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Stevan Dedijer
1911-2004

EDITOR'S NOTE **VOL 7, NO 3 (2017)**

How companies succeed and fail to succeed with the implementation of intelligence systems

Most papers in this issue deal with different sides of technological systems and managerial practices used for intelligence work in private organizations. Empirical data from a number of countries and companies are gathered to illustrate how companies work and fail to work with business intelligence and competitive intelligence in organizations.

The paper by Rezaie, Mirabedini and Abtahi entitled "Identifying key effective factors on the implementation process of business intelligence in the banking industry of Iran" identifies key effective factors on the implementation process of business intelligence. Thirty-nine factors were identified and classified in nine main groups, including organizational, human, data quality, environmental, system ability, strategic, service quality, technical infrastructure, and managerial factors.

The paper by Bisson and Gurpinar entitled "A Bayesian approach to developing a strategic early warning system for the French milk market" suggests a new strategic early warning system for companies and public organizations to better anticipate market changes and make more robust decisions.

The paper by Al Rashdi and Nair entitled "A business intelligence framework for Sultan Qaboos University: A case study in the Middle East" aims to build a customized business intelligence (BI) framework for Sultan Qaboos University (SQU). A prototype is tested with good results.

The paper by Søilen, Tontini, Aagerup and Andersson entitled "The perception of useful information derived from Twitter: A survey of professionals" is a survey of professionals about the value of the information or intelligence on Twitter. It shows that Twitter is perceived as a service for useful information but not for the reason one may expect, not because the content of the tweets gives valuable information, but because of what can be derived and extracted from the information that is being tweeted and not tweeted.

The paper by Calof, Richards and Santilli entitled "Insight through open intelligence" is an opinion piece that gives suggestions of how to broaden the CI field with the help of open innovation.

As always, we would above all like to thank the authors for their contributions to this issue of JISIB. Thanks to Dr. Allison Perrigo for reviewing English grammar and helping with layout design for all articles and to the Swedish Research Council for continuous financial support.

On behalf of the Editorial Board,

Sincerely Yours,

Prof. Dr. Klaus Solberg Søilen
Halmstad University, Sweden
Editor-in-chief

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Identifying key effective factors on the implementation process of business intelligence in the banking industry of Iran

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ABSTRACT Though many organizations have turned to developing and using business intelligence systems, not all have been successful in implementing such systems. These systems have social-technical dimensions with many elements and are very complicated. Numerous studies have been carried out on implementation and employment of business intelligence, but in the past studies only specific aspects and dimensions have been addressed. The aim of this study is to identify key factors in the implementation process of business intelligence in the Iranian banking industry. The present research is objectively applied as a survey study in implementation strategy. Also it is a descriptive study in terms of the research plan and data collection where two documentary and field study methods have been used for collecting data. The statistical population of this study comprises experts and professionals in information technology who are active in implementing solutions for business intelligence in the banking industry of Iran. In this study, 16 people were chosen based on non-random judgment sampling combined with targeted and snowball sampling as a statistical sample and their viewpoints were extracted and refined using the Fuzzy Delphi Technique. First through studying past research records and reviewing literature of effective factors in implementing business intelligence process, 37 factors were identified. Then by implementing five rounds of the Fuzzy Delphi Technique, 39 factors were confirmed as significant among 37 factors affecting the business intelligence implementation process in past studies and 10 factors proposed by experts. Also, these 39 factors were classified in nine main groups including organizational, human, data quality, environmental, system ability, strategic, service quality, technical infrastructure, and managerial factors. Managers and executives of business intelligence projects in Iran's banking industry can achieve the given objectives and results by considering such significant factors in planning and taking measures related to effective implementation of business intelligence.

KEYWORDS Banking industry, business intelligence, fuzzy Delphi technique, implementing business intelligence, key factors

1. INTRODUCTION

In recent years, business intelligence technologies have become a significant concept in information systems management, mixed with progressive organization culture and placed in the forefront of information technologies in supporting decision making. In order to have a quick reaction to the market changes, organizations need managerial information systems to make different causal analyses about an organization and its environment. Meanwhile, business intelligence systems, which are the most complicated information systems, provide a tool based on which information needs of the organization are properly fulfilled. In fact, business intelligence systems provide updated, reliable and sufficient trade information making it possible to deduct and understand concepts lying in trade information through process of discovery and analysis (Azoff and Charlesworth 2004).

Gartner (2009), a leading company in business analysis, carried out research on 1500 information senior managers throughout the world and identified business intelligence as the first priority of technology. Thus, implementation and establishment of business intelligence systems have turned into a major priority for organizations' information senior managers (Yeoh and Koronios 2010). But implementation of business intelligence systems, like other organizational solutions for information technology, had different results in different companies. Some organizations have reported that their business intelligence systems have been successful while others reported that they failed in its implementation (Sangar and Iahad 2013). In fact today many organizations have adopted business intelligence systems for improving decision making process, however, not all implementations have been successful despite being used by so many organizations (Zare-Ravasan and Rabiee 2014).

Implementation of information systems at organization level has been a vital step that can lead to disorder and problems in the organization, especially regarding implementation of business intelligence systems where there are more complications and problems since such systems relate to decision making, which is a complex and abstract task influenced by an environment's potential and condition. Implementing a business intelligence system requires diverse infrastructure and is financially considered to be an expensive project implemented throughout an organization. Research shows that about 50-70 percent of business intelligence projects fail at the stage of implementation (Taqwa and Noori 2014). In fact, implementing business intelligence technology is often accompanied by much suffering of failures leading to waste of time and resources (Bargshady et al. 2014). Thus, while the market for business intelligence seems turbulent, establishment of business intelligence systems is complicated and expensive. Generally, development and implementation of business intelligence has high risks and hazards for organizations (Farrokhi and Pokoradi 2012). Therefore, despite the fact that implementing business intelligence has become a major priority for organizations' information senior managers, not all have been successful in its implementation (Yeoh and Koronios 2010).

Though most studies have been carried out on information systems to increase the understanding of information technology implementation and evaluate information technology, involvement in improving organizational performance and effectiveness, the majority of these studies consider implementation to be one of the general phases of technology transfer while for successful implementation it is required that each phase is considered and their activities are taken into account (Lai and Mahapatra 1997). Based on studies on business intelligence literature, different studies have been carried out on different fields including: vital factors of implementation success (Zare Ravasan and Rabiee 2014; Hwang et al. 2004; Yeoh and Koronios 2010; Ariachandra and Watson 2006; Olsak and Ziemba 2012; Yeoh and Popovic 2015; Hawking 2013; Vodapali, 2009), application and implementation of business intelligence (Ramarkrishnan et al. 2012; Popvic et al. 2012; Seah et al. 2010; Boyer et al. 2010; Wixom and Watson 2001; Grubljesic, 2014; Doodly 2015; Chasalow 2009), system performance (Lin et al. 2009), business intelligence system adoption (Ramamurty et al. 2008; Hwang et al. 2004), capabilities and applications of business intelligence (Isik et al. 2013; Moro et al. 2015; Isik et al. 2011), intelligence maturity (Najmi et al. 2010; Popovic et al. 2009), implementation readiness factors (Bagshady et al. 2014; Anjariny et al. 2012), and performance evaluation (Lin et al. 2009; Rouhani et al. 2012). But in each of these studies, implementation and establishment of business intelligence process has been examined in a different dimension, angle and aspect. In fact, in these studies, business intelligence implementation has not been inclusively examined by a systemic and holistic approach. Thus, the present study examines factors affecting the implementation process of business intelligence based on process theory and approach. Therefore, it has identified and classified factors through studying related literature and considering factors affecting the implementation process of business intelligence such as organization readiness, system design and development, project management, system adoption, system abilities and intelligence maturity in the Iranian banking industry environment. In fact, the main problem in this study is to identify key effective factors in the implementation process of business intelligence in the banking industry of Iran.

2. RESEARCH: THEORETICAL PRINCIPLES AND BACKGROUND

In this section, given the subject, problem and methodology, the literature and research history including business intelligence, business intelligence in the banking industry, factors affecting business intelligence implementation, Delphi method and fuzzy sets are reviewed.

2.1 Business intelligence

Business intelligence is an umbrella term introduced by Howard Dresner of Gartner group in 1989 as a series of concepts and methods which, using fact-based computer systems, lead to improved decision making (Rouhani et al. 2012). Business intelligence is a comprehensive concept through which the whole organization decides to use information systems in the most effective manner in order to acquire timely and high quality information for decision making so that competitive advantages are created (Hocevar and Jaklic 2010). In the age of information explosion and information system formation and development in organizations, insular or integrated, the appropriate use and report making of information is an inevitable necessity. Thus, due to competitive economy and business, making organizational data meaningful and facilitating decision making process has been at the center of attention of experts in information technology and management science and business professionals (Howson 2008). Since the introduction of business intelligence, information systems have witnessed fast growth of systems and decision support software applications, as well as business intelligence systems, while organizations started moving toward a business intelligent environment to have a single image of reality through organizational data presented by the integrated architecture (Isik 2010).

Companies have increasingly recognized the significance of information technology as an enabler to achieve their own strategic objective. Regarding this, the concept of using information systems to support decision making has been companies' objective since the introduction of business based computer technologies. One information system with a specific purpose is named the "decision support system". Decision support systems are responsible for providing timely, related information with analytical abilities for managers' effective decision making. With increased demands for information systems for supporting decision making terms have been used such as data warehouse, knowledge management, data mining, participation systems, online analytical processing and finally business intelligence systems, which covers all of the preceding terms (Hawking 2013). Business intelligence systems are an integrated collection of tools, technology and programmed products used for collecting, integrating, analyzing, and accessing data. In simple words, the main tasks of business intelligence systems include intelligent exploration, integration, storage and multi-dimensional analysis of data taken from different information sources (Olszak and Ziemba 2007).

2.2 Business intelligence in the banking industry

Banking is a dynamic market with changing customer demands, intense competition, a need for strict control and management of risk. These are only some of the business environment features where modern banks do their operations. Better decision making management and processes in such a market determine the success or failure of banks. Thus, it is important to use business intelligence solutions in banks to provide decision makers with information sources in all of the bank's business sections in order to take action for solving problems and to have timely, high quality decision making (Erfani 2013). In fact banks need related and timely information to adapt to the new challenges of the complicated dynamic environment. To do so, banks collect data from different inside and outside sources while business intelligent tools lead to intelligent decision making using information technologies such as online analysis and data mining in the complicated banking environment. Implementation of business intelligence systems in banks begins with collection, improvement and refinement of daily operational data from inside and outside sources while more low-cost data help banks use business intelligence possibilities to boost their relationship with customers, attract potential customers, and increase growth. In fact, business intelligence effectively relates business strategy to information technology to make use of the present infrastructure of information technology and skills (Curko and Bach 2007).

Banking is an arena where plenty of data is produced, thus, business intelligence applications can potentially benefit banks and increase the validity of this study. On the whole, banking has been significant as an active industry in adopting innovations related to information systems and technologies so that banking areas such as credit evaluation, branches' performance, electronic banking, and customer retention and classification have excelled in widely applied concepts of business intelligence and data mining techniques, data warehouse, and decision support systems (Moro et al. 2015).

2.3 Factors affecting business intelligence implementation

Implementing business intelligence systems can be very complicated. In addition to common problems in implementing information systems, there are other complicated problems such as integration, security, system scalability, managing the data warehouse, analysis tools and dashboards. Generally there are many problems regarding business intelligence implementation, the most significant of which include: system development and need for integration, profit and cost and its justification, confidentiality and legal problems, present and future of business intelligence, business process management, documentation and security of support systems, and moralities in failure of business intelligence projects (Turban et al. 2011). The costly and difficult project of business intelligence is distinct from other information technology projects in some fundamental aspects. The key distinctions identified between business intelligence projects and other information technology projects include: 1) these projects are business based, 2) support of business and information technology analysts is required in such projects, 3) the perfect definition of project requirements is impossible, 4) project management requires different approaches, 5) implementing solutions of business intelligence is the beginning of the work thus, broad tests are needed for system assessment, 6) due to the connection of users to project tools, changing management styles is vital, and 8) establishment of business intelligence in organizations is a program rather than a project (Analytics 2010).

Moss and Atre (2003) suggested that 60% of business intelligence projects have failed due to inappropriate planning, weak project management, non-fulfillment of business requirements, undefined tasks, undesirable data, not understanding the significance of some parameters such as meta data, and those that have been implemented were of low quality (Moss and Atre 2003). In general, many business intelligence application programs have failed due to infrastructure, cultural, organizational and technical problems. Also, many business intelligence solutions have failed due to the final users' lack of access and not effectively meeting the final users' needs. Business intelligence projects have also failed due to not considering activities at the organizational level, non-commitment of business supporters, disinclination or lack of access of business representatives, lack of skillful and trained staff, lack of business activity analyses, lack of understanding of the impact of acquired information on business profitability, and lack of using information by users and staff (Chuah and Wong 2013).

As a whole it can be said that organizations implement decision making support systems to improve and deliver information required by decision makers and to support decision making activities. But results of studies indicate that all these systems are not successfully implemented, and predicted interests are not always realized. Thus, it is not surprising that business researchers and experts have become sensitive about determining key factors affecting implementation (Hartono et al. 2007). In this regard, it is said that the interventions to improve the success of information technology implementation is rooted in behavioral science, which using theories and models determines conditions and factors effective in its successful use (Kukafka et al. 2003). Also, in the past decades, contingency theory has become a stabilized basis in information systems and seven success variables in information systems have been determined as basic factors including size, environment, strategy, structure, technology, duty and individual characteristics. Size refers to the volume indices, such as the number of employees or amount of income. Environment refers to the space around the system such as related industries. Strategy refers to the information property and quality of explaining the company's strategy. Structure refers to an organization's proportion to information system structure. Technology refers to the type of technology or complication of the implemented technology. Duty refers to various activities and their features, and finally individual characteristics refers to individual differences and their proportion to information system activities (Raber et al. 2013).

In general, in this study with regard to business intelligence system implementation as a process, it can be noted that choosing appropriate methodology for the system development, project team formation, project correct management and development requirement identification are topics raised in the system implementation stage. Success of the implementation stage depends on previous stages. When pre-implementation actions are fully done and there is enough readiness, the design and implementation stage begins. Post-implementation actions for business intelligence systems are summarized in topics such as business intelligence maturity, continuous improvement, performance management, and profitability of business intelligence. This stage indicates that system implementation in the organization is not periodical (Taqwa and Noori 2014). Thus, effective factors in implementing process of business intelligence include different factors in the implementing stage such as an organization's readiness, designing and methodology of development, project management, performance assessment and system maturity, system adoption, system capabilities, business and beneficiaries needs, and environmental factors. Therefore, in the present study, effective factors in implementing processes of business intelligence are reviewed through deep examination of the theoretical and empirical history related to the aforementioned dimensions and aspects. Based on this study's results, a list of factors affecting implementation of the process of business intelligence with the most popularity in the literature and research background is presented in Table 1.

Table 1 List of factors affecting the business intelligence implementation process.

Factors		References
F1	Flexible and extensible technical infrastructure	(Ansari et al. 2014) ; (Olbrich et al. 2012) ; (Yeoh and Koronios 2010) ; (Bargshady et al. 2014) ; (Vodapall 2009) ; (Anjariny et al. 2012) ; (Sangar and lahad 2013) ; (Yeoh et al . 2008) ; (Watson and Wixom 2007)
F2	Clear vision and objectives for business intelligence	(Bargshady et al. 2014) ; (Zare Ravasan and Rabiee 2014) ; (Ansari et al. 2014) ; (Hoseini et al. 2015) ; (Raisivanani and Ganjalikhan Hakemi 2015) ; (Yeoh and Koronios 2010) ; (Vodapall 2009) ; (Anjariny et al. 2012) ; (Sangar and lahad 2013) ; (Yeoh et al. 2008) ; (Dawson and Van Belle 2013)
F3	Planning and effective project management	(Bargshady et al. 2014) ; (Zare Ravasan and Rabiee 2014) ; (Hoseini et al. 2015) ; (Raisivanani and Ganjalikhan Hakemi 2015) ; (Hawking 2013) ; (Vodapall 2009) ; (Anjariny et al. 2012) ; (Sangar and lahad 2013) ; (Yeoh et al . 2008) ; (Ojeda and Ramaswamy 2014) ; (Ojeda-Castro et al. 2011) ; (Mungree et al. 2013)
F4	Senior manager's commitment and support	(Bargshady et al. 2014) ; (Piri,2014) ; (Zare Ravasan and Rabiee 2014) ; (Ansari et al. 2014) ; (Hoseini et al. 2015) ; (Ramamurthy et al. 2008) ; (Hawking 2013) ; (Grubljesic 2014) ; (Olbrich et al. 2012) ; (Yeoh and Koronios 2010) ; (Vodapall 2009) ; (Anjariny et al. 2012) ; (Wixom and Watson 2001) ; (Hwang et el. 2004) ; (Seah et al. 2010) ; (Sangar and lahad 2013) ; (Dawson and Van Belle 2013) ; (Yeoh et al. 2008) ; (Foshay and kuziemsky 2014) ; (Yeoh and Koronios 2010) ; (Howson 2008) ; (Watson and Wixom 2007)
F5	Usefulness and easy use of business intelligence system	(Haqiqatmonfared and Rezaei 2011) ; (Ramamurthy et al. 2008) ; (Grubljesic 2014) ; (Anjariny et al. 2012) ; (Sangar and lahad 2013) ; (Almabhoud and Ahmad 2010) ; (Dawson and Van Belle 2013)
F6	The flexibility and speed of response to changes in the business intelligence system	(Ronaqi and Feizi 2013) ; (Zare Ravasan and Rabiee 2014) ; (Hoseini et al. 2015) ; (Haqiqatmonfared and Rezaei 2011) ; (Ronaqi et al. 2014) ; (Raisivanani and Ganjalikhan Hakemi 2015) ; (Dooley 2015) ; (Yeoh and Koronios 2010) ; (Isik et al. 2011) ; (Sangar and lahad 2013) ; (Almabhoud and Ahmad 2010) ; (Dinter et al. 2011) ; (Howson 2008)
F7	Strong and suitable framework for data governance and quality	(Raisivanani and Ganjalikhan Hakemi 2015) ; (Hawking,2013) ; (Yeoh et l. 2008)
F8	User training	(Babamoradi 2012) ; (Zare Ravasan and Rabiee 2014) ; (Ansari et al. 2014) ; (Hoseini et al. 2015) ; (Raisivanani and Ganjalikhan Hakemi 2015) ; (Hawking 2013) ; (Grubljesic 2014) ; (Vodapall 2009) ; (Anjariny et al. 2012) ; (Sangar and lahad 2013) ; (Almabhoud and Ahmad 2010)

F9	User support	(Zare Ravasan and Rabiee 2014) ; (Ronaqi and Feizi 2013) ; (Ansari et al. 2014) ; (Hoseini et al. 2015) ; (Boyer et al. 2010) ; (Vodapall 2009) ; (Almabhoud and Ahmad 2010)
F10	Project leader and championship to lead and facilitate participation	(Hawking 2013); (Seah et al. 2010); (Chasalow 2009); (Ansari et al. 2014); (Hwang et el. 2004) ; (Yeoh et al. 2008) ; (Grubljesic 2014)
F11	Organization's ability to provide sufficient resources	(Piri 2014) ; (Zare Ravasan and Rabiee 2014) ; (Ansari et al. 2014) ; (Hoseini et al. 2015) ; (Raisivanani and Ganjalikhan Hakemi 2015) ; (Hawking 2013) ; (Grubljesic 2014) ; (Olbrich et al. 2012) ; (Anjariny et al. 2012) ; (Wixom and Watson 2001) ; (Watson and Wixom 2007) ; (Brooks et al. 2015)
F12	Integration capability of business intelligence system	(Nazari 2014); (Rouhani et al. 2012) ; (Ronaqi and Feizi 2013) ; (Ansari et al. 2014) ; (Haqiqatmonfared and Rrezaei, 2011) ; (Ronaqi et al., 2014) ; (Isik et al. 2013) ; (Dooley 2015) ; (Mahlouji 2014) ; (Yeoh and Koronios 2010) ; ; (Isik et al. 2011) ; (Vodapall 2009)
F13	Analysis capability of business intelligence system	(Najmi et at. 2010) ; (Ronaqi and Feizi 2013) ; (Hoseini et al. 2015) ; (Ronaqi et al.,2014) ; (Mahlouji 2014)
F14	Role of organizational communications	(Babamoradi 2012) ; (Olbrich et al. 2012) ; (Almabhoud and Ahmad 2010)
F15	Level of automation and maturity of organizational processes	(Ansari et al. 2014) ; (Hawking 2013) ; (Olbrich et al. 2012) ; (Grubljesic 2014) ; (Brooks et al. 2015)
F16	Involvement of end users	(Piri 2014); (Zare Ravasan and Rabiee 2014); (Hoseini et al. 2015); (Haqiqatmonfared and Rezaei 2011); (Raisivanani and Ganjalikhan Hakemi 2015); (Hawking 2013); (Grubljesic 2014); (Olbrich et al. 2012) ; (Vodapall 2009); (Anjariny et al. 2012); (Sangar and lahad 2013); (Dawson and Van Belle 2013) ; (Lupu et al. 2007); (Watson and Wixom 2007)
F17	Interaction and collaboration between business and information technology units	(Zare Ravasan and Rabiee 2014); (Ansari et al. 2014); (Khodaei and Karimzadehgan Moqadam 2014); (Vodapall 2009); (Thamir and polis 2015); (Dinter et al. 2011) ; (Williams and Williams 2004)
F18	Culture of continuous process improvement	(Khodaei and Karimzadehgan Moqadam 2014) ; (Lonnqvist and Pirttimaki 2006) ; (Williams and Williams 2004)
F19	Engineering culture of decision making process	(Khodaei and Karimzadehgan Moqadam 2014) ; (Popvic et al. 2012) ; (Williams and Williams 2004)
F20	Culture of using information and analytics	(Najmi et at. 2010) ; (Khodaei and Karimzadehgan Moqadam 2014) ; (Popvic et al. 2012) ; (Grubljesic 2014) ; (Chasalow 2009) ; (Foshay and kuziemsky 2014) ; (Lonnqvist and Pirttimaki 2006)
F21	The use of iterative development approaches in business intelligence projects	(Ansari et al. 2014) ; (Raisivanani and Ganjalikhan Hakemi 2015) ; (Hawking, 2013) ; (Grubljesic 2014) ; (Derarpalli 2013) ; (Yeoh and Koronios 2010) ; (Anjariny et al. 2012) ; (Castra and Ramaswamy 2014) ; (Howson 2008)
F22	The alignment of business intelligence strategy with organization's strategy	(Zare Ravasan and Rabiee 2014) ; (Khodaei and Karimzadehgan Moqadam 2014) ; (Hawking 2013) ; (Boyer et al. 2010) ; (Yeoh and Koronios 2010) ; (Dinter et al. 2011) ; (Tarokh and Mohajeri 2012) ; (Esmaeili 2015) ; (Mungree et al. 2013) ; (Williams and Williams 2004)
F23	Laws and regulations related to business requirements and limitations	(Ramarkrishnan et al. 2012) ; (Olbrich et al. 2012) ; (Sangar and lahad 2013)
F24	Quality and reliability of data resources	(Olbrich et al. 2012) ; (Isik et al. 2011) ; (Vodapall 2009) ; (Anjariny et al. 2012) ; (Wixom and Watson 2001) ; (Almabhoud and Ahmad 2010); (Dawson and Van Belle 2013) ; (Ansari et al. 2014) ; (Thamir and polis 2015)
F25	Sharing and presentation of Information	(Dooley 2015) ; (Hawking 2013) ; (Popvic et al. 2012)
F26	Choosing technology and tools appropriate to organization's conditions	(Zare Ravasan and Rabiee 2014) ; (Hawking 2013) ; (Grubljesic 2014) ; (Vodapall 2009) ; (Wixom and Watson 2001) ; (Sangar and lahad, 2013) ; (Castra and Ramaswamy 2014) ; (Ojeda-Castro et al. 2011)
F27	Effective change of management	(Zare Ravasan and Rabiee 2014) ; (Ansari et al. 2014) ; (Hawking 2013) ; (Yeoh and Koronios 2010) ; (Vodapall 2009) ; (Almabhoud and Ahmad 2010) ; (Olsak and Ziemba 2012) ; (Williams and Williams 2004)
F28	Using outside consultants	(Raisivanani and Ganjalikhan Hakemi 2015) ; (Hawking 2013) ; (Anjariny et al. 2012) ; (Yeoh et al. 2008) ; (Yeoh and Koronios 2010) ; (Sangar and lahad 2013)
F29	Interaction with vendors and choosing suitable suppliers	(Hawking 2013) ; (Sangar and lahad 2013)
F30	Balanced and strong combination of project team	(Ansari et al. 2014) ; (Hoseini et al. 2015) ; (Olbrich et al. 2012) ; (Yeoh and Koronios 2010) ; (Vodapall 2009) ; (Anjariny et al. 2012) ; (Yeoh et al. 2010) ; (Almabhoud and Ahmad 2010) ; (Ojeda - Castro and Ramaswamy 2014) ; (Ojeda - Castro et al. 2011)
F31	Competition setting in business	(Grubljesic 2014); (Olbrich et al. 2012); (Yeoh and Koronios 2010); (Hwang et el. 2004)
F32	Skills of information technology, business and analytical	(Hawking 2013); (Foshay and kuziemsky 2014); (Sangar and lahad 2013); (Friedman et al. 2003); (Cuza 2009); (Watson and Wixom 2007); (Tabarsa and Nazari poor 2014); (Olbrich et al. 2012)
F33	Quality of access to information	(Ronaqi and Ronaqi 2014); (Popvic et al. 2012); (Dooley 2015); (Isik et al. 2011); (Isik et al. 2013)
F34	Quality of information content	(Ronaqi and Ronaqi 2014); (Popvic et al. 2012); (Dooley 2015); (Lin et al. 2009)
F35	The precision, accuracy, and perfectness of data	(Ansari et al.,2014); (Hoseini et al. 2015); (Sangar and lahad 2013); (Almabhoud and Ahmad 2010)
F36	User friendliness and easy learning of business intelligence tools	(Hoseini et al. 2015); (Raisivanani and Ganjalikhan Hakemi 2015); (Sangar and lahad 2013)
F37	Precision of information at system output	(Haqiqatmonfared and Rezaei, 2011); (Dooley, 2015); (Isik et al., 2011); (Sangar and lahad 2013)

2.4 An overview of the Delphi method

The Delphi technique is one of the qualitative research methods used for reaching consensus in group decision making. Practically, the Delphi method is a series of questionnaires or consecutive rounds with controlled feedback attempting to reach consensus among a group of experts on a particular subject (Hasson and Mckenna 2000). This method relies on the supposition that consensus among experts is stronger than individual viewpoints. Thus, unlike survey research methods, the Delphi method's credit depends not only on the number of participants but on the scientific credit of expert participants. Thus, a number of participants between 5 and 20 would be enough (Rowe 2001).

