting strategic decision [42]

The design focus is on the knowledge mining engine. The conventional association mining steps is extended by considering constraints that are posted by analyzers to search related objectives association rules accompanied by irrelevant rules elimination. The churn data in telecommunication industry is used for implementation [68, 90]. The first step in implementation is defined as feature selection experimentation which are consists of state, account length, area code, international plan, voice mail plan, messages, total day calls, total eve calls, total night calls,, number of customer service calls, and then the insignificance inducing models are removed. It can be noticed that when the number of constraints increasing simultaneously the number of association rules in the final result decreases considerably in addition to running time decrement. As The objective of this kind of analysis is to gain insight into consumers' behavior who are about to leave for another service company, timely detection is believed to prevent these customers from attrition. Retaining current customers are known to take less effort and budget than acquiring new customers. The cost effectiveness is even higher if customers are valuable ones [56]. Data mining techniques in intrusion detection which defines as an illegal act of entering, seizing, or taking possession of another's property is surveyed. It means a code that disables the proper flowing of traffic on the network or steals the information from the traffic [100].

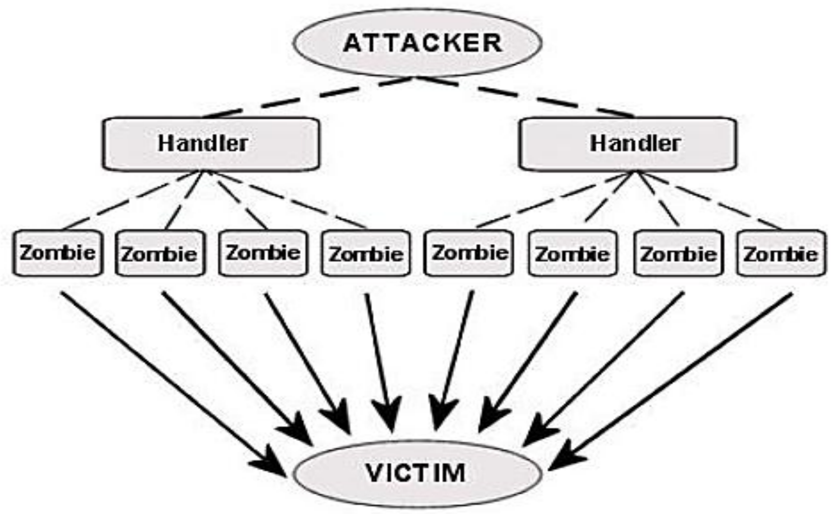

Figure 4: Dos attack scenario

The various divisions of intrusions consists of DoS Attack, remote to User (R2L), user to Root (U2R), probing and intrusion detection methodologies comprise anomaly detection and misuse detection. The main purpose is to get the more correct rate of intrusion detection to reduce the rate of false negatives which assumes so efficient in banking industry in regard to its nature. In [106] a constructing method in banking customer's behavior imitation corresponding to future online service preference is proposed and has incorporated heterogeneity into the models using a random coefficient model as well as interaction between the primary bank services attributes and individual demo graphics and characteristics and also the results are consistent with the conventional rank-ordered logic model and implemented by conjoint analysis, preference methods state and discrete choice modeling. The results of rank-ordered log it estimation includes the parameter estimates asymptotic t-statistics, willingness-to-pay of consumers for each attribute of the future banking services and the relative important attributes. In [120] a data mining approach in financial accounting fraud detection is proposed.

