A strategic management support architecture: integration of the balanced scorecard and enterprise resource planning

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Abstract: The power of information technology to support strategic management at the executive level may currently be underutilised. A recently developed strategic management system incorporating extensive domain knowledge can be integrated with advanced data utilisation technology to form a comprehensive strategic management architecture. Specifically, we propose an information architecture that exploits the synergies between the balanced scorecard business model, data warehousing and data mining to more completely support management and performance measurement. Our proposed strategic management support architecture may provide new perspectives on how information technology can add value to enhance strategic management.

Keywords: strategic management system; enterprise resource planning; ERP; balanced scorecard; strategic management support architecture; business information systems.

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1 Introduction

The next step beyond data integration and process integration1 is utilising Information Technology (IT) to enhance support of the strategic management process. Recent developments in both IT and business process modelling make integration feasible (Zhu et al., 2004; Golfarelli et al., 2004; Brignall and Ballantine, 2004; Frolick and Ariyachandra, 2006; Chand et al., 2005). Management’s need to better use strategic information makes integration necessary. However, meshing the analytical needs of management with IT capabilities has presented a challenge to both management and IT personnel (Chan and Lewis, 2002; Møller, 2005). The literature has suggested the need to employ domain knowledge for better data utilisation and more strategic performance (Hormoz and Giles, 2004; Hendricks et al., 2007). To our knowledge, a generalised application of domain knowledge to data mining and strategic utilisation has not been proposed. Literature discussing strategic performance measurement ranges from the use of heuristic methods to specifying appropriate metrics for use in performance
measurement models (Kaplan and Norton, 1996; Kaplan and Norton, 2000; Kaplan and Norton, 2006). However, this literature contains little mention of non-heuristic means for deriving and testing the models.

We offer one possible model that integrates IT and business knowledge to meet the needs of management while providing IT professionals with a framework for providing value added services. Our proposed strategic architecture may support a new perspective on how information technology can enhance the strategic management system. Specifically, we develop an information architecture that exploits the synergies between the balanced scorecard business model, data warehousing, and data mining to facilitate a more complete management performance measurement system. The balanced scorecard method is a business process modelling technique intended to translate strategies into measurable actions.

1.1 Enterprise data integration

Our model relates an architecture of enterprise data integration at the highest level, one that is stakeholder comprehensive, and facilitates strategic decision-making by executives managing an organisation. Figure 1 illustrates the executive strategic information level that our paper targets along with the two other information levels which organisations typically possess and the hierarchy supporting technology driven information.

**Figure 1** Management pyramid supported by information technology
Operational Control and Monitoring is the lowest functional level of the organisation. Routine control and operation of an organisation occurs on a daily basis. This level of management uses specific types of systems such as transactional information systems, process control systems, and management information systems such as Material Requisition and Planning (MRP) systems. These information systems support automation of particular functions or tasks and are referred to as ‘islands of automation’ because they lack system-wide integration.

Management Planning and Coordination is the second functional level of the organisation, involving both planning and controlling across functional boundaries. Data warehousing and Enterprise Resource Planning (ERP) systems for business process integration were developed during 1990s to support information needs at this organisational level (Møller, 2005). Top-level managers generally derive little utility from data and process integration because at this level the quantity and detail of information are overwhelmingly difficult to use. Data from this level require some coherent form of summarisation, synthesis, and analysis. Our strategic management model provides executives with the power to use information from lower levels of organisational information that might otherwise be under-utilised.

Strategic Planning and Control is the highest functional level of the organisation. Overall planning and control, including strategic vision, goals and action plans are performed at this executive level of management. Monitoring organisational performance is critical to assure that meeting and updating strategic goals as needed. Managers at this level require intelligence that combines business knowledge with all forms of available and usable information. An emerging trend for companies wishing to utilise investments in ERP and data warehouses is the attempt to leverage these investments by further connecting ERP and data warehouse systems to business process measurement. However, merely integrating ERP with data warehouses constitutes an incomplete strategic management system. Some research has reported that ERP systems fail to provide competitive advantage unless integrated with social and intellectual capital of the organisation (Lengnick-Hall et al., 2004). Information technologies alone cannot support knowledge needs at this level because the ability of executives to identify opportunities and make strategic decisions about these opportunities remain the core assets of an organisation (Al-Mashari et al., 2008). Therefore, the objective of our paper is to set forth a model that integrates business knowledge possessed by executives with information technology used in their organisation.