The classic Delphi technique has always suffered low convergence of experts' opinions, high implementation cost and potential exclusion of some individuals' viewpoints. Thus, the traditional Delphi method concept of integration with Fuzzy theory was raised and in this regard, fuzzy Delphi method was invented by Kaufman and Gopta in 1990s (Cheng and Yin 2002; Hsu and Yang 2000). The Fuzzy Delphi method application for decision making and consensus on problems where parameters and objectives are not defined leads to valuable results. The significant feature of this method is presenting a flexible framework covering many obstacles related to imprecision and inaccuracy. Many problems in decision makings are related to imperfect and inaccurate information. On the other hand, decisions taken by experts are based on their individual qualification and are strongly subjective. Thus it is better for the data to be displayed by fuzzy numbers rather than definite numbers. The Fuzzy Delphi method's implementation rounds in fact is a combination of Delphi method implementation and analyses of information using definitions of fuzzy sets theory (Toy and Garai 2012).

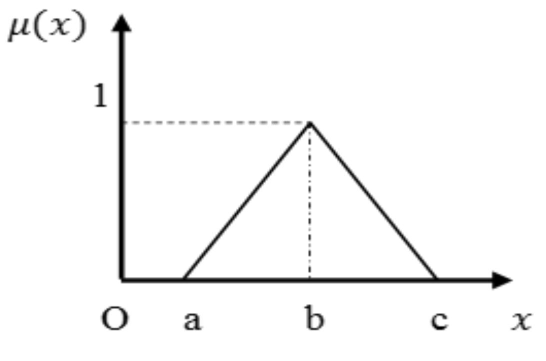

Figure 1 Triangular fuzzy number.

2.5 Fuzzy sets

In order to deal with the vagueness of human thought, Zadeh (1965) first introduced the fuzzy set theory. A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function which assigns to each object a grade of membership ranging between zero and one. Fuzzy sets and fuzzy logic are powerful mathematical tools for modeling. Fuzzy sets theory provides a wider frame than classic sets theory, and this has contributed to its capability of reflecting the real world. Modeling using fuzzy sets has proven to be an effective way for formulating decision problems where the information available is subjective and imprecise (Kahraman et al. 2003b). It is possible to use different fuzzy numbers according to the situation. In applications, it is often convenient to work with triangular fuzzy numbers (TFNs) because of their computational simplicity; moreover, they are useful in promoting representation and information processing in a fuzzy environment. Therefore, in this paper, we use triangular fuzzy numbers. Triangular fuzzy numbers are a special kind of fuzzy set. A triangular fuzzy number can be denoted as: N = (a, b, c). Figure 1 is an illustration of the membership function of a triangular fuzzy number.

The membership function of triangular fuzzy numbers is:

$$\mu(x) = \begin{cases} \frac{x-a}{b-a} & \text{if} \quad a \le x \le b\,; \\ \frac{c-x}{c-b} & \text{if} \quad b \le x \le c; \\ 0 & \text{else} \end{cases}$$

Particularly, when a = b = c, triangular fuzzy numbers become crisp numbers.

That is, crisp numbers can be considered to be a special case of fuzzy numbers (Daghighi Masouleh et al. 2014). In this paper, after the data were collected, the fuzzy triangular numbers were converted into absolute fuzzy numbers by means of Minkowski.

3. RESEARCH METHODOLOGY

Since the results of the present study have the potential of being applied to planning and actions taken to implement business intelligence in the banking industry of Iran, this study is applied objective research and a survey in implementation strategy. Also, based on the research plan and method of data collecting, it is a descriptive study which uses two methods of documentary and field studies for collecting information. The statistical population of this study comprises experts and professionals in the field of information technology who are active in implementing solutions for business intelligence in Iran's banking industry. In the present study, 16 people were chosen in a nonrandom judgment sampling combined with targeted and snowball samplings as a statistical sample. Using the fuzzy Delphi method their opinions were extracted and refined. Experts' information was collected using a questionnaire so that each expert using the fuzzy approach expressed his/her opinion on the level of significance of factors affecting business intelligence implementation as well as on how to classify such factors in Liker fivefold spectrum and through verbal variables (very low, low, average, high and very high).

Following the initial framework preparation resulting from the research literature review, a questionnaire was set and designed. Then, 6 experts' opinions were used to evaluate the questionnaire. They were university professors and experts in information technology. Thus following the review of the questionnaire by these experts, their proposed ideas were exerted. Also given the fact that their factors and dimensions have been verified by experts using the Delphi technique, nominal and content validity of the measuring tool was confirmed by experts with a high score. To determine the questionnaire's reliability, the Cronbach alpha method was used with an alpha coefficient of 0.91 obtained for the questionnaire indicating an acceptable reliability.

3.1 Research implementation process

In this study, first a recognition of the present condition of this field was attained through examining the past research history. Then the research literature background related to factors affecting the implementation process of business intelligence was closely reviewed. As a result of this review, 37 factors affecting the implementation process were identified that are shown in Table 1. Then, using the initial framework of factors and running five rounds of the fuzzy Delphi technique, key factors affecting the implementation process of business intelligence in the Iranian banking industry were identified then classified. The method for running the fuzzy Delphi technique in the present study is explained in the following.

As pointed out, the Delphi panel members in this study were chosen in a non-random sampling and a combination of targeted (judgment) and chain (snowball) methods. In order to select experts and professionals, criteria such as sufficient knowledge and experience on the subject, inclination and enough time for cooperation in the research, and effective communication skills were considered, based on which 16 people were nominated as qualified by researchers for this study. These people were involved in implementing solutions, and plans and projects of business intelligence in the Iranian banking industry. The demographic situation and features of the Delphi panel experts in this study is presented in Table 2.

Table 2 Frequency distribution and percentage of respondents based on demographic characteristics.

	Activity background			Education			Age				Sex	
	+10 yrs	6-10 yrs	-5 yrs	PhD	Master	Bachelor	+45	36-45	26-35	-25	F	M
Frequency	2	9	5	8	5	3	4	5	6	1	5	11
Percent	12.5	56.25	31.25	50	31.25	18.75	25	31.25	37.5	6.25	31	69

In this study all experts expressed their opinions through a questionnaire on the significance and classification of factors affecting the implementation process of business intelligence on a Likert fivefold spectrum and trough verbal variables (very low, low, average, high and very high) using a fuzzy approach. Given Table 3 and Figure 2, the mentioned factors and variables are defined as triangular fuzzy number (Mousavi et al. 2015; Mirsepasi et al. 2013; Cheng and Lin 2002; Daghighi Masouleh et al. 2014). In the present study, absolute fuzzy numbers (χ) in Table 3 are calculated using a Minkowski equation as the equation (1) .

$$\chi = m + \frac{\beta - \alpha}{4}$$

Equation 1

In the above formula (α) is expressed as the lower limit (bound), (β) is expressed as the upper limit (bound) and (m) is the biggest membership degree. Also, each variable in the rounds of the fuzzy Delphi technique was obtained using equations (2) and (3):

$$A_i = \left(a_1{}^{(i)}, a_2{}^{(i)}, a_3{}^{(i)}\right), \qquad i = 1,2,3,\dots,n$$

Equation 2

$$A_{ave=}(m_1, m_2, m_3) = \left(\frac{1}{n}\sum_{i=1}^{n} a1^{(i)}, \frac{1}{n}\sum_{i=1}^{n} a2^{(i)}, \frac{1}{n}\sum_{i=1}^{n} a3^{(i)}\right)$$

Equation 3

Where A_i stands for the expert's opinion, ith and A_{ave} stand for the experts' opinion fuzzy mean. In this study, if in running Delphi technique rounds, the difference of opinions between experts ($\chi_i - \chi_j$) on the rate of significance and/or their agreement on their classification is lower than 0.1, consensus is reached and the opinion poll process stops (Cheng and Lin 2002). It is noteworthy that conditions for reaching consensus in the Delphi method are determined by the experts of the research and there isn't any particular rule for that, but the higher the number of procedures and the stricter the consensus condition, the more valid the Delphi results are (Fink 1984). Also to screen improper factors, a threshold must be chosen. Usually, the threshold is determined by the experts' subjective deduction and there is no general way or rule for determining that value. Threshold values affect the number of factors to be screened. Thus, given the objective of this study for identifying key factors affecting the implementation of business intelligence, threshold value for accepting factors was determined to be 0.75, i.e. equal to crisp value "high" for verbal variables in Table 2. In fact, in case of expert consensus, if the experts' final opinions mean (χ_j) on the rate of significance of factors and /or classification of factors reaches 0.75, then that factor is considered to be significant and/or the factors' classification is approved by experts. But if the experts' final opinions mean is lower than 0.75, then that factor is not considered to be significant and/or the factors' classification is rejected by them.

Table 3 Triangular fuzzy numbers of verbal variables.

Linguistic variables	Symbols	Fuzzy triangular numbers (m , α ,β)	Absolute fuzzy numbers (χ)
Very high	VH	(1, 0.25 , 0)	0.9375
High	H	(0.75, 0.15, 0.15)	0.75
Medium	M	(0.5, 0.25, 0.25)	0.5
Low	L	(0.25, 0.15, 0.15)	0.25
Very low	VL	(0, 0 , 0.25)	0.0625

Table 4 Mean expert opinions on the significance of factors affecting implementation of business intelligence in the first round of the opinion poll.

Factors	Triangular fuzzy mean (m,α, β)			Factors	Triangular fuzzy mean (m,α, β)			Factors	Triangular fuzzy mean (m,α, β)		
F	m	α	β	F	m	α	β	F	m	α	β
F1	0.86	0.21	0.07	F14	0.61	0.22	0.20	F27	0.63	0.19	0.19
F2	0.77	0.19	0.12	F15	0.64	0.21	0.19	F28	0.48	0.20	0.22
F3	0.78	0.20	0.11	F16	0.66	0.18	0.16	F29	0.53	0.21	0.21
F4	0.81	0.20	0.08	F17	0.73	0.20	0.14	F30	0.72	0.23	0.15
F5	0.67	0.19	0.18	F18	0.75	0.21	0.13	F31	0.58	0.22	0.19
F6	0.77	0.21	0.13	F19	0.72	0.18	0.16	F32	0.77	0.19	0.12
F7	0.64	0.23	0.17	F20	0.77	0.19	0.15	F33	0.69	0.18	0.15
F8	0.64	0.19	0.18	F21	0.58	0.19	0.19	F34	0.78	0.19	0.12
F9	0.53	0.21	0.21	F22	0.78	0.19	0.13	F35	0.80	0.18	0.11
F10	0.67	0.21	0.18	F23	0.61	0.21	0.21	F36	0.73	0.18	0.14
F11	0.78	0.23	0.10	F24	0.81	0.20	0.11	F37	0.80	0.19	0.11
F12	0.80	0.21	0.11	F25	0.61	0.22	0.20				
F13	0.78	0.20	0.11	F26	0.70	0.17	0.17				

Table 5 New factors proposed by experts in the first round.

Proposed factors affecting the implementation process of business intelligence in the Iranian banking industry	
F38	Standardization of technical infrastructure in the bank
F39	Senior managers' risk taking in modern technologies investment
F40	Quality of data extract, transformation, and loading process
F41	Appropriate architecture for business intelligence system
F42	Level of security in the business intelligence system
F43	Business intelligence technology compatibility with existing technologies
F44	Data integrity and consistency of data sources
F45	The use of project risk management
F46	Tendency of managers to adopt information technology innovations
F47	Set up business intelligence strategy

Table 6 Mean expert opinions on significance of factors affecting implementation of business intelligence in the second round of the opinion poll.

Factors	Triangular fuzzy mean (m,α, β)			Factors	Triangular fuzzy mean (m,α, β)			Factors	Triangular fuzzy mean (m,α, β)		
F	m	α	β	F	m	α	β	F	m	α	β
F1	0.89	0.20	0.07	F17	0.81	0.19	0.08	F33	0.77	0.16	0.13
F2	0.84	0.18	0.09	F18	0.88	0.20	0.07	F34	0.80	0.19	0.12
F3	0.86	0.19	0.08	F19	0.81	0.18	0.11	F35	0.86	0.19	0.08
F4	0.88	0.21	0.06	F20	0.80	0.18	0.12	F36	0.77	0.17	0.13
F5	0.70	0.18	0.17	F21	0.66	0.19	0.19	F37	0.84	0.19	0.08
F6	0.81	0.19	0.10	F22	0.86	0.19	0.08	F38	0.53	0.20	0.20
F7	0.75	0.18	0.14	F23	0.75	0.16	0.15	F39	0.73	0.19	0.15
F8	0.77	0.17	0.14	F24	0.88	0.20	0.08	F40	0.81	0.20	0.11
F9	0.64	0.19	0.19	F25	0.64	0.19	0.19	F41	0.72	0.19	0.16
F10	0.77	0.17	0.14	F26	0.86	0.19	0.08	F42	0.77	0.21	0.13
F11	0.81	0.21	0.10	F27	0.75	0.15	0.15	F43	0.67	0.21	0.18
F12	0.84	0.20	0.09	F28	0.66	0.19	0.19	F44	0.77	0.19	0.13
F13	0.80	0.19	0.12	F29	0.67	0.18	0.18	F45	0.70	0.21	0.16
F14	0.64	0.21	0.19	F30	0.81	0.19	0.11	F46	0.50	0.20	0.21
F15	0.66	0.19	0.19	F31	0.73	0.17	0.15	F47	0.80	0.19	0.12
F16	0.78	0.19	0.13	F32	0.80	0.19	0.11				

Table 7 Experts' difference of opinions on effective factors significance in the first and second rounds.

Factors	Mean defuzzificated opinion		Difference of opinions rate	Factors	Mean defuzzificated opinion		Difference of opinions rate	Factors	Mean defuzzificated opinion		Difference of opinions rate
F	χ_1	χ_2	$\chi_2 - \chi_1$	F	χ_1	χ_2	$\chi_2 - \chi_1$	F	χ_1	χ_2	$\chi_2 - \chi_1$
F1	0.83	0.86	0.03	F17	0.72	0.79	0.06	F33	0.68	0.76	0.08
F2	0.75	0.82	0.07	F18	0.73	0.84	0.11	F34	0.76	0.78	0.02
F3	0.76	0.83	0.07	F19	0.71	0.80	0.089	F35	0.78	0.83	0.05
F4	0.78	0.84	0.04	F20	0.76	0.78	0.02	F36	0.72	0.76	0.04
F5	0.67	0.70	0.03	F21	0.58	0.66	0.08	F37	0.78	0.82	0.04
F6	0.75	0.79	0.04	F22	0.77	0.83	0.06	F38	-	0.53	-
F7	0.63	0.74	0.11	F23	0.61	0.75	0.14	F39	-	0.72	-
F8	0.64	0.76	0.12	F24	0.79	0.84	0.05	F40	-	0.79	-
F9	0.53	0.64	0.11	F25	0.61	0.64	0.03	F41	-	0.71	-
F10	0.66	0.76	0.09	F26	0.70	0.83	0.13	F42	-	0.75	-
F11	0.75	0.79	0.04	F27	0.63	0.75	0.12	F43	-	0.66	-
F12	0.77	0.82	0.05	F28	0.49	0.66	0.17	F44	-	0.75	-
F13	0.76	0.78	0.02	F29	0.53	0.67	0.14	F45	-	0.69	-
F14	0.61	0.64	0.03	F30	0.70	0.79	0.09	F46	-	0.50	-
F15	0.64	0.66	0.02	F31	0.57	0.73	0.16	F47	-	0.78	-
F16	0.65	0.77	0.12	F32	0.75	0.78	0.03				

Table 8 Mean expert opinions on the significance of factors affecting implementation of business intelligence in the third round of the opinion poll.

Factors	Triangular fuzzy mean (m,α, β)			Factors	Triangular fuzzy mean (m,α, β)			Factors	Triangular fuzzy mean (m,α, β)		
F	m	α	β	F	m	α	β	F	m	α	β
F7	0.78	0.16	0.13	F27	0.75	0.15	0.15	F41	0.77	0.17	0.14
F8	0.81	0.19	0.11	F28	0.75	0.16	0.16	F42	0.81	0.19	0.11
F9	0.69	0.18	0.18	F29	0.77	0.16	0.15	F43	0.77	0.17	0.14
F16	0.86	0.19	0.09	F31	0.77	0.17	0.14	F44	0.81	0.18	0.11
F18	0.91	0.21	0.05	F38	0.58	0.22	0.22	F45	0.78	0.19	0.13
F23	0.77	0.15	0.14	F39	0.78	0.18	0.13	F46	0.56	0.23	0.23
F26	0.89	0.21	0.07	F40	0.88	0.20	0.08	F47	0.86	0.19	0.08

Table 9 Expert differences of opinions on effective factors' significance in the second and third rounds.

Factors	Mean defuzzificated opinion		Difference of opinions rate	Factors	Mean defuzzificated opinion		Difference of opinions rate	Factors	Mean defuzzificated opinion		Difference of opinions rate
F	χ_2	χ_3	$\chi_3 - \chi_2$	F	χ_2	χ_3	$\chi_3 - \chi_2$	F	χ_2	χ_3	$\chi_3 - \chi_2$
F7	0.74	0.77	0.03	F27	0.75	0.75	0.00	F41	0.71	0.76	0.05
F8	0.76	0.79	0.03	F28	0.66	0.75	0.04	F42	0.75	0.79	0.04
F9	0.64	0.69	0.05	F29	0.67	0.76	0.09	F43	0.66	0.76	0.1
F16	0.77	0.84	0.07	F31	0.73	0.76	0.03	F44	0.75	0.80	0.05
F18	0.84	0.86	0.02	F38	0.53	0.58	0.05	F45	0.69	0.77	0.08
F23	0.75	0.76	0.01	F39	0.72	0.77	0.05	F46	0.50	0.56	0.06
F26	0.83	0.86	0.03	F40	0.79	0.84	0.05	F47	0.78	0.83	0.05

Table 10 Key factors affecting the implementation process of business intelligence based on related dimensions in the banking industry of Iran.

Dimensions (D)		Factors (F)
D1	Technical infrastructure	Flexible and extensible technical infrastructure (F1) - Choosing technology and tools appropriate to organization's conditions (F26) - Appropriate architecture for business intelligence system (F41) - Business intelligence technology compatibility with existing technologies (F43)
D2	Strategic	Clear vision and objectives for business intelligence (F2) - the alignment of business intelligence strategy with organization's strategy (F22) - Set up business intelligence strategy (F47)
D3	Managerial	Planning and effective project management (F3) - effective change of management (F27) - Balanced and strong combination of project team (F30) - The use of project risk management (F45)
D4	Organizational	Senior manager's commitment and support (F4) - Organization's ability to provide sufficient resources (F11) - Interaction and collaboration between business and information technology units (F17) - Culture of continuous process improvement (F18) - Engineering culture of decision making process (F19) - Culture of using information and analytics (F20) - Senior managers' risk taking in modern technologies investment (F39)
D5	Data quality	Strong and suitable framework for data governance and quality (F7) Quality and reliability of data resources (F24) - The precision, accuracy, and perfectness of data (F35) - Quality of data extract, transformation, and loading process (F40) - Data integrity and consistency of data sources (F44)
D6	Environmental	Laws and regulations related to business requirements and limitations (F23) - Using outside consultants (F28) - Interaction with vendors and choosing suitable suppliers (F29) - Level of competition setting in business (F31)
D7	Human	User training (F8) - Project leader and championship to lead and facilitate participation (F10) - Involvement of end users (F16) - skills of information technology, business and analytical (F32)
D8	System ability	The flexibility and speed of response to changes in the business intelligence system (F6) - Integration capability of business intelligence system (F12) - Analysis capability of business intelligence system (F13) - Level of security in the business intelligence system (F42)
D9	Service quality	Quality of access to information (F33) - Quality of information content (F34) - User friendly and easy learning of business intelligence tools (F36) - Precision of information at system output (F37)

Table 11 Expert opinion means on the rates of agreement in the classification of factors affecting implementation of business intelligence in the fourth round of the opinion poll.