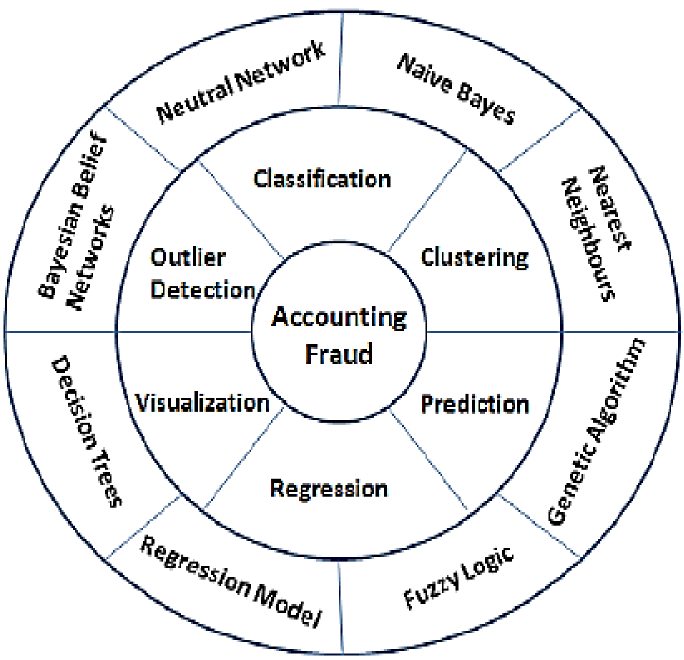

Figure 5: The Conceptual Framework for Application of Data Mining to FAFD [120]

Conceptual framework description is consists of 6 data mining application classes (classification, clustering, outlier detection, prediction regression and visualization) which each of the them is supported by a set of algorithmic approaches to extract the relevant relationships in the data that handle different problem . Data mining methods in financial accounting fraud detection are engaged with regression models [39], neural networks [44, 20, 62, 49].Bayesian belief network [79], decision trees[7, 121, 112], naïve bays [48, 57], nearest neighbor[121, 9, 3], fuzzy logic and genetic algorithm[69, 70, 91, 11, 51, 59, 33, 34, 35, 64], expert Systems methods [88, 122, 97, 92, 125, 36, 12]. Regression analysis is widely used for fraud detection since it has great explanation ability besides neural networks are also considered as an important tool for data mining and shows no strict requests for data and has a strong generalization and adjustment as known advantages. Though researchers have not yet made any comparison in effect detecting and accuracy of these mentioned schemes. In [23] a customer retention strategy in customer relationship management(CRM) via data mining is proposed.

It is defined that the customer relationship is neither a concept nor a project, considered as a business strategy that results in recognizing, anticipating and managing the needs of current and future customer. The term CRM is generally used to refer to software based approach for handling customer relationship and most CRM software vendors stress that a successful CRM strategy require a holistic approach. The basic building blocks of CRM are titled as customer databases, customer intelligence, business modeling, Learning and competency managing and the customer life style also could be marked in 3 stages: customer acquisition, retaining good customers, making the relationship of customers.

The data mining areas includes customer retention, sales and services, marketing, risk assessment & fraud detection and implemented by association rule learning, classification & prediction, clustering, regression, visualization. Common challenges mostly caused via dealing with highly and unavoidably noisy data, getting real-world result validation, developing deeper models of customer behavior, managing the cold start/bootstrap problem, encountering diverse data types, pre integration of data, DM chaining. The outstanding benefits of CRM utilization summarized in information database leveraging, getting loyal customers, maintenance and expansion cost decrement, investing on upon profitable client, making higher revenues and lower cost which leads to fasten up the process of searching the large databases then extract customer buying patterns, to classify customers into groups which also make databases to be handled efficiently.

5. BI IMPLEMENTATION WITH DECISION SUPPORT SYSTEM

A decision support system is defined as a computer information system which comprises data & models for solving semi-structured and unstructured issues in extensive functional environment. Many companies have turned up towards decision support system to upgrade their decision making level. The major reason that mentioned by them significantly is their need to access to precise information at high speed rate and also tracing commercial acts and part of the existing systems which are not able to recognize special commercial requirements automatically[38, 76, 5]. The characteristics of the a main decision support systems is as follows:

- A decision support system is based on Computer system and takes advantage from its technologies and methodologies.
- It helps the decision making process but could not be replaced by an expert person.`
- Its use of analytical & artificial expert systems models in issue solving.
- Having the capability of employing in semi structured and unstructured issues
- Applicable in all management levels.

