Business intelligence in risk management: Some recent progresses

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ABSTRACT

Risk management has become a vital topic both in academia and practice during the past several decades. Most business intelligence tools have been used to enhance risk management, and the risk management tools have benefited from business intelligence approaches. This introductory article provides a review of the state-of-the-art research in business intelligence in risk management, and of the work that has been accepted for publication in this issue.

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1. Introduction

We are very pleased to see the completion of this special issue on Information Sciences: Business Intelligence in Risk Management. Risks exist in every aspect of our lives, and can mean different things to different people, while negatively they always in general cause a great deal of potential damage and inconvenience for the stakeholders. For example, recent disaster risks include terrorist leading to the gassing of the Japanese subway system, to 9/11/2001, and to the bombings of the Spanish and British transportation systems, as well as the SARS virus disrupting public and business activities, particularly in Asia. More recently, the H1N1 virus has sharpened awareness of the response system world-wide, and the global financial crisis has resulted in recession in all aspects of the economy [59].

Risk management has become a vital topic in both academia and practice during the past several decades. Integrated approaches are required to manage the risks facing an organization, and sometimes effective risk-taking strategies may involve new business philosophies such as enterprise risk management. Most business intelligence tools have been used for enhancing risk management, and the risk management tools benefit from business intelligence approaches. For example, artificial intelligence models such as neural networks and support vector machines have been widely used for establishing the early-warning system for monitoring a company's financial status [38,2,36]. Agent-based theories are employed in supply chain risk management [27,34]. Business intelligence models are also useful in hedging financial risks by incorporating market risks, credit risks, and operational risks [59]. The investigation of business intelligence tools in risk management is beneficial to both practitioners and academic researchers.

In this issue, we present papers addressing recent advances in using business intelligence for enterprise risk management.

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2. Risks and risk management

All human endeavors involve uncertainty and risk. In the food production area, science has made great strides in genetic management. But there are concerns about some of the manipulations involved, with different views prevailing across the globe. In the United States, genetic management is generally viewed as a way to obtain better and more productive sources of food in a more reliable manner. Nonetheless, there are strong objections to bioengineered food in Europe and Asia. Some natural diseases, such as mad cow disease, have appeared, and these diseases are very difficult to control. The degree of control accomplished is sometimes disputed. Europe has strong controls on bioengineering, but even then there has been a pig breeding scandal involving hazardous feed stock and prohibited medications [57]. Bioengineering risks are important considerations in the food chain [50,14]. Genetic mapping offers tremendous breakthroughs in the world of science, but involves political risks when applied to human resources management [37]. Even applying information technology to better manage healthcare delivery risks involves risks [54]. Reliance on computer control has been applied to flying aircraft, but has not always worked [13].

Risks can be viewed as threats, but business exists to cope with risks [45]. Different disciplines have different ways of classifying risks. In order to explain the risk management lessons from the credit crisis, Jorion [26] classified risks into: known knowns, known unknowns and unknown unknowns. This is actually based on the degree of risk and is similar to what Olson and Wu [45] discussed (see page 6 of Chapter 1).

We propose the following general classification of risks: Field-based and Property-based.

- *Field-based type*
  Financial risks, which basically include all sorts of risks related to financial sectors and financial aspects in other sectors. These comprise, but are not restricted to, market risk, credit risk, operational risk, operational risk, and liquidity risk. Non-financial risks, which include risks from sources that are not related to finance. These include, but are not restricted to, political risks, reputational risks, bioengineering risks, and disaster risks.
- *Property-based type*
  Risks can have four properties: uncertainty, dynamics, interconnection and dependence, and complexity. The first two properties have been widely recognized in inter-temporal models from the behavioral decision and behavioral economics areas [3]; the last two properties are well studied in finance disciplines.
  Risk probability applies probability theory and various distributions to model risks. This approach can be dated back to the 1700s, leading to Bernoulli, Poisson, and Gaussian models of events as well as general Pareto distributions and general extreme value distributions to model extreme events. The dynamics of risks mainly involves the use of stochastic process theory in risk management. This can be dated back to the 1930s where Markov processes, Brownian motions and Levy processes were developed. The interconnection and dependence of risks deals with correlation among risk factors. Various copula functions are built and Fourier transformations are also used. Risk complexity needs to be handled further through the use of various models based on complexity science, such as agent-based modeling approaches.

