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Creating Knowledge for Business Decision Making through Planning and Forecasting

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1. INTRODUCTION

Business forecasts and predictive models are rarely perfect. A paraphrase of the Nobel winning physicist Neils Bohr is apt in this context: *Prediction is difficult, especially if it is of the future*. However, executives and managers in enterprises ranging from retail and consumer packaged goods (CPG) to high tech and semiconductors have to resort to forecasting and planning about the future. Phenomenal growth and spectacular failures are associated with organizations depending on their ability to understand market directions and respond quickly to change. Relatively minor improvements in forecast accuracy and predictive modeling at detailed levels can translate to significant gains for the enterprise through better strategic decisions, continuous performance management and rapid translation to tactical decisions. The key to these processes is the knowledge-based enterprise, which can effectively utilize information from multiple sources as well as the expertise of skilled human resources, to develop strategies and processes for creating, preserving and utilizing knowledge. These efforts, spanning revenue generation endeavors like promotion management or new product launch, to cost cutting operations like inventory planning or demand management, have significant impacts on the top and bottom lines of an enterprise.

Advances in scalable mathematical model-building, ranging from advanced statistical approaches and data mining (DM) to operations research (OR) and data assimilation, can extract meaningful insights and predictions from large volumes of data. Information technologies and e-business applications can enable a degree of process automation and collaboration within and among enterprises. Enterprises of the new millennium can truly take advantage of scalable but cutting-edge data dictated approaches to understand the past and predict the future, and then focus valuable planner resources on key value drivers or exceptional situations through human-computer interaction, which in turn utilizes tools like on-line analytical processing (OLAP) and automated or planner-driven decision support systems (DSS).

Analytic information technologies enable managers of the knowledge-based enterprise to choose the path to new revenues, new markets, good customer service and competitive advantage over their rivals. The ability to produce "one-number forecasts" that reconcile information from multiple sources and blend disparate points of view is a critical first step for enterprise-scale strategic, operational and tactical planning (Fig. 1). However, this is a challenging process, especially in recent years owing to short product life cycles, mass customizations, and dynamic markets, combined with the ever-increasing service expectations of consumers and trading partners on the one hand, versus the need to reduce operating and inventory costs on the other. The need to manage product life cycles and promotions or pricing decisions, factor in market signals or competitive intelligence, analyze consumer behavior, and achieve buy-in from multiple participants within and across enterprises has fundamentally changed the way the forecast generation process is perceived. Corporate data repositories, collaborative information technologies and processes, syndicated data vendors and the Internet, provide large volumes of historical and real-time information. The challenge is to acquire, manage, analyze and reconcile the information for knowledge extraction and predictive purposes in an optimal fashion.