- Improves the quality, speed and accuracy of decision making level
- Decision support systems is leading to getting
- Creativity capabilities and ease of operation
- Decision support system are easy to made and use
- Could support personal and gregarious solution

Decision support within various tasks in industrial businesses typically needs to consider both economical as well as technical aspects—with the latter often coming in extremely detailed and high-dimensional form. Usually, the respective types of analyses also require the consideration of information that is only available in a semi-structured or unstructured form, e.g. service reports that sketch technical and geometric specifications in quality protocols or technical drawings. A comprehensive framework for BI in the manufacturing sector therefore needs to include both: an integrated presentation interface to connect structured and unstructured data as well as analytics of structured descriptions to unstructured files. In [83] a personal and intelligent decision support system [98] in bank telemarketing is proposed to predict the bank telemarketing success in selling long-term deposits. The research focus on targeting through telemarketing phone calls to sell long-term deposits [84, 78, 115, 28].

Two knowledge extraction techniques are also applied to the mentioned model [27] a sensitivity analysis, which ranked the input attributes and showed the average effect of the most relevant features in the NN responses; and a decision tree, which learned the NN responses with a low error and allowed the extraction of decision rules that are easy to interpret within a campaign. The human agents execute phone calls to a list of clients to sell the deposit (outbound) or, if meanwhile the client calls the contact-center for any other reason, he is asked to subscribe the deposit (inbound). Thus, the result is a binary unsuccessful or successful contact.

Data collection is done for big enough intervals to include the financial crisis effect and four DM models are implemented and compared with each other[26, 32, 50, 31], logistic regression, decision trees (DT), neural network (NN) and support vector machine. LR and DT have the advantage of fitting models that tend to be easily understood by humans, while also providing good predictions in classification tasks.

NN and SVM are more flexible when compared with classical statistical modeling (e.g., LR) or even DT, presenting learning capabilities that range from linear to complex nonlinear mappings. Due to such flexibility, NN and SVM tend to provide accurate predictions, but the obtained models are difficult to be understood by humans. When comparing DT, NN and SVM, several studies have shown different classification performances.

For instance, SVM provided better results in [32, 31], comparable NN and SVM performances were obtained in [28], while DT outperformed NN and SVM in [93]. These differences in performance emphasize the impact of the problem context and provide a strong reason to test several techniques when addressing a problem before choosing one of them [46]. Above models were compared using two metrics, area of the receiver operating characteristic curve (AUC) and area of the LIFT cumulative curve(ALIFT), both at the modeling and rolling window evaluation phases. For both metrics and phases, the best results were obtained by the NN then proposed DSS creates value for the bank telemarketing managers in term of campaign efficiency improvement by reducing client intrusiveness and contact costs.

6. BI implementation in cloud

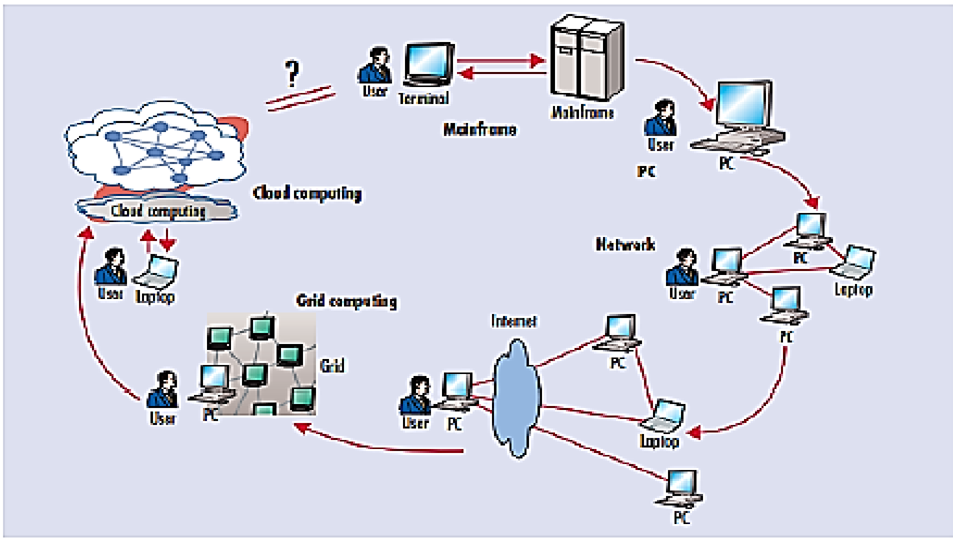

Figure 6: Computing paradigm shift of the last half century [86]

