Knowledge on Demand Approach Using Business Intelligence and Ontology

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Abstract
Organizational knowledge can be treated as a valuable strategic asset. Organizations are lacking well-developed strategic models today that can aidin connectingknowledge-oriented technology and organizationaltypesto business strategy. The integration of BI (Business Intelligence) with ontology is observedas a potential method to formulate the strategy and helps in filling the gap in executing the strategy. It has been seen as a potential solution to business decision-makers as an efficientway to increase enterprise "soft power" and add value to the revolution and reconstruction of conventionalbusiness systems for achieving long-term profitability in a sustainable business environment. About 85% of DW projects in the US have failed to meet the intended business objectives (CGI white paper, 2004) with the traditional approach of building data warehousing and data mining approaches. So this paper has attempted to propose a hybrid approach for building Ontology-based Integration of Business Intelligence to achieve semantic interoperability by integrating DWH, OLAP, DM, and Ontology and Semantic Engineering technologies for achieving Semantic capability in Business Intelligence Services.
Keywords: Semantic Business Intelligence, Enterprise Data Warehousing, Ontology Integrated Business Intelligence

Introduction

The idea of treating organizational knowledge as a significant strategic asset is mentioned in [50]. Utilizing knowledge to produce strategic advantage and corporate value makes intuitive sense, but the latest technology quickly dominates strategic challenges. Today's organizations lack well-developed strategic models that may relate knowledge-oriented organizational structures and technology to business strategy. The act of balancing a company's performance between the external environment and internal capabilities is known as strategy [50]. The traditional approach of dealing with business strategy based on marketing is mentioned by Porter's model. Further,many strategic models are available in the strategic management literature such as the contingency model, resource-based model, and knowledge management model. Traditionally, most organizations rely on resources, competencies, and capabilities, particularlyorganizational skills and practices to achieve competitive advantage.However, the knowledge-based concept of the business proposes that knowledge is the organizational asset that permits sustainable competitive advantage in hypercompetitive contexts [2]. So objective of this paper is to elicit the technology-based insights that support in formulating the knowledge, based on the knowledge management paradigm. The rate of knowledge generation is increasing, which is creating a greater demand for knowledge management that is more efficient [34].Market-based assets are mostly intangible and may be acquired through developing distinctive, difficult-to-replicate information, skills, and resources.Thus, knowledge has been made one of the strategic components of the e-enterprise model proposed by [6].

The strategy process is concerned with choices that affect both the strategic position and execution of the firm.Strategy formulation requires the application of a company's political philosophy, which in turn could be driven by a spiritual belief (e.g. Saudi Arabia etc.) or by a secular belief (e.g. United States of America, United Kingdom, etc.) or a combination of it (e.g. India etc.). [35] classifiedthe knowledge management systems into:(i) technological (ii) socialization and (iii) personalization thatis matching with the top three layers of[7] mentioned layers of the ASCP Model, i.e. Standardization, Customization and Personalization respectively, which can be used to position the strategy formulation[8].

However, how managers mobilize their core competencies, scan, interpret as well and share information from their environment based on scientific knowledge or conceived information as a basis to enact [35] is what has been viewed as the driving methodology of this paper.

A critical decision facing every business leader is how to organize various elements of an enterprise system to execute the strategy [10]. A sustainable business uses unconventional tactics to improve social equity, restore environmental quality, and boost long-term profitability [1].

Earlier research efforts focused on structural integration [23] or Enterprise Data Warehousing, as a means to achieve Enterprise Data Management to help build and achieve business strategies.

The operational and functional performance of the enterprise can be indicated by the efficient and accurate measurement and analysis of corporate efficiency at the tactical and strategic levels. This requires the definition of appropriate performance indicators as well as efficient reporting and analytical capabilities to convert the data into useful and actionable information. Business Intelligence may offer predictive capabilities to the management team so that organizations can expand this information to successfully monitor their business operations. Therefore, firms must determine the suitable metrics for their company and establish an organizational mechanism for how the measures are presented throughout the company since frameworks help speed processes and give focused guidance.

The agreement on and execution of integrated data, a primary aim for an EDW, is frequently a big difficulty when large businesses seek to construct an EDW (Enterprise Data Warehouse) for this reason. In this scenario, data integration entails combining data from several sources and giving consumers a single perspective. It is the capacity to specify typical entities and characteristics related to business-relevant topics and to source, map, and load into typical structures. Typically, a company consists of numerous LoBs (“Lines of Business”), each with overlapping and unique information requirements. Although many LoBs may agree that integrated data is necessary to get that crucial 360-degree view of the enterprise, this view is often defined from each business's point of view [19].