Risk management can be defined as the process of identification, analysis and either the acceptance or mitigation of uncertainty in investment decision making. Risk management is about managing uncertainty related to a threat. Traditional risk management focuses on risks stemming from physical or legal causes such as natural disasters or fires, accidents, death and lawsuits. Financial risk management deals with risks that can be managed using traded financial instruments. The most recent concept, enterprise risk management, provides a tool to enhance the value of systems, both commercial and communal, from a systematic point of view. Operations research (OR) is always useful for optimizing risk management.

Various areas that relate to **business intelligence in risk management** can be identified in the literature.

3. Different perspectives and tools

The last several decades have also witnessed tremendous progress in computational intelligence including fuzzy logic, neural networks and genetic algorithms, evolutionary computation and optimization approaches such as linear programming, nonlinear programming, game theory, and multicriteria decision analysis. Optimization approaches have been widely applied in industry in many areas of forecasting, performance evaluation, automatic control, and function approximation. This section presents a survey on key areas, along with its associated techniques.

3.1. Early-warning systems

Many papers have addressed the value of early-warning systems as a means to control risk. Krstevska [30] cited their use in macroeconomic models, with specifics to the economy of Macedonia. A number of models have been implemented

through computer systems. Flores [15] dealt with early warning in insurance using stochastic optimization. Castell and Dacuycuy [9] discussed macroeconomic and financial surveillance mechanisms. Hua [23] reviewed methods used for early warning in real estate. Within industrial applications, Xie et al. [61] described a procedure to identify logistics risks for small-to-medium enterprises.

3.2. Neural networks-based risk analysis

Neural networks are artificial intelligence tools that have proven very useful in identifying patterns in complex data structures, especially those involving nonlinear relationships. Schneidewing [51] presented results of work applying neural networks to assess software reliability, where the goal was to reduce the risk of project failure. Jin and Zhang [25] gave another application demonstrating the value of artificial neural network models in projects, in this case projects involving public–private partnerships. Applications in industry include banks utilizing artificial neural network models to analyze credit card applications [62], allowing banks to more efficiently control their risk following the post-2008 bubble. Neural network models have also been combined with test mining applications as in Groth and Muntermann [20], where the model was applied to financial risk in day-trading. [12] applied artificial neural network models to manage the risk of small enterprise default in Italy.

3.3. Risk-based decision making

Using computer tools for risk-based decision making has been widely studied in the information systems field as decision support systems since the 1970s [28,56]. Warenski [58] employed artificial intelligence to provide another application of loan-risk analysis, in this case demonstrating financial modeling in the paper and pulp industry. Otim et al. [46] provided a recent analysis specifically addressing the evaluation of value and risk in information technology investments. Such investments involve complex sets of stakeholders, leading to the need to consider organizational politics. Kozhikode and Li [29] studied the role of political pluralism in the expansion of commercial banks in India, including consideration of risk management. Industrial decision making not only involves multiple stakeholders, but also multiple criteria [44], driven in part by the very existence of these multiple stakeholders. Silvestri et al. [53] provided a multiple criteria risk assessment technique for risk analysis in manufacturing safety. Lakemond et al. [32] gave a method for consideration of risk in product development, enabling early assessment of risk and other challenges.

3.4. Game-based risk analysis

Nash provided one of the most seminal works in game theory [42], by studying the role of competitive strategy. This well-studied field is a major focus in industrial risk management. Zhao and Jianq [63] considered a non-cooperative complete information game model that looked at multiple emerging risks in a project management environment. Merrick and Parnell [39] extended game theoretic models to include probabilistic risk analysis in the context of counterterrorism. Their application involved screening containers for radiological materials. Lin et al. [35] used game theory to model vertical differentiation in online advertising, finding that a higher ad revenue rate may lead to lower service prices. Game theory has also been applied to small and medium-sized enterprise risk management by Gnyawali and Park [19].