Dimensions and factors (D, F)		Triangular fuzzy mean (m, α, β)			Dimensions and factors (D, F)		Triangular fuzzy mean (m, α, β)			Dimensions and factors (D, F)		Triangular fuzzy mean (m, α, β)		
D	F	m	α	β	D	F	m	α	β	D	F	m	α	β
D1	F1	0.78	0.20	0.12	D4	F17	0.73	0.19	0.15	D6	F31	0.73	0.21	0.14
	F26	0.73	0.19	0.15		F18	0.75	0.20	0.14	D7	F8	0.77	0.19	0.13
	F41	0.75	0.20	0.14		F19	0.75	0.20	0.14		F10	0.73	0.22	0.14
	F43	0.72	0.20	0.15		F20	0.78	0.19	0.13		F16	0.77	0.18	0.13
D2	F2	0.77	0.21	0.13		F39	0.73	0.21	0.14		F32	0.78	0.20	0.12
	F22	0.77	0.19	0.13	D5	F7	0.72	0.20	0.15	D8	F6	0.77	0.18	0.13
	F47	0.81	0.19	0.11		F24	0.77	0.18	0.13		F12	0.77	0.18	0.13
D3	F3	0.77	0.19	0.13		F35	0.80	0.18	0.12		F13	0.77	0.19	0.13
	F27	0.71	0.20	0.14		F40	0.78	0.21	0.12		F42	0.73	0.19	0.15
	F30	0.73	0.21	0.14		F44	0.73	0.18	0.15	D9	F33	0.77	0.21	0.13
	F45	0.72	0.20	0.15	D6	F23	0.77	0.21	0.13		F34	0.80	0.19	0.12
D4	F4	0.75	0.20	0.14		F28	0.73	0.21	0.14		F36	0.77	0.21	0.13
	F10	0.77	0.19	0.13		F29	0.72	0.19	0.16		F37	0.80	0.18	0.12

Table 12 Expert opinion mean based on the rate of agreement on the classification of factors affecting implementation of business intelligence in the fifth round of the opinion poll.

Dimensions and factors (D, F)		Triangular fuzzy mean (m, α, β)			Dimensions and factors (D, F)		Triangular fuzzy mean (m, α, β)			Dimensions and factors (D, F)		Triangular fuzzy mean (m, α, β)		
D	F	m	α	β	D	F	m	α	β	D	F	m	α	β
D1	F1	0.83	0.18	0.10	D4	F17	0.77	0.17	0.14	D6	F31	0.75	0.18	0.14
	F26	0.78	0.16	0.13		F18	0.78	0.18	0.13	D7	F8	0.78	0.18	0.13
	F41	0.80	0.17	0.12		F19	0.77	0.17	0.14		F10	0.77	0.18	0.13
	F43	0.80	0.17	0.12		F20	0.81	0.18	0.11		F16	0.78	0.16	0.13
D2	F2	0.80	0.17	0.12		F39	0.77	0.18	0.13		F32	0.81	0.19	0.11
	F22	0.80	0.17	0.12	D5	F7	0.78	0.18	0.13	D8	F6	0.78	0.16	0.13
	F47	0.86	0.19	0.08		F24	0.80	0.17	0.12		F12	0.78	0.16	0.13
D3	F3	0.81	0.18	0.11		F35	0.84	0.19	0.09		F13	0.78	0.18	0.13
	F27	0.76	0.17	0.12		F40	0.83	0.19	0.10		F42	0.75	0.16	0.15
	F30	0.78	0.16	0.13		F44	0.77	0.16	0.14	D9	F33	0.78	0.19	0.13
	F45	0.75	0.16	0.15	D6	F23	0.81	0.19	0.11		F34	0.83	0.18	0.10
D4	F4	0.78	0.18	0.13		F28	0.77	0.18	0.13		F36	0.80	0.18	0.12
	F10	0.81	0.18	0.11		F29	0.75	0.16	0.15		F37	0.81	0.17	0.11

Table 13 Expert difference of opinions based on the rate of agreement on the classification of factors affecting the implementation of business intelligence in the fourth and fifth rounds of the opinion poll.

Dimensions and factors (D, F)		mean defuzzificated opinion		difference of opinions rate	Dimensions and factors (D, F)		mean defuzzificated opinion		difference of opinions rate	Dimensions and factors (D, F)		mean defuzzificated opinion		difference of opinions rate
D	F	χ_4	χ_5	$\chi_5 - \chi_4$	D	F	χ_4	χ_5	$\chi_5 - \chi_4$	D	F	χ_4	χ_5	$\chi_5 - \chi_4$
D1	F1	0.76	0.81	0.05	D4	F17	0.72	0.76	0.04	D6	F31	0.72	0.74	0.02
	F26	0.72	0.77	0.05		F18	0.73	0.77	0.04	D7	F8	0.75	0.77	0.02
	F41	0.73	0.79	0.05		F19	0.73	0.76	0.02		F10	0.71	0.75	0.04
	F43	0.71	0.79	0.08		F20	0.77	0.80	0.03		F16	0.75	0.77	0.02
D2	F2	0.75	0.79	0.04		F39	0.72	0.75	0.04		F32	0.76	0.79	0.03
	F22	0.75	0.79	0.04	D5	F7	0.71	0.77	0.06	D8	F6	0.75	0.77	0.02
	F47	0.79	0.83	0.04		F24	0.75	0.79	0.03		F12	0.75	0.77	0.02
D3	F3	0.75	0.80	0.05		F35	0.78	0.82	0.04		F13	0.75	0.77	0.02
	F27	0.70	0.75	0.05		F40	0.76	0.80	0.05		F42	0.72	0.75	0.02
	F30	0.72	0.77	0.05		F44	0.73	0.76	0.04	D9	F33	0.75	0.77	0.02
	F45	0.71	0.75	0.04	D6	F23	0.75	0.79	0.05		F34	0.78	0.81	0.03
D4	F4	0.73	0.77	0.04		F28	0.72	0.75	0.04		F36	0.75	0.78	0.04
	F10	0.75	0.80	0.05		F29	0.71	0.75	0.04		F37	0.78	0.80	0.02

4. DATA AND FINDINGS ANALYSIS

As stated in the previous section, researchers have examined and reviewed the research literature related to factors affecting the implementation process of business intelligence. The results of these reviews, according to Table 1, were the identification of 37 factors affecting the implementation process. Using this initial framework of factors and running five rounds of fuzzy Delphi, key factors affecting implementation processes of business intelligence in the Iranian banking industry were identified and classified. A summary of the results from running several rounds of the Delphi technique is presented as follows. In the first round of the Delphi technique, experts commented on the significance rate of factors affecting implementation processes of business intelligence in the Iranian banking industry. Using Table 3 and equations (2) and (3), fuzzy mean experts' opinions in the first round (m, α, β) are presented in Table 4. Also, experts were asked to comment on other significant factors affecting the implementation process of business intelligence in the banking industry of Iran. Thus, based on the experts' opinions, 10 new factors affecting the implementation process of business intelligence were proposed, as shown in Table 5.

In the second round, in addition to reflecting

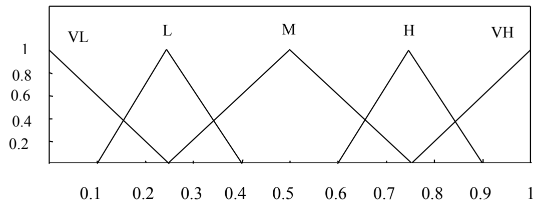

Figure 2 Verbal variable definition (Fuzzy triangular number).

the results of the first round of expert opinions, given the results of first round, they were asked to present new and corrective opinions on the significance rate of factors in the first round and give their proposed factors. Using Table 3 and equations (2) and (3), the expert opinion fuzzy mean (m, α, β) in the second round is shown in Table 6. Also, using equation (1), the expert opinion defuzzification mean in the first round (χ_1) and second round (χ_2) and expert difference of opinions ($\chi_2 - \chi_1$) in the first and second rounds on the significance of factors affecting implementation of business intelligence are shown in Table 7. Given the results shown in Table 7, regarding 26 factors affecting implementation of business intelligence from Table 1 including rows 1- 6, 10-15, 17, 19-22, 24, 25, 30, and 32-37 there was a consensus due to the mean difference of opinions ($\chi_2 - \chi_1$) lower than 0.1, so that factors in rows 5,14,15, 21,and 25 are rejected due to their final mean (χ_2) lower than 0.75 while other factors were significant and approved.

In the third round of the fuzzy Delphi technique opinion poll, experts were informed of the first and second rounds' opinion results and given the results of the previous rounds new and corrective opinions of experts on the significance rate of 21 remaining factors were obtained. Using Table 3 and equations (2) and (3), the expert opinions fuzzy mean (m, α, β) in the third round is presented in Table 8. Also, using equation (1), Table 9 shows the defuzzificated mean of expert opinions in the second round (χ_2) and third round (χ3) as well as experts difference of opinions ($\chi_3 - \chi_2$) on the significance of factors affecting implementation of business intelligence in the second and third rounds. Given the results in Table 9 on the remaining factors, consensus was reached due to the mean difference ($\chi_3 - \chi_2$) lower than 0.1 so that the three factors in rows 9, 38, and 46 were rejected due to their final mean (χ_3) which was lower than 0.75, while other factors were identified as significant key factors. In general, based on the opinion poll in rounds 1, 2, and 3, a total of 39 key factors affecting implementation of business intelligence were approved by experts and 8 factors were considered to be less significant.

Based on results of experts opinions in rounds 1, 2 and 3, 39 significant key factors affecting implementation of business intelligence were approved by consensus. First, these factors were classified in 9 groups as shown in Table 10 based on research literature, opinions of university professors, concept similarity and their role in implementation of business intelligence, then they were presented as proposed aspects for the experts' final opinion poll. It is to be noted that without going through this round it couldn't be claimed that a reliable and integrated list is prepared (Schmidt 1997). Thus, in the fourth round of the Delphi poll, experts were asked to give their opinions on the rate of agreement on this type of classification. Using Table 3 and equations (2) and (3), the fuzzy opinion mean (m, α, β) of experts in the fourth round is presented in Table 11.

In the fifth round of the Delphi technique, in addition to reflecting the result of the fourth round to experts, given the result of the previous round on classification of key factors affecting implementation process of business intelligence, they were asked to give their corrective opinions on the agreement rate with this classification again. Using Table 3 and equations (2) and (3), the expert fuzzy opinion mean (m, α, β) in the fifth round is presented in Table 12. Also using equation (1), Table 13 shows the defuzzificated mean expert opinions in the fourth round (χ_4) and fifth round (χ_5) and expert difference of opinions (χ_5- χ_4) in the fourth and fifth rounds on the rate of agreement on classification of key factors affecting implementation of business intelligence. Given the results of Table 13, experts reached consensus on the proposed classification of key factors due to a mean difference of opinions ($\chi_5 - \chi_4$) lower than 0.1 and this proposed classification was approved as the experts' final opinion mean (χ_5) was not lower than 0.75.

Therefore, it can be concluded that significant factors affecting the effective implementation of business intelligence in the Iranian banking industry includes 9 dimensions: organizational, human, data quality, environmental, system ability, strategic, service quality, technical infrastructure and managerial, as shown in Figure 3.

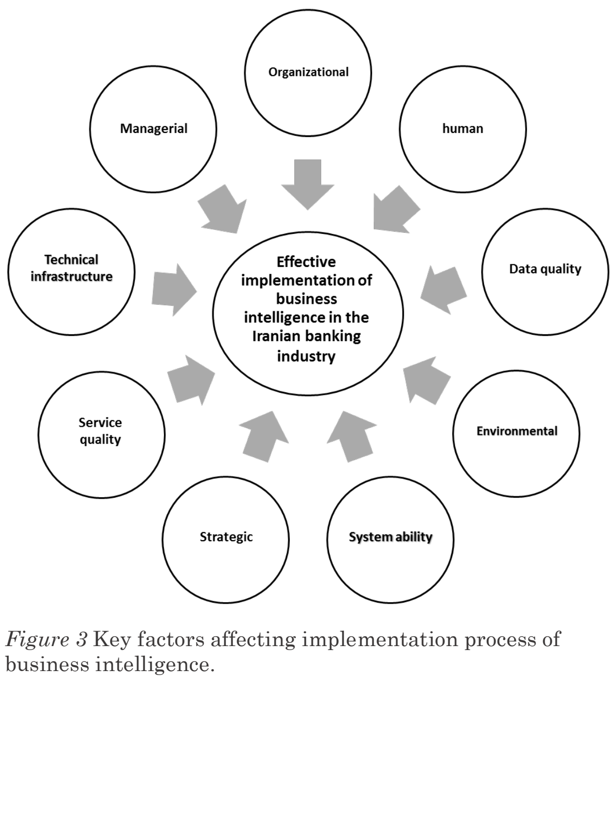

Figure 3 Key factors affecting implementation process of business intelligence.

5. CONCLUSION AND PROPOSALS

Organizations are often faced with problems such as data congestion and redundancy, insufficient information and knowledge and low quality of needed reports. Thus, for timely decision making in the minimum time by senior management, decisions are usually made based on their experiences, which in turn leads to increased risk of decision making or even decreased output of their decision making. Business intelligence is a tool to be used by organizations to collect and analyze structured and unstructured data and information, and is a suitable response to the aforementioned challenges. Though many organizations have turned to developing and using business intelligence systems, not all have been successful in their implementation. Thus, it is very important to examine the reasons for failure in implementing business intelligence projects and identify factors affecting their implementation. The aim of the present study is to identify key factors affecting implementation of business intelligence in the Iranian banking industry. Thus, in this study, by running five rounds of the fuzzy Delphi technique, among 37 factors affecting the implementation process of business intelligence in the past studies as well as 10 factors proposed by experts, finally 39 factors were identified and approved as significant. Also, the 39 factors were classified in 9 main groups, as shown in Table 10. In fact, it can be concluded that the significant factors affecting the effective implementation of business intelligence in the Iranian banking industry include 9 dimensions: organizational, human, data quality, environmental, system ability, strategic, service quality, technical infrastructure and managerial, as shown in Figure 3. Accordingly, managers and executives of implimentation projects of business intelligence in the Iranian banking industry can achieve the intended results and objectives by considering these important factors in planning and actions taken for the efficient implementation of business intelligence. Achievements of this study not only can help banks to successfully implement business intelligence systems but also help researchers in conducting future research in this field. For future research and study of how each key factor affects the efficient implementation of business intelligence systems during different phases of project implementation and to examine the rate of these factors' effects and interrelationship between them, the authors propose a cognitive mapping methodology, case studies and an interpretive structural modeling approach.

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A Bayesian approach to developing a strategic early warning system for the French milk market

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ABSTRACT A new approach is provided in our paper for creating a strategic early warning system allowing the estimation of the future state of the milk market as scenarios. This is in line with the recent call from the EU commission for tools that help to better address such a highly volatile market. We applied different multivariate time series regression and Bayesian networks on a pre-determined map of relations between macro-economic indicators. The evaluation of our findings with root mean square error (RMSE) performance score enhances the robustness of the prediction model constructed. Our model could be used by competitive intelligence teams to obtain sharper scenarios, leading companies and public organisations to better anticipate market changes and make more robust decisions.

KEYWORDS Bayesian networks, competitive intelligence, forecasting, milk market, strategic early warning system

1. INTRODUCTION

As globalisation, deregulation and the Big Data phenomenon (Bendler et al., 2014) are rendering our economy gradually more complex and uncertain, the interest in competitive intelligence (CI) is growing (Bisson, 2014; Hugues, 2017). Calof and Skinner (1998, p.38) define CI as "the art and science of preparing companies for the future by way of a systematic knowledge management process. It is creating knowledge from openly available information by use of a systematic process involving planning, collection, analysis, communication and management, which results in decision-maker action."

However, Day and Schoemaker (2008) report that only 23% of CEOs use scanning, which is the upstream part of CI allowing the transfer of information from the environment to the organisation (see for example Bisson, 2013). By using scanning, managers detect most of the time weak signals (thereby allowing to anticipate) through using their intuition (Cahen, 2010) and too often decisions are made on the basis of heuristics (Bisson et al., 2012). Therefore, in order to address challenges such as Big Data, highly volatile and uncertain environments, an era where anticipation is more important and more difficult than ever, "traditional" CI systems based on scanning appear to be limited (Accenture, 2013; Gilad, 2008). When trying to overcome these limitations and strengthen strategic planning and governance, the importance of strategic early warning systems (SEWS) has been raised (Fuld, 2010). SEWS can help decision-makers anticipate market changes, and allow organisations to have a strategy that fits the market reality and avoid industry dissonance. SEWS integrate scenario techniques which aim to "create alternative 'pictures' of the future and to challenge mental models" (Schwarz, 2005). The general framework of SEWS (Bisson, 2013; Gilad, 2008) for a market is: 1) define the scope, i.e.

the time frame, analysis to be done and participants; 2) determine the drivers of change; 3) generate scenarios; 4) explore strategic implications, options and decisions; and 5) implement the system by watching the drivers of change (through scanning), which could lead to the appearance of a pre-determined scenario, then launch an alert to anticipate either a threat or opportunity. SEWS requires updates to maintain its performances as inputs might change with time (Bisson et al., 2012). These updates regarding variables as well as other data/information must be provided by the competitive intelligence team. Our research focuses on the first three steps of the framework as we do not intend to implement it here. Although several qualitative methods of SEWS were developed which demonstrated their importance for governance (Gilad, 2003), there is room for improvements for SEWS based on quantitative methods (Fuld, 2010). Thus, we aim to address this scientific gap by applying for the first time different multivariate time series regressions and Bayesian networks following the three first steps of the general frame of SEWS to predict the impacting scenario(s) that would help to be better prepared for the future. For our experiment, we chose the milk sector in France in line with the call from the EU Commission (European Commission, 2010) for more robust tools to better predict the milk price and anticipate changes in this market. Indeed, the milk price is highly volatile. For instance, French farmers' incomes can vary by over one third from one year to the next (Momagri, 2012). For example, a 1% or 2% discrepancy between supply and demand can trigger a variation of 50% to 100% change in income (Momagri, 2012). Yet, the European Union's milk market is currently in crisis as the new Common Agricultural Policy, which went into effect in 2015, ended quotas for milk (Robert, 2015). Moreover, quotas will eventually end for other products as well (e.g. sugar in 2017).

The remainder of our paper is organised as follows: we first present the necessary theoretical background and provide an outline of the approaches used in the quantitative analysis of time series data. Next, we build the Bayesian model, apply it to our data, and we discuss the results obtained through Bayesian analysis. We conclude with comments on limitations and future research to be undertaken.

2. THEORETICAL BACKGROUND

2.1 Strategic Early Warning Systems

Although the development of SEWS is common among international companies, such as Shell (Gilad, 2003), the experiments and their details are rarely disclosed. Indeed, SEWS are central to governance, and their implementation can result in a competitive advantage synonymous to market share and profit increases (Bisson, 2013). SEWS can help to anticipate rather than react, and to detect strategic opportunities and risks (Gilad, 2003), reduce cognitive bias and intuition in the decision process, and allow for more effective contingency plans. Several types of SEWS have already been used, particularly in industry. SEWS are nowadays deemed to be compulsory for private organisations to survive and/or thrive (Fuld, 2010; Gilad, 2008). It can be argued that public organisations are also facing growing international competition, compelling them to most efficiently utilise tax funds. As a result, public organisations would benefit from implementing SEWS as well (Bisson et al., 2012) as demonstrated by the steel sector in the North American region of Pittsburgh (2008). Companies were closing one after another in 2008 (e.g. Seagate), due to the worst financial and economic crisis since 1929, and the sharp decline of the American automotive industry:

> *"the Steel Valley Authority (SVA) is an inter-municipal economic development agency incorporated by the City of Pittsburgh and eleven riverfront municipalities all within the Mon River region. The SVA has been managing industrial retention for the Commonwealth of Pennsylvania. The Authority, through a Strategic Early Warning Network (SEWN), has made significant contributions to the retention and revival of industrial enterprises, has saved and created nearly 8,000 jobs, and has impacted many more workers and communities indirectly. The SEWN Network has saved companies from Pittsburgh to Erie to Altoona, and has become a model state and nation-wide" (www.steelvalley.org).*

Thus, a SEWS that is well developed and implemented can help private and public organisations succeed by allowing them to make better and faster strategic decisions in comparison to their competitors.

2.2 Time Series Forecasting

Financial time-series forecasting is considered to be one of the most difficult challenges of modern time-series forecasting. As explained by Abu-Mostafa and Atiya (1996), financial time-series data is usually noisy, non-stationary and deterministically chaotic. The term “noise” here actually represents the unavailability of data to capture the complex and non-linear relationships between market variables from past data. The non-stationary nature of data arises from the fact that the structure of relations between variables tends to change over time. The data is said to be chaotic because it usually behaves randomly in the short-term. However, under the assumption that there is a deterministic component in the long-term financial time-series data, we proceed to analyse and build a forecasting system, where the parameters are learned from the past data. The accuracy of time-series forecasting methods plays a crucial role in the economic and social benefits of competitive intelligence systems (Bisson, 2013). For building accurate forecasting systems, there are two main methodologies employed by researchers, namely, neural networks and support vector machines. Each of these methodologies has advantages and weaknesses, as explained below. The area of time-series forecasting is influenced by linear models such as autoregressive integrated moving average (ARIMA) and non-linear models such as the threshold autoregressive model, the bilinear model and the autoregressive heteroscedastic (ARCH) models (Engle, 1982). The linear ARIMA model, however, is clearly shown to be too weak to adopt in real-life scenarios (De Gooijer and Hyndman, 2006). Given that the traditional statistical forecasting methods lack the power of explaining the underlying structure, attention has been drawn to machine learning models, especially in the last two decades (Ahmed et al., 2010). Machine learning models are also called “data-driven”, or “black-box” models due to their nonparametric and nonlinear operation, which only requires the past data to learn the structure, and therefore perform future forecasting. For instance, artificial neural networks (ANNs) are shown to outperform their traditional opponents (such as linear regression) in the task of market forecasting (Lapedes and Farber, 1987; Werbos, 1988). Following ANNs, other machine learning models such as decision trees, nearest-neighbour regression and support vector machines emerged for the task of future value forecasting (Alpaydin, 2010). Support vector machines are still widely used for classification and pattern recognition tasks, and they are shown to be a desirable alternative for classical learning methods for the task of time-series forecasting (Muller et al., 1997).

Statistical methods to analyse the structure and/or predict the future of the milk market have been implemented using a variety of methods in the previous works in the field.

Reed (1992) studied the structure of the market by optimising the parameters of different equations that are used to estimate the supply response from changes in demand and producer expectations. Another work by Saravanakumar and Jain (2009) proposes an econometric approach for determining the price of milk based on other variables of the market such as technology and input costs, by analysing the individual households of a local market.

Other research addresses the issue of better prediction for the milk market by using statistical learning methods. One example was done regarding the estimation of the entry and exit conditions to the milk market, based on quota and other policies regarding this market, by using the discrete variable of farm size in relation to other variables in a Markov chain analysis (Rahelizatovo and Gillespie, 1999). Markov chains are also employed in a recent work that studies the effect of trade quotas on milk, analysing the dairy sectors of Germany and Netherlands, again using categorical variables such as discretized milk production and firm size (Huettel and Jongeneel, 2008).

More than a decade ago, a research project funded by the European Commission resulted in the development of an economic model called Common Agricultural Policy Regional Impact (CAPRI), and aimed to deal with the complexity induced by the CAP reform in 1992 (Heckelei and Britz, 2000). A study based on CAPRI analysed the effect of removing milk quotas, and it obtained a prediction that the milk price would drop with respect to a reference scenario (Jansson and Britz, 2002). Another framework developed by the Food and Agricultural Policy Research Institute (FAPRI) examined and projected several variables related to agricultural markets. A study that utilised this framework to analyse the effect of removing milk quotas in the industry of the UK and the EU predicted a significant fall in milk

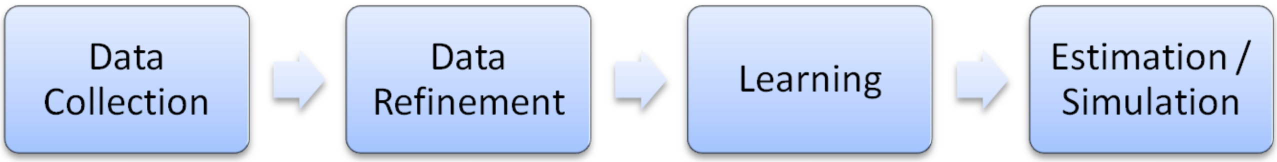

Figure 1 System pipeline.

prices, as well as a recess in the expansion of milk production by 2016 (Patton et al., 2008).