The remainder of the paper is arranged as follows: Section 2 discusses our proposed integration of IT and business process modelling into a unified management support architecture. Section 3 provides details about data mining, data warehousing, and balanced scorecard components of our architecture. Section 4 provides an example that links the balanced scorecard’s four basic business processes. Section 5 discusses the integration of data mining and the balanced scorecard and Section 6 concludes the paper and discusses pursuable future research topics.

2 Integrating IT and business process modelling

As background for our model, it is helpful to understand the evolution of IT development, strategic management tools, and the gap between IT and the strategic management process. Information technologies have rapidly developed over the past four decades into
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the sophisticated systems we see today. Computer-based information systems have evolved from Transaction Processing Systems to Management Information Systems, to Decision Support Systems, to ERP Systems. There has been a trend of IT support moving from routine operations to decision-support and ultimately the planning levels of an organisation (Ax and Bjørnenak, 2005; Vlachopoulou and Manthou, 2006).

2.1 Data management evolution

Information technologies for data management have also evolved: from programmatically inclusive data to flat or linear files separate form programs, to relational tables and databases, and ultimately to massive data warehouses. Early data technology simply included defined data in applications or programs. The file approach separated data into flat or linear files with cumbersome searching techniques for extracting information. Database management systems separated data into tables and provided more structure, indices and search algorithms. Information was more easily aggregated, statistically analysed and reported. With the data warehouse approach, data has been extracted, exported and integrated from multiple data sources.

The evolution of data management demonstrates the increasing degree of data integration available for strategic planning using business process frameworks (Lim and Lee, 2008). In addition, various data analysis tools have been developed to utilise massive data stores. Such tools include statistical packages (e.g., SPSS), On-Line Analytical Processing tools and data mining tools. Data analysis tools have evolved from hypothesis-driven statistical data analysis, to discovery-driven machine learning approaches (i.e., data mining). Examples include Intelligent Assistance for Data Analysis (IDEA) and Architecture of Integrated Information Systems (ARIS) for Enterprise Resource Planning systems. ARIS incorporates task specific software such as enterprise architectures, integrated process management, procedural models and management of ERP systems.

2.2 Measurement evolution

Measurement tools have undergone a similar evolution to meet modern demands, particularly over the last two decades. Single summary performance measures made popular in the early 1900s, such as Return on Investment or Return on Assets adequately captured business activity in the industrial era and subsequent periods. Financial information generated by the accounting information system produced these measures mostly comprised of historical data.

Decision maker dissatisfaction with summary financial performance measures and the relatively simple business models that they represent occurred over time (Woods and Grubnic, 2008). These decision makers desired performance measures that captured multi-dimensionality of organisational performance that ultimately manifested in financial results. Managers began to augment the summary financial measures with measures of operations and performance related to their customer base, such as quality measures in the production process and customer satisfaction measures. These measures preceded financial results, providing timely input about whether actions were accomplishing strategic goals or indicating necessary operational changes. To meet
the demand for a more comprehensive business model and measurement tools, the balanced scorecard was created by Kaplan and Norton in the early 1990s (Kaplan and Norton, 1992).

Kaplan and Norton asserted that although important, traditional financial measures inadequately measured operations because they merely reflected results of actions already taken, and were too simplistic. Building upon value chain analysis of business processes popularised by Porter (1980), the balanced scorecard method was created to help model the critical strategic elements in businesses processes along with performance measurements that provide feedback about these processes (Kaplan and Norton, 1992). Instead of focusing strictly on summary financial measures, the balanced scorecard also contains a series of inter-related operational and financial performance measures. In essence, the balanced scorecard is a measurement system reflecting the key processes of an organisation. We use the balanced scorecard as a comprehensive business process model for this paper because the generalised framework of the scorecard can be adapted for domain-specific needs (Albright et al., 2007).