According to [14] on Business Intelligence “The initial component in ensuring strategic alignment for the Business Intelligence initiatives is the establishment of key performance indicators (KPIs) that need to be measured on a corporate or functional basis. Each of these metrics measures some aspect of the operational or strategic performance of the organization. To ensure alignment with key business objectives, KPI identification is founded on a top-down approach that begins with the organizational objectives and identifies the relevant initiatives and functions and their critical success factors (CSFs) while defining the appropriate metrics for measurement. This process is relevant at an enterprise level as well as at a business function level.

Further [14] mentioned that the following questions can help in validating the capability of measures and their contribution to organizational performance in the form of a decision support system (DSS).

- Can action be taken as a result of the measure?
- Is the measure understandable across the organization?
- Does the measure represent something that can be measured?
- Can a performance threshold be established for the measure?
- Does the measure represent a high impact on the organization?
- Is the data available to support the measure?”

The main question that helps in finding answers to the above questions is as follows: '*What is the most appropriate approach that enables answers to the above questions?'*

Problem Statement

Enterprise Data management has two facets viz., the operational and the functional facets: Managing operational data is done by systems that execute transactions (typically in real-time), whereas managing and analyzing historical data is done with"decision support systems" that give business clientsinsight. As decision support has advanced, it has become evident that business customers prefer patterns and trends in data rather than huge amounts of data.

So business organizations are desperately looking for 'knowledge on demand' where refined patterns are pre-generated and customers onlyreceiveinformation when required while meeting not only the 'on-demand business analysis' in which the study is automatically completed beforehand. A pattern-based management system is required to access, alter, and manage these patterns in the same manner as data components are maintained.

So this paper is targeted to discuss the 'Ontology Integrated Business Intelligence' as a hybrid approach of a top-down and bottom-up approach to contemporary DSS to fulfill the research paper objective.

BI Approaches

Petrini and Pozzebon (2003) elucidated two approaches to Business Intelligence as follows:

Table1: Two Approaches of BI [39]

Managerial Approach	Technological Approach
Focus on the acquiring process and evaluating data from internal & external sources to create valuable information.	Concentrate on the technology tools that assist the process.

From the managerial approach, BI is a system that combines data from inside &outside the firm to offer information useful for decision-making.The purpose of BI in this scenario is to give the informational environment and methodology necessary for the analysis of operational data obtained from external sources and transactional systems to identify the "strategic" business factors. From this viewpoint, ideas like an "intelligent company"—a business that uses BI to make quicker and more informed choices than its rivals—emerge [31]. Intelligence is the process of turning a massive amount of data into knowledge by analyzing, filtering, as well as reporting information.

The technological approachrepresents BI as a "*set of tools"*that helps the analysis and storage of data. The technology that enables the recording, retrieving, manipulating, and analysis of information is the main emphasis, not the process itself. For example, [30] comprehend BI as DW ("Data Warehousing"); [41] classifies DM ("Data Mining") as a BI approach; [25] comprises all resources (web information, hypertext analysis, DM, and DW) in the generation of a BI system; and finally, linking Internet and the BI, [22] posit the DW integration and CRM ("Customer Relationship Management") applications.

All of these studies, whether managerial or technological, have one thing in common: (1) the collecting, analysis, and usage of information are the foundation of BI; and (2) the purpose is to assist decision-making, which benefits the business strategy.

Theoretical Foundation andFramework

The process of creating and evaluating alternatives to select one from the available options is known as decision-making. The majority of decisions include judgment, which refers to the cognitive parts of the decision-making process, and are made in reaction to a problem—a difference between a desired and an actual conclusion [29].

Supporting all stages of the decision-making process is a key performance goal of DSS [43]. Human decision-making involves three main processes, according to Simon's model: intelligence, design, and choice. At every level of the decision-making process, the word "support" denotes a wide range of various actions and tasks. In view of adopting technology-based knowledge management in this paper, another phase called the implementation phase is added in addition to Simon's model of the decision-making process. This phase is considered important because in this phase users of knowledge management are involved in realizing the actual process of building or formulating strategy using state-of-the-art technology-based enablers.