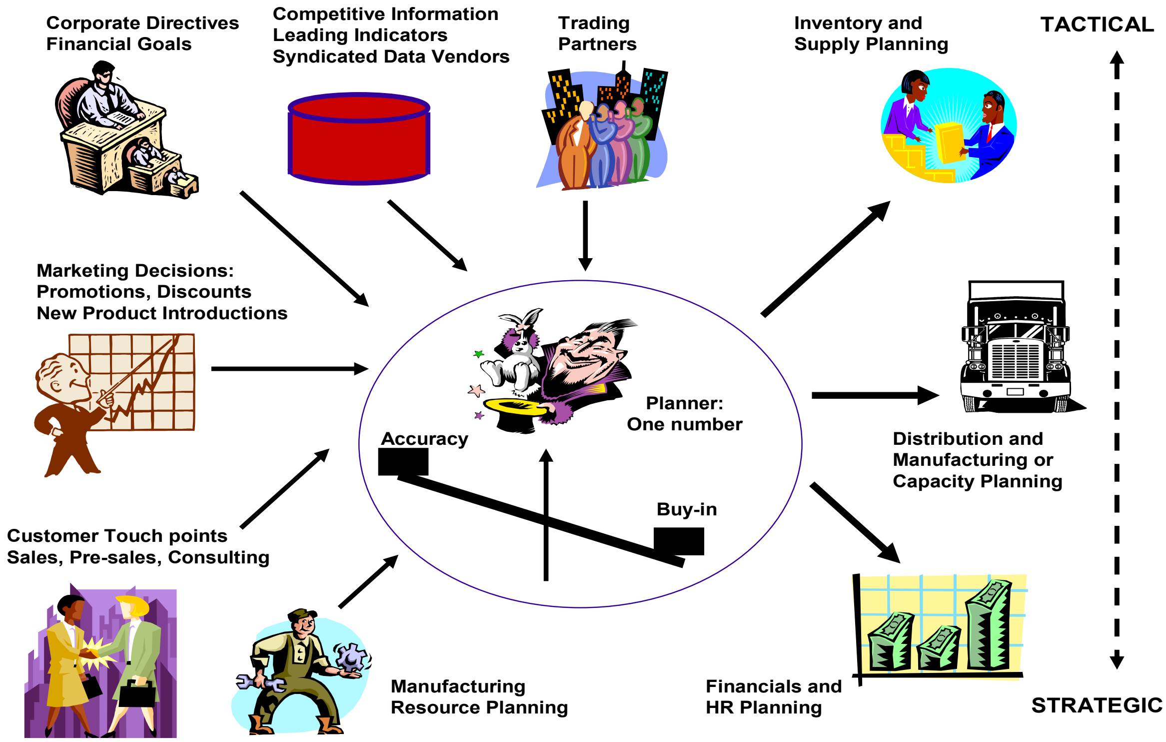

Figure 1: “One-number forecasting” for an enterprise

2. BACKGROUND

Data-derived knowledge adds value to a business through products, processes and better decision-making. Davis and Botkin (1994) describe six features of knowledge-based businesses. Manual analysis, evaluation and interpretation are the most common approaches of creating knowledge from digital data. Volumes of information can grow rapidly as every communication, interaction and transaction produces new data. Thus, manual data analysis quickly becomes slow and inexpensive, and is becoming obsolete in applications like retail, telecommunication, health care, marketing, the natural sciences, and engineering. With the advent of analytical information technologies, researchers and engineers have been exploring the possibility of constructing data dictated models by mining large-scale corporate or scientific data repositories. These approaches combine data management technologies and innovative computational or visualization methods with analytical techniques drawn from the diverse fields of statistics, machine learning and artificial intelligence (Fayyad and Uthurusamy, 2002; Hand et al., 2001). Many organizations have invested in automated analysis techniques (Ganguly et al., 2005) to unearth meaningful patters and structures from millions of records with hundreds of attributes. Automated analytical approaches like DM and statistics are combined with planner-driven analytic systems like DSS and business intelligence (BI) (Fig. 2). These are being integrated with transactions systems producing insights into how effectively a company does business, responds to or forecasts trends, understands and reacts to market conditions and develops customer-focused products and services. The knowledge mined from objective data and generated by human experts is encapsulated through adaptive information systems. This knowledge becomes an asset in current business conditions where supply-driven “push” of products and services has yielded to demand-driven “pull” as well as one-on-one or mass customizations. Management scientists (Aviv, 2001; Cachon and Lariviere, 2001; Chen et al., 2000, Lee and Whang, 1998) have theoretically demonstrated the value of collaborative forecasting on the supply chain and modeled the impact of information sharing among trading partners as well propagation of uncertainty (Gilbert, 2005). A research report by the analyst firm Gartner (Peterson et al., 2003) indicated the opportunity, need and confusions surrounding the generation of “one-number forecasts”, and highlighted the “opportunity for intra-enterprise forecast improvement”.