While huge leaps in automation, data processing and management have occurred, a widening disconnect between IT and its contribution to the strategic management support process has developed. The power of IT investment has not been realised at the highest functional level of the organisation for strategic planning and control (Huang and Qing, 2007). According to the eight annual surveys of Critical Issues of Information Systems Management done by Computer Science Corporation from 1988 to 2001 ‘Aligning information systems and Corporate Goals’, has been in the ten most challenging management issues identified by top information systems executives. The fact that this issue remained a major concern year after year for this period exemplifies the importance in justifying IT investment in organisations. It could be that corporate strategies are continuously changing to meet the dynamic business environment, causing the gap between IT and corporate goals to grow. Nevertheless, the survey results indicated that IT development and applications had not remained linked with rapidly evolving business strategies.

2.3 Linking IT and strategic management

Our model attempts to bridge the gap between IT and the strategic management process by forming direct linkages between IT applications and the strategic management process. Inherent synergies between IT and strategic management processes can be realised through their integration. We believe that domain knowledge possessed by executive management is necessary ingredient for any management support process utilising IT. Data warehouses and data mining can assist top management in discovering meaningful patterns among data elements suggesting ways to improve operations, revise strategies and actions, and providing information about how well strategic initiatives are being accomplished. The strategic management support architecture we propose provides a feedback loop to managers so that they may verify and revise their business model. Figure 2 provides an overview of the integration of ERP systems, the balances scorecard and the strategic domain.
2.4 Strategic management support architecture

The strategic management support architecture that we propose is shown in Figure 3. The model consists of three components: the data warehouse, the data-mining tool, and the balanced scorecard. A generic balanced scorecard functions as a business model that captures business knowledge, providing feedback about the effectiveness of strategic activities. Our general strategic management architecture may be adapted to the specific needs and circumstances of different businesses, as well as governmental entities, or non-profit organisations.

Figure 3 Strategic management support architecture
3 Detailed descriptions of proposed model components

3.1 Data warehousing

We begin detailing the key components of our model depicted in Figure 3 with a discussion of the data warehouse. To generate data for management support, the data warehouse consists of integrated data, extracted from various data sources (e.g., operational database tables) both internally and externally. Data warehousing involves consolidating data from disparate sources into a consistent format. The quality of data in a data warehouse in terms of validity, availability, level of detail, accessibility, completeness and consistency is superior to the quality of data found in the collective set of functionally oriented data sources. It provides the infrastructure for supporting a wide variety of data analysis and information needs. For example, different business functional areas such as financial accounting systems, materials resource planning, and customer relationship management may use the integrated data to support the formulation and revision of strategic initiatives.

One challenging issue in building and maintaining a data warehouse is determining what data should be extracted from other data sources. The kinds of external data that should be integrated with internal operational data must be determined. The investment in the data warehouse itself will not create significant business value. However, the return on this investment will be catalysed by the use of the high quality data via data mining and other data analysis techniques. We suggest that a comprehensive business model, such as the balanced scorecard, be employed to decide what data should be integrated into the data warehouse. At a minimum, the data warehouse should have adequate data to derive all performance measures specified in the balanced scorecard. Therefore, the contents of the data warehouse will evolve over time as actions are fine-tuned or adjusted.

3.2 Data mining

Data mining, also known as knowledge discovery in databases, is a relatively new approach to data analysis that attempts to discern patterns, trends and relationship among data, including non-obvious and unexpected patterns. It is a discovery-driven approach requiring no pre-supposed hypotheses. Data mining techniques and tools are developing to assist with analysing huge amounts of data to find critical knowledge. The amount of data collected and warehoused by organisations is growing at a phenomenal rate. For example, Wal-Mart typically handles 800 million data transactions per day using 700 data marts. These data marts are now being consolidated into an enterprise level data warehouse as Wal-Mart’s data needs continue to grow (Havenstein, 2007). Ad hoc techniques such as statistical analysis tools and query languages, are no longer adequate for sifting through vast collections of data, and are giving way to data mining and knowledge discovery tools to exploit corporate data for competitive business advantages (Brachman et al., 1996; Frolick and Ariyachandra, 2006).

