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ABSTRACT

Value chain management has gone through various stages of automation, integration and optimization in the past decades. While an optimization model for value chain deals with business scenarios under known circumstances, a predictive value chain model deals with probable circumstances in the future. Predictive analytics is succeeding optimization in the evolution of technologies supporting value chain management. This paper proposes a forward looking value creation model that combines the important concepts of value chain management and predictive analytics. An enterprise model for value chain predictive analytics that facilitates the convergence of information, operations and analytics is presented.

INTRODUCTION

The demands of the new economy fueled by globalization and the Internet have changed the focus of companies from internal efficiency to the creation of value in the extended enterprise that includes their customers, suppliers, distributors and alliance partners. Value chain management has evolved through various stages of automation, integration and optimization in the past decades. Along a different but related path, business intelligence has taken a center stage in information management evolving from rudimentary database queries and reporting, to online analytical processing and data mining. While value chain management and business intelligence have crossed paths many times before, these two disciplines will meet again in the future in predictive analytics. The convergence of these two important concepts in management and technology will create new means for value creation in the new economy. This paper proposes a predictive model for value chain management. It explores the concept of predictive analytics and its role in each activity of the value chain model. While the paper points out the importance of predictive analytics in value chain management, it also points out the obstacles in its implementation. As articulated by Nobel price physicist Niels Bohr, "prediction is very difficult, especially about the future". Beside some elements of luck, predictions require information and intelligence. The paper discusses the challenges to predictive analytics posed by disparate systems and the disconnections between information, operations and analytics. An enterprise model of information, operations and analytics convergence that facilitates predictive analytics for the value chain will be explored.

PREDICTIVE ANALYTICS

The evolution of technologies under the name of business intelligence (BI) has taken various shapes and forms in the past decade. They encompass technologies in query and reporting, statistical analysis, OLAP, data mining and in its latest fashion, predictive analytics. In principle, these technologies can be divided into two domains based on the problems they solve: problems pertaining to past and present, and problems pertaining to the future. Operational reporting for instance falls into the first category whereas projections, forecasts and predictions fall into the latter.

Data mining is the discovery process of identifying trends and patterns from large sets of data (Groth 2000). The term data mining is also used to describe knowledge discovery in large databases utilizing quantitative and artificial intelligence models (Turban et al. 2005). In the literature, the term predictive analytics is used in many ways, as synonymous with data mining, as a branch of data mining, as an extension of data mining with the predictive elements or as a subsequent phase that uses the results from data mining to provide predictions and recommendations for future actions. Apte et al. (2003) described predictive modeling as the most-used subfield of data mining, drawing from statistics, machine learning, database techniques, pattern recognition, and optimization techniques. Sze (2005) described predictive analysis as a data mining technique that works on the premise that the past can be used to predict the future. It differentiated "traditional" analytics that focuses on the past, from predictive analytics that focuses on the future. SearchCRM (2005) described predictive analytics as the branch of data mining concerned with the prediction of the future probabilities and trends. Economist (2004) described predictive analytics as an advancement of data mining, in using historic data not just to explain past trends, but to predict future ones. Agosta (2004) characterized the differences between data mining and predictive analytics in that data mining deals with continuous changes, projection by extrapolating the past into the future and validation of preconceived hypotheses; whereas, predictive analytics is capable of prescriptive analysis, envisioning discontinuous changes, predicting the future and formulating new hypotheses. A common thread to these definitions of predictive analytics is that there exist predictive elements in the analytical process that may be used in conjunction with the discovery process of data mining.