2.3 Bayesian Networks

Bayesian networks are data structures that represent the relations between multiple parameters of a system. Bayesian networks, sometimes termed belief networks, causal networks or influence diagrams, are probability distributions factorised over a Directed Acyclic Graph (DAG). Although Bayesian networks were first introduced in the literature by Wright in 1921 to analyse the failures in crops, they are still widely used in dealing with uncertainty in knowledge based systems. Bayesian networks, as structure learning tools, are usually constructed with directed acyclic graphs where the leaf nodes are the observed variables and the lower-order nodes are the hidden (or cause) variables. Most of the time, the set of relations between the variables are given a priori. An example by Kiiveri, et al. (1984) analyses causal relations using a probability distribution factorised over a DAG. There are also variants of Bayesian networks to analyse dynamic systems such as Hidden Markov Models (HMMs) (Durbin, 1998) and Dynamic Bayesian networks, as introduced by Murphy (2002).

Although we analyse a more complicated graph structure representing the relations of the major variables of our market, we also construct a DAG in order to represent a subset of variables, which have available time series data, by establishing the strength of relations using an expert evaluation, and we further investigate the data using this Bayesian network to get future value estimations, as described in Section 3.3.

3. METHODOLOGY

In this section, we apply Bayesian analysis in order to estimate and evaluate future scenarios for the milk market. Next we discretise the data and use the K-means clustering algorithm to classify the data in terms of amounts of change. This is followed by obtaining the prior probabilities needed to construct the Bayesian model. Finally, we evaluate the performance of our forecasting system and measure the probability for each scenario. To establish a broader understanding, we present our work in

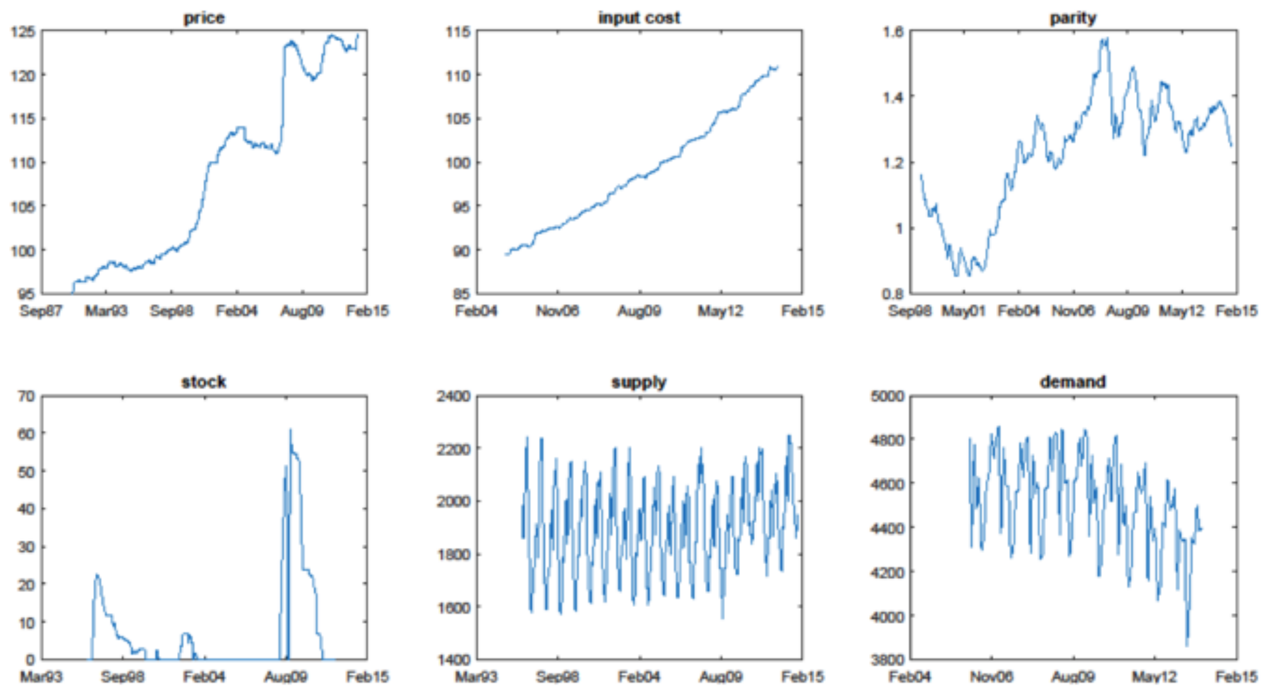

Figure 2 Raw data.

the form of a work flow diagram, as shown in Figure 1.

3.1 Data

A questionnaire was first sent to a French milk expert (we were asked to keep his/her name confidential) to obtain all the drivers of change of the milk price which are macro-economic indicators. Thereafter, we started the quantitative analysis by collecting time series data for various price change drivers related to milk, which are world milk demand and production, the consumer price index for milk-related products, livestock and input costs (e.g. energy). We collected time series data for the period from January 1990 to February 2015, and normalised each time series vector by mapping its values between 0 and 1. Annotating the time t = 0 at the beginning of our observations, we have T = 319 time points where observations are recorded (see Figure 2). The time series data can be found at the website of INSEE (the French Public Official Statistic Organisation), an example data link is in the National Institute of Statistics and Economic Studies (2015). We also visualised the data and the autocorrelation function in Figures 3 and Figure 4, respectively.

Since the time series data for various indicators mentioned above came from different sources, some of them were measured in different units of time, such as monthly, quarterly and yearly. Therefore, to establish a consistent data set, we used linear interpolation and extrapolation to convert all the time series to monthly-observed variables. In order to impute the missing samples, we used least-squares approximation from applicable input variables, and thereby obtained the best linear unbiased estimation for the missing samples.

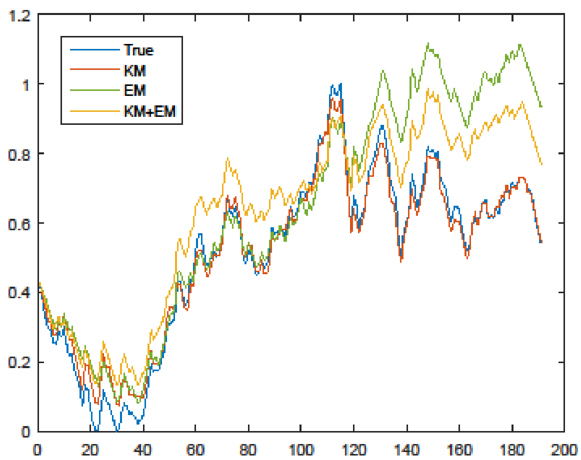

Figure 3 Reconstruction with different algorithms. KM: K-Means clustering, EM: expectation maximization.

3.2 Clustering

Next, we simplified the learning problem by converting the time series signals to discrete classes, then any given signal x is transformed to f(x)=x_d. In the new form x_d, every element x_{di} could have a value between 1 and V , where V is the number of states. So, intuitively, the values of x_d represent changes in the data (1: Big drop, 2: Smaller drop , ... V: Big rise). In Figure 4, we show that a higher number of cluster centres reduce the reconstruction error, however this means increasing the complexity of the classification system.

Therefore, to avoid overfitting and to be consistent with the 5-point Likert scale, we chose to set V =5 in our experiments. In order to find a reasonable set of changes, we used a K-means clustering algorithm which performs vector quantisation by finding optimal sets of clusters, and assigned each member of the vector to a cluster centre (MacQueen, 1967). We used the VL Feat library (Vedaldi et al., 2008) for the parallelised K-means implementation, which uses Lloyd's algorithm (Lloyd, 1982) and L2 distance measure for optimisation. We started with a random initialization, repeated the clustering 10 times and chose the solution that gives the minimum energy. We found that K-means clustering provided better classification and forecasting accuracy than expectation maximization clustering.

In our application, we converted the signal to a format x_c where this represents changes in the data such that: $x_{ci} = xi - x_i - 1$. We applied clustering on this change vector x_c , to find the V most observed change values in the samples, and assigning each sample to one of the V cluster centers, we obtained the discrete vector x_d as defined above.

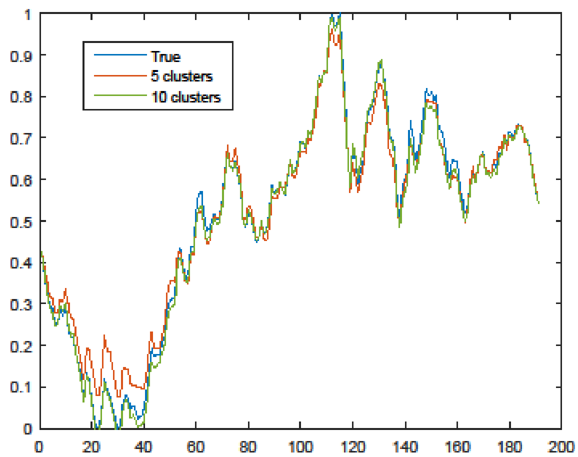

Figure 4 Reconstruction with K-means algorithm and different number of clusters. KM: K-Means clustering, EM: expectation maximization.

3.3 Bayesian Analysis

Since our aim is to estimate the future values of dependent variables, we first needed to obtain prior probabilities to feed our Bayesian decision system. To this end, we used two different probability definitions, which can then be combined in a single set of matrices. Two different probability estimations are explained below. We started by finding the probability distributions of single variables over different time lags. In other words, we constructed probability distribution function (PDF) tables to establish the prior probability of observing variable i having the value $k1 \in$ [1: V] when observed that it has the value $k2 \in$ [1: V], on time $(t - lag)$. Thus, we established a seasonal model where we have an estimation of probabilities of observing a single variable.

After normalisation, this yields a (VxV) PDF table T. Where $T_{t,l,i} = p(x_t \backslash x_{t-1})$, in other words the probability of observing $x = j$ when we know that $x = i$ [lag] periods before. Similar to the intra-variable approach, we construct prior probabilities which represent the effect of indicator variables on the dependent variables over different time lags, more formally $p(y_t\text{-} \mid x_{1,(t-1)}, x_{2,(t-1)}, \ldots, x_{Iy,(t-1)})$. Finally, we obtained a set of $V{-}by{-}V$ probability distribution matrices from the collected set of data. For the representation of PDFs, assuming that each variable depends on each other (a complete graph), we have a data structure of size $N^2 byV^2$ where N is the number of variables in the model, and V is the number of classes. We compute the prior probabilities as described above, and use the posteriors to forecast the time series vectors and evaluate scenarios, which will be described next.

Having collected all the data and the prior probability distributions, we used our system for simulation, to determine the probability of a scenario happening T_f time periods after the last observation. Therefore in our case, a scenario S is simply represented as an N by 1 vector where each member Si represents the numerical value of variable i, at the time period designated by $T + T_f$. Since we cannot measure the accuracy of our system's prediction with a large T_f value, we make validation tests with forward chaining, as we explain next.

3.4 Performance Evaluation

In order to measure the accuracy of our forecasting system, we ran validation tests using the forward chaining strategy, which means for each data point, we use the previous observations to construct our model, and measure the out of sample RMSE of the prediction on the point of interest. We use all five variables as explanatory variables and price of milk as the output. Averaging the results over all folds, the classification accuracy was 80.94% and the average RMSE was 0.0189. We also provide the performance with each input variable in Table 1. Here we keep the autoregressive component and compare the contributions of each explanatory variable. Therefore, the first row corresponds to estimation with only previous values of price.

Table 1 Forward chaining estimation accuracy of price with different input variables.

Input	Accuracy (%)	RMSE
Price	67.14	0.0229
Input Price	67.28	0.0227
USD/EUR Parity	67.58	0.0238
Livestock	**68.67**	**0.0219**
Production	64.71	0.0271
Demand	65.10	0.0249

3.5 Scenario Assessment

Using the prior probabilities explained in Section 2, we used Bayes' decision theorem to forecast the future values of our time-series signals. We represented our system's state by N discrete time-series signals of length T, hence a *T-by-N* matrix. We fed this matrix into our simulation code and we obtained a new scenario of size *(T +1) x N*. The process is repeated until we reach time T_f, and converting the discrete signals back to the numerical values, we estimated the final values of variables. To analyse the probability of scenarios, we repeated this process many times, hence we obtained a probability distribution function for the scenario at time T_f.

3.6 Simulation

Since our aim was to obtain a probability density function for the final values of the variables, we ran 1,000 simulations to forecast the values of the discrete time series vectors, and converting them back to continuous signals, we obtained one final value per parameter for each turn. Collecting all the final

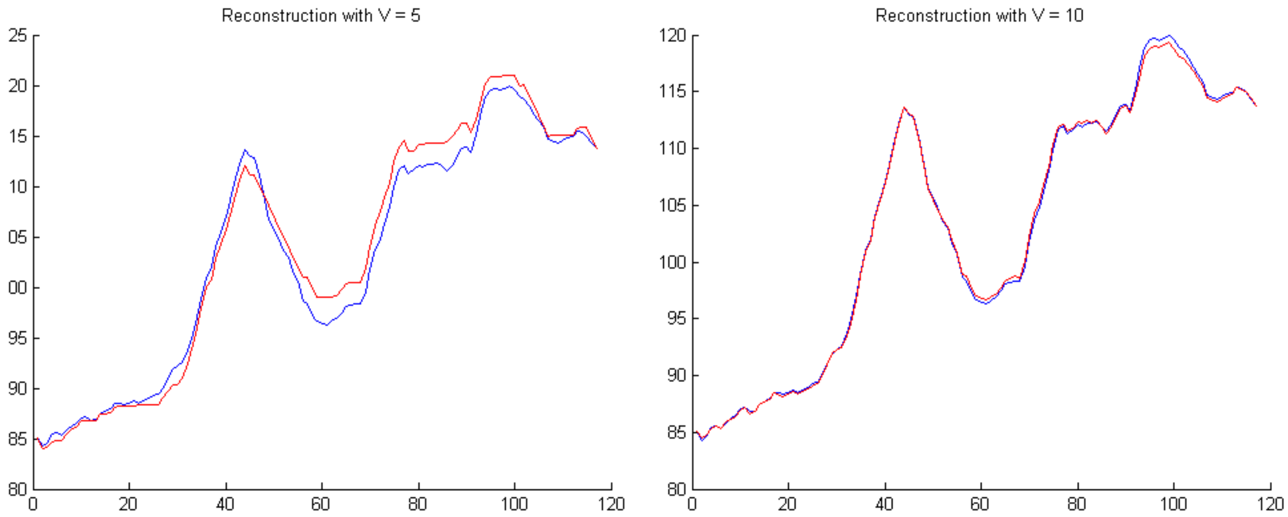

Figure 5 Reconstruction with: (a) 5 and (b) 10 cluster centres.

values, we obtained a data distribution. By fitting a normal distribution on this data, we obtain a probability for a given scenario.

4. RESULTS AND DISCUSSION

To evaluate the accuracy of our framework, we ran some tests on different parts of the machine learning system, and we report performance scores in the following.

4.1 Signal Reconstruction Accuracy

Here, we analyse the accuracy of our signal conversion system. As explained above, we convert our time series data into discrete values. Hence we need to reconstruct the signal back to a "continuous" time-series form, which inevitably causes information loss. Intuitively, increasing the number of cluster centres, k, in K-means clustering should decrease the reconstruction error. Here, we present a chart for a sample signal (namely the USD/EUR parity) which shows the relationship between the number of cluster centres and the Root Mean Square Error (RMSE) for signal reconstruction, in Figure 5 (an example signal reconstruction for 5 and 10 cluster centres are shown).

As expected, the reconstructed signal converged to the original one as the number of cluster centres increases. As is shown, there might still be room for improvement, but increasing the number of cluster centres is equivalent to increasing the complexity of the learning algorithm, and with a fixed amount of data, a high number of cluster centres might lead to over-learning. In order to evaluate the accuracy of our prediction system, we again used the RMSE error measure, with a performance test similar to a machine learning application. In this test, we used the parameter $\tau \in [0, 1]$ which is the ratio of training set size to the data set size D. In other words, we used the first τD number of observations for the learning (see Section 3.3), and we ran a simulation for the remaining $(1 - \tau)$ D unobserved time periods, and thus constructed a scenario which is of size D. After obtaining a large (~10^3) number of scenarios, and taking the mean of them, we estimated the signal S' for the variable of interest. Since we already knew the original signal S, we represented our system's performance with the Root Mean Square Error RMSE*(S,S')*. Below in Table 2 are some results for different variables and different values of τ.

Table 2 Forecast error vs. τ.

	τ : Training Set Ratio					
Variable	**0.3**	**0.5**	**0.7**	**0.8**	**0.9**	**Multiplier**
Price	93.8	49.7	49.4	13.7	3.8	10^{-3}
Livestock	15.4	12.7	4.2	1.9	0.1	10^{2}
Demand	11.1	9.5	11.5	6.6	2.6	10^{0}

4.2 Scenario Probability Evaluation

Finally, we used our framework to estimate the probability of different scenarios relevant to the milk market. Two scenarios were given in terms of milk price, and another one about the milk demand in the European Union (Pole Economie & Prospective Normandie, 2014). We tested these scenarios by propagating the market's state up to the year 2020, with the method explained in Section 3.6. The results for the 3 scenarios are shown in Table 3.

We tested our algorithm with different scenarios for the variables of price and demand. As expected, the likely scenario resulted in a high probability value, whereas the probability of the pessimistic scenario (price decreases by 15 % scenario) resulted in a low probability value. However, the highest probability is for the optimistic scenario. Hence, we observe a difference between the results obtained with the prospective (or foresight) approach (which is purely qualitative and for the long term) and the approaches obtained with our simulation for SEWS.

Table 3 Scenario probabilities.

Scenario	Probability
Optimistic : Price + 15%	43.48 %
Pessimistic : Price - 15%	6.11 %
Most Likely : Demand + 2%	32.9 %

About the milk market, although prices are currently lower compared to before the end of quotas on the first of April 2015, our optimistic scenario might occur in 2020, as after a price drop the market will certainly concentrate and price might increase again.

A competitive intelligence team could use, feed and update this model by entering new variables, new inputs such as new prices and production levels among others and see the most probable scenarios in the coming months and years. Therefore, it would help organisations to be better prepared for the future and lead toward stronger decisions.

5. CONCLUSION

We applied for the first time different multivariate time series regression and Bayesian networks to predict the impacting scenarios which are the heart of SEWS. Our model could inspire competitive intelligence teams in order to seek more accuracy regarding scenarios, leading to better anticipate opportunities and/or threats, and to more robust decisions.

6. LIMITATIONS

Our work models both small and big changes, but to create better scenarios, we need more data for such complex relationships. Experts in the field together with competitive intelligence experts could make further searches to get a stronger understanding of the underlying procedures.

7. FURTHER WORK

Our regression is learned in one shot, so there are no iterations, and therefore there is no correction. Thus, by using machine learning algorithms, we could get automatic corrections and potentially proffer toward better accuracy of scenarios. As such, it could lead to better anticipation and decisions. Furthermore, this technology would help to process more data and dig into "Big Data".

Understanding the strategic needs, guiding through data modelling and interpreting the results is where competitive intelligence specialists will add increasingly great value to companies and public organisations.

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Stevan Dedijer
1911-2004

A business intelligence framework for Sultan Qaboos University: A case study in the Middle East

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ABSTRACT Higher education institutions generate big data, yet they are not exploited to obtain usable information. Making sense of data within organizations becomes the key factor for success in maintaining sustainability within the market and gaining competitive advantages. Business intelligence and analytics addresses the challenges of data visibility and data integrity that helps to shift the big data to provide deep insights into such data. This research aims to build a customized business intelligence (BI) framework for Sultan Qaboos University (SQU). The research starts with assessing the BI maturity of the educational institutions prior to implementation followed by developing a BI prototype to test BI capabilities of performance management in SQU. The prototype has been tested for the key business activity (KBA): teaching and learning at one college of the university. The results show that the aggregation of the different KBAs and KPIs will contribute to the overall SQU performance and will provide better visibility of how SQU as an organization is functioning, which is the key towards the successful implementation of BI within SQU in the future.

KEYWORDS Business intelligence, decision making, key business activity key performance indicator, maturity assessment, performance management

1. INTRODUCTION

The business environment is rapidly changing through different market transitions. These transitions introduce disrupting technologies and new ways of working. At the same time there is a massive growth of data within organizations. Making sense of data within organizations becomes the key factor for success in maintaining sustainability within the market and gaining competitive advantages. One of the major trends disrupting business is the evolution of business intelligence and analytics (BIA). However, business intelligence (BI) is not new as a concept, it has evolved over the past few years in terms of maturity and sophistication (Tapadinhas, 2014) (Sarma & Prasad, 2014). Organizations are facing double challenges when dealing with such trends. From one side, organizations have huge and diverse data sources, yet many of them are not doing much to capitalize on those data and convert them into useful and usable information. From another side, there is a lost opportunity on improving the data integrity and quality for providing better ways for decision makers/stakeholders to make the right decisions. BIA is one of the methods that could be used to address the challenges of data visibility and data integrity that will help to shift the existing data from different resources and hence provide deep insights into the data.

Information management and analytics enable innovation and transformation in how different organizations conduct business. The importance of BIA is distilled from the fact that it is important to provide the right information and the right analysis to make the right decisions. The paradox that many organizations face today is how best to optimize their data, yet many of them often limit BI initiatives to focus on technology selection, neglecting the organizational approaches, processes and best practices necessary for success.

At first glance, one would think that educational institutions would be a prime area to utilize BI. The reason for such a belief is that educational institutions have a lot of data and often lack visibility to the importance of such an asset. There is often a struggle on how to use the data and how best the huge data coming from different sources could be utilized. If educational institutions want to get a competitive advantage from it, there is a need for these institutions to explore an efficient use of data. BI provides the ability to combine data sources in one place to analyze and improve the decision-making process. The success of the BI implementation journey can enhance productivity and improve efficiency. On the other hand, it creates the impression that every implementation will indeed be unique because no two institutions work in the same way. Though BI can be very important, it is still a developing process.

The major objective of this research is to develop a BI framework to be used for educational institutions. The study utilizes Sultan Qaboos University (SQU) as a case study to build this framework. Furthermore, in order to build the framework, there is a need to understand the maturity level of the university initially. Once the maturity level is understood, then the framework can be developed based on the maturity level assessment and the future direction of the university. Although this framework will use SQU as the main case study, it is assumed that this framework can later be used by other educational institutions within Oman (or even outside) to help implementing BI initiatives in their organizations. In addition, the study will also involve building a prototype of how BI can be used as a strategic initiative for SQU.

2. LITERATURE REVIEW

Looking at the evolution of business analytics, there are other areas where BI can be used. For example, it can be used to model business challenges and for using predictive analysis to generate a future prospective (Sherman, 2014). Depending on the business challenges and the business maturity, different organizations use BI in different ways. The main difference between the different methods is how efficient the use of data is. Since data is the main ingredient of any BI analysis, Sherman argues that in order for the BI to provide such benefits, the data has to meet five criteria; it has to be clean, consistent, conformed, current and comprehensive. However, the reality is that not all organizations will have all the above criteria for their data. Thus BI implementation within organizations becomes very challenging and prone to failure (ShaokunFana, Y.K.Laub, & LeonZhaob, 2015).

Traditional BI uses OLAP tools and reporting, which are currently in use today. If such reports exist today, what is so special about using BIA? The simple answer can be evolution. However, the initial enthusiasm about BI was generated from e-commerce by companies such as Amazon, where consumers' data is used to anticipate future purchases. In addition, there are other benefits anticipated from BI. One study (Ramanigopal, Palaniappan, & Mani, 2012) lists the number of key benefits that BI can provide; such as:

- BI can enhance the time to take action by making it shorter,
- BI is used to analyze market trends against the company capabilities and help in making informed decisions,
- BI enhances business agility by improving the communications among departments and enables the company to respond quickly to market changes.