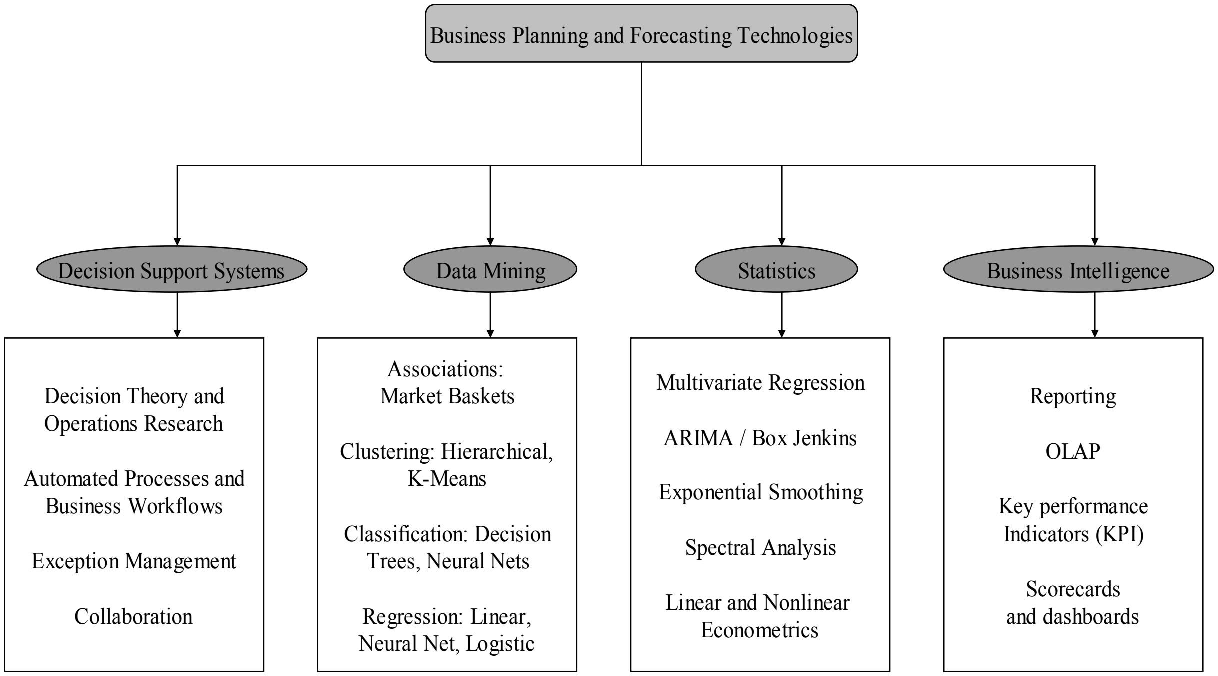

Figure 2: Examples of technologies used for business planning and forecasting

3. TOOLS AND PROCESSES FOR CREATING KNOWLEDGE FOR BUSINESS DECISION MAKING

3.1 Data Management

Data warehousing provides an infrastructure to process vast amounts of data as well as discover and explore important business trends used for knowledge creation and decision making. Inmon (1992) and Kimball (1996) suggested a data warehouse that integrates data from diverse operational databases to aid in the process of decision making. A data warehouse is the first component of a knowledge system where all available information is acquired from on-line transactional processing (OLTP) sources, cleansed, stored and processed, and made available for use by knowledge creation systems like business planning and forecasting. The information might range from point of sales (POS) data for the retail industry to income, marital status, location, demographics and credit history for a financial or a phone company. A few key data warehousing activities include data cleaning or scrubbing, data transformation, data condensation, data aggregation, data refreshing, data reporting, and metadata synchronization.

3.2 Planning and Forecasting Tools

Businesses need to react quickly to evolving market conditions, especially in these days of mass customizations, global competitions and corporate consolidations. As early as 1999, Forrester Research and Meta Group reported that 30% of firms' data warehouses contained over one trillion characters of data worldwide (Bransten, 1999), and the total sum of data is increasing every hour. Creation of knowledge from this data efficiently through analytical information technologies, and utilizing the knowledge for driving business decisions quickly, is a key requirement.

Data mining refers to diverse technologies suited for extracting knowledge and insights from vast quantities of data in an efficient manner. Most DM tools use traditional statistical techniques coupled with highly efficient pattern recognition and machine learning algorithms (Breiman et al., 1984; Ganguly, 2002; Quinlan, 1992). DM methods are used in conjunction with database-centric approaches for knowledge discovery in databases (KDD) (Fayyad, 1996). The type of knowledge created by DM and KDD tasks determines the categories into which these tasks are grouped together (Table 1). Heinrichs and Lim (2003) gave an insight into integrating web-based DM tools with business models to understand changing customer requirements, monitor product performance, uncover market opportunity, and manage customer relationships in real-time. Web-based software tools help skilled knowledge workers identify and understand their competitors' strategy, thus preparing them to respond to potential competitive threat quickly (Lim et al., 1999).

Dependency Analysis • Associations • Sequences *Class Identification* • Mathematical taxonomy • Concept clustering *Deviation Detection* • Anomalies • Changes	*Concept Description* • Summarization • Discrimination • Comparison *Data Visualization* • Pixel oriented • Geometric projection • Graph based

Table 1. A taxonomy of data mining tasks (Shaw et al., 2001).