Predictive analytics has made inroads into many business applications. In customer relationship management, predictive analytics can leverage the wealth of customer information to generate models targeting the likelihood of future behavior in a given segment, help customer retention, predict which products would be best-suited for a particular customer, predict customer churn and customer profitability (Kloss 2002, Krauss 2003, Gincel 2005, Monash 2005). In supply chain management, predictive analytics can help more accurately decide when to increase capacity and when to pull back, recommend the best possible amount of production capacity, get early warnings of future capacity shortfalls, and quickly pick up changes in ordering patterns (Malykhina 2005). Other applications include crime fighting in law enforcement, cutting theft of tools in retail, predicting warranty problems for automobile manufacturers, predicting which customers for late payments, predicting change in stock price, anticipating and blocking fraudulent insurance claims (Callaghan 2003, Hall et al. 2003, Sullivan 2005, Mitchell 2005). Predictive analytics is becoming a critical element for businesses to gain competitive advantages through forward looking strategies. IDC research projects a $3B business for predictive analytics by 2008 (Mitchell 2005). In this paper, the role of predictive analytics in the management of value chain will be explored.

FROM VALUE CHAIN OPTIMIZATION TO PREDICTIVE ANALYTICS

The value chain is the set of all the activities through which a product or service is designed, produced, marketed, delivered and supported. Porter (1985) described the value chain as a systematic way of examining all the activities of a firm and how they interact. It further described the concept of extending a firm's value chain to a value system to include the value chains of the suppliers, channels and buyers. The focus of value chain management has been on the integration of processes, information and technology platforms across the value system (Handfield et al. 2002). Porter (2001) described the five overlapping stages in the evolution of technologies in business: automation of discrete transactions, functional enhancement of activities, cross-activity integration, integration of the entire value chain, and the optimization of various activities in the value chain in real time.

While real-time optimization of value chain can affect effective execution in operations under known circumstances, future actions based on probable circumstances require the element of prediction. Such predictive capability can be the differentiator in attaining competitive advantages for businesses. Leveraging business intelligence based on effective projections, forecasts and predictions is becoming an important element in formulating a firm's forward looking strategies. Predictive analytics succeeds real-time optimization as the next evolutionary stage of technology in business.

VAUE CHAIN PREDICTIVE ANALYTICS

In the following, we shall describe the role of predictive analytics in each of the value chain activities.

Marketing and Sales

The marketing and sales functions promote and sell a firm's products and services. They deal with activities associated with providing the means by which buyers can purchase the product and inducing them to do so (Porter 1985). Marketing identifies customer needs and market conditions. It manages market researches, product strategies, marketing campaigns, advertising, channels and lead generation. Sales, on the other hand, converts leads generated by marketing into deals. Sales activities include prospecting, qualification of leads, problem identification, product demonstration, proposal development and presentation, negotiation and contracting. Customer relationship management (CRM) typically falls within the marketing and sales functions.

While companies can easily determine which customers are purchasing most of their products using CRM and BI tools, predicting which customers will purchase the most products over their lifetimes will require the new discipline of predictive analytics (Harney 2003). Predictive analytics has a wide range of applications in marketing and sales. They include predicting customer behaviors, customer needs, customer responses, customer churn rate, and customer profitability. Predictive analytics can help determine what to sell to whom at what price and time, what products to rollout and how products and services should be bundled, what sales channels to use, cross-selling and up-selling strategies. Predictive analytics is an important tool to generate accurate forecasts in demand and sales, which help anticipate the required capacities in production and inventory.

Shearer (2004) described that predictive analytics can be used to determine if the current marketing campaign is generating the expected results, to provide instant insight into current customer behavior, and to help marketers predict future activity. The capability of predicting customer responses can help better plan marketing campaigns. Siegel (2005) described the use of predictive analytics as a reliable campaign response predictor. Kloss (2002) described how predictive analytics can target customers for marketing campaigns, and boost customer profitability by generating models targeting the likelihood of future behavior in a given segment. Predictive analysis can also be used to reduce customer churn. Nelson (2001) described that 75% of customers who defect to a competitor claim that they were satisfied with the enterprise from which they have defected. Anticipating the circumstances under which customers may defect can help companies to implement preventative measures before a customer defects and thereby increasing the probability of retaining the customer. Predictive analytics can help telemarketers optimize calling schedules. Tate (2005) described the use of best-time-to-call predictive analytics to determine the probability that each customer will be available to take a call and willing to make a purchase.