3.5. Credit risk decisions

The financial industry's primary task in risk management is to assess the probability of default. Gurny and Tichy [21] presented a scoring model for US banks using linear discriminant analysis. Chen et al. [11] offered another study, in this case using the Six Sigma DMAIC methodology to reduce financial risk. Wu and Olson [60] demonstrated how predictive score-cards have been used for large bank risk management of credit worthiness. Caracota et al. [8] gave a scoring model for small and medium enterprises seeking a bank loan. Poon [48] reviewed the effectiveness of government-sponsored enterprise (Freddie Mac and Fannie Mae) credit scoring, showing how credit bureau scoring led to support for the opposing strategies of risk averse and risk avaricious investment.

3.6. Data mining in enterprise risk management

Data mining has become a very popular means to apply statistical and artificial intelligence tools to the analysis of large data sets. Among the many applications to risk management, Shiri et al. [52] applied data mining tools to corporate finance, to include management fraud detection, credit risk estimation, and corporate performance prediction. Jans et al. [24] focused their data mining study to address the risk of internal fraud, finding that data mining tools provided better results than univariate analysis. Holton [22] also addressed occupational fraud, applying text mining to support fraud audits. In other industries, Nateghi et al. [43] applied data mining techniques to better predict power outages, especially those related to

hurricanes. Ghadge et al. [17] reviewed text mining applications to support risk management in supply chains. Two studies specifically addressed the use of data mining to reduce the risk of occupational injury [5,41].

3.7. Agent-based risk management

Artificial intelligence is often implemented through the use of agent-based systems, having computers emulate human decision makers. This approach has been applied to risk management in supply chains by Smeureanu et al. [55] with specific examination of peer partner company risk of bankruptcy. Giannakis and Louis [18] also addressed supply chain risk management through agent models, in this case examining the inherent risks in both the demand for and supply of resources in economic downturns. Agents have also specifically been applied to simulation models, enabling the use of simulation models for the analysis of more complex problems. Caporale et al. [7] presented an optimal model for financial markets under conditions of crisis, combining simulation and game theory through agents. A related approach is particle swarm optimization, which was applied by Chang Lee et al. [10] to project risk management and by Kumar et al. [31] to design more robust supply chain designs. This approach was found to allow modeling of more complicated situations. Mizgier et al. [40] applied agent-based modeling of supply chains, modeling the risk of bankruptcies of the participating firms in self-emerging networks.

3.8. Engineering risk analysis based on optimization tools

Optimization tools are fundamental to engineering efforts to design better systems [4]. The existence of uncertainty violates many of the required assumptions for many optimization models. The presence of risk implies the presence of uncertainty, making the development of optimization models more difficult. However, there have been models presented to optimize engineering systems. Ahmadi and Kumar [1] presented a model that considered the increased probability of failure in mechanical systems due to aging. Buurman et al. [6] introduced a framework for the dynamic strategic planning of engineering systems using real options analysis, finding that this approach had considerable advantages over static design. Popovic et al. [49] applied complex optimization to maintenance systems involving risk.

3.9. Knowledge management and data mining for natural disasters risk management in industry

Knowledge management is a very broad area of study, evolving from decision support systems, expert systems and artificial intelligence, to include data mining and business analytics. Knowledge management also includes considering how tacit knowledge within organizations can be captured in computer systems such as case-based reasoning. A few articles are found in the application of knowledge management to industrial risk management. Folino et al. [16] employed grid technologies in geoscience through data mining to analyze and manage natural disasters such as landslides, earthquakes, floods, and wildfires. Their system was intended to aid disaster prevention and response. Li et al. [33] focused on the prediction of natural disasters using domain knowledge and spatial data to develop a Bayesian network.

