Agile Business Intelligence: Combining Big Data and Business Intelligence to Responsive Decision Model

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Abstract

Big data and instant information on the external environment of enterprises are critical for decision-making; however, little attention is paid to contemporary business intelligence (BI) theories and practices. This study proposes a new business decision model, agile BI (ABI), which integrates external big data and internal BI to facilitate decision-making for enterprises in a dynamic and rapidly changing environment. This novel model presents two contributions to research in this field: (1) it proposes a new architecture combining external and internal information and (2) it integrates external big data, such as hot searches, social media, news, popular issues, and competitors' information, to increase the accuracy of BI. This study takes international expansion as an example and simulates the international investment decisions of Taiwanese firms by importing data from a search engine, competitors, and firm-specific datasets. The results show that the proposed ABI model not only responds quickly to the external environment but also enhances decision-making efficiently.

Keywords: Big data, Business intelligence, Decision making

1 Introduction

Business intelligence (BI) conveys different levels of operational information, transforms this information into knowledge, and facilitates firms' decision-making as they address various problems. BI tools permit a decision-maker to access up-to-date business performance and generate appropriate performance indices. Enterprises obtain significant value from BI systems [1] and develop better strategies, tactics, and decisions based on more comprehensive information [2].

Although BI facilitates the way enterprises obtain value, it is limited by internal and lag information in comparison with big data, which exists externally of these enterprises and changes instantly. Enterprises manage and analyze useful information and formulate decision routines and capabilities to benefit firms exploiting new opportunities and create a competitive advantage [3-4]. Besides the inside-out point of view in traditional decision-making, enterprises require outside-in information to promote the speed and precision of the decision-making.

Approaches to analyze big data are currently at the peak of development among Internet and communication technology companies. Morris Chang, for example, the president of Taiwan Semiconductor Manufacturing company described the concept of Internet of Things (IoTs) in a speech in 2014. Since then, IoTs has become a popular search topic in various search engines; it has even caught the attention of other enterprises and influenced the policies of some governments.

Because the impact of big data on competitiveness according to the consumer and marketing perspectives has been demonstrated [5-6], conceptual models that allow quick decision-making are necessary. Although some enterprises have been able to use big data to generate useful information and create value to their customers and operations, others continue to endeavor to integrate big data into their business decision-making. Chang's [7] prior study highlighted imports from outside data but these were restricted to competitors' information.

The present study proposes a new agile BI (ABI) model that integrates external big data with internal operational information and facilitates responsive decision-making. After extracting big data from social media, news media, search engines, review sites, and public databases from the external environment, the ABI model combines these data with internal operational information and engages in data processing. By using the international expansion decisions of enterprises to simulate the functions of the proposed ABI model, this study demonstrates the data processing, decision-making processes, and its benefits for business decision-making. This study makes two contributions to research in the field. First, this study proposes a new architecture to combine external and internal information in a contemporary BI structure. Second, this study integrates external big data, such as hot searches, news, and competitors' information, to

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increase the accuracy of BI. The ABI model can assist decision-making in dynamic environments and enhance decision-making efficiently.

2 Related Works

2.1 Business Intelligence

The concept of BI was first introduced by Howard Dresner in 1989, who referred to a set of concepts and methods to enhance business decision-making through computerized support systems [8]. BI implementation aims to improve business performance by creating suitable contexts and information to help make decisions in the organization.

The BI process involves acquiring data, transforming them into information, producing suitable and readable knowledge, and helping organizations make intelligent decisions. In other words, BI helps extract information deemed central to the business and manipulate data into information via query, reporting, and analysis functions to support managerial decisions.

Prior studies have used diverse approaches to promote BI. For example, interpretation of ambiguous weak signs in environments is important for strategic decision-making, and the cognitive process of managers and decision-makers by tracking and link information and sign [2]. BI supports also management by providing both structured and unstructured data [9]. However, a large body of literature indicates that many enterprises fail to use their BI investments effectively to exploit the data from internal systems. In fact, some BI technologies fail to support organizations' managerial decision-making not only at the operational but also at the strategic level, ultimately failing to enhance business value [10-12]. The challenges of BI rooted in the underlying architecture are not built on agility; instead, they are built on reliability and robustness over time.