Procurement

Although procurement is described as a support activity in the traditional value chain model (Porter 1985), it has become a strategic element in supply management in the digital economy. Companies can create competitive advantages by implementing electronic procurement to reduce operational costs and increase efficiency. Notable examples include Covisint and Eastman Chemical (Turban et al. 2006). Predictive analytics can help to determine what and how much to procure, from which suppliers, at what price and at what time. Ordering large lot sizes yields benefits in terms of quantity discounts and lowers annual setup costs, but it increases the amount of safety stock and hence the carrying costs and can create the bullwhip effect (Stevenson 2005). Ordering small lot sizes reduces carrying costs, but it increases ordering costs and may result in shortage and not meeting customer demands. By anticipating the varying circumstances in demand, lead time, unit costs, vendor commitment, and environmental factors, predictive analytics can help optimize inventory while meeting customer demands. Supplier selection is an important element of purchasing. It can become a very complex process as the number of suppliers grows into the thousands and purchasing spending in the tens and hundreds of millions. Supplier selection criteria may include a combination of cost, quality, delivery commitment, service, lead time, sourcing methods, financial viability, profile of goods, and technology (Norman 2004, Relevant 2005). Predictive analytics enables buyers to quickly access how suppliers can be expected to perform against multiple variables on a given purchase order, or to predict which vendor can be expected to perform best given the parameters of a specific purchase (Relevant 2005).

Inbound and Outbound Logistics

The Council of Logistics Management defines logistics as “the process of planning, implementing and controlling the efficient, effective flow and storage of goods, services and related information from the point of origin to the point of consumption for the purpose of conforming to customer requirements” (Handfield 2002). Inbound logistics deals with the functions of receiving, storing and dissemination of inputs, which include raw materials and parts for manufacturers, finished goods and sub-assemblies for distributors and retailers. Activities in inbound logistics may include material handling, inventory control, vehicle scheduling, and returns to suppliers (Porter 1985). Outbound logistics deals with functions in the final storage of goods from the last production process to the distribution of the goods to the customers. Activities in outbound logistics include collecting, storing, and physically distributing the product to buyers, warehousing, material handling, delivery vehicle operations, order processing and scheduling (Porter 1985). Predictive analytics can be used to enhance the operations for inbound and outbound logistics. Miemczyk et al. (2004) described the need for responsive inbound logistics operation between component suppliers and vehicle assemblers, and the ability to predict the right inventory, to avoid excessive stocks for the assemblers in the case of building to order in the automobile industry. Haughton et al. (1997) described a regression model that predicts the expected magnitude of the resulting efficiencies on a route modification strategy based on real-time customer demand.

At the core of logistical operations are transportation and warehousing. Predictive analytics can be used to enhance transportation operations in the management of carrier capacity planning, routing and scheduling. Predictive analytics can enhance warehousing operations in the management of inventory control, space utilization and costs. Accurate demand and supply forecasts enabled by predictive analytics can help optimize the logistics operations. SPSS (2005a) described the problem of product shrinkage, an unexplained absence of product in the retail industry, and attributed a cause to the way the products were shipped to the store. With the use of RFID, predictive analytics can provide early detection of shrinkage and can help identify variables connected with shrinkage (Kxen 2005). Monitoring inbound logistics activities in receiving, storing and distribution of raw materials and parts for production can provide critical data for predictive analytics in anticipating supplier performance, replenishment quantity, frequency of shipment, stock-out and inventory excess. Predictive analytics plays an important role in outbound logistics to help control multi-echelon warehouse inventory, determine optimal picking, loading, routing and just-in-time delivery strategies.

Operations

Operations transform inputs into the final product. They include activities in machining, packaging, assembly, equipment maintenance, testing, printing, and facility operations (Porter 1985). Predictive analytics can be used in many areas of operations including production planning and scheduling, facility and capacity planning, utilization forecasts, inventory management, preventative maintenance, process control and quality management. Using predictive analytics, companies can more accurately decide whether and when to increase capacity internally or outsource to another manufacturer (Malykhina 2005). Predictive analytics is useful in preventing stock-out situations, reducing order cycle time and can eventually lead to automatic replenishment systems (Kxen 2005).