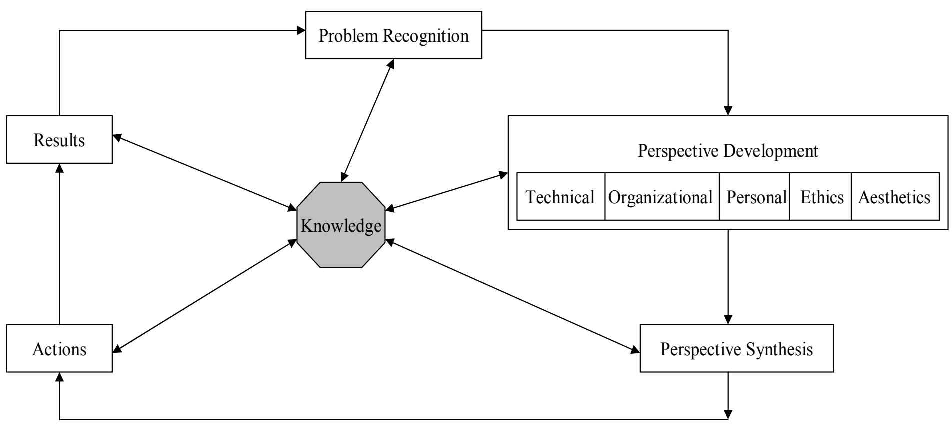

Figure 3. A new decision paradigm for DSS. Source: Courtney (2001).

The ability to anticipate, react and adapt to market trends and changes, through appropriate business strategies and implementation, are the characteristics of a successful company. Given the uncertainties inherent in the forecasting planners, some companies rely on the "gut feel" of senior decision makers and executives. However, as business conditions are getting more dynamic, it is becoming more and more important to continuously visualize and monitor the state of business through tools like DSS and BI, and to develop predictive modeling capabilities through tools like DM and KDD, for creating knowledge and insights about the future. Originally, the concept of DSS was provided by Gorry and Mortan (1971), who integrated Simon's description of decision types like unstructured, semi-structured, and structured (Simon, 1960) and Anthony's categories of management activities like strategic planning, management control, and operational control (Anthony, 1960). Courtney (2001) described a new paradigm for DSS where a centralized knowledge model is influenced by every step of the process. The model recognizes the problem, creates perspectives to gain insight into the nature of the problem, finds its possible solutions, and continually updates itself. Today, a number of fields like database technologies, management science, operations research, cognitive science, artificial intelligence and expert systems (Bonczek et al., 1981), in addition to software engineering, assist in the design of DSS. Management science and operations research tools like linear and nonlinear programming, optimization, Monte Carlo simulation and dynamic programming, help to develop mathematical models for use in model-driven DSS. The use of the Internet and communication technology in DSS allows organizations to become global and connects suppliers, producers and customers through collaborative planning, forecasting, and replenishment (CPFR) processes. This helps to achieve full collaboration, develop and share "one-number forecasts" through the extended ("n-tier") supply chain, thus helping in the sales and operations planning (S&OP) process, improving forecasting accuracy, reducing inventory levels, improving customer service levels, designing effective promotions, and maximizing profits through revenue generation and cost cutting.

BI tools like querying or reporting are used to pull information from data stores and present it to end users in the language and structure of a specific business. Key performance indicators (KPIs) are used to monitor critical factors within the business on an ongoing basis. OLAP tools specify fast, consistent and interactive ways of analyzing multidimensional enterprise data and providing end users analytical navigational activities to gain insights into the knowledge contained in large databases. Drill-down, slice-dice, reach-through, and rotation are the activities of OLAP used for many business applications including product performance and profitability, effectiveness of a sales program or a marketing campaign, and sales forecasting.