Scholars have noted the issue of big data in BI and proposed diverse aspects of data analysis and its application areas. Some academic scholars have proposed new skills for BI in the big data environment [13], while others have developed new applications in the cloud by proposing alternative services for BI [14]. Although several works have highlighted the importance of big data in BI, the contributions of these articles are restricted to techniques and methods. Schema and conceptual models to enable decision-making in a rapid and responsive manner are limited. In a prior work on BI, the value of employing outside data, such as competitors' actions, was stressed [7]. The present study reviews related articles and proposes an ABI model to resolve the limitations of prior works.

2.2 Big Data

The term "big data" describes complex and large data sets that traditional data processing applications are unable to process smoothly and efficiently. The well-known attributes of big data include volume, variety, and velocity [15]. Volume is the most apparent attribute of big data, variety depicts the multiple sources of diverse data sets containing structured and unstructured data, and velocity highlights the speed of data processing for analysis. Although some articles also include veracity and value as characteristics of big data, the spirit of the concept reflects the movement, analysis, and utilization of data at a rapid rate [16].

The attributes of big data have generated new analysis tools. For example, new techniques have been developed to address the different steps of data processing; these techniques include data collection and processing methods, data extraction and monitoring, data programming, data management, modeling, and analytics.

Miller and Mork [17] recommended a data value chain based on the value chain proposed by Porter, and composed of data discovery, data integration, and data exploitation. Big data sources may include social media, customer reviews, blogs, web traffic, news media, and search engines. The sensors assist devices transferring information to the Internet in the environment of IoTs also collect voluminous amounts of data for analysis [18]. The researchers note that big data use enables managers to decide based on evidence rather than intuition [16, 19]. Although the value and implication of big data on decision-making rely on the flows rather than stocks [20], present research has limited conceptual model to stress the needs. For example, enterprises may have interest in knowing immediately information or topics they concerned. Therefore, analyzing, deciding, and acting quickly are important endeavors, especially in big data environments.

2.3 Decision-making Models

Appropriate decision-making is critical for the development and sustainability of an organization. For general decision-making, managers define the problems they face, set up goals, collect related information, and choose the appropriate decision.

Simon [21] developed a decision-making model and defined three stages of intelligence, design, and choice. In the intelligence stage, decision-makers search for and gather information and define the impending decision. In the design stage, alternative decisions are developed; these decisions are then evaluated and implemented in the following choice stage.

The decision-making process includes at least three conditions when making decisions under certainty, under risk, and under uncertainty. In managerial practice, managers mostly make decisions under uncertainty. Under this condition, decision-makers require techniques to enable better estimation of the probabilities of their decisions, as well as possible alternatives.

A decision tree is an estimation technique that helps in decision-making; it is used to classify and forecast, and the classification of decision tree is from a set of irregular instances using the top-down recursive method. Nodes compare attribute values, and branches stem from these nodes according to different attributes. Conclusions are obtained at the leaf nodes of the decision tree.

Decision tree technology is a very effective method for classifying massive data sets. By constructing a decision tree model, valuable classification rules to help decision-makers make accurate predictions have been applied in many fields. The decision tree algorithm is a method of approximating discrete function values. It is a well-known method, and the data processing using induction algorithm to generate classification rules and decision trees, and operating data analysis. Essentially, a decision tree is a process of sorting data through a set of rules.

Simon [22] introduced a preliminary theory of bounded rationality, which is more realistic in a human being, and is a new beginning of behavior theory of the firms. The author proposed that decision-making is a search process guided by aspiration levels and that performance triggers either local or distant searches.

The search behavior of an organization refers to the ways it seeks information, resources, and solutions. Search behaviors may be triggered by different drivers; for example, problem searches may be performed when performance is below expected levels, and slack searches may be performed when the organization has excess resources.

Different theories have highlighted the factors influencing and triggering search behavior, and researchers based on institutional theory, industrial organizational economics, evolutionary theory, and organizational theory have devoted significant efforts to studying the field. For instance, institutional pressure and competitive force in the external environment may influence the exploitation and exploration behaviors of an organization.

Because organizations' routines and strategies are developed in a path-dependent manner, previous search behaviors and experiences may influence current and latter actions.

