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Knowledge Management, Business Intelligence, and Business Analytics

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Ⅰ. Introduction

In the past few years, business analytics has emerged as one of the most popular and important issues for both researchers and practitioners with an explosion of large-scale or big data characterized by "high volume, high velocity, and high variety" (Ka and Kim, 2014; Watson, 2014). According to a Gartner survey (Gartner, 2015), business analytics is considered to be the No.1 business investment priority. Similarly, IDC reported that the business analytics software market grew by 6.5% in 2014 to reach just over $40 billion, and predicts it to grow at an 8.0% compound annual growth rate (CAGR) over the next 5 years (Vesset et al., 2015). Managers across all industries are looking for opportunities to increase efficiencies and gain competitive advantage through the analysis of big data using a variety of quantitative techniques such as statistics, operations research methods, data mining, and social mining. Many researchers in a variety of disciplines have paid a great deal of attention to the business analytics, resulting in the fast growing literatures (Holsapple et al., 2014; Kim et al., 2014). While some studies have focused on capability set of business analytics (Davenport et al., 2010; Kiron et al., 2011), others have investigated technologies and tools for business analytics (Bose, 2009; Davenport and Harris, 2007).

Kiron and Shockley (2011) defined business analytics as "the use of data and related insights developed through applied analytics disciplines (for example, statistical, contextual quantitative, predictive, cognitive and other models) to drive fact-based planning, decisions, execution, management, measurement and learning" (p. 58). Business analytics can be classified into three major perspectives: descriptive, predictive, and prescriptive. Descriptive analytics refer to knowing what is occurring in organizations and understanding causes of such occurrences (Davenport, 2013). Predictive analytics focus on what may or will occur in the future by analyzing historical data

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and relationships in the data (Evans, 2013). Prescriptive analytics aim to examine current trends and use them to make decisions based on optimization (Sharda et al., 2013). Due to advances in information technologies and big data, business analytics have raised decision-making to a completely new level (Cao et al., 2015). It allows researchers and managers to see what was previously invisible (Barton and Court, 2012), leading to better decision-making and improved performance.

Business analytics is not a new concept and evolves continuously even though it always focuses on supporting managers to make better decisions. It was introduced to represent main component in business intelligence which has been used since the 1950s (Chen et al., 2012). Business analytics recently have been used to process large and complex data based on powerful and innovative new tools and technologies (Cao et al., 2015). According to Davenport (2013), business has evolved from Analytics 1.0 (i.e., era of business intelligence) to Analytics 2.0 (i.e., era of big data) and now to Analytics 3.0 (i.e., era of data-enriched offerings). In a similar way, Chen et al. (2012) classified the evolution of business analytic into business intelligence/analytics 1 (i.e., DBMS-based analytics), business intelligence/ analytics 2 (i.e., Web-based analytics), and business intelligence/analytics 3 (i.e., Mobile and sensor-based analytics).

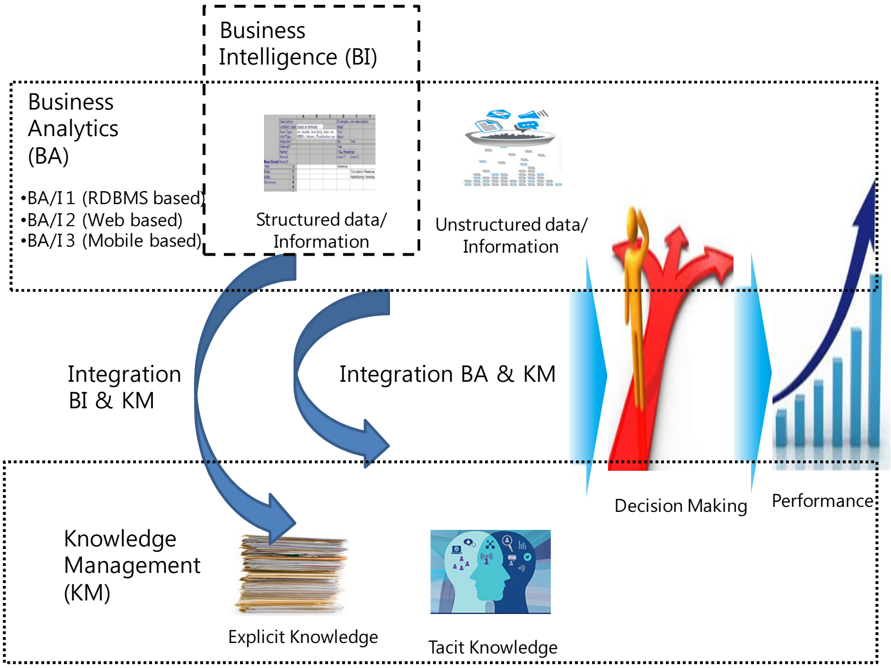
Business analytics/intelligence will continue to evolve, driven by the recent advancement in many related business practices, particularly, knowledge management (KM). Knowledge management and business analytics/intelligence play an important role in decision making by improving the qualitative and quantitative value of data and knowledge (Rostami, 2014). Data do not reveal their full value until knowledge such as insights is drawn from them (Herschel and Jones, 2005). In addition, knowledge management focuses on integrating knowledge or information from a variety of sources to provide the insights required for effective decision making (Erickson and Rothberg, 2015). We can clearly see an opportunity for cross-fertilization between knowledge management and business analytics/intelligence (Erickson and Rothberg, 2015). The question that arises is how to best capture the value by combining business analytics and knowledge management. As an initial step to answer the question, it is essential to identify the relationship between knowledge management and business analytics/intelligence.