BI provides comprehensive and flexible access to data (Fouche & Langit, 2008). In addition, it provides near real-time access to information, making it easier and faster for decision makers to make decisions. Although the authors (Fouche & Langit, 2008) were referring mostly to Microsoft BI tools, the same benefits can be achieved by other BI tools from other vendors.

At this point, it is important to mention that the value of BI can only be seen when the BI initiative is well integrated within the organization's decision making process (Ramanigopal, Palaniappan, & Mani, 2012). In addition, the choice of technology can also affect the speed of the decision making. The evolution of in-memory computing technologies gave birth to a new breed of what the industry refers to as ‘engineered systems’. These engineered systems provide faster access to the data in near-real time, hence, improving the speed of the decision making (Muntean & Surcel, 2013).

In addition, the importance of BI is very clear from trends in the industry. Gartner classified BI as a top priority for CIOs in the 2015 CIO Agenda. Furthermore, Gartner also classified BI as one of the top 4 technologies for CIOs in the higher education sector making this study very important and relevant to the university.

2.1 Business Intelligence Maturity Models

The benefits of BI that any organization would like to exploit are presented. Nevertheless, in order for organizations to embark on the BI journey, there is a need to assess its current maturity. A business intelligence maturity assessment is required to determine the organization's business needs, its capabilities, and the availability of the information sources (TDWI, 2015) (Chuah & Wong, 2012). The literature provides several maturity assessment models that can be used to assess an organization's readiness for implementing BI.

The Business Information Maturity Model is focused on assessing the BI importance within the organization. It assesses the organization's maturity based on three different criteria: alignment and governance, leverage, and delivery (Rajterič, 2010). The results of the assessment are then divided into 3 different levels with level 3 representing a mature organization. Although this model sounds interesting, it lacks full coverage of the usage of BI and its business value.

Gartner developed a maturity model for BI and performance management (PM). The model assesses an organization's maturity in five levels: unaware, tactical, focused, strategic, and pervasive (Rajterič, 2010). Gartner assesses the level of maturity based on three dimensions: people, processes, and metrics and technology.

Although the Gartner model has a good coverage of the different elements of BI within an organization, there is limited literature available on its reliability. Furthermore, only Gartner (or maybe a special consultancy firm) will be able to help in assessing the maturity level.

Advanced Market Research (AMR) developed a maturity model for BI (Rajterič, 2010). The model consists of 4 stages; reacting, anticipating, collaborating, and orchestrating. AMR was acquired by Gartner in 2009 although this acquisition doesn't necessarily mean that the maturity model can't be used. However, since Gartner has its own maturity model for BI, it is very likely this model will be made redundant.

Another business intelligence maturity model was developed by MIT Sloan Management. The model comprises of 3 maturity stages; aspiration, experienced and transformed and has 6 evaluation dimensions, namely: motive, functional proficiency, business challenges, key obstacles, data management and analytics in action (Gudfinnsson, Strand, & Brendtsson, 2015). This maturity model for BI was tested with 3000 executives from 108 countries and 30 industries mostly in manufacturing (Lavalle, Hopkins, Lesser, Schokely, & Kruschwitz, 2010). Although this model is well established and tested, it is mostly used to evaluate BI maturity in manufacturing. Since this research paper is focused in measuring the BI maturity in educational institutions, this model will not suffice.

The Data Warehouse Institute (TDWI) developed a maturity model for BI (TDWI, 2015). Although this model is primarily focused on the technical aspects of maturity, it is considered to be more practical in assessing any organization maturity for BI. The model has 5 different assessment dimensions: organization, infrastructure, data management, analytics, and governance. There are 5 stages which the organizations go through in their maturity journey namely: infant, child, teenager, adult, and sage (Rajterič, 2010). However, this model was modified later to have different names for the maturity levels. The new model stages are nascent, pre-adoption, early adoption, corporate adoption and mature or visionary (TDWI, 2015). In addition, the model also describes an interesting stage that exists between early adoption and corporate adoption called chasm. The TDWI model describes the chasm as the stage in which the organization must overcome certain obstacles for the transition to the corporate adoption stage. Furthermore, these struggles can be overcome through the use of proper funding, good governance, improved skill sets, and better management of change management.

Due to the TDWI maturity model simplicity, it was decided to use it in this research. Furthermore, the TDWI maturity model has developed 35 questions to help organizations assess their maturity level. Although the questions are general, there is a need to customize them to suite the educational institutions.

2.2 BI in Educational Institutions

Although there are not many articles found in the literature that cover the implementation of BI in educational institution, there are a few that are critically analyzed that have some insight on the use of BI within higher education sectors. One study (Guster & Brown, 2012) discusses the BI system structure that can assist a strategy map for higher education whether achieved or not achieved. This also focused on the linkage between a strategy map and MOLAP system, which reads from different databases and its article makes use of the strategy map to measure how well the performance is done. In addition, there are some challenges regarding how the information got extracted from different data sources such as in the use of the metrics and fine-tuning the data warehouse to calculate the performance. Furthermore, the data modelling took a lot of time and suffered in assessing the data quality.

Aziz & Sarsam (2013) investigate on how a BI system called GLIS influences the decision making process in Uppsala University. The author concludes that GLIS has a big positive impact on the decision making process in Uppsala University. León-Barranco et al. (2014) use an analytical model for analyzing decision making in educational institutions. Although the study covered only two semesters and the authors have selected specific careers, the developed model seems to help in analyzing the data required for making decisions. Randy (2014) carried out a survey on implementing BI in educational institutions and concluded that key performance indicators (KPI) are important for successful implementation of BI in educational institutions.

Zilli (2014) discusses the self-service usage of BI for students. The author developed dimensional modelling utilizing the Excel PowerPivot modelling tool. Although the impact of BI on relative technical efficiency of higher institutions was not assessed in this research, it provided some evidence that PowerPivot can be used as a BI method. The second part of the research focused on undergraduate retention and detection of obstacles to successful graduation. While a self-serving portal will help students, the implementation of the BI and how best to ensure its success could be better covered. Rajterič (2010) proposes an overview of BI maturity models detailing the pros and cons of six maturity models.

2.3 BI Frameworks

The purpose of BI initiatives within many organizations is to create value out of existing data that will provide either improved decision making or give a competitive advantage. Hence, BI frameworks are supposed to provide the basic elements of how organizations should identify direction, standards and best practices required to ensure that BI meets organizational requirements. In addition, the framework will guide the development of the implementation roadmap (Washer, 2007).

In order to develop a BI framework for SQU, it is important to understand the different frameworks available for BI in the literature. Most of the frameworks available in the literature are either technical (Chu, 2013) or specific to develop a BI solution (Ortega, Avila, & Gomez, 2011). Therefore, for the purpose of this research it has been decided to shift our review to the available framework in the industry. Hence, focus has been on two main frameworks that are widely used Gartner's Business Analytics Framework and the Business Intelligence Framework 2020.

Gartner's Business Analytics Framework: This is based on an approach to integrate people, processes and platforms to create an approach to BIA and PM initiatives (Tapadinhas, 2014). The framework was established as early as 2006 but gained more momentum recently due to the organization's increased appetite to invest in BI and analytics.

The center of the framework focuses on three main pillars: people, processes and platform. The 'people' element refers to the human element for producing, consuming or enabling the activities required for successful business analytics. The 'processes' element addresses the different processes used within the business. These processes vary to include decision making processes, analytics processes and information governance processes. The final pillar is the platform which is the technology part of BI. There are three capabilities that the technology needs to provide. Firstly, decision capabilities that will enable organizations to build applications that help to learn and understand the business. Secondly, analytic capabilities, that will develop applications which have predefined data and process workflows, and models for the analysis capabilities. The third capability has to do with information. As organizations create more and more data, the search for such information can be tedious. The solution is to develop an information infrastructure that will unify all these technologies, services and schemas under one umbrella to be used as a source for other capabilities as well.

The bottom of the framework represents information which is the most important ingredient in the BI implementation. Metadata, program management, and business models, strategy and metrics form different layers of how the center is integrating with the rest of what's going on inside the organization. Above all, the true measure of how successful the BI framework is, is the performance it generates for the organization. In other words, BI success should be measured on how well it helps the business achieve its strategic goals.

BI Framework 2020: It is one of the recent approaches to try to create an ecosystem for implementing BI solutions. In this framework, multiple reporting and analysis systems can be used and they are designed to help business people use information to make smarter decisions. The BI team in this framework needs to disseminate standards that govern the use of data. This framework defines four domains of intelligence and maps them to end-user tools, design environments and architectures.

3. RESEARCH METHODOLOGY

3.1 Research Background

There are two schools of thought when educational institutions are embarking on business intelligence initiatives. The first school of thought questions the real need for BI within educational institutions based on the fact that BI initiatives tend to be expensive, time consuming and they don’t deliver the anticipated business results. This school of thought argues that most universities around the world are traditional education institutions and therefore their prime focus should be in providing quality education rather than investing time and resources in BI tools. The second school of thought is the opposite of the first one. It supports the idea of BI and positions it as the main stream to enhance the university both academically and professionally. This school of thought has an assumption that BI brings value to educational institutions in terms of visibility of the university data and increases productivity.

The basis of our research is to support the second school of thought primarily due to the fact that educational institutions need to evolve and innovate. The more insight such educational institutions have into their dark data, the more capable they become to face future challenges. This was evident from the journey that the University of Minnesota and the University of Indiana took to invest in BI tools. Furthermore, BI, if used properly, can provide a competitive advantage for the university over other educational institutions. Although SQU is a government funded university, any improvement made within the university will derive value.

SQU has a huge volume of data. The processing of such data quickly and accurately can improve the decision making process, by making the use of such data more effective and efficient. For example, modeling the student’s grades and subjects can provide the university an advantage in responding quickly to changes in the industry, making the university more agile.

3.2 Research Questions

Based on the above, this research aims to provide answers to the following main research questions:

1. What are the future cases in SQU that use BI?

It is important during the maturity assessment to understand how BI is used currently and how BI will be used in the future. The first part describes the as-is situation while the second part describes the future aspirations of SQU.

2. If an educational institutions want to implement a BI solution, what is the best approach?

From the maturity assessment, it will be clear what the current situation and BI status of SQU is. Educational institutions are different in nature than commercial organizations and therefore it is important to develop the best approach for implementing BI. This will be clear during the development of the BI framework. Once SQU begins to implement the BI framework, it will improve the success rate of the BI implementation.

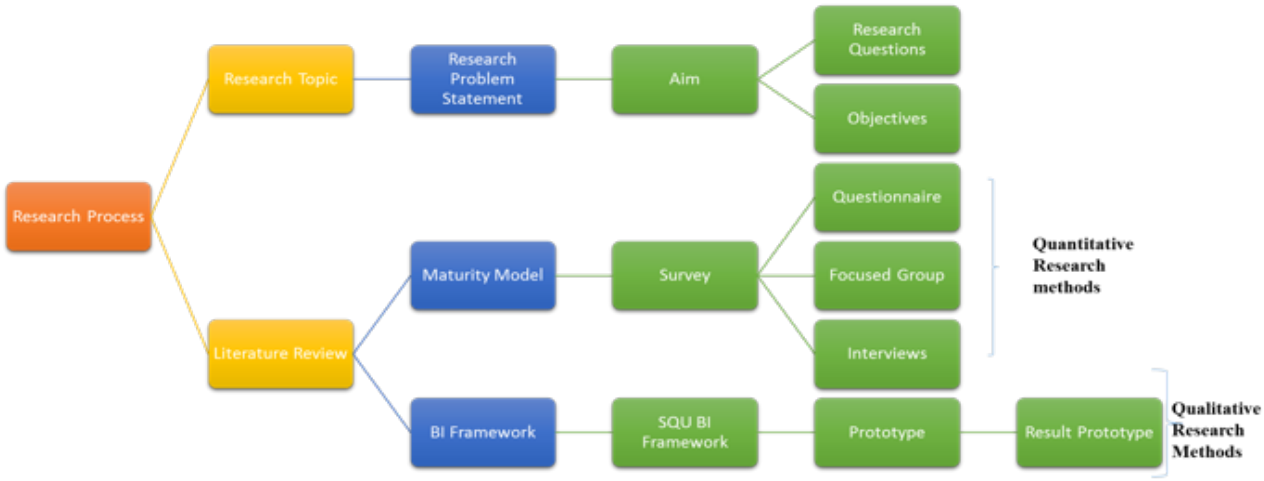

Figure 1 Research methodology.

3. How can BI be used in SQU to address strategic decision making challenges?

As stated in the literature review, the field of BI is wide. Furthermore, BI tools can be used as descriptive, diagnostic, predictive or prescriptive tools. In order to know what's best suited for SQU, a prototype will be developed to demonstrate the value of BI in addressing the strategic decision making challenges.

3.3 Proposed Methodology

The objective of this research is to develop a BI framework to be used for educational institutions. Furthermore, the research will use SQU as a case study to build this framework. In this research, both qualitative and quantitative research methods have been utilized. As can be seen from Figure 1, the research process uses two important approaches. The first approach is the selection of the research topic that followed certain steps starting from identifying the problem statement to identifying the aim and research objectives. The aim is divided into two-sub sections which are the research questions and objectives of the research. From a literature review, the maturity model and BI framework have been selected. Finally ending up with using both the quantitative approach (through questionnaire and interviews) and the qualitative approach (through the development of framework and using that framework to develop a prototype).

3.4 Data Analysis

The data analysis method followed two main approaches. The first approach was to use secondary data analysis such as literature reviews and case studies to identify the different BI maturity models and BI framework available in the industry. Two main frameworks were evaluated, namely, Gartner and BI 2020. In addition, five maturity models, namely, TDWI (TDWI, 2015) (Chuah & Wong, 2012), the business information maturity model (Rajterič, 2010) , Gartner's maturity model, advanced market research (AMR) (Rajterič, 2010) and MIT Sloan (Lavalle, Hopkins, Lesser, Schokely, & Kruschwitz, 2010) were evaluated. Once a maturity model was identified, we started using the primary data to create a custom questionnaire that suits SQU requirements. A number of interviews with the executive board of SQU were conducted to provide strategic direction and business priority for the BI implementation in SQU. Figure 2 shows a graphical overview of the data analysis approach.

4. BI FRAMEWORK DESIGN FOR SQU

The objective of the BI framework is to provide a formal structure to be adopted by the organization (in this case: SQU) when implementing BI. In addition, another objective of the BI framework is to provide a practical guide to help SQU understand the different considerations it needs to include when embarking on the BI journey. It is important to note that frameworks might be implemented in different ways depending on the maturity level and the type of industry. Nevertheless, BI frameworks are mostly used within business organizations and rarely used within educational institutions. Although general frameworks are commonly used in educational institutions to describe structures

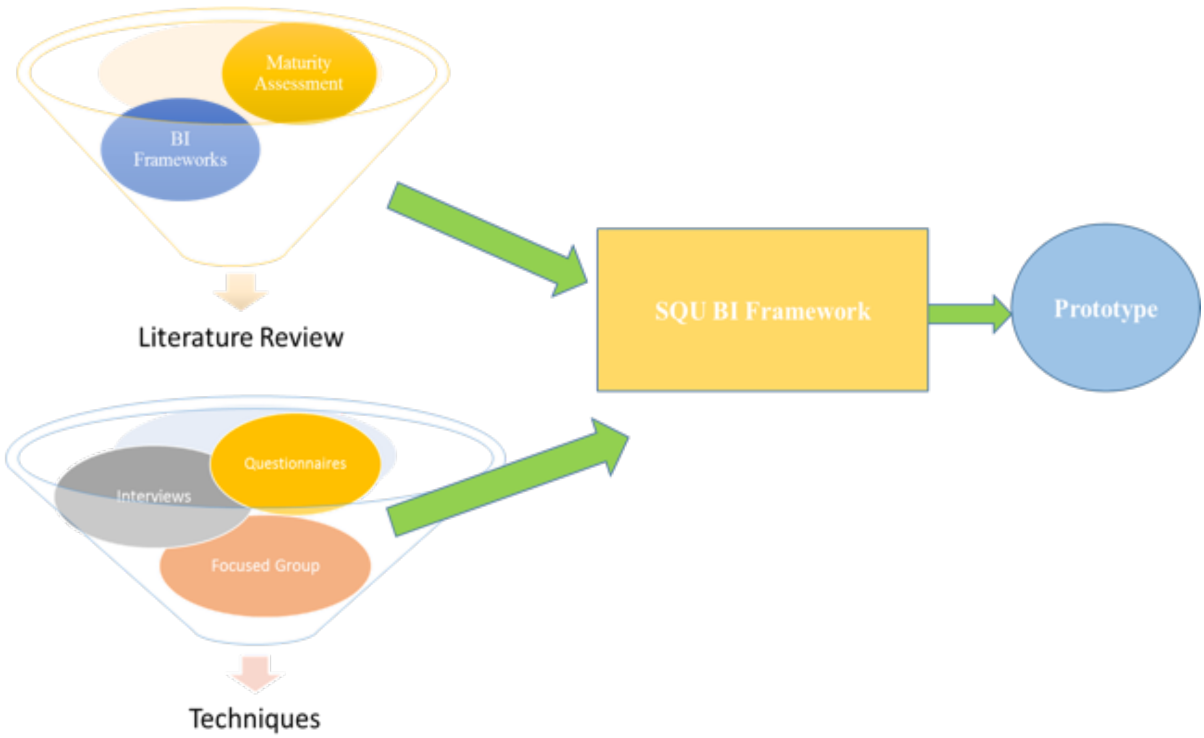

Figure 2 Data analysis approach.

and hierarchy (QAA, 2014), the literature provided little evidence on the use of BI frameworks in educational institutions. This prompted the development of a BI framework to be used specifically for SQU.

4.1 Basis of the Framework

In order to select which framework is suitable for SQU from Gartner and BI 2020, the following criteria were developed:

1. Framework should cover people, process and technology elements.

2. Framework should be flexible to include elements from the maturity assessment without affecting its structure.

3. Framework can be easily fragmented into different layers where accountabilities and responsibilities can be defined for each layer.

4. Framework should be simple and easy to understand.

Comparing the two frameworks, Gartner's framework met the above criteria. Therefore, the basis for our BI framework was Gartner's business analytics framework. Figure 3 shows the proposed BI framework adopted from Gartner.

4.2 BI Framework Components

As depicted in Figure 3, the framework is divided into five main components:

1. People:

This component will describe the main user groups within the university. It is important to identify the main users of BI within SQU in order to develop the different applications that each group will use. Three main user groups were defined for SQU; student, administration and faculty. Each user group has a different set of requirements. Furthermore, this component also covers the skills required by each user group to utilize and benefit from the BI implementation within SQU. In addition, this component addresses the organizational structure required for having successful BI implementation.

It is important to note that in Gartner's Framework, the definition of people is different from the one used in this research. In Gartner's Framework, people are divided into producer (mainly IT), consumers (mainly business) and enablers (mainly information managers who facilitate analytics). Due to the maturity level of SQU, the three groups will be mainly consuming BI. This is due to the fact that in order for SQU to start producing analytics, it needs to be mature. This can be achieved in

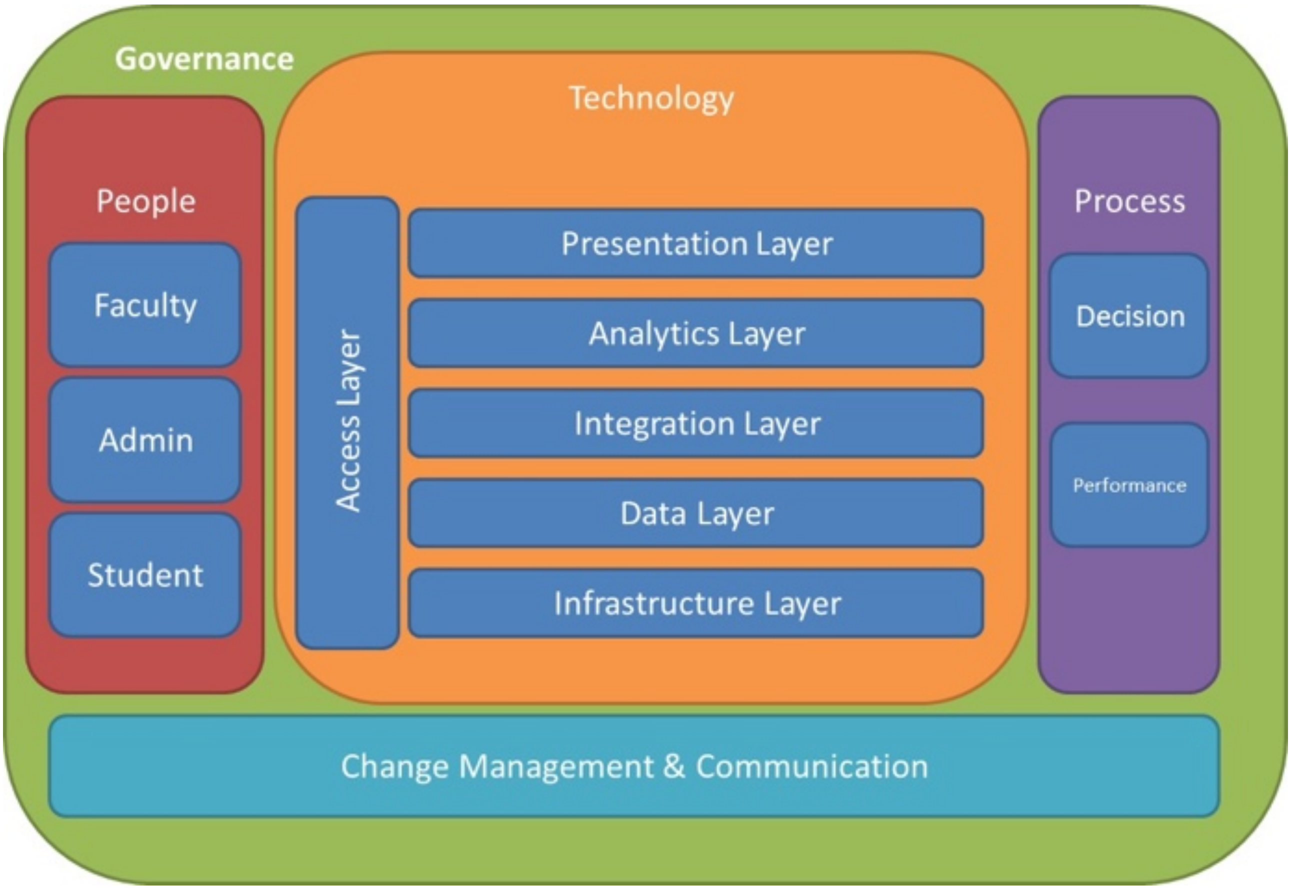

Figure 3 Proposed BI framework.

phases and not necessarily from initial BI implementation.

2. Technology:

In Gartner's framework, this section is referred to as the platform. Gartner classifies the platform into capabilities such as decision capabilities, analytics capabilities and information capabilities. Since SQU BI maturity is low, the classification is done based on different technology layers. This was clear from the maturity assessment since the respondents were more interested to see the BI framework covering different layers such as access, infrastructure, data, integration, analytics and presentation. The description of each layer is as follows:

- Infrastructure Layer: describes the different components of servers, network, storage, etc.
- Data Layer: describes the different databases and data warehouse used to store data.
- Integration Layer: describes the different tools used to extract and load data.
- Analytics Layer: smart analysis takes place. It represents the different BI applications that are used for decision analysis or even performance management.
- Presentation Layer: covers the different dashboards that are used for representing analyzed or processed data.
- Access Layer: During the maturity assessment, many respondents complained about data accessibility. This layer is to ensure that the different user groups are able to access data they are authorized to access.

3. Process:

During the maturity assessment, there are two main use cases for BI within SQU: decision making and performance management. Since these two are the main use cases for BI in SQU, it is essential to develop processes for using BI tools to help in performing the above two use cases. For example, in order to perform performance management, there is a process, which will define the different stages that performance management undertakes. At each stage of the process, there is a need to define where BI plays a role. This will become clear during the prototype stage.