Besides the behavioral aspect of decision-making and individual search behaviors, researchers in game theory and competitive dynamics take the possible actions of competitors into consideration when making decisions, which broadly rely on the signals competitors' release.

Although identification of institutional, industrial, and firm-specific factors is important to search behavior, the ability to engage in environmental scanning is also crucial for organizations in dynamic and complex environments.

Organizations either adapt to changes in the environment or review the firms' historical path to make decisions. These firms rely on flexibility to respond quickly to changing conditions or build on their organizational capability to adjust and exploit opportunities resulting from environmental changes and evolution [23].

In the field of environment scanning, the sources of information search contain macro and industrial environments in contemporary management studies; however, research has highlighted the limited influence of the big data available outside of firms on their decision-making. This finding is not surprising because information acquisition may be constrained by limitations in previous technological developments. However, with the development of Web 2.0 and the growth of social media, searching and identifying public issues is now possible. Hence, this study proposes a new ABI model that utilizes big data from outside the organization and suggests a method of information extraction to support decision-making.

3 Methods

3.1 The Agile Business Intelligence Architecture

This study proposes a novel ABI model that combines big data on the external environment with internal operational data to support management decision-making and enhance response accuracy.

The proposed ABI architecture is shown in Figure 1. In the acquisition phase, the ABI model extracts data from the Internet and information relating to competitors based on rules defined by the enterprise and acquires these data from web services. Adding these data to other data from customer relationship management, supply chain management, and enterprise resource planning systems, the ABI platform performs extract-transform-load (ETL) steps to facilitate loading of the original data into a data warehouse in the integration phase [24]. In the collaboration phase, the data warehouse consisted of modeling process. The ABI model then combines data from internal operations and the external environment to progress into the delivery phase, where it generates reports and information for decision-making. The complete process is responsive to rapidly changing and dynamic environments.

Large datasets on the Internet can be obtained by the data crawler technique or various web services, as shown in Figure 2. Besides developing crawler applications on their own, some digital companies have developed related services in data scraping to provide exact information on the enterprise expect. For example, LargitData scrapes popular issues from diverse search engines and social media, such as Google, Yahoo, and Facebook, and provides useful information to its users. LargitData was also successfully