Ⅱ. Knowledge Management and Business Analytics/Intelligence

Knowledge management and business analytics/intelligence have been developed and evolved for a long time (Rostami, 2014). Knowledge management has focused on creating, sharing, storing, and using knowledge to improve organizational performance based on knowledge management enablers (Lee and Choi, 2003). Knowledge management enablers such as structure, culture, and information technologies provide the infrastructure for an organization to increase the efficiency of knowledge processes (Lee and Choi, 2010). Knowledge management processes refer to a structured coordination for managing knowledge effectively (Gold e al., 2001) and represent the basic operations of knowledge (i.e., creation, sharing, storage, and usage). Knowledge can be classified into tacit and explicit; the former is hard to formalize and to transfer to others while the latter is easily transmitted in formal and systematic language (Nonaka and Takeuchi, 1995).

Business analytics/intelligence has been used to obtain fact-based insights to support decision making and managerial actions through extensive use of data, qualitative and quantitative analysis (Davenport and Harris, 2007). Business analytics/intelligence handles a variety of data and sources, and applies to diverse domains. According to Chen et al. (2012), business analytics/intelligence has analyzed structured data which are collected by companies through various legacy systems including relational database management systems in the 1990s. With advance of the Internet and the web in the early 2000s, it has focused on analyzing data collected through cookies, server logs, social network services, and crowd-sourcing systems. In the 2010s, many researchers and practitioners are interested in analyzing data collected from mobile and sensor-based systems although it is not clear how to analyze the data yet. Similar to knowledge management, business analytics/intelligence needs a variety of supporting factors such as data-driven culture, strategy, structure to guide and enable its activities (Davenport and Harris, 2007; Kiron and Shockley, 2011).

Many studies have attempted to identify the relationship between knowledge management and business intelligence (Cody et al., 2002; Rostami, 2014). For example, Zarghamifard and Behboudi (2012) has considered knowledge management as a helping hand of business intelligence while Wang and Wang (2008) have seen business intelligence as an integral part of knowledge management activities. Although knowledge management has many similarities with business intelligence, it is different from business intelligence in many aspects. First, knowledge management deals with unstructured tacit knowledge which business intelligence fails to address (Marwick, 2001). Second, knowledge management places its em-



<Figure 1> Relationship between Knowledge Management and Business Analytics/Intelligence

phasis on subjective human knowledge, not on objective data/information (Nonaka and Takeuchi, 1995). Unlike business intelligence, business analytics deal with relatively unstructured data such as audio, video, click stream, and text. It enables managers to harvest value from unstructured data in the sense of supporting knowledge acquisition, insight generation, and problem solving to support decision making, resulting in improved organizational performance (Holsapple et al., 2014). In sum, the relationship between knowledge management and business analytics/intelligence can be summarized as shown in <Figure 1>.

Ⅲ. Papers in This Special Issue

This special issue aims to bring together scholars who investigate organizational performance and sustainable competitive advantage in the domains of knowledge management and business analytics/intelligence. With the aims, four papers have been selected for publication. The first paper, titled "*The Role of Application Rank in the Extended Mobile Application Download*" by Youngsok Bang and Dong-Joo Lee, empirically investigates the effect of mobile application download rank, which appears to users when they decide to download a new application, on the extended mobile application download, which refers to downloading an additional application in the same category as those they have already downloaded using large scale transaction data from a leading telecommunications company in Korea. The effect has been examined with the consideration of IT characteristics, user characteristics, and application type that might be associated with the extended application download. Results of the analysis suggest that a higher rank of a new application encouraged the extended application download, but not in a linear fashion. Furthermore, no quadratic effect of rank was found in the extended application download. From a theoretical perspective, this study suggests that the effect of rank may not follow a smooth curve such as linear or quadratic, which is contrary to the extant literature where the effect of rank is modeled as linear or quadratic. From a managerial perspective, this study urges managers in the mobile application market to identify and pay their attention to the critical points where they could benefit from the rank effect in the extended application download.