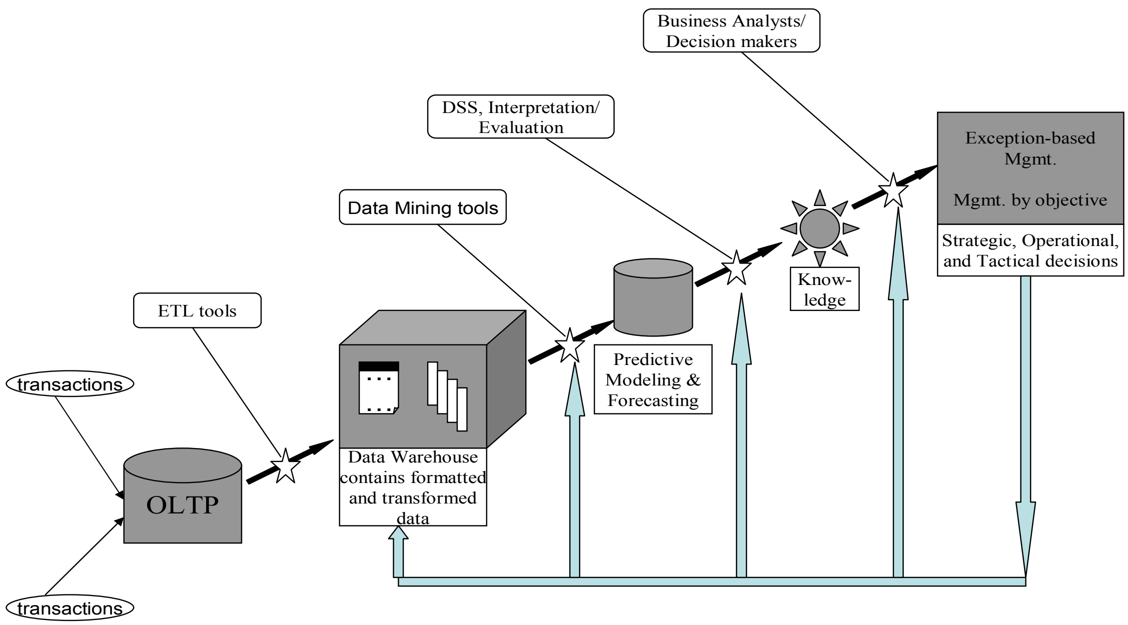

Figure 4. An overview of the steps involved in business planning and forecasting.

3.3 Planning and Forecasting Processes

Extract, transform, and load (ETL) tools extract data from heterogeneous sources like OLTP systems, syndicated data vendors, public domain sources like the Internet, legacy systems, real-time data repositories maintained by business analysts, decision makers, internal or external collaborators, consultants and executives for business planning and forecasting (Fig. 4) applications (Gung et al., 2002; Peterson et al., 2003; Wang and Jain, 2003; Yurkiewicz, 2003). The data is crunched and transformed into a standard or desired format and then loaded into a data warehouse or a data mart. The data is further processed inside the data warehouse to make them available for online analysis and decision support. DM and KDD tools access the data from the data warehouse to discover new patterns and fit models to predict future behavior. The results of predictive models are presented and utilized in the form of structured business workflows, interactive formatted data models for visualization, graphic models (Pearl, 1988; Whittaker, 1990), planning cycles, automated predictive and forecasting outputs which can be used as baselines by business planners and decision makers. DSS and BI tools like OLAP (Hammer, 2003) are utilized to interpret and evaluate predictive and forecasting models for creating knowledge about the future, which in turn helps analysts and decision makers to make strategic and tactical decisions.

3.4 Data Mining Technologies (DMT) and Decision Support Systems

Managers and business planners use DMT to extract meaningful patterns about their business and customers which can be interpreted as useful or interesting knowledge. Machine learning and pattern recognition algorithms along with statistical methods like classification, clustering and regression are used to fit a model to data, to find structure from data and derive high-level knowledge from the voluminous data present in data warehouse. Some of the commonly encountered business problems are described below using examples from the retail, credit cards and telecommunications industries.

Predictive and forecasting models generated by DM or KDD tools are interpreted and analyzed by business analysts, planners and executives using DSS and BI tools to understand trends, manage metrics, align organizations against common goals, develop future strategy and drive action. In this highly competitive world where different manufacturers offer the same category of products, trade promotions and advertisements can result in larger return on investment (ROI) from the perspective of a CPG company if the marginal increase in promotional sales is caused by increase in brand share. There is a need to distinguish these from natural variability in demand (e.g., seasonal, weather, economic, demographic or other effects), as well as ancillary effects like cannibalization, drag or pre- and post- sales dips.