Maintenance of equipments for operations has evolved from preventative maintenance to predictive maintenance. The capability of predicting equipment failure for given factors can help quality control in the manufacturing process (Harney 2003). Stevenson (2005) described the use of predictive maintenance to determine when to perform preventive maintenance activities, ideally just prior to a breakdown or failure which may result in the longest possible use of facilities or equipment without a breakdown. Bevevino R.E. (2005) described the use of a predictive approach to determine the longest interval between plant shutdowns. Toyota Motor Corporation uses predictive maintenance to cut downtime and reduce costs (Koelsch 2005). Haridas et al. (1999) described the use of predictive analysis in medical product design and development. Stevenson (2005) indicated that process capability can be improved by reducing the process variability that is inherent in a process. Predictive analytics can be used to predict and identify the causes of variability, which can result in appropriate actions being taken to improve quality (Emerson 2005). Wray et al. (2003) described the use of artificial intelligence technologies such as genetic algorithm and artificial neural network to predict factory performance based on dynamic shop floor data.

Services

Services deal with functions in providing added value to products by ways of performing after-sales works which include installation, implementation, maintenance and repair, warranty services, and customer services. After-sales services can benefit from predictive analytics in the anticipation of problems. For instance, the capability of predicting product failure and applying the necessary remedies before a breakdown can reduce total costs of maintenance and repair.

Customer service has come out of a support function to become a strategically important differentiator for businesses. It can be an effective means for cross-selling and up-selling when additional needs for the customers are identified. Customer service encompasses a wide range of customer situations that may involve general inquiries of products, checking order status, billing issues, complaints, and technical support. Services can be provided through various touch points including customer contact or call centers, help-desks, customer service desks, and self-service through the Web. Predictive analytics can help anticipate customer situations and provide timely and useful solutions through all these touch points. Case-based reasoning, a branch of artificial intelligence, has been demonstrated to be an effective means of automating help desks (Turban et al. 2005, Bolloju 1996), where previous problems and solutions are used in the formulation of future solutions. In a self-service mode through the Web, predictive analytics can help customers navigate to the right Web page and receive relevant information. The capability of predicting customer needs and behaviors while servicing a customer can result in further selling opportunities. A notable example is Amazon.com's use of collaborative filtering software to prepare personalized book recommendations (Laudon et al. 2004). Service quality is a key differentiator in gaining business competitive advantages. The SERVQUAL model developed by Parasuraman et al. (1988) has been widely used to measure service quality. The attributes of the SERVQUAL dimensions included dependability, accuracy, prompt service, knowledge, and individualized attention. Predictive analytics can enhance customer service quality in many of these dimensions, by anticipating product issues, customer needs and problems, and taking appropriate actions at the right time.

Technology Development

Technology is a key enabler of business strategies and supports a wide range of value activities in the value chain across different functional areas. Technology management encompasses the management of hardware, software, databases, telecommunications and networking. Predictive analytics plays an important role in technology management ranging from predictive maintenance of equipments, to increasing Internet security by the anticipation of system vulnerability that would allow intrusions to a company's internal resources. Neugebauer et al. (2003) described methods in predicting network load and performance. It pointed out that using user models and a wide range of hardware models, the performance of future IT-infrastructure can be emulated and predicted. Vilalta et al. (2002) described the use of predictive algorithms in the prediction of failures in computer systems regarding long-term performance, short-term abnormal behavior and system events. It pointed out that predictive algorithms can enable the anticipation of the occurrence of events related to system failures, such as CPU overload, threshold violations, and low response time. Chen (2004) described the use of simulation software in network traffic modeling and server capacity planning.