(I) The Intelligence Phase: Itinvolves examiningthe environment, either continuously orintermittently. It covers many exercises designed to find circumstances or opportunities. Monitoring the outcomes of the decision-making process' implementation phase may also be included in this phase.

(II) The design phase: It includes finding, creating, and considering potential courses of action. These include understanding the problem and assessing the viability of proposed solutions. We create, evaluate, and test a paradigm of the decision-making issue.

(III) The choice phase: It is the one where the actual choice is made and where the determination to carry out a particular course of action is made. In other words, the choosing step also involves finding, assessing, and suggesting a suitable model solution. A problem-solving recommendation results from the model's solution. The problem is deemed to be resolved only if the suggested solution is effectively implemented.

(IV) The implementation phase:The beginning of a new order of things or the introduction of change, which should be managed, is the execution of a recommended solution to a problem. Only one strategy for this implementation has been addressed in this work.

In the intelligence stage, human decision-makers are crucial in determining the issues to be resolved on the basis of raw data acquired and information processed by TPS ("Transaction Processing Systems") and MIS ("Management Information Systems"). [3] proposes 7 various forms of DSS on the basis of the "degree of action implication of DSS outputs" (i.e., the extent to which the choice might be directly influenced by the DSS's output). The following 3 DSS kinds are very helpful in the intelligence stage: (1) File drawer systems that allow online access to specific data objects; (2) systems for data analysis allowing users to obtain, alter, and display both recent and historical data; and (3) Analysis information systems that provide management information by the manipulation of internal TPS data and the addition of external data using a number of different packages and other small models.

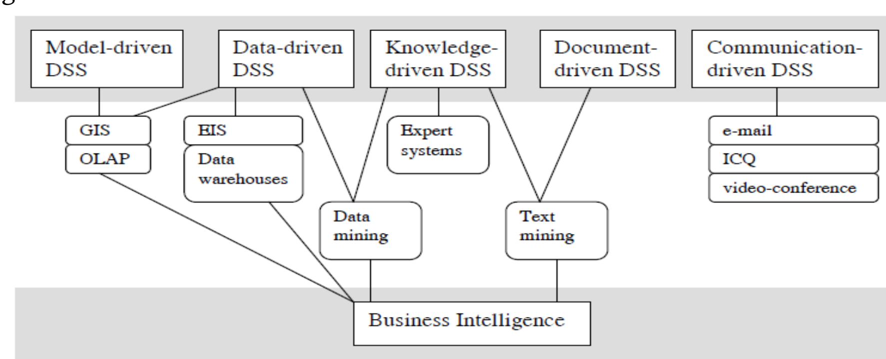

Fig-1: Different types of DSS emanating from BI (Source: [29])

The top-down methodology used in MIS planning entails identifying the information requirements for a series of management levels. The system might satisfy MIS needs if the information needed at the top remains mostly steady in terms of the amount of frequency,content,and detail. This strategy may be appropriate for companies when the types of information needed at the various levels vary. This strategy may be appropriate for companies when the types of information needed at the various levels vary [32]. However, there are serious questions regarding the practicability of this approach. According to [42], the top-down approach may not withstand conceptual validity.
Ralph Kimball's bottom-up method data marts are initially constructed to give reporting and analytical capabilities for particular business processes to rapidly recover the business value [47] during MIS installation. However, the bottom-up method is not a traditional technique of function point analysis. [42], mentioned Zani's version who wrote that disappointment over MIS in practice can be traced to bottom-up MIS development. So,designing and building of DSS that follows a hybrid approach has been given as discussed below:
When the business environment has been subjected to the impact of dynamic trends as a result of globalization that is leading to uncertainty, the enterprises must respond to this kind of situation very quickly as a part of either a competitive struggle or to protect from the undesirable affects of externalities on the nations sustainable business environment. So to address this situation a hybrid approach or Total-system approach is what needs to be considered and followed while designing frameworks for enterprise-oriented MIS.
This hybrid approach has been considered and adopted as a basis and subject of current discussion. The interrelationships of the fundamental data are specified in this technique before implementation. Design and implementation of data collecting, archiving, and processing are performed inside the framework of the whole system. This strategy may be effectively used in emerging organizations [32].
The top-down strategy could be used inthe first planning phase. The bottom-up strategy might potentially be used to boost estimation accuracy after receiving additional system parameters at later phases [49]. Top-down analysis is used to identify the data that is required and to decide how best to store it in the database. Bottom-up design is then used to make sure that managers have access to important information to improve their decision-making [21]. Elicitation of data semantics can increase application comprehension, lower maintenance and testing expenses, and improve application management [16].
Hybrid approaches have emerged to make use of the rapid turnaround time of bottom-up design as well as the top-down design's[47] enterprise-wide data consistency.
Adopting a hybrid methodology is essentially required to avoid the gap of translating the strategy formulated using a top-down approach irrespective of whether the strategy is built based on scientific knowledge or fuzzy logic to the executive body for enactment. Many times the executive body finds difficulty in actually understanding and following this translation of strategy, either because of the lack of maturity and/or intellectual capability in case it is scientific knowledge based or it could be because of a lack of realizing and visualizing the strategy in case of fuzzy logic based. Whatever may be the nature of the gap; a technological representation of a hybrid approach is believed to fill this gap and discussed below. While the Service Quality Approach mentioned in [8] helps in formulating the Gen-Spec strategy as a form of top-down approach,on the other hand,Figure 6: 'Approach to build reference framework for Public Policy'[4]helps in formulating Gen-Spec strategy as a form of bottom-up approach. It helps in filling the gap of translating it for achieving a higher level of quality in executing the strategy. It is a form of bottom-up approach because when the strategy is realized as a form of ontology, the figure shows how to build this ontology.