BI solutions are often unpractical and unattractive without taking cloud computing into consideration. The available models while deploying BI components on Cloud consists of public cloud-based IaaS, public / hybrid cloud based PaaS, public or hybrid cloud based SaaS BI, private cloud-based. Cloud BI solution has special interest for organizations that desire to improve agility while at the same time reducing IT costs and exploiting the benefits of Cloud Computing. On the other hand nowadays there is a current strong investment in cloud based BI and growing interest in tapping into the cloud's benefits. Theoretical contribution comes with the combination of theories on agility with the design of BI architectures. It needs to be acknowledged that there are limitations to the study – most notably the number of cases .In order to address these issues of external validity and to limit the extent of a possible introduction bias, all results have been critically reflected for their generalizability and their consistency with the existing body of knowledge on BI. To begin the study agility requires significantly more structure than a standard solution in order to do not endanger the integration and efficiency goals associated with it [22].

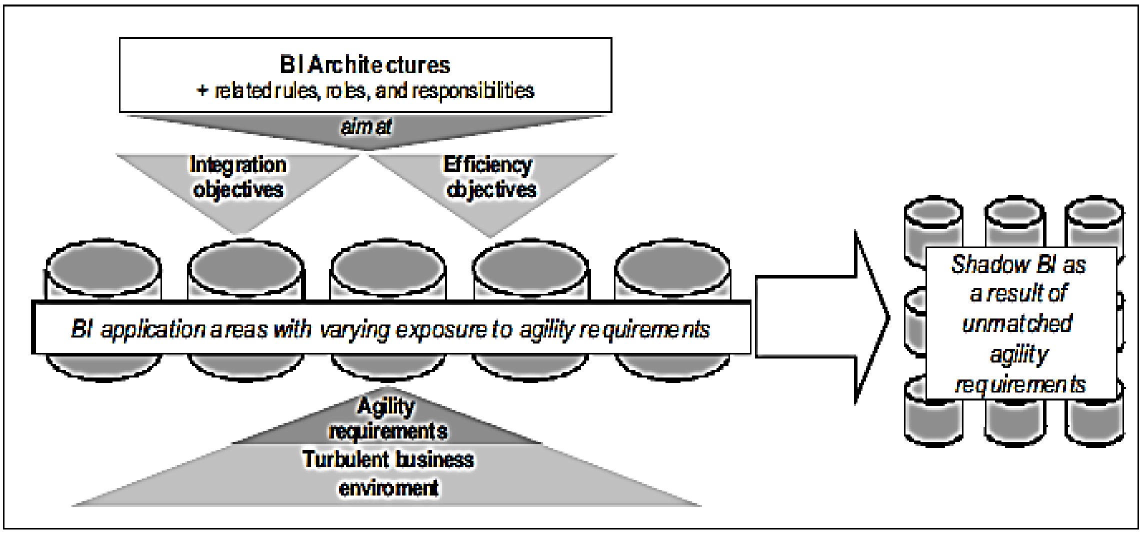

Figure 7: Conceptual framework of improving agility through BI

Relationally there are several operational and financial factors that work in favor of cloud business intelligence (BI)[15] considering agility,

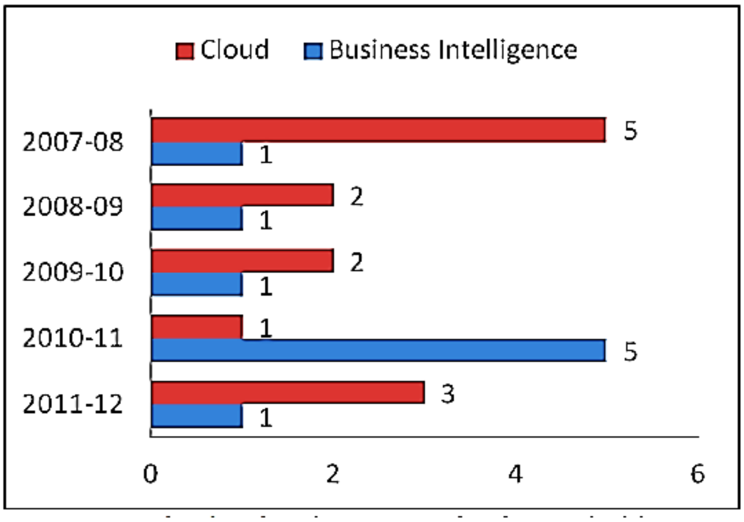

Figure 8: Cloud and BI in CIOs Technology Priorities [15]