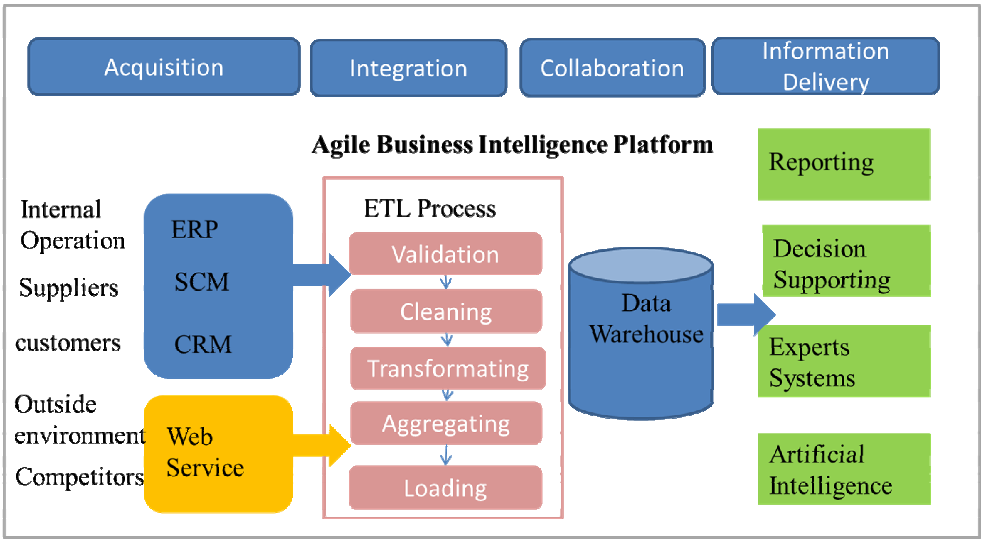

Figure 1. Agile business intelligence architecture

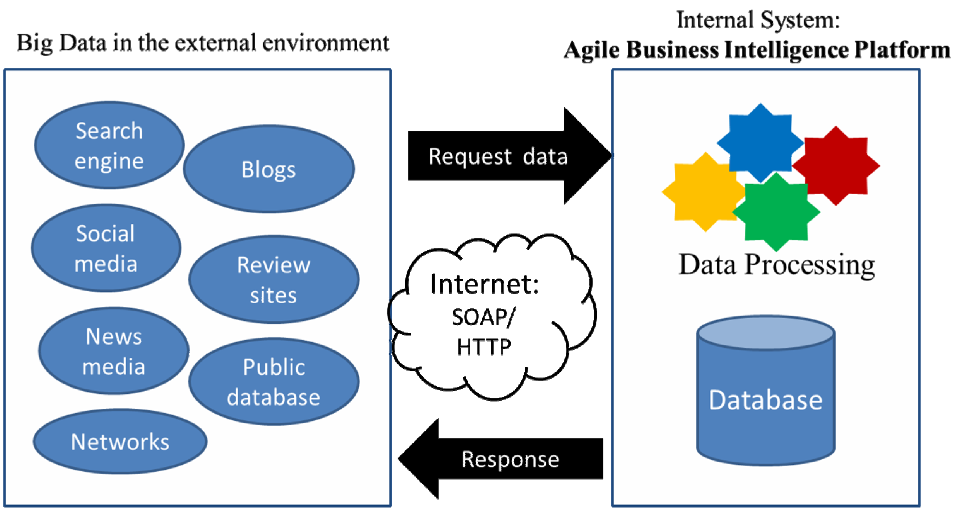

Figure 2. Big data acquisition process

used to collect online discussions for candidates of the Taipei mayoral election campaign in 2014. The team of Ko Wen-je used this system to define their strategies and events and won the campaign.

Another case of international moves is the policy of Donald Trump. The informaiton of domestic investment promotion of USA has diffused all over the world and became the popular search on the Internet. News outlets then announced that companies such as General Motors and Foxconn had expected to build factories in the US.

Search behaviors on search engines or share-and-like behaviors on social media represent psychological intentions and motives for decision-making. Thus, this study proposes that data sources, such as Google, Yahoo, or Facebook, are highly relevant.

During big data acquisition, the model requests data via Simple Object Access Protocol and HTTP from diverse sources. These data sources include search engines, social media, news media, networks, blogs, review sites, and public databases. The extracted data are imported into the ABI platform, ready for subsequent data processing.

3.2 Data Processing and Decision-making Processes for the ABI Model

In this section, the procedures of the data processing and decision-making processes are described and shown in Figure 3.

Data processing involves data discovery, data integration, and data exploitation [17]. In the first step of data discovery, the model creates data sources and metadata that define them. In the second step, the model defines access and control rules and creates an access plan. In the third step, the model identifies a syntax and structure for each data source. During data integration, the model establishes a data representation and maintains data provenance. The first step of data exploitation is analysis of the integrated data; this step is followed by visualization, which reports analysis results to the decision-maker. The final step of decision-making requires the decision-maker to determine appropriate actions to take based on the results of data analysis.

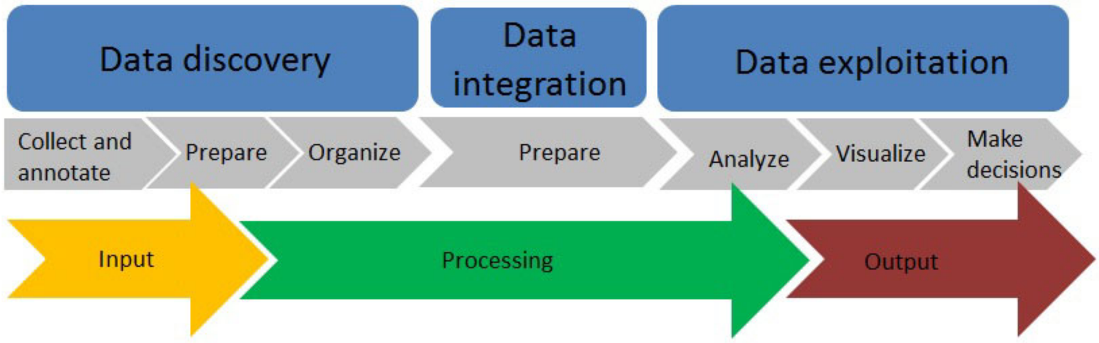

Figure 3. Procedures for data processing and analysis

After obtaining data inputs from multi-channels, data extraction, data cleaning, feature extraction, and data analysis are performed; here, the original data are subjected to an ETL process to facilitate loading into a data warehouse [24]. The ETL process includes validation, cleaning, transforming, aggregation, and loading. The model generates reports and forecasts as data outputs and suggests possible decision actions.