Designing and building contemporary DSS with a Hybrid approach

The current section is targeted to describe the design stage of the decision-making process based on the knowledge-on-demand approach of Business Intelligence. It can be adaptable for 'analysis on demand', and hence consideredas a hybrid approach to building contemporary DSS against actual decision-making.

BI Paradigms

The Data Analysis Model: in which individuals search through data to find information. This model focuses on the "analysis on demand" method, where analysis is done when a user requests knowledge.

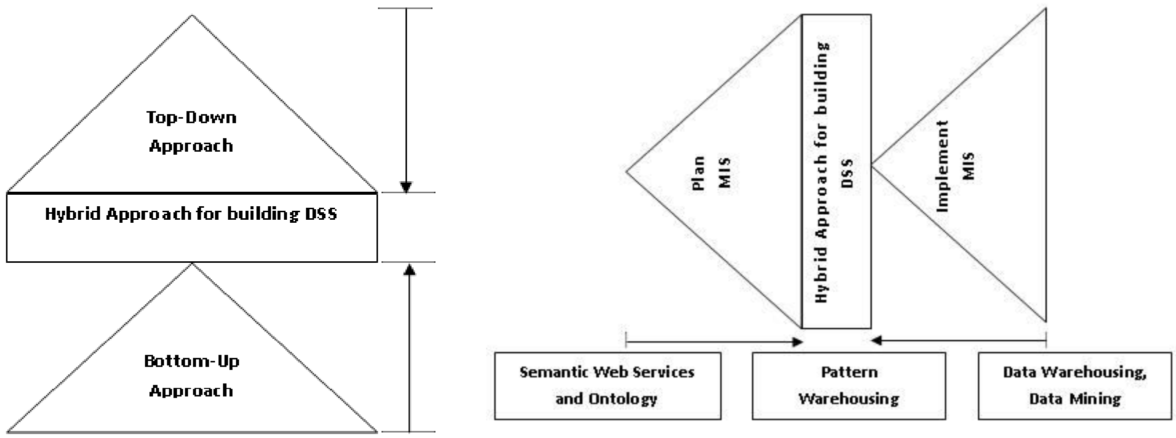

Fig-2a and 2b: Hybrid approach to designing and building contemporary DSS

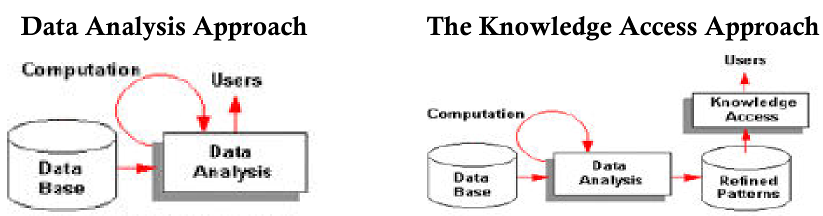

Fig –3a and 3b: Business Intelligence Paradigms (Source: [38])

The Knowledge Access Model: The "knowledge on demand" method is one in which analysis is performed automatically in advance, improved patterns are pre-created, and users only get information when required.