4. Article synopsis

The papers collected in this special issue include four papers modeling risk management: two regarding financial risk management, one about security risk management, and one based on Enterprise Resource Planning project risk management. The first set of financial risk management papers cover all typical topics: new stock trading method using Kansei evaluation integrated with a self-organizing map model for the improvement of a stock trading system, case-based reasoning hybrid models for predicting financial business failure, and an agent-based auction stock market based on scaling analysis.

The article **Dynamic Risks Modelling in ERP Maintenance Projects with FCM** authored by Cristina Lopez and Jose Salmeron studies the risks in Enterprise Resource Planning (ERP) projects. In particular, they have built Fuzzy Cognitive Maps (FCMs) of ERP maintenance risks. The main advantage of FCM lies in their being capable of modelling complex phenomena based on the experts' perceptions. This tool models uncertainty and related events, imitating human reasoning. The tool proposed specifically models ERP maintenance project outcomes and risk perceptions, as well as their hidden interactions. The authors show that FCMs enable the development of forecasting exercises through simulations. Practitioners would thus assess the joint influence of ERP maintenance risks on project outcomes. The tool proposed would help practitioners to manage ERP maintenance project risks in a more effective and proactive way.

The article **Hybrid Kansei-SOM Model using Risk Management and Company Assessment for Stock Trading**, authored by Hai Pham, Eric Cooper, Thang Cao, and Katsuari Kamei, presents a new stock trading method using Kansei evaluation integrated with a self-organizing map model for the improvement of a stock trading system. The proposed approach aims to aggregate multiple expert decisions, achieve the greatest investment returns, and reduce losses by dealing with complex situations in dynamic market environments. Kansei evaluation and fuzzy evaluation models are applied to quantify trader sensibilities regarding stock trading, market conditions, and stock market factors with uncertain risks. In

Kansei evaluation, group psychology and the sensibility of traders are quantified and represented by fuzzy weights. Kansei and stock-market data sets are visualized by SOM, together with aggregate expert preferences in order to find potential companies, matching with trading strategies at the right time and eliminating risky stocks. The authors test the proposed approach in daily stock trading on the HOSE, HNX (Vietnam), NYSE and NASDAQ (US) stock markets. The authors show that the new approach of applying Kansei evaluation enhances the capability of investment returns and reduces losses. The authors also show that the proposed approach performs better than other current methods when dealing with various market conditions.

The article **A Security Risk Analysis Model for Information Systems: Causal Relationships of Risk Factors and Vulnerability Propagation Analysis**, authored by Nan Feng, Harry Jiannan Wang, and Minqiang Li, develops a security risk analysis model to identify the causal relationships among risk factors and analyze the complexity and uncertainty of vulnerability propagation. In the proposed model, a Bayesian network (BN) is developed to simultaneously define the risk factors and their causal relationships based on the knowledge from observed cases and domain experts. The authors conduct the security vulnerability propagation analysis to determine the propagation path with the highest probability and largest path risk exposure. The ant colony optimization is used in SRAM to establish the BN structure and determine vulnerability propagation paths and their occurrence probabilities. SRAM enables organizations to establish proactive security risk management plans for information systems.

The article **Calibration of the Agent-based Continuous Double Auction Stock Market Scaling Analysis** authored by Yuelei Li, Wei Zhang, Yongjie Zhang, Xiaotao Zhang, and Xiong Xiong, proposes a calibration method for the agent-based continuous double auction (CDA) stock market using scaling analysis based on the work by ([47]). The authors design and build an agent-based CDA stock market and uses the same trading mechanism as the Chinese stock market. The authors also perform a scaling analysis of the absolute returns in both the artificial and real stock markets, and show volatility correlations as power laws in all of the markets, where the power-law exponent is not unique, and all such exponents follow a multi-scale behavior.

5. Concluding remarks

Business intelligence models have been and are being applied in risk management contexts worldwide. They have proven effective for over half a century. We hope that this special issue provides a glimpse of how business intelligence can be applied by more readers faced with enterprise risk.

Acknowledgements

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