In our model, data mining techniques and tools allow executives to confirm or discover evidence supporting the cause-effect relationships among strategies, actions and the measurement of their performance. For example, it is important to know how product quality affects customer behaviour, and ultimately profitability. Knowledge discovered through data mining may suggest potentially new strategies or performance measures.
3.3 The balanced scorecard

Though a recently new development, the balanced scorecard has gained acceptance in the business community and beyond. Numerous large businesses have adopted the balanced scorecard including: Motorola, Analog Devices, FMC Corporation, Amoco Corporation, Metropolitan Life, Mobil Oil, Chemical Bank and Advanced Micro Devices (Kaplan and Norton, 1992; Kaplan and Norton, 1996; Kurtzman, 1997). The balanced scorecard has also been adopted by Federal agencies including the Veterans Benefit Administration, Department of Transportation and Federal Aviation Agency, along with cities such as Charlotte, North Carolina and St. Charles, Illinois (Kaplan and Norton, 2001). Additionally, prominent consulting practices have experienced growth in the area of balanced scorecard consulting. The balanced scorecard has also been used as a major theme for some statistical software (Ids, 2007; Cohen, 2003).

Balanced scorecards allow executive managers to translate their strategies into actions that can be measured, communicated to personnel in the organisation, and provide feedback about how well the organisation is meeting strategic objectives. However, the balanced scorecard itself is more than a collection of performance measures; it is one of the tools that is part of the strategic management process. It represents the cumulative domain knowledge possessed by managers accumulated through their experiences. With the portfolio of key performance measures, the balanced scorecard functions for managers in the same way dials, gauges, and meters help pilots to fly an aircraft.

Recommendations for selecting critical activities and measurements of performance to be included in the scorecard have been largely heuristic, including brainstorming, focused observation, and inquiry. Feedback from subsequent observations, concerning how well the scorecard represented an organisation’s critical activities, was recommended to fine tune or modifies the scorecard. There is a critical element missing in the creation and subsequent modification (organisational learning) of effective balanced scorecards. Internal operating data, external data about the economy, customers, suppliers and competitors should be mined for knowledge discovery and hypothesis confirmation.

The balanced scorecard employs a series of performance measures to provide managers with information about how well the organisation is achieving its strategic objectives from four basic organisational processes: learning and growth (employee-related), internal/business process (operations), customer, and financial. These four processes broadly relate to each other, and as seen in Figure 4.

**Figure 4** Balanced scorecard processes

<table>
<thead>
<tr>
<th>Employee and Infrastructure Processes</th>
<th>Operating Processes</th>
<th>Customer Processes</th>
<th>Financial Processes</th>
</tr>
</thead>
</table>

4 Linking balanced scorecard basic processes – an example

An example will help to illustrate the linkages between the four basic processes. Suppose that an insurance company wanted to boost its profits and return on assets (Financial processes). The strategy of acquiring and retaining clients only in the most profitable
lines of insurance and reducing the costs of servicing clients in less profitable lines might be pursued. At the Customer process level, advertising and incentive schemes for agents may be put into place to attract and retain the most profitable clients. To measure the results of these actions, executives may monitor client acquisition and retention numbers in all insurance lines. Additionally, customer profitability measurements will allow executives to understand whether the client niches acquired and retained are fulfilling strategic objectives of keeping the most profitable clients, and reducing the costs of servicing clients that historically have not been as profitable.

To support the Customer processes, claims processing, adjustments, and disbursement processing (operating processes) may be enhanced for the most profitable insurance line clients to increase the satisfaction of current customers. The enhanced service features will also act in concert with increased sales efforts to attract more clients. Measurements of these functions may include average days to process a claim and average time to process a disbursement. Additionally, the company may send customer survey forms to solicit feedback on how satisfied customers were with the service they received.