4. Change Management & Communication:

It was evident from the maturity assessment that there are gaps identified in communication. Apart from the fact that SQU has a low BI maturity, the survey questions revealed a need to address the communication gap between the different levels within the university. Therefore, as part of the framework, communication is included. Furthermore, any introduction of new technology has to be accompanied with change management. This is required in general for any change in technology environment and it is essential for SQU to have one due to the low level of maturity and high expectation for BI success. Therefore, it is important to allow for a better management of change when introducing BI.

5. Governance

The assessment of BI governance during the maturity assessment proved that SQU has a low level of governance. The policies are still maturing and there is a need to develop a better governance model around data that will help in improving the data integrity. In addition, there is a lack of clarity in the roles and responsibilities of who is supposed to do what in a business intelligence environment. It is essential that a governance structure has to be in place to address these gaps.

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4.3.1 Start with Business Demand

Three main user groups will be the main users of BI within SQU. The initial judgment based on the maturity assessment and structured interviews provided the current demand for performance management and decision-making. Although this might sound like a complete demand, it is not. Therefore, it is important when using the framework to capture specific needs related to performance and decision making requirements. This can be in the form of different capabilities (i.e. the tool should be capable of doing so and so) or a particular feature (i.e. the tool needs to be colorful). Regardless of the type of requirements, once all the requirements are captured, an overall synergy needs to be done to arrive at the different user groups' expectations.

During the maturity assessment and the structured interviews, few requirements were captured from the administration and faculty. Respondents to the survey expect easy access to the BI tools. They expect training to be an integral part of any solution. They also expect that there is a need to centralize the BI support and to have a single ownership for the solution. While these expectations will drive some of the design principles of the technical solution, this is only the initial assessment and doesn't cover the full BI requirements of SQU.

4.3.2 Technology is an iterative process

Once the demand is identified, the technology can be determined. During the maturity assessment and the structured interviews, it was clear that the university needs to revamp its technical capabilities to address BI requirements. Under the technology element, there are different layers that need to be addressed. It is important to note that when designing a BI solution for the university, the solution will need to undergo several iterations before determining the best fit. For example, it is clear from the maturity assessment that the university doesn't have a data warehouse and doesn't have the tools for extracting and loading the data. In order to address this gap, the data layer (in the framework) needs to be designed to include a data warehouse. The infrastructure layer needs to have all the different components (servers, storage and databases) to enable the development of the data warehouse. The integration layer will have all the ETL tools required to extract and load the data while the analytics layer will be responsible for executing different algorithms to help data analysis. It was also clear from the maturity assessment that the user groups demand easy access and good representation of data. The presentation layer is responsible for presenting the analyzed data in a format that is understood by the user groups.

It is clear from the above that when designing the solutions there are interdependencies between the different layers. Thus, it is important to do the first iteration rather than correct any misalignment in the following iterations.

4.3.3 Agree the target process

Technology will not solve defects in the process or the organization. It is important when capturing the user demands to develop the target process. For example, one of the SQU target processes is performance management. This process needs to be clarified prior to implementing the technology element to understand how the different users will use performance management to address their needs and how the technical infrastructure can help. Therefore, it is important that once the technology solutions are finalized (as an initial or detailed design), the two main processes (i.e. decision making and performance management) are designed to work in harmony with the technical solution and people's expectations.

4.3.4 Plan the change

The BI solution is new to the university and it is going to change the way they carry out decision making and performance management. The university has a style of doing things at present that will need to evolve once BI tools are introduced. Managing the transition between the old and new way of making decisions and managing performance will be one of the key success criteria for BI project. Therefore, it is important to plan for the change and to develop a comprehensive communication plan.

Since the awareness level of BI is low in SQU, the first step will be to increase the level of awareness. It is important at this stage to plan how the change will be managed and communicated. Once decided, communication can be done through a series of presentations, posters, circulars, etc. The different communication channels will be determined by the current policies within SQU for communicating project information or changes to the status quo.

Table 1 Main differences between the Gartner and SQU BI frameworks.

Dimension	Gartner BI Framework	SQU BI Framework
Components	Gartner model has 3 core components: people, processes, and platform and 4 non-core components: program management, performance, metadata and information.	SQU Framework has 5 core components: people, processes, technology, change & communication and governance.
Framework Focus	This framework is focused to ensure the BI strategy in place before organizations start to implement BI	The focus is on BI implementation. There is an assumption that a BI strategy already exists within SQU.
People	Focuses mainly on people as produce, consume and enable.	People are users of BI but they also support BI and thus there is a need to include training & development as part of this dimension.
Technology or Platform	Process driven and focuses mainly on 3 main capabilities; Decision, Analytics and Information.	Technically driven and focuses on how the access, infrastructure, integration elements will work together.
Processes	Very general and focuses on 3 processes: decision, analytics and information processes.	Specific to educational institutions needs and focuses on processes related to SQU and what is important for the BI framework to deliver.
Change & Communication	Not clear in the framework.	The importance of managing change and communication is clearly visible as an important part of the framework.
Governance	Focused mainly on information governance.	Focused on how to govern the overall implementation of BI within SQU.

4.3.5 Govern and Improve

Governance is important to make sure that things are implemented in the right order. Currently, the university has no policies for data management. These policies need to be created and implemented. There is a need to have a body within the university to oversee BI implementation and steer the direction of the implementation. In addition, any improvement initiatives need to be captured and fed back to the framework to ensure that the different layers are working together to deliver the maximum value to the university.

The result from the above five steps is an implementation plan for BI within the university. This plan can be used by the system integrators to implement the BI solution for the university.

4.4 BI Framework Features

Although the BI framework in Figure 3 is adopted from Gartner's BI framework, there are a few differences between the proposed framework and Gartner's framework. Table 1 illustrates the main differences.

5. THE IMPLEMENTATION OF BI

5.1 Introduction

As discussed previously, SQU's interest in BI is driven towards performance management. In order to demonstrate how BI analytics can help the university, it is important to develop a prototype of the BI system. The objective of developing a BI prototype is to provide a closer insight into the design of the BI solution and highlight issues and risks associated with the implementation. Furthermore, the prototype will highlight challenges that the university might face during the implementation of the performance management part.

In order for the prototype to reflect reality, the prototype design will be aligned to the industry's best practices. There are many vendors who have developed BI solutions for different organizations and it will be very useful to utilize their architecture as a reference for this prototyping exercise. In addition, the prototype will use available tools for academic use. These tools (such as Microsoft SQL and Microsoft Visual Studio) might not necessarily provide the best of breed scenario, but they are mainly used to demonstrate the concept. Although the prototype is based on simple tools, the university might have to use a more sophisticated BI solution from BI companies such as Microsoft or Oracle in the future.

5.2 BI Architecture

In order to develop a prototype, there is a need to examine the real life setup of a typical BI implementation. Since the university doesn't have a BI solution in place, it was difficult to find a company in Oman that would allow access to its BI solution setup. Therefore, it was important to search for the top providers for BI solution and see if there is a way to examine their BI solutions. Two main vendors were identified, Microsoft and Oracle, who have a local presence in Oman. Since Microsoft Office tools are widely used, Microsoft Business Intelligence Solution was selected. In addition, it was easier to get support from Microsoft, due to their strong local presence in Oman.

Microsoft BI Architecture is divided into three tiers:

1. Data Tier: This tier is based on the Microsoft database server (SQL Server) and has four main elements:

   - SQL Analytics Tools: mainly analytics.
   - SQL Reporting Tool: creating dashboards.
   - SQL Integration Tool: main ETL tool for loading and extracting data from other non-Microsoft sources.
   - SQL DBMS: where the database tables are located.

2. Microsoft SharePoint provides the main content management and search. This is where all the delivery aspects of BI will happen.

3. End User Reporting Tools such as Microsoft Excel and Performance Point Dashboard.

In addition, Microsoft introduced Power view BI as part of their BI solutions to aid organizations to get a better view of their data. There are a number of options for Power BI, the desktop, mobile and cloud options. When trying the cloud option, SQU IT department blocked the use of any Power BI usage in the cloud. Since SQU already has Office 2013 and Excel

2013, Power BI is integrated as part of that option so as to utilize the existing tool.

5.3 Prototype Design

It was decided when building the prototype that one key business activity (KBA) (Teaching and Learning) will be used among 1. Teaching and Learning 2. Research and Consultancy 3. Community Service and 4. Resources and Facilities. Under this KBA, there are 15 different KPIs with different algorithms to calculate, as follows:

1 -Percentage of course section with 30 or less students
2 -Percentage of reviewed programs during the past 4 years
3 -Percentage of courses assessed and evaluated
4 -Growth in the total number of student enrolled
5 -Percentage of undergraduate students achieving CGPA ≥ 2.7
6 -Percentage of undergraduate students on probation
7 -Percentage of postgraduate students on probation
8 -Percentage of international undergraduate students
9 -Percentage of international postgraduate students
10 -Percentage of undergraduate student withdrawn
11 -Percentage of postgraduate student withdrawn
12 -Percentage of student transferring into the college
13 -Percentage of students transferring out of the college
14 -Full time equivalent (FTE) student-staff ratio
15 -Percentage of students graduated within expected period of graduation of concerned cohort

Furthermore, since the university has nine colleges, it was difficult to demonstrate this using a prototype. Therefore, it was decided to focus the prototype in one college initially. The initial prototype design was based on the three tier model:

- Data layer: MS Access.
- BI layer: MS Excel using Power BI.
- User interface layer: Excel or Web page integration.

Figure 4 Architecture of the prototype solution showing the user interface.

However, during the development work, Power BI in Excel didn't provide the right level of analytics required by the university. Therefore, it was decided to use a new prototype design that reflects in close proximity with the Microsoft BI solution. The final prototype design was based on the three tier model as well:

- Data layer: All tables were created in Microsoft SQL Server 2008 R2.
- BI layer: The algorithm for calculating and analyzing the performance data was scripted using Visual Basic (VB) coding in Microsoft Visual Studio 2013. The reason for selecting visual basic is due to its simplicity and wide adoption in SQU.
- User interface: Login page distinguishes between different user profiles. There are two user profiles created. The interface for the whole solution was developed in SQL reporting.

Figure 4 shows the architecture of the prototype solution showing the user interface: SQU dashboard.

When designing the different layers for the prototype, the following were the main considerations:

1. Simple user interface. Although we focused our efforts on one KBA and one college, there are 15 different KPIs to be represented. The initial interface design had multiple web pages to show the different KPIs in different years. However, after a number of iterations, it was decided to simplify the interface with one page that represents the 15 KPIs.

2. Use of real data. The College of Science was selected to be the first college to run their KPIs using the prototype. In order to make the prototype more realistic, it was decided to use real data from the college.

3. Segregation of users. Two types of users were identified during the prototype design. One user that has access to the final performance dashboard. Another user that has access to the data entry and performance dashboard. The roles of each should be segregated.

4. Availability for staff to test the prototype. In order to ensure that the BI prototype meets the university expectations, two users were identified; one user from the college of science and another from the planning and statistics department. Their role is simply to ensure the prototype meets the expected requirements. Since agile methodology is utilized for the development of this prototype, it was important to have someone to own the requirements as they change during the different iterations.

5.4 User Acceptance Testing Results

The current performance calculation for the university is done by the Planning and Statistics Department in SQU. There is no dashboard currently to show the status of different KBAs for the different colleges. The following is the feedback from the acceptance test:

- The overall performance result for College of Science in Teaching and Learning KBA is shown as low in this dashboard. This reflects reality while we didn’t have this visibility of the college performance before. We thought they are doing fine.
- It is easier using this dashboard to track the changes of the different KPIs in different years. It provides solid evidence of which KPI needs more attention and which KPI doesn’t change over the years.
- It would have been nice if each KPI has a traffic light showing if it is above or under target. This can be added as part of the interface improvements.
- The thing I like most about this dashboard is its simplicity. I assume that the real life dashboard will have all four KBAs aggregated to the SQU level and the overall college performance will be represented in a similar fashion.

5.5 Research Analysis and Discussion

The maturity assessment questionnaire was sent to key staff in SQU including staff working in technical, faculty and administrative positions. The total number of key staff was 200 but only 68 responded. This means that the response rate was 34% which is considered to be a good rate. Table 2 shows the main findings of the maturity assessment questionnaire.

As discussed previously, the SQU BI framework consists of a number of elements.

Table 2 Main findings (maturity assessment questionnaire).

Maturity Assessment Questionnaire Main Findings
The breakdown of the survey respondents are; 47.1% technical staff, 30.9% administrative staff and 22% faculty.
The overall maturity of BI within SQU based on TDWI Model is 1.4, which is considered low.
Majority of respondents do understand BI although the initial assumption when this research commenced was the opposite.
Majority of the people who understand BI think that BI is mostly used to predict and not necessarily to describe or analyze.
Majority of staff within SQU don't understand how BI can be used in SQU.
Majority of staff in SQU (91.2%) expect the BI initiative to be more than 60% successful.
There is a need for a better communication strategy for BI initiatives within SQU.
80% of respondents stated that SQU doesn't have any mechanism to ensure data quality while 20% believe it exists somehow.
All the interviewed executives agreed that the university should invest on BI solution.
Improved strategic performance management is the first priority for SQU management.
Majority of executives agreed that BI should be owned by the Planning and Statistics Department.
Executives believed that BI will help in improving the decision making process.

The prototype reflects the technical element of the framework only. This is due to the fact that the main focus of the prototype is to demonstrate the applicability of BI to the performance management within SQU. Table 3 shows the main findings from the SQU BI framework and prototype.

Table 3 . Main findings (SQU BI framework & prototype).

Main Findings (SQU BI Framework & Prototype)
The framework has a wide coverage on the main elements that will contribute to a successful BI implementation.
Prototype covered one college and one KBA, yet provided overall feasibility on the college KPI.
The data sources for the prototype are manually entered but in real implementation integration points need to be in place to extract the data. Thus, use of a data warehouse is recommended.
The use of agile methodology provided a faster feedback cycle to correct and optimize the prototype design.
The real value of the prototype was to give the college the aggregated performance of that particular KBA in addition to visibility on all KPIs as related to benchmark.

6. CONCLUSION AND FUTURE WORK

This research was carried out to develop a framework to implement BI solutions for higher education institutions with SQU as the case study. In order to develop a customized BI framework, the study utilized Gartner's Business Analytics Framework and the results from the BI maturity assessment. Although the results of the BI maturity assessment came as no surprise, the effort needed to ensure that SQU implemented BI successfully, was dramatically increased due to its low maturity level. This was challenging initially and changed management needs which played a major role in ensuring successful implementation.

In addition, the research developed a BI prototype to test the concept of performance management utilizing the BIA capabilities. It was clear from the maturity assessment and the stakeholder engagements that BI is positioned as a performance management improvement tool. This encouraged the development of the prototype using the KBA and KPI that the university had. Furthermore, the prototype has to be based on a real life scenario to increase its success and its reality check. Microsoft BI Architecture was used as the main reference for the BI prototype. Thus, the prototype consists of 3 main elements, namely a database where performance data are stored, an analytics tool using Excel Power BI, and a web interface representing the visualization of the dashboards. Although the focus of the prototype was limited to one KBA in one college (College of Science), it provided critical insight into how the College of Science has been performing during the last three years. Such insight into this information is a critical part of the value proposition the BI is recommending.

To our knowledge, this research is the first of its kind to build a BI implementation framework for educational institutions, especially in the Middle East sector. It is important to note that while SQU scored low in the BI maturity assessment, other educational institutions might not have the same maturity level. Therefore, it is recommended that the BI framework is tested against different maturity levels to see how it works.

As discussed previously, the prototype developed during this research was limited to one KBA and one college. There are 4 KBAs within SQU and 9 colleges that need to be examined with this prototype. By building such a prototype, the credibility of BI will be established and tested in real life. Moreover, the aggregation of the different KBAs and KPIs will contribute to the overall SQU performance and will provide better visibility of how SQU as an organization is functioning. This is the key towards the successful implementation of BI within SQU in the future.

Future researchers can use this framework to test how BI should be implemented in educational institutions. They can focus on testing the SQU BI framework through using comparative analysis of two organizations with and without using the BI framework. Also, the future research will expand the prototype to include all SQU colleges and all four business KBAs.

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The perception of useful information derived from Twitter: A survey of professionals

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ABSTRACT In this study we gathered data from 220 professional users of information via a survey. Twitter is perceived as a service for useful information but not for the reason one may expect, not because the content of the tweets give valuable information, but because of what can be derived and extracted from the information that is being tweeted and not tweeted. Professional users are aware that tweets are being manipulated by communication departments so they adjust for this in their understanding of the content that is being delivered. For the same reason "fake news" is not seen as a problem either by professionals. Twitter is seen as valuable alongside other social media software (additional software solutions) and used directly together with other software (integrated software solutions). As a stand-alone service it is found to be of less value to experienced users and there are no signs that Twitter is a valuable tool for learning.

KEYWORDS Bots, business intelligence, competitive intelligence, consumer opinion mining, sentiment analysis, social media, Twitter

1. INTRODUCTION

For this research project we wanted to know if the online news and social networking service Twitter is a source of useful information, as useful information, or intelligence, is the core of what makes companies thrive. Previous studies have shown how information leads to a competitive advantage (Porter and Millar; 1985) and the importance of strategic planning for company performance (Jenster & Søilen, 2013). An early study by Java et al. (2007) suggests that people tweet because they want to share daily activities and information, so it would be a natural next step to ask what the value of this information for business purposes is. This question is also important for the public company Twitter as its share price depends much on the value or perceived value of the information it makes available, which is inseparable from its product. If Twitter delivers valuable information the service is an important source of intelligence and maybe even learning. In the worst case it is a marketplace for gossip.

That the service offers a large amount of information or data is reflected in the numbers: in 2016 Twitter reported that they had 319 million active users. When we do some statistics, we see that images are posted more than videos, but that videos get more likes. Most retweets are given to texts with links/URLs. Humor seems to be the most frequent type of content, but politics, (pop) culture, food and travel are other popular categories and the categories are not mutually exclusive, either. Those accounts with the most followers are pop-stars (60% of the top 50), followed by tv-stars and other celebrities. Only five out of the top fifty are big news outlets (two accounts for CNN, BBC, ESPN and another sports channel) and three are politicians (Trump, Obama and Modi).

Previous research has shown that Twitter has an effect on political outcomes, such as the Arab Spring Movement (Kassim) or the 2012 US presidential election (Mills, 2012). The focus in this article is on valuable information for business.

Research in marketing has shown how Twitter can result in people not seeing a movie as a result of poor reviews through microblogging word of mouth (MWOM) (Hennig-Thurau et al., 2015). The phenomenon is called "the Twitter effect" and has strong economic implications for products that are sensitive to immediate success, such as movies (Hayes, 2002), music (Asai, 2009) and electronic games and it affects early adoption of new products.

Information diffusion on Twitter occurs through the process of retweeting. Suh et al. (2010) analyzed 74 M tweets and found that best chances of being retweeted occur with the use of URLs and hashtags. It is also affected by the number of followers and followees, as well as the age of the account. Naveed et at. (2011) found that retweets occur when the topic is general and public instead of narrow and personal. This is an argument for Twitter as a news platform, the authors argue. Their research also confirms the existence of the Twitter effect, that bad news travels longer and faster.

Hong et al. (2011) show, in a highly cited poster paper, some of the mechanisms for getting many likes on tweets. The likelihood of being retweeted increases with the number of followers a person has and the extent to which the tweet has been retweeted by others before, but the paper also goes into more detail.

Turning to studies more closely related to information, Haustein et al. (2016) show how Twitter can be used effectively to spread scientific information. They show how automated twitter accounts, known as Twitter-bots, which are small software programs that are designed to mimic human tweets, schedule posts automatically when the engagement and potential reach are higher, allowing for repetition of tweets. Tools like Tweriod can tell what day and times followers are most active. With a IFTTT recipe like Buffer it is possible to automatically reschedule the content posted in social media. With TwitterCamp tweets can be displayed in large-format displays. With chir.ps, AudioBoo, or Twaud.io users can send voice messages via twitter, which is also a way of getting around the 140 characters limit.

Castillo et al. (2011) look at the information credibility of news on Twitter. The authors explain why it is so easy to be misled on Twitter, especially for inexperienced users. Newsworthy tweets tend to include URLs, have deep propagation trees, come from users with many tweets and have many retweets.

Kim et al. (2016) conducted a competitive intelligence (CI) exercise comparing consumer opinions and sales performances between an iPhone and Samsung mobile phone. The analysis confirms the value of Twitter for CI. The authors found that the volume of tweets revealed a significant gap between the two products. This was confirmed by the purchase intention data and the social opinion gap. Other authors have studied how Twitter and CI are relevant for specific industries, like the film industry (Kim et al., 2015), hotels (Ye et al., 2011), restaurants (Lu et al., 2013), retail (Chen, 2010) and the food industry (Kim and Jeong, 2015).

Text data about end users are analysed using opinion mining and sentiment analysis. Both are a part of social media analytics. Social media analytics is about finding software or business intelligence solutions to gather, monitor, analyze, summarize, and visualize social media data such as that from Twitter. An evaluation of business intelligence systems along similar lines has been conducted by Amara et al. (2012), Sabanovic & Søilen (2012), Søilen (2012 b) and Fougatsaro (2009). It gives a more accurate assessment of customer responses, enabling companies to improve their market strategies (Chen and Zimbra, 2010; Liu et al., 2010; Lusch et al., 2010). Li and Li (2014) show how social media marketing is effective in increasing brand awareness of existing or new products, and can help to build a strong brand community. Most studies using social media analytics suggest that it is a powerful tool for marketing purposes.

In conclusion, many studies have dealt with a single case or a specific phenomenon. What is missing is a critical study about what perceived value Twitter has for CI and business intelligence (BI) professionals in general. There is another gap in the literature regarding the receiver of the tweets, i.e. the readers who evaluates that information. The problem is interesting for the scope of intelligence studies as outlined in Søilen (2015).

When it comes to intelligence, most research papers are of a more technical nature. Data mining, artificial intelligence and data learning technologies have come a long way when it comes to identifying and classifying the information in tweets according to names of people, organizations, locations, dates and times in what is sometimes called Named Entity Recognition (NER): findings that are highly useful in marketing and segmentation. Inkpen et al. (2017) show how it is possible to go deeper into location and identify not only countries, but province and cities.

Another related body of research looks more at alert functions for national and military intelligence. For example with large scale tweets, some events may be predicted. Alsaedi et al. (2017) propose to that an end-to-end integrated event detection framework which was tested and confirmed using a large-scale, real-world dataset from Twitter, using the August 2011 riots in England as an example. The same technology can be useful for private companies to predict new trends.

2. METHOD AND RESEARCH DESIGN

The purpose of this study is exploration, hypothesis testing and description. we have the following research questions:

RQ1: Is Twitter a source of useful information for companies?

RQ2: To what extent do managers use Twitter?

RQ3: What do managers think about Twitter in general?

To answer the first question a number of hypotheses were formulated (hypothesis testing). To answer the second question, a number of specific questions were asked (descriptive method). For the third question an open-ended question was created (exploratory method).

2.1 Hypothesis testing

The following hypotheses were defined for this study:

Hypothesis 1: Twitter is useful for competitive intelligence (Q1)

Hypothesis 2: Those who post on Twitter have valuable information (Q2)

Hypothesis 3: Those who post on Twitter whom I follow have valuable information (Q3)

Hypothesis 4: I get my most valuable information from Twitter (Q4)

Hypothesis 5: The most valuable information I get on social media is from Twitter (Q5)

As humans we tend to overestimate our own abilities. Thus, we think that we know more than others and that the people we know and follow on Twitter are more knowledgeable. This assumption is tested with the difference in answers from H2 and H3. We also want to see and compare any difference of what people understand as CI and useful information in general by comparing H1 to H4. It may be valuable to compare the information gathered on Twitter to the information we get from other social network services, such as Facebook. To make a distinction possible we split the hypotheses in two, allowing a comparison with all information sources (H4) and other social network information sources (H5). A Likert scale of 1-5 was used, including the five categories: I completely agree, I agree, neutral, I disagree and I completely disagree.