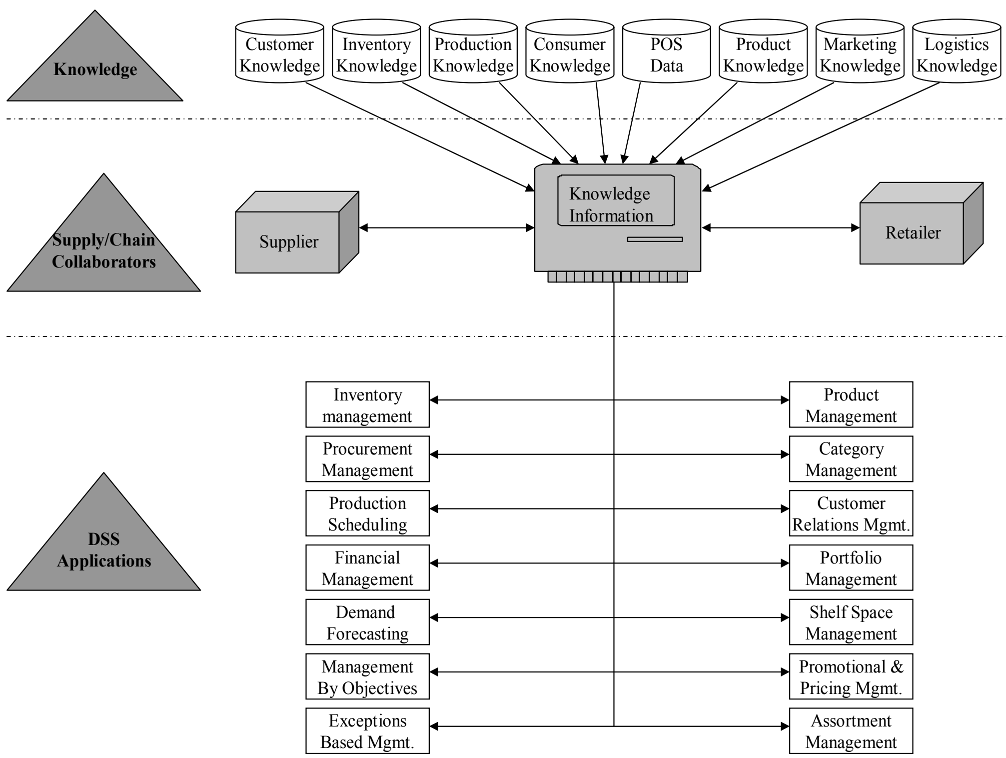

Figure 5. Inter-enterprise DSS in Supply Chain Management.

A process described in Fig. 5 involving knowledge information system where all partners can access, view, and modify the same data and knowledge to come up with “one number” demand forecasts or a common plan that is shared through the extended enterprise, thus resulting in improvements in forecasting accuracy, shorter lead times, good customer service levels, reduction of inventory levels, and maximum profits.