In the decision-making process, solutions to decision problems faced by firms in their daily operations or strategic actions consist of several steps:

1. Identify the problem faced by the firm.
2. Indicate the objectives and decision criteria.
3. Develop alternative solutions.
4. Analyze and compare alternative solutions based on estimation methods.
5. Select the best solution.
6. Carry out the chosen alternative.

However, most of the information obtained externally is imperfect because this information cannot predict which exact event will occur. In this case, the decision-maker can estimate the probability of the occurrence of an event based on example scenarios. Here, sample information can markedly improve the expected output.

In addition to prior probabilities, this model suggests calculating the posterior probabilities of low and high conditions using the Bayesian rule. Based on the data processing and decision-making process, the proposed ABI model extracts external information, and data volumes from diverse sources increase the reliability of estimation of alternative possibilities. Therefore, the accuracy of decision-making is improved.

The vertical handover decision algorithm in the data processing and analysis should be noticed. The handover across different platforms or heterogeneous networks is important because it influences how data are transmitted and exchanged [25]. The algorithm may include multi-criteria metrics, such as RSS, mobile speed, traffic class, or network occupancy [26]. The vertical handover decision algorithm should be planned and use appropriate methods because it is highly related to energy consumption.

3.3 Data

3.3.1 Sample and Data Sources

This study uses international expansion decision-making as the simulation object. By employing textile companies listed in the Taiwan Stock Exchange Corporation in the period of 2009-2016, this study analyzes diverse datasets and simulates how the ABI model imports from and responds quickly to the dynamic environment. Firm-specific, international expansion, and competitors data were collected from the Taiwan Economic Journal database, and search engine data were scraped from Google Trends.

Hot searches on the Internet are an excellent approach to track behavior on popular websites. This study uses Google Trends as the import of simulation. Google Trends collects data from Google searches, which reveal a full Google dataset that can trace back worldwide since 2004 by time, location, and popularity.

Hot searches reveal up-to-date information on Internet searches. Users can view these searches by geographic area or various categories. Google also provides information on the search volume of hot searches.

3.3.2 Variables

Firm-specific data.

Performance: Firms' operating profits demonstrate their ability for potential expansion. This study uses return on equity (ROE) [27] as an indicator.

Free cash flow: This indicator describes the slack resources of firms. Firms with higher free cash flows may be more motivated to expand internationally than those without.

Firm size: Firm size demonstrates the resources a firm may employ. This study uses the natural logarithm of total assets to measure firm size.

R&D intensity: Firms engaged in technological investments may induce foreign direct investments. This measure is calculated from research and development (R&D) expenditures divided by total sales.

Export intensity: Export intensity represents the export capability and operational experience of a firm in dealing with the international market. This measurement is calculated by the export value divided by the total sales in a given year and updated yearly [28].

International experience: International experience describes how firms learn to establish themselves in other markets. This study measures international experience in terms of years when firm entering foreign country firstly, and use the natural logarithm of international experience.

Competitors' data.

International expansion of other firms: This measure represents other firms that had previously established an international subsidiary. This variable is updated at the end of each calendar year and takes on a logarithmic form.

Hot searches on the Internet.

This study uses yearly hot searches obtained from Google Trends and collects the popularity of these searches. As one of the largest search engines currently available, Google Trends represents an appropriate data source because search behavior represents important intentions and purposes. The search scale is calculated by the number of queries for keyword divided by the total number of Google search queries. The scale is then indexed and normalized to obtain relative measures rather than absolute results.