such as time saving at high speed in implementation and deployment [114][96], lower total cost of ownership[96], leveraging the massive computing power[96], support mobile and remote users availability on-demand[96], supporting expertise[80],outsource running of BI while concentrating on core strength which all above finally lead in transforming the economics of BI and opens up the opportunity for enterprises to compete by using the BI concept and which cause a wide extent influence on the following areas as follows:

- easier evaluation of technology [113]
- Increased short-term ad-hoc analysis [113, 13]
- increased flexibility due to the avoidance of long term financial commitments [113, 13]
- drive data warehousing in MB markets [113]
- drive the analytic SaaS market [113, 55]
- Scale out‖ shared architecture [113]
- aggressive data storage
- automatic replication and fail over [29, 113]

We facing several prominent challenges when benefiting from cloud computing in business intelligence that could not be ignored and pay no attention. Implementing process should begin after taking all these challenges into account smartly. Some of most outstanding challenges observations are as follows:

- Uploading large data volumes over the internet with slow speed rate [109, 14]
- Issues concerning data security[116, 14]
- latency encountering when accessing large amounts of data[14]
- limitations in service availability from
- established BI vendors [13]
- integrating on-premise data with cloud components [96, 15]
- data controlling and data ownership[96]

- astounding in choosing the right vendor according to determined needs [96]
- Reliability of service [14,37]
- Limited ability to scale-up [14]
- Performance latency [96]
- Difficulty in budget estimating[96, 14]
- Irrespective of the age of a BI landscape the cloud model can drive increased BI adoption, improved end-user experience and better access to analytics accompany with reduced IT dependence which make it suitable and profitable in banking usage.

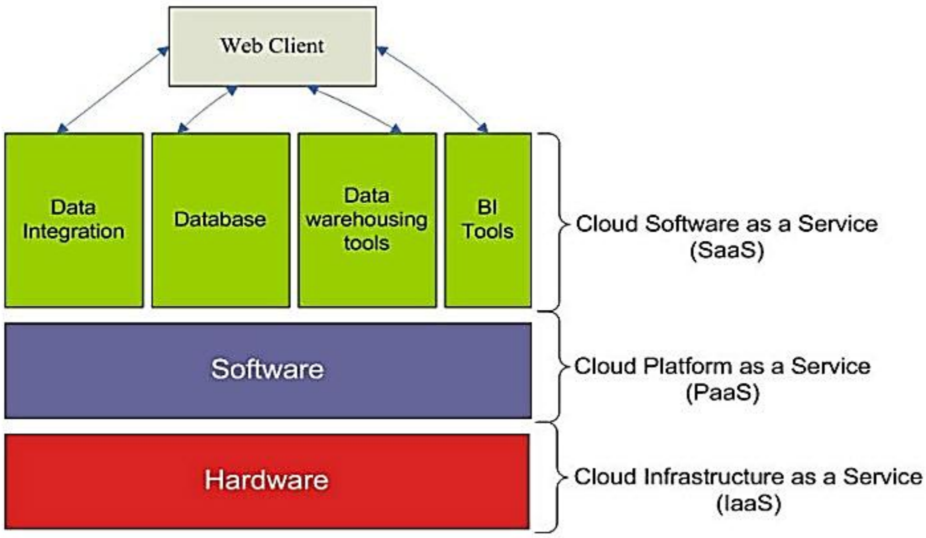

Figure 9: BI on the Cloud: Architecture [114]

7. BI implementation via data virtualization

Data virtualization is any approach to data management that allows an application to retrieve and manipulate data without requiring technical details about the data, such as how it is formatted or where it is physically located. Despite of the traditional schemes the data remains in place, and real-time access is given to the source system for the data, thus reducing the risk of data errors and reducing the workload of moving data around that may never be used.