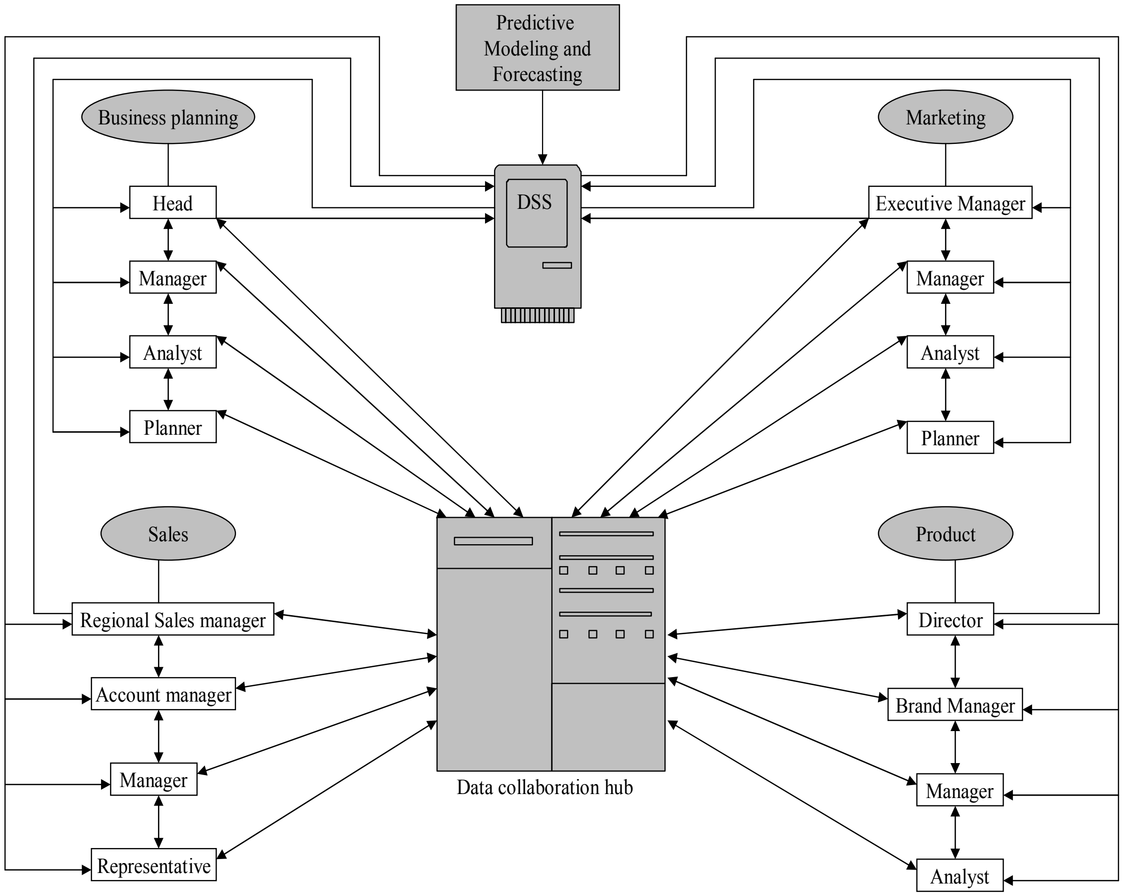

Figure 6. Intra-enterprise DSS in the CPG company.

An intra-enterprise process described in Fig. 6 having DSS used by sales people to understand sales patterns, product people for product life cycle management, marketing people for managing promotions or introducing new products, and business people for making strategic, operational, and tactical decisions. Each department analyzes and evaluates the information stored in DSS for creating knowledge about the future and stores this knowledge in the system. A centralized data "collaboration hub" collects every kind of information from business, marketing, product and sales so that every department can also access other department's information for its own use. The following activities are performed by different departments to create knowledge about the future:

- *Marketing*: Marketing people want to know (1) which products need to be promoted, where, when and at what price; (2) which existing products need to be phased out and when; (3) when and where new products need to be introduced. They might want to interact with sales people to know about historical sales or customer behaviors, product people to know the stage of the product life cycle, and business people to decide if the promotions would be effective and result in larger ROI or whether to launch a new product. They perform simulations, 'what if' analysis and scenario planning to ensure the effectiveness of promotions or advertisements. They can create knowledge in terms of the effectiveness of promotions or advertisements on the sales and determining the best time to phase out existing products and introduce new products.
- *Sales*: The sales people might want to interact with product people to understand the behavior of products, marketing people to know about promotions, and business people to understand the impact on sales based on their decisions. The knowledge created by them can be sales variability due to seasonality, customer behaviors, and change of sales patterns due to promotions or advertisements.

- *Product*: The product people might need to get POS data from sales to know the stage of the product life cycle, interact with marketing and business people to know about promotions and new products. They can create knowledge in terms of the product behaviors at different stages of the product life cycle.
- *Business*: Business planners and executives (e.g., in a CPG company) analyze the results of predictive models for promotional and baseline demand forecasts to design promotional strategies that maximize profits and ROI. The definition of maximized profits can differ, depending on whether the promotions are designed from longer-term considerations like brand acceptance or shorter-term considerations like the need to sell excess inventory. They get historical sales data or information about new opportunities from the sales department, product information from the product department and information about market conditions as well as corporate policies like promotions or advertisements from marketing department to develop future promotional strategy. They need to know if the promotions would result in lifts (e.g., increased demand due to a promotion on a specified product), drag effects (e.g., increase in sales driving the sales of associated product) and cannibalization (e.g., increase in sales reducing the sales of other products). They need to blend the natural variability of demand (e.g., seasonal and cyclical trends) with market information (e.g., competitive landscape, economic drivers, customer forecasts, demography) with direct and indirect promotional impacts. They use BI tools like querying and reporting for pulling and presenting the data relevant for planning, like past sales patterns, seasonal and cyclic patterns, economic indicators, weather patterns, demographics, and sales patterns of competitive products (and competitive promotions, if such information is available), as well as OLAP for viewing multidimensional data to get a better understanding of the information. OLAP related activities have been described by the OLAP council (1997). Broadly, OLAP tools are well suited for *Management by objectives* and *Management by exceptions.*

The analysis and evaluation of information through mathematical models and by business analysts and planners produce a wealth of knowledge which can be stored in the system for future use. For example, waterfall accuracy charts can be used to compare forecasts with actual values as they become available, for continuous evaluation and improvement. Similarly, audit trails and comments entered by planners during manual adjustments can be preserved and mined for evaluation and use in forecasting. The results of prior forecasts and the previous insights of knowledge workers are key building blocks in the process of knowledge creation about the future.