During simulation, the popularity of hot searches from Google Trends is determined using the keyword "foreign direct investment." Global investment trends include macroeconomic, political, or societal conditions that decision-makers may take into consideration.

3.3.3 Model Specification

This study uses the proportional hazards Cox model during simulation. The Cox model can address the influence of time-dependence without specifying a parametric functional form. By using this model, the study estimates the hazard rate at which focal firms will engage in international expansion. In other words, this model estimates the possibility of making a positive international expansion decision. The likelihood function is shown below:

$$Li(t) = \exp[Z_i(t)\beta] / h_0(t) \sum_{j \in R_t} \exp[Z_i(t)\beta], \qquad \textbf{(1)}$$

where $Li(t)$ is the likelihood at time t for firm i, $h_0(t)$ is the baseline hazard rate at time t, $Z_i(t)$ is a matrix of covariables that may or may not be time-varying for firm i, and j is the index for firms in the risk set R at time t.

4 Results

Table 1 demonstrates the Pearson correlations of the variables. The Cox model was employed to simulate the international expansion decisions of the studied firms. In addition to internal data sources of ROE, free cash flow, firm size, R&D intensity, export intensity, and international experience, this study acquired data of hot searches from search engines and competitors' data from external databases. The results shown in Figure 4 demonstrate that ROE, firm size, and free cash flow are positively correlated with each other.

Competitors' expansion was also found to be positively associated with a focal firm's international expansion experience. Finally, popular searches on search engines were negatively correlated with other firms' expansion.

Figure 4 demonstrates the simulation results of the international expansion decision of firms in the textile industry. The coefficient of each variable represents the influence of the given variable on the decision of future international expansion. ROE, free cash flow, firm size, R&D intensity, export intensity, international experience, other firms' expansion, and popular searches were all positively associated with the probability of international expansion. By contrast, free cash flow and R&D intensity were negatively associated with the probability of international expansion.

Table 1. Pearson correlations

	Variable	Obs	Mean	S.D.	1	2	3	4	5	6	7
1	ROE	451	-0.005	0.496							
2	Free cash flow	451	12.333	1.658	0.3074*						
3	Firm size	451	14.710	1.463	0.2088*	0.6846*					
4	R&D intensity	423	0.631	0.999	-0.1622*	-0.0692	-0.1205*				
5	Export intensity	441	48.582	32.117	0.1055*	0.3426*	0.3545*	0.0093			
6	International experience	231	2.506	0.525	-0.0289	0.1036	0.0265	0.1042	0.0791		
7	Other firms' expansion	451	1.998	0.030	0.0431	0.1428*	-0.01	-0.0551	0.0505	0.2754*	
8	Popular searches	451	36.826	5.978	-0.0874	-0.0414	0.0216	0.0227	-0.0291	-0.1307*	-0.4489*

* p<0.05

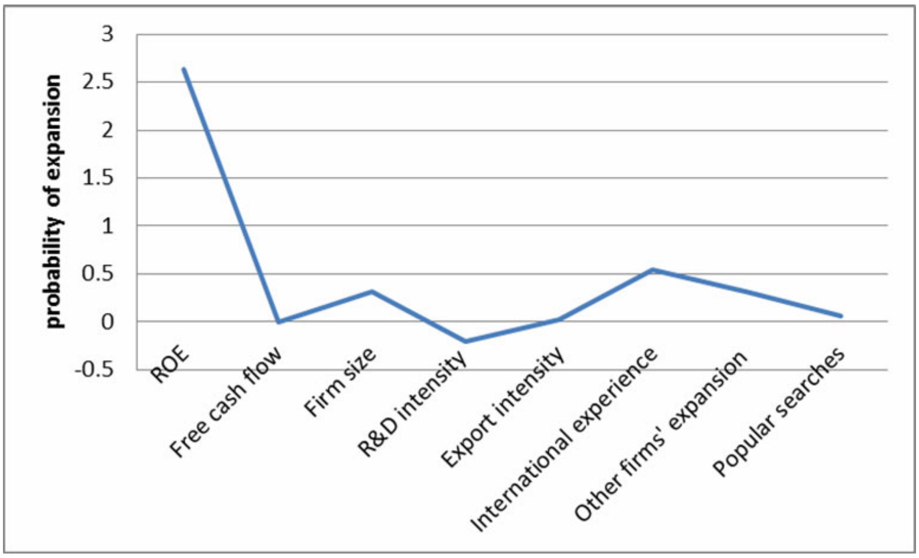

Figure 4. The simulation of international expansion decisions

5 Conclusion and Discussions

Big data and information in the external environment of enterprises are critical for decision-making. This study proposes an ABI model that integrates external big data with internal operations data. The ABI model developed in this work transforms the inside-out perspective of general BI models into an outside-in perspective and promotes responsive decision-making.