Issues in Data Warehousing and Data Mining

[38] elucidated the issues with data warehousing. Issue-1: The majority of business customers considered the data mining task's technical elements to be more than they had anticipated. Issue-2: The central warehouse started to provide conflicting findings from piecemeal and fragmented analysis; for example, depending on how 10 business users accessed the data, they may each come up with 8 different conclusions. Issue-3: Knowledge extraction would frequently be slowed down by the response time for follow-up studies from a huge warehouse and the requirement for analyst intermediates.

Significance of Semantically Integrated BI Delivery

The two aspects of data management are operational and functional. Operational data is managed by systems that perform transactions (typically in real-time), while functional data is managed and analyzed with decision support systems that give business insight. With the development of decision support, it has become clear that business users are more interested in the patterns and trends that data holds than they are in large amounts of data. Similar to how data items are maintained, these patterns also require to be accessed, changed as well and managed.

Pattern Warehousing

In the 1990s, it became evident that business users needed considerably more specialized expertise since data in warehouses is frequently too coarse and unmanageable for precise decision-making.

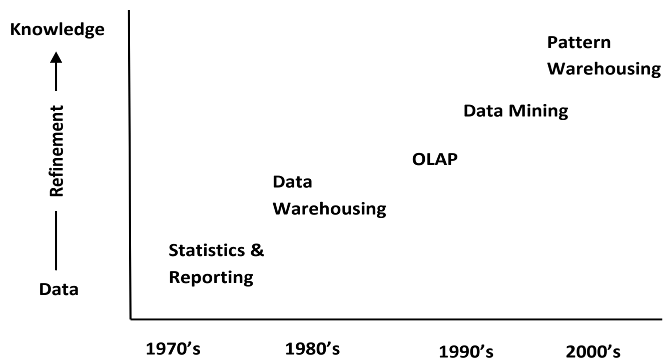

Fig-4: Progress of Knowledge Discovery (Source: [38])

Furthermore, the majority of firms understood that they needed the information, patterns, and trends included within the data rather than the data itself. The necessity for information extraction from data became increasingly recognized as the notion of "data mining" gained popularity. The expectation for business users is to receive enhanced knowledge rather than data.

Therefore, the Pattern Warehouse saves patterns in a similar way to how a data warehouse stores data. It is a data repository that holds connections between data objects but not the actual data. In contrast to the data, a pattern expresses connections between data items. Influence patterns (often indicating probabilities or probability) as well as affinity patterns that deal with relationships (such as market basket patterns) or comparison patterns that highlight differences across data sets are just a few of the several types of patterns that may be found. Each pattern class has certain rules of inference for the purpose of manipulating patterns [38].

Pattern-Based Management System

Patterns are knowledge artifacts such as clusters, and association rules. Patterns may use data processing techniques like pattern recognition, data mining, and knowledge extraction to significantly decrease the size and volume of databases so that people can manage them while retaining as much of the information that is available, hidden, or interesting as possible. These patterns must be modeled, processed, stored, as well as queried similarlyto data in conventional DBMSs [45]. An effective illustration of Pattern Base is Pattern Base an object-relational database in the Oracle 10g DBMS (Oracle) that stores pattern forms, patterns, and classes. Patterns of such pattern kinds are examples of these ADTs ("Abstract Data Types"), which are specifically implemented as pattern types. Classes are implemented as tables written over the associated ADT since they are collections of certain pattern-type instances. Additionally, the Pattern Base includes PQL and PML interfaces that were created using PL/SQL functions and processes that are called by the PBMS Engine [45].

Plan MIS

Information planning highlights the significance of selecting a small number of strategic information (Benbasat andReich, 2000), which raises a paradox about the abundance of information we already have: the challenge of BI is precisely to convert quantity to quality [39].

Furthur[39] suggest that information necessary for decision-making is likely to already exist within the organization or to be well defined in the managers' ideas [15]. Similar to this, we have the well-known "*critical success factors"* (CSF) technique, which identifies and selects executive objectives, indicators, measurements, and reports through a series of interviews with senior management [40].The promotion of a realist ontology that downplays the socially constructed along withthe political nature of information "producing" in any organization is shared by both information planning and critical success factors.