In the second paper, titled "*Forecasting the Box Office Performance of Movies Using Hierarchical Linear Models*" by Jongmin Park, Yeojin Chung, and Yunho Cho, the authors attempts to identify dynamic structure of a film's successes across different time points. For this purpose, they propose a method to predict the daily performance trajectory of running movies using hierarchical linear model. To improve predictability of movie performance, this study fitted the mean trajectory of the cumulative audience size as a cubic function of time, and allowed the intercept and slope to vary movie-to-movie. Furthermore, the study fitted the linear slope with a function of online word-of-mouth predictors to help determine the shape of the trajectories. The analysis results show that the mean trajectory of a film's box-office performance is larger when the film is domestic, is released in the summer, enjoyed positive online reviews after its release, or had significant attendance in the first week after its release. This study contributes to expand our knowledge on the impact of online WOM on success of movies measured by cumulative audience size. The study explicitly and systematically models the shapes of the cumulative audience sizes' trajectories over time through inclusion of movie-level covariates, leading to improved flexibility to explain the various types of the growth curve.

The third paper, titled "*Multi-Class SVM+MTL for the Prediction of Corporate Credit Rating with Structured Data*" by Gang Ren, Taeho Hong, and YoungKi Park, attempts to show applicability of new techniques such as support vector machines+ (SVM+) and SVM+MTL (multi-task learning) to a multi-class classification problem in the corporate credit rating. Furthermore, they attempts to identify the most powerful technique to predict corporate credit rating by comparing SVM, SVM+ and SVM+MTL using empirical data from Korea bond rating market. For this purposes, this study adopted four multi-class approaches (i.e., one-against-all, one-against-one, directed acyclic graph, and error correcting output codes) that have been widely used to solve multi-class SVM problems. The analysis results show that SVM+MTL outperformed both conventional SVM and novel SVM+ in the prediction of corporate credit rating. Furthermore, the results show that directed acyclic graph is the most effective and efficient approach in the four multi-class approaches. This study contributes to the literature by showing the applicability of new techniques such as SVM+ and SVM+MTL and the outperformance of SVM+MTL over conventional techniques, thereby enriching our knowledge about the techniques for tackling multi-class problems such as corporate credit rating prediction. In addition, the proposed credit rating approach of this study shows greater explanatory powers by transforming a binary bankruptcy prediction problem into multi-class credit rating analysis.

The fourth paper of this special issue, titled "*Capability, Service Orientation, and Performance in the Investment Management Industry*" by Kang Duck Lee, Chang Ho Jung, Yong Jin Kim, examines how service orientation conceptualized as a type of dynamic capability affects firm performance. For this purpose, they proposed a research model including job competency, risk management capability, operational capability, service orientation, and service performance, and tested the model using data from 86 teams in 37 investment management companies. The analysis results reveal that job competency positively affects both risk management capability and operational capability, which in turn influence service orientation. Furthermore, the result indicates that risk management capability affects service performance through service orientation while operational capability influences perceived service performance directly. Service orientation significantly affects the service performance perception of fund managers. This study contributes to the service orientation literature by introducing service orientation to the financial industry, and measuring and testing team-level service performance. This study also highlights the importance of service-oriented operational practice for improving service performance in the financial field.

Ⅳ. Conclusion

This special issue deals with a variety of issues relating to knowledge management and business analytics/intelligence. First three papers examine different aspects of business analytics/intelligence (i.e., mobile analytics, web analytics, and data analytics respectively) while the last paper focuses on knowledge management. This special issue contributes to expanding our understanding of knowledge management and business analytics/intelligence. In addition, we hope more efforts will made to investigate the integration between knowledge management and business analytics/intelligence because such integration is essential to improving the effectiveness of decision making and organizational performance.

<References>

[1] Barton, D., and Court, D. (2012). Making Advanced Analytics Work for You. *Harvard Business Review, 90,* 78-83.

[2] Bose, R. (2009). Advanced Analytics: Opportunities and Challenges. *Industrial Management and Data Systems, 109*(2), 155-172.

[3] Cao, G., Duan, Y., and Li, G. (2015). Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis. *IEEE Transactions on Engineering Management, 62*(3), 384-395.