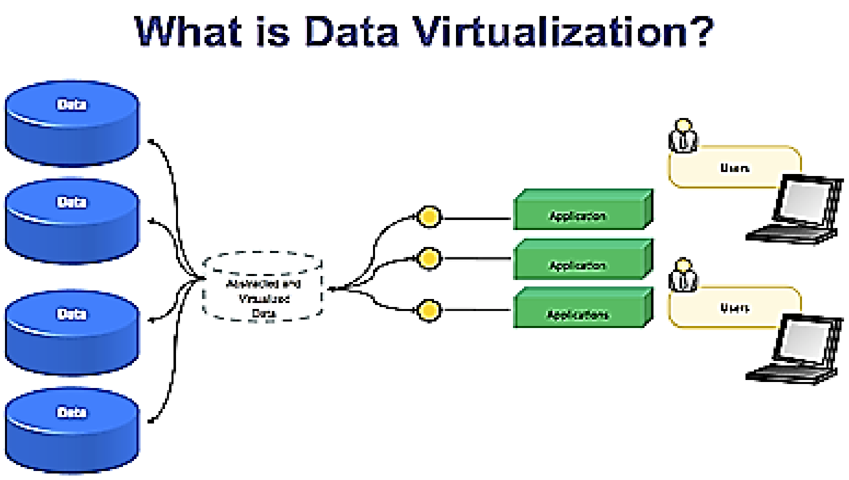

Figure 10: Abstract model of data virtualization process

Data virtualization has evolved as an agile data integration concept to enable more agile BI. However traditional BI approaches including data integration, data warehousing and other complex data processing are not going away anytime soon. This is because data will continue to be, heterogeneous, dirty and semantically different across systems [63]. To succeed, data virtualization must coexist, reuse and complement existing infrastructure and investments made to solve these problems rather than be a Band-Aid for a small subset of special use cases. It must also involve the business user early and often to ensure that the data is trustworthy. The trick is to gain competitive advantage by accelerating the delivery of critical data and reports and able to trust and consume them instantly. But data virtualization must be done right to support the critical success factors. Very often data virtualization borrows heavily from its data federation legacy. The primary use of data federation is to access and merge already cleaned and conformed data in real time. So the time advantage gained is lost as one realizes the federated data had to be prepped for federation.

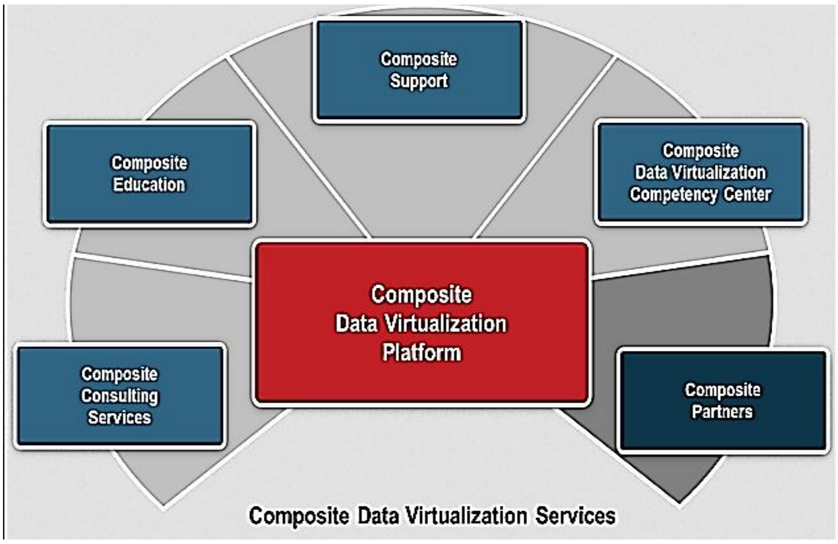

Figure 11: the data virtualization process stages

Data virtualization involves capabilities like stored data information abstracting, data sources virtualization (databases, Web content, application environments), processing connection, making single point logical access, data transformations, data quality improving, data integration in distributed sources, heterogonous data federation, data delivery flexibility, required consistent data presentation. Identification of data sources and the attributes that are required and available for the final application and application of the data model for getting data from various data sources in real time. An analysis of the companies implementing or intending to implement data integration solutions reveals some dominant market trends [63].