Implement MIS

Business decision-makers have viewed the integration of BI as an efficient way to increase enterprise "soft power" and add value to the renovation and revolution of conventional business processes. Users of BI systems are given access to a reporting system with preset reports, data models, metrics, anddimensions. According to a US survey, 85percent of DW initiatives based on the aforementioned techniques failed to achieve their intended goals. To integrate DW, OLAP, and DM with semantic interoperability, BI must be ontology-based. It is necessary to develop a hybrid ontological framework that combines a conceptual perspective with a physical and analytical view. User interfaces, DWs, and business information systems, respectively are matched with these perspectives [13].

The entire method of developing a BI system—from data preparation to intelligence discovery and to enabling dynamic and adaptive integration of both EIS and DW—is now emerging as a crucial problem to be resolved.

Therefore, setting up a productive and practical BI system that can follow the knowledge access paradigm, lexical and semantic [17], transformation as well as integration of heterogeneous data hidden in the business system and operational systems is necessary to deliver a semantically integrated BI.

[13] developed a three-level ontology space that contains an EIS ontology for operation support systems and/or underlying business, a DW ontology for the DW, and a business ontology for user profiles.This external channel and its design are suggested for giving business people access to a business-oriented analysis and reporting portal instead of one that is technology-centered. This portal manages all business-focused analysis and reporting and incorporates BI from user profiles, DW, and EIS.

The goal is to offer a smooth mapping between the top-level user-defined keywords/phrases and the metadata items in DW or the physical entities/attributes scattered throughout the operational tables of OSS/BSS.

One type of knowledge model is the semantic model. The semantic model is composed of a network of ***Concepts*** and the links between them. ***Concepts*** are a specific notion or area of interest to the user. ***Ontology*** refers to the semantic model that explains knowledge, which is comprised of concepts and relationships. In a natural approach, users may query the data using semantic models, which can aid in seeing patterns and trends in the data and establishing connections between disparate bits of information.

There are 4-level views that coexist in the ontology integration system paradigm: (i) a top-level user profile conceptual representation that encourages user portal interaction(ii) an Analytical View for DW-based data modeling and analysis, (iii) a low-level Physical View for EIS that encompasses several operation/business support systems, such as an accounting system, billing system, and others and (iv) an Ontology Mapping and

Query parsing and ontology mapping are supported at the Query Parsing mediator level. These elementshandle directory/transport/mediation/naming of ontologies,metadata management,data model,user interaction, and services for every level, query parsing andtransformation, and data sources integration.

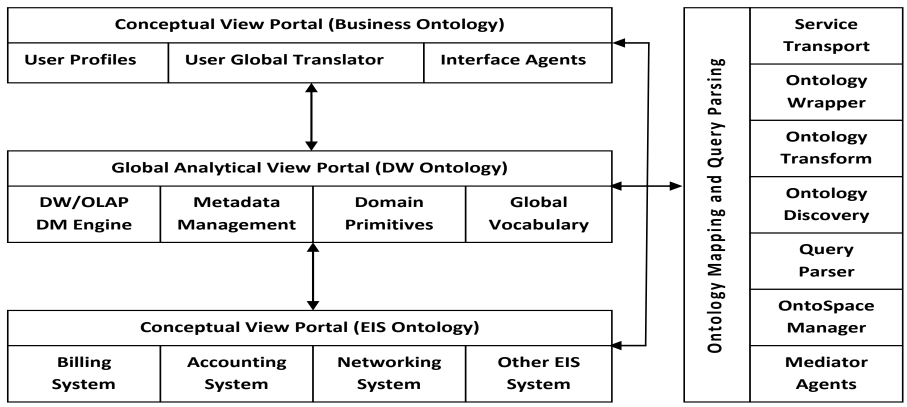

Fig-5: Integrating Business Intelligence with Ontology-based Services(Source: [13])

Ontology-based BIintegration

The following is the fundamental concept for ontology-based BI integration:

Business Ontologies are built for human-system interaction in business profiles. DW Ontologies are built for analytical purposes. Multiple Enterprise Information System ontologies are various business domains such as billing, and accounting etc, (Gomez-Perez et al., 2004) [24]. To integrate the above ontological domains, logical link communication channels, and ontology engineering techniques are used. This kind of approach can handle the integration dynamic capability, adaptation &presentation of BI (Cao Lingbing et al. 2004) [13].