[4] Chen, H., Chiang, R. H. L., and Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly, 36*(4), 1165-1188.

[5] Cody, W., Kreulen, J., Krishna, V., and Spangler, W. (2002). The Integration of Business Intelligence and Knowledge Management. *IBM Systems Journal, 41*(4), 697-713.

[6] Davenport, T., and Harris, J. G. (2007). *Competing on Analytics*. Boston: HBR Press.

[7] Davenport, T., Harris, J. G., and Morison, R. (2010). *Analytics at Work: Smarter Decisions, Better Results*. Boston: HBR Press.

[8] Davenport, T. H. (2013). Analytics 3.0. *Harvard Business Review, 91*, 64-72.

[9] Erickson, S., and Rothberg, H. (2015). Big Data and Knowledge Management: Establishing a Conceptual Foundation. *The Electronic Journal of Knowledge Management, 12*(2), 108-116.

[10] Evans, J. R. (2013). *Business Analytics: Methods, Models, and Decisions*. Englewood Cliffs, NJ: Prentice-Hall.

[11] Gartner. (2015). *CIOs Name BI and Analytics No. 1 Investment Priority for 2015*. http://gartnerevent.com/NABI13Survey.

[12] Gold, A. H., Malhotra, A., and Segars, A. H. (2001). Knowledge Management: An Organizational Capabilities Perspective. *Journal of Management Information Systems, 18*(1), 185-214.

[13] Herschel, R. T., and Jones, N. E. (2005). Knowledge Management and Business Intelligence: The Importance of Integration. *Journal of Knowledge Management, 9*(4), 45-55.

[14] Holsapple, C., Lee-Post, A., and Pakath, R. (2014). A Unified Foundation for Business Analytics. *Decision Support Systems, 64*(130-141).

[15] Ka, H.-K., and Kim, J.-S. (2014). An Empirical Study on the Influencing Factors for Big Data Intented Adoption: Focusing on the Strategic Value Recognition and TOE Framework. *Asia Pacific Journal of Information Systems, 24*(4), 443~472.

[16] Kim, T., Jung, W.-J., and Lee, S.-Y. T. (2014). The Analysis on the Relationship between Firms' Exposures to SNS and Stock Prices in Korea. *Asia Pacific Journal of Information Systems, 24*(2), 223-253.

[17] Kiron, D., and Shockley, R. (2011). Creating Business Value Analytics. *MIT Sloan Management Review, 53*(1), 57-63.

[18] Kiron, D., R. Shockley, N. Kruschwitz, G. Finch, and M. Haydock. (2011). Analytics: The Widening Divide. *Sloan Management Review, 53*(3), 1-22.

[19] Lee, H., and Choi, B. (2003). Knowledge Management Enablers, Processes, and Organizational Performance: An Integrative View and Empirical Examination. *Journal of Management Information Systems, 20*(1), 179-228.

[20] Lee, J.-N., and Choi, B. (2010). Determinants of Knowledge Management Assimilation: An Empirical Investigation. *IEEE Transactions on Engineering Management, 57*(3), 430-449.

[21] Marwick, A. D. (2001). Knowledge Management Technology. *IBM Systems Journal, 4*(4), 814-829.

[22] Nonaka, I., and Takeuchi, H. (1995). *The Knowledge Creating Company*. New York: Oxford University Press.

[23] Rostami, N. A. (2014). Integration of Business Intelligence and Knowledge Management – A literature review. *Journal of Intelligence Studies in Business, 4*(2), 30-40.

[24] Sharda, R., Asamoah, D. A., and Ponna, N. (2013). Business Analytics: Research and Teaching Perspectives.

35th International Conference on Information Technology Interfaces, Cavtat/Dubrovnik, Croatia.

[25] Vesset, D., McDonough, B., Olofson, C. W., Schubmehl, D., Woodward, A., Bond, S., and Wardley, M. (2015). *Worldwide Business Analytics Software Forecast, 2015-2019*, IDC.

[26] Wang, H., and Wang, S. (2008). A Knowledge Management Approach to Data Mining Process for Business Intelligence. *Industrial Management & Data Systems, 108*(5), 622-634.

[27] Watson, H. J. (2014). Tutorial: Big Data Analytics: Concepts, Technologies, and Applications. *Communications of the Association for Information Systems, 34*, 1247-1268.

[28] Zarghamifard, M., and Behboudi, M. R. (2012). Exploring the Underlying Relations between the Business Intelligence and Knowledge Management. *International Journal of Science and Engineering Investigations, 1*(2), 31-35.

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