Human Resource Management

Human Resource management consists of activities involved in the recruiting, hiring, training, development, and compensation of all types of personnel (Porter 1985). The new economy has fundamentally changed some traditional principles in human resource management across the globe. Life-time employment has been replaced by opportunistic employment for both employers and employees. Massive layoffs are being experienced in many industries where jobs are replaced by technology and outsourcing. Retooling of employees with the latest skills in management and technology is an ongoing requirement. Globalization of workforces has become a norm. All these factors contribute to the complexity of human resource management functions. Predictive analytics can be used for better decision making in investments in human resources and in sourcing strategies.

At the core of human resource management is human capital, which represents the knowledge, skills, and competencies of employees that allow them to be productive (Gora 2005). Tying human capital to business strategies and performance is becoming a critical factor of determining how a company should invest in human capital. Hewitt (2004) described that human resources departments can develop predictive models of employee behavior and resulting performance similar to marketing departments using data from customer behavior and resulting sales to guide decision making. The models can support decisions regarding people investments such as pay, communications, training and development, merger and acquisition (Hewitt 2004). Gora (2005) described various human resource predictive models available in public domain. For instance, the Accenture model predicts the consequence of different combinations of resources, value drivers, and transformations; and the Watson Wyatt model can be used to predict the impact of HR activities on a firm's shareholder value.

Firm Infrastructure

Firm infrastructure consists of activities including general management, planning, finance, accounting, legal, government affairs, and quality management (Porter 1985). Similar to technology infrastructure, it supports a wide range of value activities in the value chain across different functional areas. Predictive analytics can play a critical role in many aspects of management and administration, such as forecasting, financial management, risk management and compliance. Brown (2005) discussed the use of predictive models in predicting revenue-generation, assessing credit risks, and maximizing collections.

Forecast by definition is a statement of the future value of a variable interest such as demand (Stevenson 2005). The use of forecasts spans across many areas in a business organization such as profit projections in Accounting, equipment replacement needs in Finance, and hiring in Human Resources. Predictive modeling techniques such as time series, moving averages, trend analysis and regression are commonly used in forecasting. Operational asset management can be enhanced by predictive analytics through monitoring and predictive maintenance. Peregrine (2005) described the use of predictive analytics in managing IT assets. IBM (2005) described real-time asset monitoring in predictive maintenance of assets. Predictive analytics can be used across many industries in fraud detection, risk management and debt management (thinkAnalytics 2005). Doshi (2003) described the use of predictive models to generate the probability of default for each customer in managing credit risk. Predictive analytics can also help corporations in compliance. Outlooksoft (2005) described the use of predictive analytics as part of business performance management to meet the stringent financial reporting and management requirements as set forth by the Sarbanes-Oxley Act. SPSS (2005b) described the use of predictive analytics in tax compliance.

CROSS VALUE CHAIN PREDICTIVE ANALYTICS

Porter (2001) described cross-activity integration and integration of the entire value chain as preceding stages to value chain optimization in the evolution of technologies in business. Integration of predictive analytics across the value chain is a prerequisite for an optimal predictive model for value chain management. Two aspects of cross value chain predictive analytics can be addressed: the inter-dependency of predictive analytics between value chain activities, and the design of predictive analytics across value chain activities.

Predictive analytics for value chain activities may affect and be dependent on one another. For example, the prediction of marketing program effectiveness affects sales forecasts. Predictions in demand forecasts affect the planning and projections in production capacity, procurement, inventory control and outbound logistics. Predictions of supplier behaviors and production capability affect the time-to-market strategies. The prediction of customer responses affects product development strategies.

Predictive analytics can also be designed across multiple value chain activities. For example, predictive analytics can be designed across the value chain activities of sales and service. Sales data combined with service data can be used to cross-sell and up-sell products and services based on anticipated customer needs. Similarly, predictive analytics can be designed across the value chain activities of inbound logistics and operations. Data captured from inbound logistics for defective parts combined with quality control data in operations can be used to predict specific quality issues in the production process with respect to the selection of suppliers.

As pointed out by Hagel (2002), the leveraged growth of a company requires the coordinated mobilization of resources supplied by many enterprises operating at many levels of the value chain. Predictive analytics yields maximum benefits in value optimization when it is applied across multiple value chain activities for the extended business enterprise. A predictive analytic model for the value chain requires an enterprise-wide integrated model of information, business processes and predictive analytics. In the following, an enterprise model is presented to provide the integration framework.