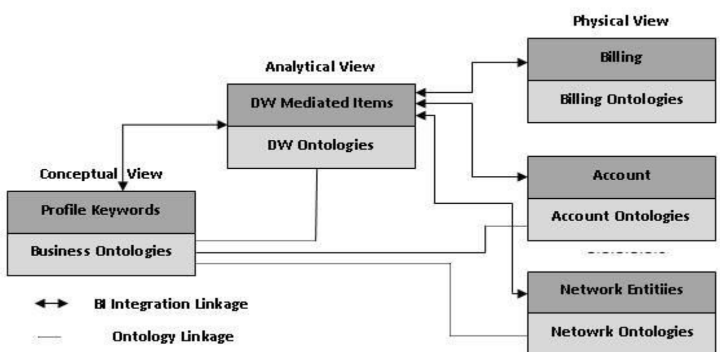

Fig-6: Ontology Integrated Business Intelligence (Source: Cao Lingbing et al. 2004) [13]

Choice

After the successful implementation of this proposed design, it facilitates the strategists in facilitating the provision producing different strategies based on the different patterns produced out of pattern warehousing but in association with the integrated ontology.

As an example of implementation, from the Figure 5. Ontology discovery service has been considered for discussion as follows:

Maninti and Vasista (2023) [45] cited that cloud business intelligence is a revolutionary idea of delivering BI capabilities as services using cloud architecture with flexibility. Finding suitable services from the increasing number of cloud services that satisfy user requirements viz., cost, performance, and security has been a contemporary issue and becoming a challenge to solve. This is where an intelligent service discovery system can be used for searching and retrieving appropriate services quickly and accurately (Ali, Shamsuddin,and Eassa) [5]. Whereas traditional search engines follow single keyword-based searching, ontology-based search requires a knowledge-based representation of cloud services more semantically.A cloud service discovery system that matches cloud service consumer requirements has been proposed by Kang and Sim (2011) [27]. Further, their research concluded that when broker agents of the service discovery system use cloud ontology at the recommendation stage, it provides better performance. The research conducted by Martino, Esposito,and Giovanni (2022) [33] proposed a system in which user requirements are analyzed by knowledge-based expert system rules and provide a semantic representation of cloud services using OWL-S. Their description of agnostic services allows for identifying vendor-specific cloud services with an optimal configuration. The resulting composed service can satisfy multiple requirements simultaneously at the same time. The research conducted by Wu, Lin Jiang & Wu (2011) [48] presented a multi-dimensional association rule mining system-based prototype that can provide intelligent assistance of ontology support to prevent ineffective pattern generation, and data mining models, discover extended rules, and provide a knowledge-based re-discovery system. It is then can be made useful to discover semantic web services in cloud computing systems or even in IoT-based edge computing systems.

Conclusion

The top-down method is good for MIS planning and the bottom-upmethod is good for MIS implementation. However, building a framework requires a different approach. It requires a hybrid approach of considering both the top-down and bottom-up methods and has to work in a horizontal approach to elicit patterns not only on the back-end side of the client-server-based web technology but also on the front-end side. Similar to this, using ontology engineering techniques, it is possible to extract user-oriented patterns from the operational and functional databases of the MIS system to create a successful BI system that could contribute to serving not only analysis ofrequirementsbut also knowledge on demand in a client-focused manner.A sizable amount of reconciliation occurs at the Meta level in the pattern warehouse prior to offering the semantically integrated Intelligent Business Services.

While there are many multi-cloud APIs exist, the semantic design patterns-based discovery of web services can better supportattainingextensibility and efficacy. But for this, a layered ontology-based architecture that uses appropriate design patterns is what is required. A broker agent is an intermediary between cloud users and providers to deliver this kind of advanced capabilities (i.e. including portability andinteroperability) to help bring both customers and providers together. Elango, Fowley & Pahl's (2017) research work, presented exactly this kind of scenario. Surprisingly this matches with AlSudairi & Vasista's (2014) idea of bringing customer and provider together as presented in CRASP methodology. However, it is also possible to extend this idea even to IoT-based edge computing analytics and service discovery. In this case, to establish horizontal communication between IoT entities, sensors, and devices, there is a need foran IoT communication network gateway that could constantly send data to the cloud from where different kinds of parties access and use it for their specific application purposes. From the perspective of Communication-based BI, Bui (2019) in their master thesis, proposed a smart API, which is a semantic data model framework for IoT applications. Smart API architecture refers to three main components, IoT central, IoT edge, and IoT dashboard. The back-end architecture protocol follows a request-response model-based protocol that communicates with the Tornado server with RESTful Python programs having an ontology-based editor. The editor facilitates giving meaning to the data being shared among objects inan IoT network environment.

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