At the Employee and Infrastructure level, actions may be taken to assure that employees are well trained in product knowledge, and able to respond to inquiries from clients. Measurements of these actions may consist of monitoring the number and type of classes employees have taken, and random tests, by phone, of employees’ ability to field questions from customers. The IT infrastructure may have changes made to it to gather more detailed information from clients, and to provide online services to clients in profitable insurance lines. The success of these actions will ultimately be measured by a tool such as customer satisfaction surveys, but can initially be measured by the amounts of funds invested in certain IT applications.

Figure 5 illustrates the balanced scorecard concept showing some of the types of performance measures that may be used for a typical business. Some businesses may have more business processes or may wish to classify one of the primary business processes into sub-categories. However, the general relationships of business processes are likely depicted by the format seen in Figure 4.

Our integrated model utilises synergies between data mining and business domain knowledge, particularly in developing hypotheses, and using discovered knowledge. Developing hypotheses through data mining often involves exploring data through passive techniques and elaboration, and automatically develops the initial hypotheses to test. However, developing hypotheses without any prior domain knowledge can results in numerous trivial, spurious, or obvious results. The data mining process may be computationally and monetarily expensive. A comprehensive business model with domain knowledge is considered to be an important component of a prototypical data mining system (Piatetsky-Shapiro and Frawley, 1991) to improve the data mining efficiency. A purely brute-force approach to data mining without the guidance of domain knowledge has its shortcomings. As stated in Fayyad et al. (1996) “Blind application of data-mining methods, rightly criticised as data dredging in the statistical literature, can be a dangerous activity, easily leading to the discovery of meaningless and invalid patterns.” Therefore, the balanced scorecard can be used *ex ante* to make the data mining process more efficient.
Figure 5  Generic balanced scorecard framework and measures

**FINANCIAL PROCESSES**

- Aggregate Financial Measures
e.g., Earnings, Return on Investment

**CUSTOMER PROCESSES**

- Market Share
  % of industry, penetration
- Customer Acquisition
  Customers acquired
- Customer Profitability
  Net profit of customer
- Customer Retention
  Customers retained
- Customer Satisfaction
  Satisfaction level

**OPERATING PROCESSES**

- Postsale Service
  Service the customer
- Operations Process
  Process cycle times
  Process quality measurements
  Process cost measurements
- Innovation
  % Sales from new products
  new product introduction vs competitors
  Manufacturing process capabilities
  Time to develop new products

**EMPLOYEE AND INFRASTRUCTURE PROCESSES**

- Employee Efficiency
- Employee Retention
  % Key staff turnover
- Employee Productivity
  Output per employee
- Employee Satisfaction
  Level of satisfaction
The real business value of data mining comes from the discovery and utilisation of newly found results, via business strategy creation and refinement. This is one of the most challenging aspects of data mining projects. Accordingly, our architecture incorporates feedback from new discoveries and verified results to the top management team for their evaluation. Results from data mining can be used to confirm the current strategies, or identify potentially new strategies to be evaluated. Strategy revisions or new strategies will then be incorporated into the balanced scorecard framework and ultimately be translated into actions.

5 Integrating data mining and the balanced scorecard

The data mining process involves numerous tasks (Brachman et al., 1996; Fayyad et al., 1996; Chen and Sakaguchi, 2000), which can be summarised into steps. The following discussion elaborates each step and discusses interrelationships and integration of the data mining process with Balanced scorecard and data warehouses for strategic management support.

5.1 Data familiarisation

Familiarisation with the data and the mining task is more significant than it sounds, especially when the data is extracted from multiple sources and the mining will not be done by the business users. The data integration research and data warehousing techniques provide the knowledge on how data from multiple sources could be integrated.

5.2 Business knowledge

Business domain knowledge including relevant prior knowledge and the goals of the organisation need to be understood. Because the Balanced scorecard captures comprehensive known business knowledge such as the organisation’s goals, strategies and performance measures, it is an ideal source of reference during implementation.

5.3 Data acquisition

Acquire and integrate the data set on which the mining is to be performed. If the required data set has been integrated into the data warehouse, this step can be simply done by retrieving required data from the warehouse.