AN ENTERPRISE MODEL FOR VALUE CHAIN PREDICTIVE ANALYTICS

Prerequisites for effective predictions beyond the elements of luck are good information and business intelligence. Challenges in getting good information and business intelligence can be attributed to problems in disparities between organizations, processes and systems. As pointed out by Fraser et al. (2003), decision making fragments across a business as different functions become entities in themselves. The lack of integration between disparate data sources is a major obstacle in predictive analytics (Anthes 2003, Vesset 2005). The disconnection between operations and analytics can create erroneous assumptions causing inaccurate predictions. Conversely, operations may not benefit from analytical results due to such disparity. A predictive model for the value chain requires the integration of information across the extended enterprise. It further requires the integration of operations and analytics. Enterprise modeling as a means of consolidating information from disparate sources is becoming a focus for predictive analytics (Kxen 2005).

In the following, a conceptual model is developed to provide the integration framework for data, operations and predictive analytics for the value chain. The model consists of five components: value chain activities, data management, predictive analytical processing, business operations and data sources. In Figure 1, *value chain* represents the primary and support value chain activities. The data management component consists of the *enterprise data model (EDM)*, *data warehouses (DW)* and *operational data stores (ODS)*. The predictive analytical processing component consists of *predictive analytic models*, *knowledge bases* and *predictive intelligence.* Business processes across the entire value chain are represented by *business operations*. Various sources of data are represented by *transactional data sources*, *legacy data sources* and *external data sources*.

Data Management

Data collected in different value chain activities are captured in transactional systems. Transactional data together with legacy and external data are consolidated for operational processing in operational data stores, and for analytical processing in data warehouses. The meta-model for data consolidation from different data sources is represented by the enterprise data model. Techniques in data modeling such as Entity-Relationship modeling (Chen 1976) can be used to develop the enterprise data model. The enterprise data model is the conceptual representation of data requirements supporting the activities across the entire value chain. It provides the roadmap for data sharing between value chain activities, business operations and systems. It further provides an integrated framework for the design of operational data stores and data warehouses (Chan 2004). While both the ODS and DW are integrated platforms for disparate data sources, they have different characteristics and serve different purposes (Chan 2005). The operational data stores support operational processes and the data warehouses support analytical processes. For example, the operational process of a direct mail campaign requires data from responses to surveys, recent purchases and inquiries, internal and external leads generation. These data come from transactional systems, legacy systems and external sources. They are integrated and consolidated through the ODS. The data warehouses on the other hand provide subject oriented, historical data for analytic processing. For example, the predictive analytic process of determining cross-selling strategies may require historical data from previous purchases for specific customers and for certain market segments, product and service affiliation data, and customer profiles. These data come from transactional systems, legacy systems, external sources and operational data stores. Data warehouses provide the data inputs for analytic processing. Even though the ODS and DW may extract data from the same data sources, their structures are different. Data warehouses differ from operational data stores by the characteristics that pertain to historical data with a long time horizon, time variance, data non-volatility and subject orientation.