This method can only give a perception of what users think, not say what they actually think. As such, this empirical study is in a tradition of perception studies. The reason for choosing this method is primarily one of economy, as other studies demand more time and resources (direct observations and experiments).

2.2 Description

A number of specific questions were formulated to find out to what extent managers use Twitter:

How often do you think you check Twitter each day? (Minutes) (Q6)

How many minutes do you think you spend on Twitter each day? (Q7)

How often do you tweet? (Number of times per day/week/month) (Q8)

What percent of your time on Twitter is for professional use (not private use) (Q9)

Questions were asked in a survey with the option to add comments and explanations to each answer. As it can be difficult (almost impossible) to know how many minutes we use on Twitter we ask what managers think they use (Q6, Q7). It is assumed that it is easier to remember how many tweets we send (Q8). The answers show we should have used "think" in the last specific question, too (Q9). Initial answers also show that it may have been wrong to use several measures as options in one and the same question, like day/week/month as respondents used different measures, which demanded unnecessary recalculations for direct comparisons.

2.3 Exploration

For the last part of the survey we wanted to know what managers think about Twitter in general.

> "Please give your personal comments about the importance of Twitter for competitive intelligence" (Q10)

An open ended question was given with enough space for comments.

2.4 Research Design

The extent of researcher interferences was moderate. All questions were sent in networks online in the form of a link to a survey using the service Surveymonkey. The online networks defined as the population were eight groups related to business intelligence in LinkedIn with from 7 000 to 1.8 million members in each group, and a mailing list of more than 900 members for the JISIB journal, as shown in Table 1.

Table 1 Population defined.

Nr.	Group's name	Members
1	Software and Technology	1,800,000
2	Business Intelligence professionals	206,000
3	Microsoft Business Intelligence	120,000
4	Software as a Service (SAAS)	101,000
5	SCIP	26,000
6	Market Intelligence Professionals	25,000
7	CI Professionals	12,000
8	Competitive Intelligence Professionals	12,000
9	JISIB membership list	900

These users are defined as experienced users, thus less likely to be manipulated by false information on Twitter (Castillo et al., 2011). There was less than a minimum of manipulation and/or control and/or simulation. The study setting must therefore be said to be contrived as it is an artificial setting and we are not studying a natural environment where the phenomenon occurs normally. The research strategy is survey research. The data collection method is a questionnaire. The unit of analysis is individuals. The measurement is scaling for the hypotheses. Items in the descriptive part are measured (times, minutes). The exploration part is based on text analysis. The study is partly longitudinal with two measures in time, with a time difference of 6 months between each. We used the same sample/survey.

Sampling size: n = 220.

The sample was 0,012% of the population, which reflects the increasing difficulty of getting users to fill in complete surveys with the increased number of users seeking attention on the internet. This gives us a confidence interval of about 7 with a 95% confidence level.

For the text analysis from the open-ended question, we use a synthesis process by which opinions are classified according to relevant dimensions identified in the process (1), narrowed down to key words (2), and analyzed for the least common denominator/meaning (3). This allows for a test of validity and accuracy as readers can largely redo the analysis from the same raw data and the empirical test can easily be replicated.

3. EMPIRICAL DATA

Table 2 summarized the responses to the first questions. In Q6 and Q7: Most respondents misunderstood this question, something that was missed in the pre-test. Respondents treated Q 6 as if it was the same as Q7, asking only for the number of minutes, not the amount of time spent.

The average answer was 16 minutes, but answers varied too much for the average to have much meaning. Many respondents do not check Twitter at all and the minutes used on Twitter vary from 1 minute to 180 minutes per day. The most frequent answer was 10 minutes (15.5%), followed by 60 minutes (12.0%), 1 minute (10.3%), and 20 minutes (6.9%). Only 3.4% of respondents never use Twitter.

Table 2 The hypotheses (Q1-Q5).

	I completely agree	**I agree**	**Neutral**	**I disagree**	**I completely disagree**
QI	23.33%	46.67%	18.33%	10.00%	1.67%
Q2	5.00%	43.33%	36.67%	15.00%	0%
Q3	18.33%	46.67%	26.67%	5.00%	3.33%
Q4	1.67%	20.00%	23.33%	36.67%	18.33%
Q5	6.67%	15.00%	28.33%	33.33%	16.67%

Q8: Number of tweets per day/week/month varied even more than the number of minutes spent on tweets. So again, an average makes little sense. Some respondents answered in days, others in weeks and others again in months. This was not an optimal way of framing the question but luckily it could easily be solved by recalculating all numbers as "tweets per day". This is shown in Table 3.

Table 3 Tweets per day.

	Day	**Week**	**Month**
	3, 1, 2, 1, 3, 3, 1, 2, ,1 10,	2, 10, 5, 2, 2, 5	30, 1, 2, 3, 30, 1
Average	*2.7*	4.3 per week	11.2 per month
Day equivalent		0.6	0.3

Those who answered in tweets had an average of 2.7 per day, in weeks they had 4.3 per week or the equivalent of 0.6 per day. Those who answered in months had an average of 11.2 tweets per month and the equivalent of 0.3 per day. The answers suggest that it may be that this division of days/weeks/months catches a more nuanced understanding of users' habits than if we had only written days. Those who answered in weeks have a far lower range of tweets than those who answer per day and those who answer per month have a far lower number of tweets than those who answer in tweets per week. The total average is 1.2 tweets a day, which for example is below the limit of 3 tweets recommended by the service Buffer. Their statistics suggest that the engagement of your followers drops first after the third tweet. See http://follows.com/blog/2016/04/times-day-post-twitter. A large percent answered that they send 0 tweets per day (27.6%).

Q9: On average, respondents use Twitter for work purposes 50.1% of the time. Answers vary greatly and often, from 0-100%. The most frequent response (mode) was 100%, which was answered by 17.6% of respondents. 15.7% answered 50% of the time. 7.8% answered 90%, 5.9% answered 1%, and 5.9% answered 0 times.

Q10: Often it is the open-ended question that brings the most meaning to the empirical work. From the 220 respondents we have taken away blank answers, irrelevant comments or pure opinions without arguments or backing. These represented 56% of comments, or 123 comments. We also took away double comments, comments with content that was too similar. These represented another 23% of comments, or 50 comments. This left 46 comments, or 21%, as shown in the tables below. These are deemed significant and worth analyzing further.

Looking at the comments, four dimensions (D) were identified as relevant for further analysis: Advantages (1), Potentials (2), Limitations (3), and Warnings (4) as shown in Table 4.

Table 4 The comments (Q10).

D/ Nr	**Advantages**	**Potentials**	**Limitations**	**Warnings**
1-4	Strongly important especially when it comes to extracting knowledge and insights from social data.	Not so useful for CI but for marketing and consumer insight teams.	Twitter may provide competitive information for some industries.	Relying completely on it would be futile for most.

5-8	Twitter's immediacy means you can get quick updates on a range of topics, products and news.	In CI we can get info regarding bigger changes in consumer attitudes and know if rivals do pilot tests with new products somewhere in the world.	Sometimes data may be available from only one category of users.	Mostly its content (which is followed, viewed and commented on by many) is banter and self-promotion by individuals.
9-12	It lets you keep up-to-date and allows you to capture the zeitgeist of your target.	Twitter is ONE source of new signals in the competitive environment.	Twitter is one of many resources, not a primary source.	Some try to use it for marketing of products or services, which by itself does not provide anything useful.
13-16	You can find the latest news posted by companies involved in a competitive landscape.	The most authentic opinions on Twitter are from politicians (they use it in a very straight-forward way),	It is one more source of information, but not focused, in near real time. Corporate accounts are mostly controlled by communication departments.	I remember once a group I worked with tried to analyze Twitter content to understand what people wanted for Valentine's Day. They ended up only with information from marketers on things people could buy for Valentine's Day. All the plans of providing new insights into the client vaporized into thin air.
17-20	The instantaneity of information, in particular "alerts" on events.	I do sometimes use it to ID human sources who we could speak with on various topics with authority.	It really depends on the industry. If none of the competitors or customers are using it, it will be useless.	Twitter is certainly not a CI tool. CI should be focused on building outside-in perspectives.
21-24	Twitter is the best source for recent/actual information (fastest social media).	It's a gap filler.	One of many resources, but not exclusive.	I think Twitter more often misleads than informs for CI work.
25-28	I think it is important but I rarely tweet.	Large potential though for text analysis and network analysis, etc.	To be integrated, but limited by itself.	I find it not worth the time required to scan all of the pointless stuff.
29-31	Twitter is useful for identifying relevant sources for CI tasks, their messaging and their networks.	Twitter can be useful because it contains very different information about the environment.	There's a huge variation in quality of content and difficult to assess these differences.	
32-34	It is useful real time news in relation to surprise events such as terrorist attacks, military moves, uprisings, disease outbreaks, [...] and for geopolitical and catastrophe monitoring.	The importance of Twitter for competitive intelligence requires sifting through the noise.	I don't regard it as important. It is merely a tool that can guide you towards leads.	
35-37	It's an indirect tool. Assess what people know, value or say.	To use Twitter, you should also use tools like Tweetdeck or Hootsuite so you can manage the Twitter stream and put key people into columns and lists.	In the age of information overload and disinformation it is as much what people don't say or omit on Twitter.	
38-40	When used seriously I think it is very valuable.	Follow the group rather than the individual. For tweeting use tools such as Buffer to schedule tweets.	I prefer FB.	
41-42		I believe Twitter is a platform where people are spontaneous.	Only for selective accounts and filters need to be applied.	
43-44		It is possible to spot trends early but you need to be following the trend setters. Identifying true trendsetters is difficult.	Interesting but like any secondary source offers guidance at best.	
45-46		Depends on who you follow and who follows you.	It is simply a source of information in which public opinion may be manipulated.	

From the classification of relevant dimensions a number of keywords could be extracted from each group of answers:

1. Keywords for Advantages: Extracting knowledge and insights from social data, fastest social media, quick updates on a range of topics, up-to-date and allows you to capture the zeitgeist, latest news posted by companies, "alerts" on events, identify people and networks, assess what people know, value or say.
2. Keywords for Potentials: Not useful for CI but for marketing and consumer insights, consumer attitudes and know if rivals do pilot tests, only one source among several, authentic opinions from politicians, ID human sources who could speak on various topics with authority, potential for text analysis and network analysis, different information about the environment, requires sifting through the noise, requires use of other tools (Tweetdeck, Hootsuite, Buffer), follow the group rather than the individual, a platform where people are spontaneous, but you need to be following trend setters, identifying trendsetters is difficult, depends on followers and who you are following
3. Keywords for Limitations: Corporate accounts controlled by communication departments, sometimes data maybe available from only one category of users, not a primary source, value depends on customers, if they use it, limited by itself, difference in scope and quality, difficult to assess, at best for leads, tells you what people are not saying, FB is better for CI work, a secondary source, easily manipulated
4. Keywords for Warnings: Futile to rely on, mostly self-promotion by individuals, a marketing tool for companies, reflects the market, not a CI tool, for inside-out perspectives, misleading, not worth time for scanning.

A look at the data shows that respondents think the advantage of Twitter is that it is a fast social media, quick with updates and alerts, on a range of topics and events. It's good for identifying people and their networks, not necessarily for finding the truth, but what individuals and institutions value and say. Twitter is not a CI tool as such, but more valuable for marketing and consumer insights, potentially easily to manipulate and controlled by communication departments. It's largely a place where individuals and corporations promote themselves and their products. In the

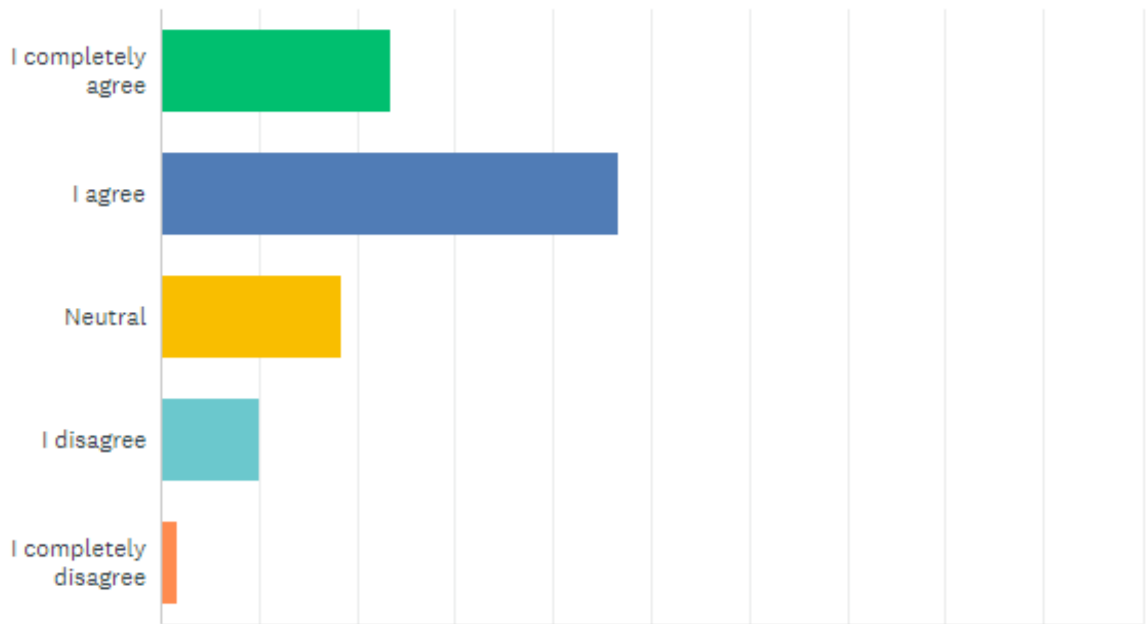

Figure 1 Results for H1.

next part we conduct an analysis to see what this may mean.

4. ANALYSIS

4.1 The results from the empirical work on the hypotheses

The first hypothesis is "Twitter is useful for competitive intelligence" (Q1). 46.7% answered "I Agree" and 23.3% "I completely agree". This makes 70%, thus we can accept Hypothesis 1 with 95% certainty even though we have a high confidence interval of 7 (Figure 1):

H1: Accepted

The results for the other hypothesis were: H2: Those who post on Twitter have valuable information (Q2). 43.3 % answered "I Agree" and 5% "I completely agree". This makes 48.3%, thus we cannot accept Hypothesis 2:

H2: Rejected

This may at first seem like a contradiction. If Twitter is useful for intelligence is it then possible that those who post on Twitter do not possess any valuable information? It may be that intelligence professionals can find valuable information about markets, industries, and products without the person tweeting having any valuable information. It would mean that the value comes from the analysis of the data, not the data itself. We find this in some of the answers above, it may be that the value of the information lies in the things that are not said. If we have knowledge about an industry we can draw our own conclusions that are not the same as what is being tweeted. In the comments above we find an emphasis on "extracting knowledge and insights" and "opinion mining and sentiment analysis". This suggests that it is not so much the raw data that is valuable as the analysis of the data.

Intelligence professionals know that corporate tweets come from communication departments and professionals. They may know how to read what they see or what is between the lines, so to speak. In that lays the valuable information.

For H3 we asked "Those who post on Twitter whom I follow have valuable information" (Q3). 46.7% answered "I Agree" and 18.3% "I completely agree". This makes 65%, thus we can accept Hypothesis 3:

H3: Accepted

Here the respondents are saying that there are also those who tweet who possess valuable information and the individuals that I follow belong to this group. Again it may be seen as a contradiction that there is no valuable information for CI on Twitter (H1), but those I follow have valuable information, but by the same logic respondents could be saying that most of those who tweet do not have valuable information, but those I follow do.

Regarding, the fourth hypothesis "I get my most valuable information from Twitter" (Q4), 20% answered "I Agree" and 1.7 % "I completely agree". This makes 21.7%, thus we cannot accept Hypothesis 4:

H4: Rejected

There are other sources that are much more valuable in terms of intelligence for professionals than Twitter. Those who disagree are 36.6% and those who strongly disagree 18.3%, in total 54.9%. It is a surprise that the percentage rejected is not even higher, as the comparison here is with all other sources. It may be that respondents thought of social media only, which is H5.

In hypothesis 5 we claim "The most valuable information I get on social media is from Twitter" (Q5). 15% answered "I Agree" and 6.7 % "I completely agree". This also makes exactly 21.7%, thus we cannot accept Hypothesis 5 either:

H5: Rejected

Respondents gave similar answers to questions 4 and 5. There was a possibility to go back and changes answers in the survey, but respondents may have ignored this. It is tempting to treat the answers given in 5 and 6 as if both were comparing with other social media only.

From the other questions, we know that users check their Twitter for 16 minutes per day on average (Q7), send 1.2 tweets (Q8) and use Twitter for professional use 50.1% of the time (Q9). We did not get any reliable data about how many times a day users check their Twitter account (Q6). From Q6-9 we see that Twitter is only one of several social media channels used by respondents and only attracts limited attention. This is also confirmed in the comments (Q10).

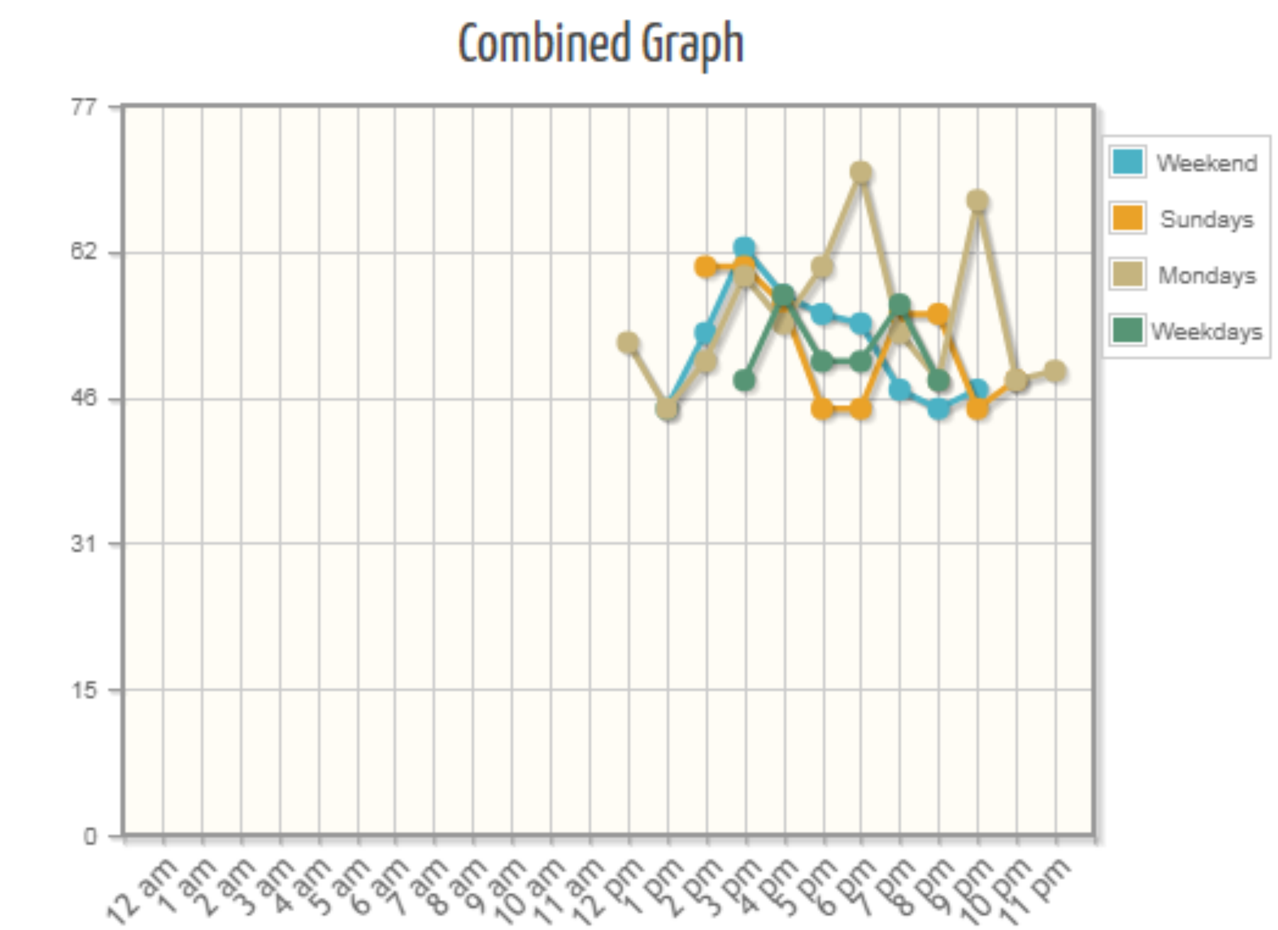

Figure 2 Analysis in Tweriod.

4.2 No stand-alone application

Twitter is not a good stand-alone application, but is best used with other software. This can take two forms, either beside and/or alongside other software (additional software solutions), for example together with Facebook and LinkedIn or in conjunction with other software, like Tweriod and Buffer (integrated software solution). Twitter is an ineffective software when used alone. When using other software in conjunction with Twitter the supportive software helps to render Twitter more effective. As an example, below we used Tweriod to find what day and times my own followers are most active, as shown in Figure 2.

The graph presents times for weekends in general, Sunday, Monday and weekdays. If we are to choose one day we should tweet on Monday at 6 pm or 9 pm. The lowest chances of tweets being seen is on Sundays. If we choose one time to tweet, Monday at 3 pm is the best. Using Buffer we can then schedule automated tweets, for example on the coming Monday at 6:00 PM.

In the example in Figure 3 we schedule extracts from my book "Geoeconomics" (Søilen, 2012c). Followers and tweet readers cannot see that the tweet comes from a bot. Integrated software solutions allow me to use my working days more effectively and better plan what is to be communicated. Without it, social media services like Twitter, where we are always asked to check what just happened, tend to steal too much of our time.