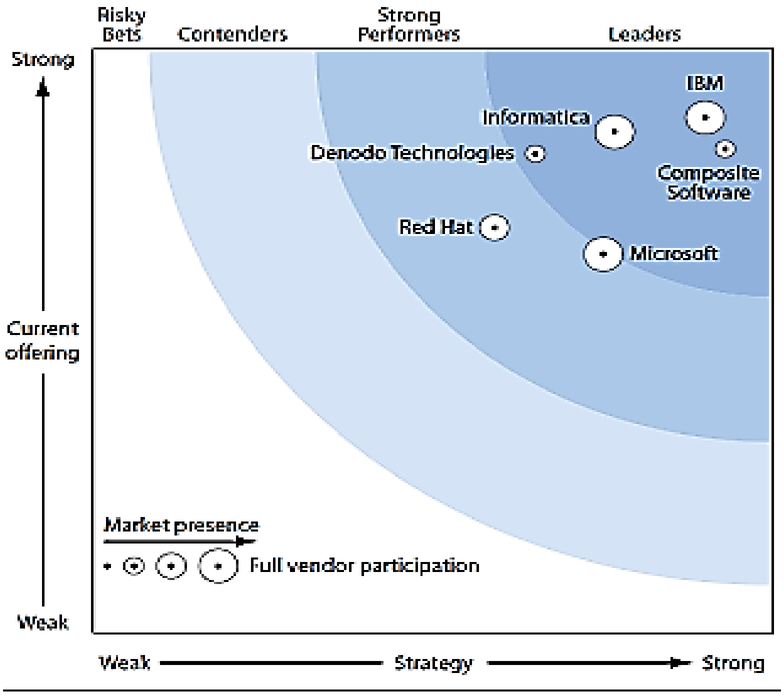

Figure 12: Data virtualization tool vendors

Such as maximum exploitation of the already existing technology, focus on read-only use cases, increasing interest in using cloud computing, data integration market tools and data quality tool which convergence in many cases. The best integration solution is the combination of virtual and physical approaches, keeping the physical data warehouse in order to benefit from its features and applying virtualization for cutting costs and getting quicker results for data source access, for data smart elimination, prototyping new data marts or data warehouses, federating multiple physical consolidated sources. Each of the issues stated above require banks to be proactive in managing and utilizing corporate data if they want to keep up with or stay ahead of the competition. Business intelligence software gives banking enterprises the capability to analyze the vast amounts of information they already have, to make the best business decisions. The software allows banks to tap into their huge databases and deliver easy to comprehend insight to improve business performance and maintain regulatory compliance. In addition, a bank will have many people in different locations with varied skill levels who need to use this information for varying purposes and everyone from executives who need high-level customized summary data with drilldown capabilities, to power users who need to create and design custom reports, to data analysts who must identify and communicate market trends.

DISCUSSTION AND CONCLUSIONS

In order to draw benefit from big data, companies need to confront the management of an almost unimaginable volume of unstructured data. Only if they do so, they will be able to respond quickly to market changes, utilize the latest information on trends and customer demand to develop entirely new services. On the other hand, maintaining and improving banking industry and financial services is due to having a secure transaction and exchanging environment facing with an uncertain global economy, strict regulations and customer expectations, banking professionals have to develop schemes for strategy implementation to conserve existing customers trust along with absorbing new customers. To be successful in the banking and financial investments, banks should recognize and support profitable customers as well as making improvements at the operational level with the help of intelligent tools. Business intelligence tools, provides past, current and future perspective for the staff's usage because competitiveness today is driven through BI so the companies will achieve high competitiveness that utilizing BI tools. The Internet is rapidly creating vast amounts of data. BI solutions have to utilize this vast amount of data and help in achieving competitive advantages such as better customers' relationships and effective resource planning. Several solutions in business intelligence domain exist but in this article we review ones which are more applicable in covering big data problems and especially banks as they are one of the most sensitive enterprises towards market changes and have to employ adaptation. Each of the methods mentioned above face to its advantages and disadvantages so could be chosen in conditions which best fitted them.

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