5.4 Data preparation

Data cleaning and preprocessing checks the quality of data for mining by removing records with errors or insignificant outliers. These procedures may take the majority effort during the overall mining process due to potentially poor data quality from multiple sources. Many data mining projects inevitably turned out to be data cleaning. It is not necessary to have a data warehouse to support data mining process. However, it is better to make sure that the quality data for mining is obtainable. Data mining may be a way to leverage and justify investments made in data warehousing.
5.5 Develop hypotheses

This step explores data through passive techniques and elaboration, and automatically develops the initial hypotheses to test. However, developing hypotheses without any prior domain knowledge can result in numerous trivial, uninteresting, and obvious results. The data mining process may be computationally and monetarily expensive. A comprehensive business model with domain knowledge is considered an important component of a prototypical data mining system (Brachman et al., 1996; Chan and Lewis, 2002; Weir, 1998). A pure brute-force approach to data mining without the guidance of domain knowledge has its shortcomings. As stated in Fayyad et al. (1996) “Blind application of data-mining methods, (rightly criticised as data dredging in the statistical literature) can be a dangerous activity, easily leading to the discovery of meaningless and invalid patterns.” Therefore, the Balanced scorecard can be used ex ante to make the data mining process more efficient.

5.6 Knowledge discovery

This is the core of the data mining process – implementing a set of data mining algorithms to verify hypotheses developed prior to this step, or to reveal new patterns.

5.7 Interpretation and verification

Interpretation and assessment of discovered knowledge by removing redundant or irrelevant results, and translating the useful ones into terms understandable by business users (Hormozi and Giles, 2004). Another role of balanced scorecard is used ex post to verify the reasonableness of data mining results.

5.8 Using discovered knowledge

Including incorporating the verified results into the performance evaluation system, taking actions based on new discoveries, or simply documenting it and reporting results to interested parties. Also checking for and resolving potential conflicts with previously believed knowledge. The real business value of data mining investments accrues from the adoption and utilisation of discovered results, via business strategy creation and refinement. However, this is the most challenging task of data mining projects. Accordingly, our architecture incorporates the feedback of verified results and new discoveries to the top management team. Results from data mining can be used to either check and confirm the current strategies, or identify potentially new strategies to be evaluated. Strategy revisions or new strategies will then be incorporated into the Balanced scorecard framework and translated into actions to be performed.

Interactions between data mining, data warehousing, and the balanced scorecard make our model dynamic and able to respond to changes in economic or operating environments. At the front-end of the process, the balanced scorecard provides guidance in focusing the data mining effort by potentially reducing the number of, or refining the hypotheses to be tested. Subsequent outputs from data mining may then be used as feedback to modify strategies made for a firm’s comprehensive business model. The synergy between data mining and business models extends in both directions. Results from data mining may be used to verify the assumptions underlying the business model.
and to modify the model to reflect operations. Successive iterations of data mining and comprehensive business model modifications will result in information that becomes increasingly useful to the executive decision maker. The changing nature of the business environment makes the interactions among the components of our comprehensive business model an ongoing process.

6 Conclusion

The integrated architecture for strategic management support that we have outlined bridges the gap between executive management and information technologies that has developed. Our model is sufficiently flexible for use by a wide variety of entities from service and manufacturing sectors to profit and non-profit organisations. The balanced scorecard holds the potential to focus the data mining process and assist in verifying the results of the process. In a symbiotic vein, results from data mining may help modify and improve the balanced scorecard application for a particular business concern.

Future research should consider issues surrounding the implementation of strategic management support systems similar to the one proposed here. The benefits of an integrated system might be evaluated by noting the contributions of integrating data mining and the balanced scorecard through successive iterations of the process. For instance, data mining might discover though certain associations that when examined with domain knowledge seem spurious or uninteresting. The results of data mining may also uncover new associations that add to executives understanding of their business, and such findings may modify the balanced scorecard or even corporate strategies.

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References


**Note**

1 Data integration has taken the form of data warehouses. Enterprise Resource Planning systems are a prime example of process integration.