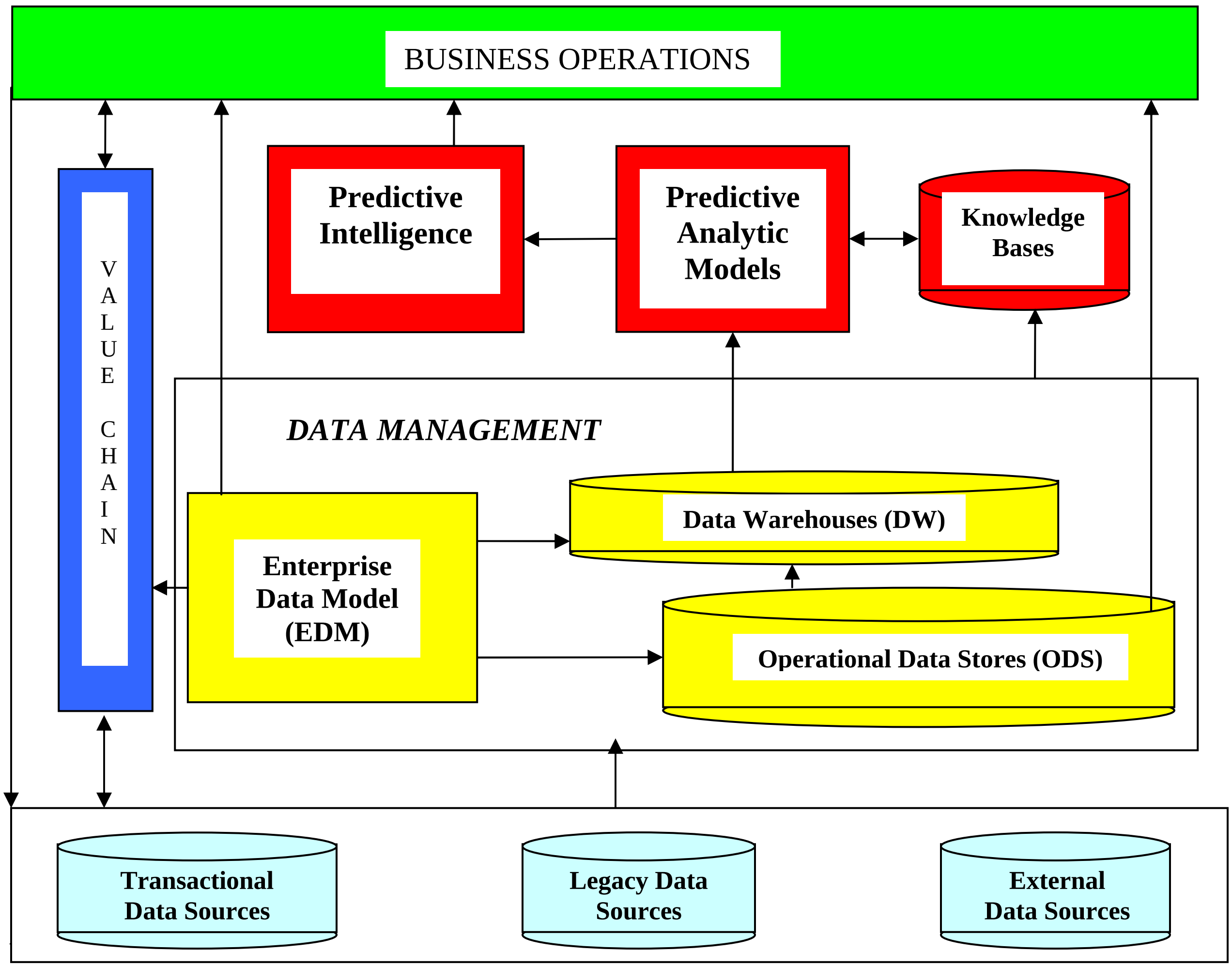
Predictive Analytic Processing

The predictive analytic models consist of quantitative and algorithmic methods of analysis to create projections, forecasts, extrapolations and predictions. They may include methods in statistical analysis, optimization, data mining, machine learning, pattern recognition, and information retrieval. Knowledge bases are part of the predictive analytic processing architecture. Knowledge captured through the knowledge acquisition process from sources such as human experts, textbooks, multimedia documents, databases, research reports and the Web, is stored in a knowledge base, which contains the relevant knowledge necessary for understanding, formulating, and solving problems (Turban et al. 2005). There are bidirectional relationships between predictive analytics and knowledge bases. The rules in a knowledge base can be used in predictive analytic processing, and conversely, results from predictive analytics such as data mining can create new rules in the knowledge base. Predictive analytic models take inputs from data warehouses and knowledge bases and transform the data and knowledge into intelligence for predictions (*predictive intelligence*).