This study proposes a new architecture involving several data sources, as well as data processing and decision-making procedures. A simulation of enterprises' decisions on international expansion demonstrated the significant influence of outside data on decision-making and confirmed the reliability and accuracy of the proposed BI model.

This study proposes data scraping from external environments, such as search engines, social media, review websites, and public databases. By employing web services or application programming interface techniques, enterprises can define relevant keywords or targets they intend to acquire. In the data processing step, the architecture executes an ETL procedure and develops the modeling methods. In the final step of decision-making, the model uses game theory, decision-making, or Bayesian probability to define the rules of alternatives and the weights of the factors that may influence decision-making.

The simulation example demonstrated the international investment decisions of the proposed ABI model. This study not only takes internal operational data into consideration but also includes information on external competitors' actions and hot searches on the Internet. Acquisition of diverse data sources updated yearly or daily benefits decision-making, especially in a dynamic and competitive environment.

In summary, the ABI model developed in this work presents two contributions: (1) it proposes a new architecture combining external and internal information and (2) it integrates external big data, such as hot searches, social media, news, popular issues, and competitors' information, to increase the accuracy of BI. The ABI model can respond quickly to the external environment and enhance decision-making efficiently.

Future research may scrape external big data using a number of applications and return the data automatically by schedule setting. Technological innovations, such as web crawlers or related tools, may play crucial roles in acquiring and analyzing data in future research.

The most challenging issues related to big data are the accuracy and authenticity of the data. Rumors are spreading around the Internet, confirming the accuracy of data we acquired is related to our decision performance and validity. Future research may develop confirmation techniques, such as blockchains, to validate each block in the developed procedures.

References

[1] V.-H. Trieu, Getting Value from Business Intelligence Systems: A Review and Research Agenda, *Decision Support Systems*, Vol. 93, pp. 111-124, January, 2017.

[2] K. Rouibah, S. Ould-ali, PUZZLE: A Concept and Prototype for Linking Business Intelligence to Business Strategy, *The Journal of Strategic Information Systems*, Vol. 11, No. 2, pp. 133-152, June, 2002.

[3] S. F. Wamba, S. Akter, A. Edwards, G. Chopin, D. Gnanzou, How "Big Data" Can Make Big Impact: Findings from A Systematic Review and A Longitudinal Case Study, *International Journal of Production Economics*, Vol. 165, pp. 234-246, July, 2015.

[4] I. D. Constantiou, J. Kallinikos, New Games, New Rules: Big Data and the Changing Context of Strategy, *Journal of Information Technology*, Vol. 30, No. 1, pp. 44-57, March,

2015.

[5] S. Erevelles, N. Fukawa, L. Swayne, Big Data Consumer Analytics and the Transformation of Marketing, *Journal of Business Research*, Vol. 69, No. 2, pp. 897-904, February, 2016.

[6] S. Fan, R. Y. K. Lau, J. L. Zhao, Demystifying Big Data Analytics for Business Intelligence Through the Lens of Marketing Mix, *Big Data Research*, Vol. 2, No. 1, pp. 28-32, March, 2015.

[7] B.-J. Chang, Improving Sequential Investment Business Intelligence with Imitation and Experiential Learning, *Journal of Internet Technology*, Vol. 18, No. 1, pp. 215-222, January, 2017.

[8] A. L. Nylund, Tracing the BI Family Tree, in: *Knowledge Management*, Curtco Freedom Group, 1999, pp. 70-71.

[9] H. Baars, H.-G. Kemper, Management Support with Structured and Unstructured Data— An Integrated Business Intelligence Framework, *Information Systems Management*, Vol. 25, No. 2, pp. 132-148, April, 2008.