4. FUTURE TRENDS

The pace of rapid industry consolidations suggests that marketplaces of the future may well be characterized by a few leaders in each vertical, and laggards who run the risk of eventually fading into oblivion. In verticals like retail and CPG where the leaders have probably achieved long-term sustainability, one of the key differentiators between the leaders and the laggards has been the ability to create, retain and utilize knowledge about the future through forecasting, predictive modeling and planning efforts. Giants in retail and CPG are known to be superior to their peers in areas like demand forecasting, inventory management, promotion planning, pricing strategies, store and factory placements as well as product allocations or placement. These leaders have developed the best analytical models, as well as planning and execution systems, in the business, and strive to maintain their superiority. This is indicated by the strong analytical and planning groups in these enterprises, as well as by developments like the use of radio frequency ID (RFID) tags on each product mandated by large retailers. Similar developments are expected in the high tech industry in the longer term. While innovative newcomers are probably more likely to emerge in these areas even during relatively mature stages, the industry is expected to consolidate around leaders who are not necessarily (or only) the active pioneers and state of the art researchers, but who (also) have the best processes for knowledge creation, retention and utilization. The advent of globalization will enhance this trend of consolidation around a few large multinationals, who will strive to maintain their superiority by creating knowledge about the future. Mathematical models for extraction of knowledge from vast quantities of information, as well as efficient processes that enable interaction among planners and computers within and among organizations and enterprises are expected to be ubiquitous in this business scenario. The competition among multinationals to maintain their edge over rivals and innovative challengers may well spawn the age of ubiquitous analytical information technologies, which encapsulates data mining, knowledge discovery, predictive modeling and decision support.

5. CONCLUSION

The ability to create, preserve and utilize knowledge about the future for efficient decision-making is a key to competitiveness and survival for a business in this age of globalization, Internet commerce and rapidly fluctuating economies. Forecasting and predictive modeling is a challenging process, and is never perfect. However, even minor improvements can lead to significantly better tactical and strategic decisions, and improve the ability of an enterprise to react quickly to change. The tools, technologies and processes that enable knowledge creation about the future have been presented in this article. The ability to create knowledge by meaningfully blending data-dictated predictive modeling with the expertise of business planners and executives, as well as retaining and utilizing this knowledge effectively, remains a key requirement for efficient business processes and better decision-making, which in turn can make the difference between the leaders and laggards of an industry vertical.

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TERMS AND DEFINITIONS

Knowledge creation: It can be divided in both explicit knowledge, which can be formulated in terms of words and numbers and distributed as data, reports, and scientific formulas, and tacit knowledge, which is related with ideas, emotions, intuitions and experience.

Business Intelligence (BI): Software and set of tools that allow the end users to view and analyze the data and business knowledge through automated analytics or human-computer interaction.

Collaborative planning, forecasting and replenishment (CPFR): A process where the entire extended supply chain including manufactures, distributors and retailers is using the same information through collaborative process to improve sales and forecast accuracy, reduce inventory levels, and prevent stock outs due to promotions.

Data Mining Technologies (DMT): Statistical, artificial intelligence, machine learning, or even database-query based approaches that are capable of extracting meaningful insights or knowledge from large volumes of information.

Data Warehouse: A formal definition is given by Inmon: "It is a subject-oriented, integrated, time-variant, nonvolatile collection of data in support of management's decision making process".

Decision Support Systems (DSS): Holsapple and Whinston specify: "A DSS must have a body of knowledge, a record-keeping capability that can present knowledge on an ad hoc basis in various customized ways as well as in standardized reports for either presentation or for deriving new knowledge, and must be designed to interact directly with a decision maker in such a way that the user has a flexible choice and sequence of knowledge-management activities." (Power 2002)

Key performance indicators (KPIs): These are quantifiable measurements that help an organization evaluate how it's progressing towards organizational goals.

On-line analytical processing (OLAP): A software and set of tools that enable analysts, managers, and executives view multidimensional data in the language and structure of business for decision making.

On-line transactional processing (OLTP): A type of software and set of tools that facilitate real-time processing of transactions for transaction-oriented applications used in many industries including retails, airline, and banking.

One number forecasts: Forecasts that provide a objective and unified view of the future evolution of the enterprise, with buy-in from multiple stakeholders representing the internal organizations of an enterprise as well as its trading partners, and utilized for planning tactical, operational and strategic planning endeavors.

Sales and Operations planning (S&OP): The process that facilitates integrated demand and supply management among internal departments such as sales, marketing, and manufacturing through effective and efficient sharing of information across the supply chain to enhance business performance.