Business Operations

Business operations consist of all enterprise business processes that span across various value chain activities. The integration of value chain activities, the optimization of the entire value chain and the holistic approach to predictive analytics across the value chain all converge to the ultimate objective of enhancing business operations to attain organization goals. Business operations are supported by data from operational data stores and enhanced by the predictive intelligence created from predictive analytics. For example, in a call center operation, a customer may complain about a product, make inquiries to new or additional products and complete a sales transaction, all in the same process that spans across multiple activities in the value chain including service and sales. The operational process requires up-to-the-minute information from operational databases regarding the most recent transactions, inquiries and complaints by the customer. It also requires predictive intelligence to determine what additional products and services can be bundled, and to make preventative resolutions by anticipating customer behaviors and potential problems.

Figure 1: A Conceptual Model for Value Chain Predictive Analytics



Applications in CRM

Customers can interact with a firm through many channels and via many touch points. Data collected about customers get buried in information and organizational silos and are not shared across the enterprise. Disparate views of customers and the inability to predict customer behaviors and anticipate problems can cause ineffective and slow responses, resulting in the loss of opportunities for the firm. Effective customer relationship management requires a unified view of customers and predictive customer intelligence across the entire value chain.

A current trend in the lodging industry is to provide the best experience to customers while they are staying in the hotel. In so doing, a hotel needs to be able to combine customer information from various touch points across hotel properties in the franchise. A customer may interact with sales for reservation, with marketing for promotional programs, with house keeping and restaurants while staying at the hotel. The total experience of a customer includes previous interactions, current interactions, and the anticipation of future values such as the points-based reward programs across all touch points. A service representative at the check-in counter needs to know a customer's profile such as room preferences, recent interactions such as reservations and requests, and predictive intelligence for the customer, to provide personalized services and anticipate customer needs and resolutions. Combining predictive intelligence with the most current operational data may be required to respond to the up-to-the-minute situation with customers. Kontzer (2004) described Hilton's OnQ system's ability to match customer reservations with profile database records, and to establish the value of a customer based on personal history and on predictive modeling of the business the person is likely to do. Wyndham's ByRequest program utilizes intelligence from the ByRequest data warehouse which combines guest profiles with guest-stay information extracted from property management systems across the franchise (Applegate 2007).

The Significance of the Enterprise Model

The lack of an enterprise strategy, the lack of an integration strategy and the lack of an approach to analytics were among the foremost reasons for the failure of past enterprise systems implementations (McKenzie 2001, Greenberg 2002, and Bannan 2004). The enterprise model provides the blue-print for the three-way convergence of enterprise data, predictive analytics and business operations across the value chain and disparate systems. Porter (2001) emphasized the importance of real-time optimization of the value chain in the evolution of technology in business. The optimization requires an integration framework for information, business processes, and technology platforms across the value chain. The proposed enterprise model adds another dimension of predictive intelligence to the integration framework. It extends Porter's description of the value chain optimization model to a value chain predictive model in the evolution of technologies in business.

CONCLUSION

Competitions in the new economy driven by globalization and the Internet have emphasized two separate but related disciplines in the design of business models: the creation of values through collaboration across the value chain and the creation of forward looking strategies through predictive analytics. While past endeavors of value chain management focused on automation, integration and optimization; the future of value creation requires the capability of prediction. While past endeavors of business intelligence focused on query and reporting, OLAP, and data mining; the future of business intelligence points towards predictive analytics. A forward looking value creation model is created by merging these two important concepts of value chain management and predictive analytics. The concept of real-time optimization of the value chain as described by Porter (2001) is extended to a predictive model for the value chain. As businesses move from an operational efficiency model that focuses on the past and present to a forward looking value creation model that focuses on predicting the future, predictive analytics will play a significant role in value chain management. This is evidenced by the many examples and applications in each of the value chain activities presented in this paper. However, the implementation of the predictive value chain model will be challenged by the disparity of information, operations and predictive analytics across the value chain. An enterprise model is presented in this paper to provide an integration framework for the convergence of these disparate dimensions in value chain management.

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