[10] M. T. Lee, S. K. Widener, The Performance Effects of Using Business Intelligence Systems for Exploitation and Exploration Learning, *Journal of Information Systems*, Vol. 30, No. 3, pp. 1-31, Fall, 2016.

[11] M. Z. Elbashir, P. A. Collier, S. G. Sutton, M. J. Davern, S. A. Leech, Enhancing the Business Value of Business Intelligence: The Role of Shared Knowledge and Assimilation, *Journal of Information Systems*, Vol. 27, No. 2, pp. 87-105, Fall, 2013.

[12] Ö. Işık, M. C. Jones, A. Sidorova, Business Intelligence Success: The Roles of BI Capabilities and Decision Environments, *Information & Management*, Vol. 50, No. 1, pp. 13-23, January, 2013.

[13] B. Wixom, T. Ariyachandra, D. Douglas, M. Goul, B. Gupta, L. Iyer, U. Kulkarni, J. G. Mooney, G. Phillips-Wren, O. Turetken, The Current State of Business Intelligence in Academia: The Arrival of Big Data, *Communications of the Association for Information Systems*, Vol. 34, No. 1, pp. 1-13, January, 2014.

[14] V. Chang, The Business Intelligence As a Service in the Cloud, *Future Generation Computer Systems*, Vol. 37, pp. 512-534, July, 2014.

[15] D. Laney, *3D Data Management: Controlling Data Volume, Velocity, and Variety*, Meta Group, 2001.

[16] A. McAfee, E. Brynjolfsson, Big Data: The Management Revolution, *Harvard Business Review*, Vol. October, pp. 60-68, 2012.

[17] H. G. Miller, P. Mork, From Data to Decisions: A Value Chain for Big Data, *IT Professional*, Vol. 15, No. 1, pp. 57-59, January-February, 2013.

[18] W. Zhang, Z. Zhang, H.-C. Chao, Cooperative Fog Computing for Dealing with Big Data in the Internet of Vehicles: Architecture and Hierarchical Resource Management, *IEEE Communications Magazine*, Vol. 55, No. 12, pp 60-67, December, 2017.

[19] F. Provost, T. Fawcett, Data Science and Its Relationship to Big Data and Data-driven Decision Making, *Big Data*, Vol. 1, No. 1, pp. 51-59, March, 2013.

[20] T. H. Davenport, P. Barth, R. Bean, How “Big Data” Is Different, *MIT Sloan Management Review*, Vol. 54, No. 1, pp. 21-24, Fall, 2012.

[21] H. A. Simon, *The New Science of Management Decision*, Prentice-Hall, 1977.

[22] H. A. Simon, *Models of Man*, Wiley & Sons, 1957.

[23] M. L. Ouakouak, O. Ammar, How Does Strategic Flexibility Pay off in Terms of Financial Performance?, *International Journal of Business Performance Management*, Vol. 16, No. 4, pp. 442-456, December, 2015.

[24] P. Vassiliadis, A Survey of Extract-transform-load Technology, *International Journal of Data Warehousing & Mining*, Vol. 5, No. 3, pp. 1-27, July-September, 2009.

[25] S. Lee, K. Sriram, K. Kim, Y. H. Kim, N. Golmie, Vertical Handoff Decision Algorithms for Providing Optimized Performance in Heterogeneous Wireless Networks, *IEEE Transactions on Vehicular Technology*, Vol. 58, No. 2, pp. 865-881, February, 2009.

[26] G. Mahardhika, M. Ismail, R. Nordin, Vertical Handover Decision Algorithm Using Multicriteria Metrics in Heterogeneous Wireless Network, *Journal of Computer Networks and Communications*, Vol. 2015, Article ID 539750, pp. 1-8, 2015.

[27] C. Bouquet, A. Morrison, J. Birkinshaw, International Attention and Multinational Enterprise Performance, *Journal of International Business Studies*, Vol. 40, No. 1, pp. 108-131, January, 2009.

[28] J. W. Lu, P. W. Beamish, International Diversification and Firm Performance: The S-CURVE Hypothesis, *Academy of Management Journal*, Vol. 47, No. 4, pp. 598-609, August, 2004.

Biography

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