4.3 Fake news

We see that users did not find "fake news" to be a problem in general on Twitter. Users expect the information from companies to have a certain angle, to be manipulated or come as propaganda so they analyze the data based on this assumption. We may assume that professionals and experienced users know what to look for to avoid being tricked (for example, number of followers, number of retweets, links/URLs, likes). Those who are being tricked tend to be more inexperienced users. This does not mean that experienced users cannot be tricked with false data, but they themselves do not see "fake news" as a problem for the value of the information they get from Twitter. It may be that they have a low self-criticism ability, we do not know. For Twitter as a company this is good news, as

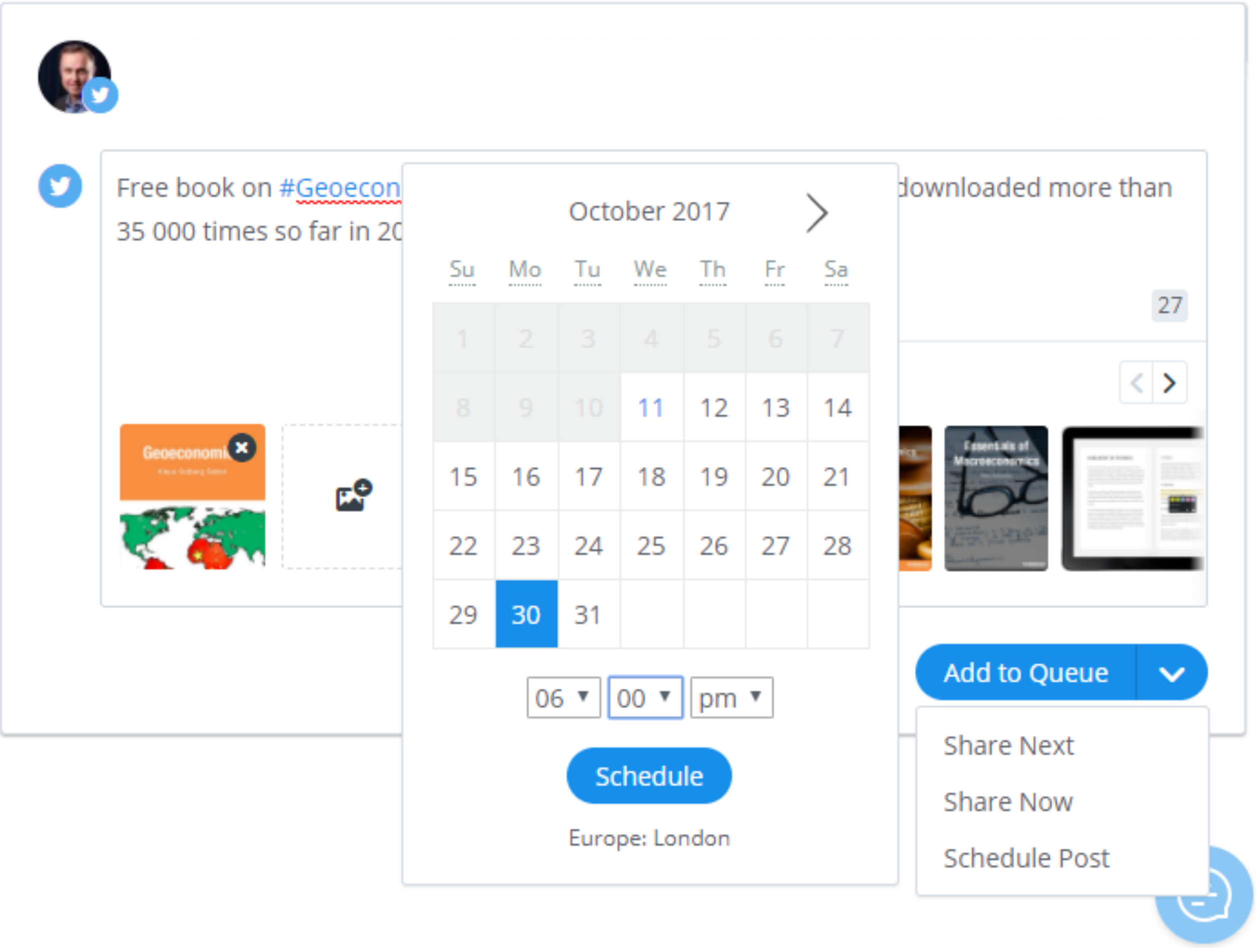

Figure 3 Example of Twitter scheduling.

professional users are not concerned about being tricked or bombarded with fake news and are not considering leaving Twitter for this reason.

Even though the biggest accounts (most followers) are connected to pop stars and celebrities, the fact that BBC and CNN rank high is a sign that there are also those searching for more objective news and content that have a broader bearing on life. Among the smaller accounts there are many examples of valuable information coming from experts and professors like Richard Dawkins (2.5 million followers), Yanis Varoufakis (1 million), Joseph Stiglitz (200,000) Michael Porter (151,000) Niall Ferguson (127,000) and Steve Keen (46,000). Thus valuable information is very much a question of whom we chose to follow. This again assumes that we know who knows and who we can trust.

4.4 Comparing findings to theory

Much existing theory is confirmed. Professionals find Twitter valuable for alerts, breaking news and events.

When compared to theory, respondents in the sample miss part of the deeper insights of social media analytics for its value to market intelligence. In comparison with traditional data, social media content is much richer and contains a diverse range of information. In this regard, business intelligence gleaned from social media can enable business analysists and decision makers to develop market insights into consumer behavior, discover new marketing ideas, improve customer satisfaction, and ultimately increase returns on business investments (Chau and Xu, 2012; Chen et al., 2012).

5. FUTURE STUDIES

I always find conclusions to be of less value in papers as they just repeat what is said elsewhere. For the same reason we do not like introductions because they do not get to the point.

Most tweeting happens “on the go” with people using smartphones (McGee 2012). Does this affect the quality of the information conveyed? Or does it make the information more actionable, more up to date with what is happening in the market?

Most studies are on likes and retweets, but it would also be interesting to see what value comments have on tweets as the third active possibility to give a reaction. What is more effective: using time on commenting, retweeting or liking a post?

A study by Chu et al (2012) found that 10.5% of Twitter accounts are bots, with an additional 36.2% classified as “cyborgs” (defined as a “bot-assisted human or human-assisted bot”). Future studies should find out how much of this is pure spam, thus less valuable information. Bots are also used to spread viruses. There is a risk that social media is being filled not only with more information but less valuable information not only in the US but also in other countries like Russia (Kelly et al., 2012) and that the valuable information is getting harder to locate. To avoid manipulation it is important to separate between and identify what information comes via human, cyborg, and bot accounts.

Twitter as a microblogging platform has vast potential to become a collective source of intelligence that can be used to obtain opinions, ideas, facts, and sentiments. But, what are the incentives for sending valuable information out for free unless in anger or as a revenge? Those who possess valuable information tend to sell it as reports or consultancy. Is the information more valuable if it comes from organizations instead of from individuals? These are some suggestions for future studies in this field.

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Stevan Dedijer
1911-2004

OPINION

Integration of business intelligence with corporate strategic management

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ABSTRACT The traditional model of competitive intelligence and its operationalization in most organizations appears to be inadequate to address the intelligence challenges arising from the speed of change in the environment, increasing data complexity, and growth of international activities. To address this challenge, this article borrows concepts from open innovation, applying them to all CI activities. We are suggesting going beyond the traditional model of an in-house CI unit with activities largely conducted by the units personnel and moving towards a cross pollination approach whereby others in the firm contribute to all CI activities including, for example, the selection of key intelligence topics and being involved in analysis and eventually towards a full open intelligence model in which key stakeholders and external experts also assist the organization in all aspects of competitive intelligence activity. In proposing a more open approach for intelligence, the authors recognize the concern that CI professionals will have regarding sharing intelligence and intelligence activities outside the CI unit and outside the organization. However, as pointed out in this article, organizations around the world have been moving quickly towards an open innovation model generally concluding that the benefits associated with opening up all elements of the innovation process, including R&D, outweigh the risks of intellectual property loss.

KEYWORDS Analytics, big data, competitive intelligence, open innovation

1. INTRODUCTION

With over 60 years of combined experience in competitive intelligence practice, research, consulting, teaching and writing (and areas related to intelligence) the authors of this article propose a reconceptualization of competitive intelligence. Weaknesses in the current definition and practice of competitive intelligence lead us to broaden out those involved in helping organizations' intelligence programs by incorporating several concepts from open innovation. We propose the integration of principles from analytics as well. We are calling this new intelligence concept "open intelligence". We feel that the current practice of competitive intelligence does not address challenges arising from the speed of change, the growth of international activities (not just selling internationally but sourcing) and increasing data complexity, but that by incorporating ideas from open innovation and analytics that these challenges can be met by tomorrow's competitive intelligence practitioners.

2. OBJECTIVE OF THE ARTICLE

The Journal of Intelligence Studies in Business has served for several years as the primary outlet for the exchange of intelligence ideas. The journal has had articles that attempt to define competitive intelligence. For example, Du Toit (2015) looked at academic scholarship in CI from 1994 to 2014, looking for a common definition and parameters for the field. Soilen (2016) through a survey of CI experts and an examination of articles in SCOPUS that contained the words competitive intelligence, attempted to develop a definition of CI and establish and a research agenda for the field. While these and other authors of papers in the journal have tried to define competitive intelligence, others have proposed the need to extend the domain of competitive intelligence. Nienaber and Sewdass (2016) proposed to expand the domain of CI to include workforce related competitive intelligence. Vriens and Soilen (2014) proposed extending the domain of CI to include disruptive intelligence. The idea of adding like this to the domain of intelligence generally represents an acceptance of the definition of competitive intelligence, but an expansion of its role or, put another way, a broadening of the key intelligence topics, to use Jan Herring's terminology. Still others have sought to broaden the domain of intelligence, pushing into or absorbing other similar or related areas. For example, Rostami (2014) wrote about integrating knowledge management with business intelligence. Calof, Richards and Smith (2015) suggested extending foresight to include both foresight and analytics and, in fact, many articles in the Journal of Intelligence Studies in Business have focused on business intelligence, for example Alnoukari and Hanano (2017) and Gauzelin and Bentz (2017). In short, the Journal of Intelligence Studies in Business has served not only as one of the primary journals for publishing scholarship about CI (Soilen 2016) but it is also a journal that has sought to define competitive intelligence including what it is, its scope and research agenda. In fact, the journal, in defining its publication topics, notes that it "publishes articles on topics including marketing intelligence, marketing intelligence, strategic intelligence, business intelligence, competitive intelligence, collective intelligence and scientific and technical intelligence".

With this article, the authors seek to add to this theme within the journal. We propose a reconceptualization of competitive intelligence with the incorporation of concepts from open innovation and contributions from analytics. We write this article to the CI community and in doing so invite feedback from those who read it. A version of this article has been published in Competitive Intelligence Magazine (Summer 2017) but this is geared more towards an academic audience. It is our collective view that how we look at and practice competitive intelligence has to change in light of several changes in the environment that will be described in this article. We draw upon many concepts in open innovation as we seek to push the boundaries of competitive intelligence and expand the role played by both those within organizations and outside of it in driving the organizations' intelligence initiatives. We seek to be part of a growing dialog within the pages of the Journal of Intelligence Studies in Business about how competitive intelligence should evolve in the future, and invite those who read this article to lets us know what they think.

3. THE CHALLENGE

While there have been many changes in the business environment that competitive intelligence has had to address, there are three that the authors of this article seek to highlight, that we feel are amongst the most important changes and also those for which we feel traditional views of intelligence have had difficulty addressing, at least according to our experiences and discussions we have had with leading practitioners and researchers in competitive intelligence:

1. Speed of change,
2. Increasing data complexity
3. Growth of international activities (not just selling internationally but sourcing)

These challenges are explained in greater detail in this section.

3.1 Speed of change

In 2011, Harvard Business School professor and noted management thinker John Kotter wrote:

> "Anyone in the business world – even casual observers of it – knows that it's currently experiencing a rapid rate of change. New companies spring up seemingly overnight. Products and services that were revolutionary two years ago are rendered obsolete if they don't adapt to market

changes fast enough. The rate of change in the world today is going up. It's going up fast, and it's affecting organizations in a huge way. The evidence of this can be seen almost everywhere—life-cycle of products, number of patents filed in the US Patent Office, amount of cell phone activity across national boundaries—on and on and on. And what's particularly important is that it's not just going up. It's increasingly going up not just in a linear slant, but almost exponentially."

What does this mean for competitive intelligence? Many intelligence projects will need to be done on a frequent, almost daily basis to reflect the rate of change in these areas. Looking for both the emergence of threats and opportunities needs to be done in time so that managers can act in a timely manner, but the rate of change is also greatly compressing the amount of time available to gather, analyze and make sense of the information.

3.2 Increasing data complexity

At the SCIP conference in Atlanta (May 2017), a dominant theme among many of the keynotes was increasing data complexity and the need to develop approaches to deal with and in fact take advantage of big data. Steven Hughes opened the conference with a talk "Big Data is our Future" and day two had Major General Neeraj Bali present a case study from the Indian army in which big data figured prominently. Among the numbers quoted in the presentations: 31.25 million messages sent every minute, 30 billion pieces of shared content on Facebook every month, 2.77 million videos viewed every minute, Google users perform 40,000 searches per second, more than 196,000 databases published annually by the U.S government, and by 2019 one million minutes of video will be uploaded every second. It would take five million years to watch all the videos posted each month.

The internet of things (IoT) with increased machine to machine communications, data gathering sensors, and more, was also mentioned as both an opportunity and challenge for competitive intelligence. Social media, Twitter, and blogs also generate data that can be used in intelligence programs. It's not that the traditional primary sources from interviews are not important for intelligence, but the growth and availability of these online videos, discussions, and materials does provide great opportunities on the collection side of intelligence. The problem, however, is coming up with a way to cope with all this data. IBM, in their big data and analytics hub, wrote about the four Vs of big data (IBM, 2017) which we are collectively terming "data complexity":

1. Volume or scale of data. For example, most companies in the US have 100 terabytes of data stored, six billion people have cell phones;
2. Velocity/analysis of streaming data. For example, 1 Terabyte of trade information captured by the New York stock exchange each day, 18.9 billion network connections – 2.5 per each person on earth;
3. Variety or different forms of data. For example, 400 million tweets sent per day, 4 billion hours of video watched on YouTube each month, 30 billion pieces of content shared on Facebook each month;
4. Veracity or uncertainty of data: Notably, 1 in 3 business leaders don't trust the data they use to make decisions, poor data quality is estimated to cost the US economy alone $3.1 trillion per year.

3.3 Growth of international

For many organizations, tomorrow or even today's competitor can come from outside their country. Customers may also come from countries from outside the organization's country. Technology and other changes can come from anywhere in the world. Managing in this environment requires the development of intelligence programs that gather information from many different countries, knowing what the best sources of information are in foreign environments and in some cases dealing with the fact that the best information for their intelligence program may not be in English.

The challenge for CI is how to integrate the opportunity provided by this volume of data along with our more traditional information sources while addressing the problems related to data volume, variety, velocity, veracity and internationalisation.

The combination of the rate of change, international factors and the big data challenge means that CI teams will need to come up with a way to increase the frequency of their intelligence project updates while integrating a broader array of data. Doing this in the traditional one or two-person intelligence team is going to be difficult. The following lays out how we are proposing to add to the concepts of competitive intelligence to address these challenges. It is a reconceptualization of the phases of intelligence and the addition of concepts from open innovation to intelligence.

4. NEW IDEAS WITHIN THE WHEEL OF INTELLIGENCE

Traditional CI approaches revolve around some version of the wheel of intelligence approaches we have seen on leading organizations' use terms, such as:

1. Issue identification
2. Plan generation
3. Data acquisition
4. Data analysis
5. Recommendation

There are many variations of this approach based on corporate management structure and decision-making authority, size of the organization, and the type of issue to be resolved. But these five steps are really the crux of any "generic" CI effort in an organization. The Du Toit (2015) article explores these ideas in great detail and serves as a useful review of the CI literature.

The problem with this traditional approach is that the time for all of this to happen can exceed weeks or months before actionable insight can be developed. The sequential nature of the wheel of intelligence has been challenged in many past studies, but it is clear that in fast changing environments time can be a challenge for doing all these steps. Add to that the time for the organization to actually act on the insight and we are talking additional months added to the overall CI lifecycle.

Given the time frames involved, the impact of the 4 Vs associated with big data can make this traditional approach grossly inadequate and subsequently useless. Business disruptors and industry changes occur in the blink of an eye and through the globalization of the digitized world we live in, can affect regions and potentially world economics in a fraction of the time it took only 10 years ago. Data and insights that are months out of sync with reality cannot provide a competitive advantage to any organization,

Rather, an approach must be developed that takes into consideration the volume of information, the sources, the ability to manage the content, and the organizational flexibility to not only adapt, but to flawlessly execute on a regular basis, will be needed. There are several strategies that can be employed to help navigate the challenges stemming from this environment during this important data collection and analysis phase.

4.1 Data Generation

First, in terms of data generation, the sources and volume of data overall are exploding. As mentioned earlier, this growth is expected to continue at an exponential rate. There is essentially no such thing as a suitable environment for "batch" processing – anything not done as close to real time as possible will become useless. So, it is critical to know that the longer from the time the data is generated to analysis, the more misleading and outdated the data becomes – and all downstream activities of analytics, processing, insights and execution eventually snowball into an extremely high-risk business strategy.

That is not to say that one should just hang up the proverbial CI hat and chalk this environment as a no-win scenario. Rather, there are techniques available for moving closer to the "real-time" environment that will provide valuable insights and ultimately a competitive advantage for organisations.

There are many techniques (albeit some more advanced than others) that have shown great promise in a) getting better data, b) getting it quickly, and c) expanding the breadth of data collection to include more value-rich content. These techniques include:

1. Concurrent analyses methodologies – simultaneously collecting, analyzing and sharing the data with stakeholders in a reiterative parallel process, rather than serially collecting and vetting the data with stakeholders, which can take magnitudes longer in time and resources
2. Organizational efficiencies – built-in hierarchical structures that encourage quick data sharing and communication without long lag times to decision making and execution
3. Real-time data collection methods – ability to harvest content from thousands of sources to effectively pull valuable "golden nuggets" from the vast amount of overall data.

4.2 Tools for data generation and analysis

Secondly, the use of specific data-management tools becomes a necessity in this data-rich environment. Public domain search engines fall woefully short in providing the content in a format that is user-friendly, and throwing low-cost physical resources at the problem only leads to more confusion and frustration in coordination and results in a reduction in speed to insights. Knowledge management tools or related automation mechanisms are crucial in order to navigate the volume of data coming from the web. This includes not only public domain source content, but social media, customer feedback, and paid sources. The key determinant in the appropriateness of the result will often depend on the robustness of the input content. Identifying and managing the resources that provide data into the automation tools is a critical area of development. Letting the tool do the "heavy-lifting" of analytics with source content that routinely numbers in the thousands or tens of thousands or more of sources and will ultimately provide a much better outcome over time.

From a practitioner's perspective, the value of the tool cannot be overstated. It has allowed organizations to be far more efficient and, overall, more effective in improving the analytics and arriving at actionable insights far faster than without the tool. An example of such a tool is one by which a comprehensive database repository can capture data and categorize it into several areas:

1. Content Repository – funneling hundreds or thousands of data sources into a central location
2. Content Search – performing Boolean, phrase, truncation or other searching mechanisms
3. Communication / Sharing – ability to cross-functionally share this information readily
4. Knowledge Visualization – transforming the data analysis into a useable, easily understood visualization for fast deciphering and application
5. Actionable Insights Decisions – arriving at the quickest time possible, the actionable insights to make organizational decisions

4.3 Analysis / Taxonomy

First off, it is important to know what is meant by "taxonomy" – this is the ability to categorize content in the classifications best suited to achieve the intelligence initiative. Think about the objective – if it is about a product launch or about how a competitor is performing, there is a set of criteria that needs to be established that acts as a catalyst to achieving the objective. What initial segments of the industry? Geographical areas? Specific products or general applications? How defined do you want to get into the details of what you are trying to determine? Therefore, the ability to analyze this data with the desired taxonomy is important, but one is not looking for a simple listing of relevant sources for a business need. Rather, the key OUTPUT element is to appropriately analyze the data that allows the user to identify and derive key content that can be immediately adjusted to include in the insights for recommendations. Many tools have dashboards that are customizable for the user's preferences and can be adjusted based on the parameters that the user requires. This is something used extensively by many successful organizations and is key to being able to get the data in the right format so that it is easily ported to a recommendations output.

Additionally, people-engagement is key here – ensuring that the content driven from the automation is relevant, timely, and actionable. You still have to utilize individual perspectives to make sure the dashboard outputs are in line with the company objectives and requirements for the need being investigated.

4.4 Organization- structure and culture

It's not just the process of competitive intelligence that needs to be modified in light of the new environment, but the organization itself will need to be looked at. There are two elements of this, one is the structure itself in that if the information is to be acted on quickly then mechanisms need to be in place to get intelligence into the hands of decision makers quickly. The idea, for example, of the pinnacle of CI being that it is included in the weekly or monthly senior management meetings needs to give way to real time, possibly daily intelligence updates. There is also the cultural element of organization. Far too many times senior management will be aware of the content of the intelligence, but will either chose not to act upon it (due to internal feelings outside of the data results), or simply ignore it as a "nice to know" sort of factoid. Obviously, both are potential catastrophic behaviors that will only improve the competitor's chances of getting an advantage in the marketplace, especially given the speed of change mentioned earlier.

Therefore, company structures have to be shallow and decision making has to be quick. "Analysis-paralysis" has to be avoided at all costs. This can only be achieved where you have a "sponsor" at the executive levels of the organization who values the CI contributing efforts and can therefore prioritize and include the results in the strategic direction of the company.

5. OPENING UP THE INTELLIGENCE PROCESS: OPEN INTELLIGENCE

With the above ideas implemented in organizations, it becomes more likely that organizations will have the ability to handle the four Vs of data and the corresponding international and speed components of insight generation. However, there are concerns that with most intelligence units being one or two people, it will be difficult for the user to actually cope with frequent intelligence projects integrating massive amounts of data, dealing with fast changing environment and incorporating international elements into the model. Not only will it be difficult as will be pointed out in the next part of this article, but it might even be undesirable. Perhaps a better approach will be to open up the intelligence process. In the next section, we look at a very popular topic – open innovation, the opening up of organizations' innovation activities including research and development to people outside the organization – even competitors – and applying the concepts of open innovation to competitive intelligence.

6. OPEN INNOVATION

Our notion of open intelligence is based on open innovation concepts which were pioneered by Henry Chesbrough. In 2003, Chesbrough wrote "open innovation is fundamentally about operating in a world of abundant knowledge, where not all the smart people work for you so you'd better go find them, connect to them, and build upon what they can do". He went on to explain that:

> "open innovation is a paradigm that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as the firms look to advance their technology. Open innovation combines internal and external ideas into architectures and systems whose requirements are defined by a business model".

Up to this time, innovation was seen as an exclusively internal organization function: R&D inside the organization came up with the ideas and then the organization determined (again internally) which ones to pursue to development and commercialization. Open innovation implies opening up the entire innovation process to "smart people" outside the organization. Elaine Watson in 2012 wrote about Coca Cola's open innovation program. Coca Cola's Chief Procurement Officer, Ron Lewis, summed up open innovation and its importance to Coca Cola when he said:

> "…our goal is to be the best at innovation in the industry and the way we're doing that is via an open network. And there is a good chance that the source of such innovation may well come from outside Coke's R&D department. We want to be the best at connecting the dots."

Finding ideas outside the organization and connecting the dots are certainly the objectives in open innovation and definitely areas where CI has a role to play. In a 2008 Harvard Business Review article by Huston and Sakkab on Procter & Gamble's (P&G) open innovation initiative, it was noted that as of the 2006, 35% of their new products had elements of open innovation with 45% of the initiatives in the product development portfolio having elements that were discovered externally, with a goal for 50% of innovation to come from outside the company. P&G even established a policy of licensing new products/technology to competitors if P&G had not commercialized it within three years of development.

In opening up the innovation process, open innovation researchers do note that part of this opening up is also to parts of the organization that traditionally had not been consulted/included in innovation efforts. For example, Volkswagen, in looking at car engine design, allowed individuals from outside the engine group to bring ideas forward and become involved in the selection of which ideas would go forward into design.

Hansen and Birkinshaw linked open innovation to each element of the innovation value chain. In their Harvard Business Review article "The Innovation Value Chain," they looked at key questions to ask and performance indicators to identify how "open" the innovation process was (Table 1). The typical company has virtually all idea generation done in-house. To open up the R&D process to other "bright" people, they talk about cross-pollination with other units across the organization providing input to R&D, and external input from people outside the organization who contribute to the R&D idea generation process. We have seen examples of this in many industries. We mentioned earlier about Volkswagen opening up engine R&D to people outside the R&D department. Bed, Bath and Beyond, in working with "Edison Nation," put a call out for inventors from around the world to provide ideas that could result in new products sold in Bed, Bath and Beyond. This goes beyond idea generation to using an open approach for both idea generation and conversion with Bed, Bath and Beyond doing the diffusion. After 14 years of research and writing on open innovation (14 years after Chesbrough introduced the topic) there have been enough case studies and papers written that it is safe to say that there are examples of each element of the innovation value chain, idea generation, conversion and diffusion being done through open innovation.

7. FROM OPEN INNOVATION TO OPEN INTELLIGENCE

Innovation was opened up because despite the risks (e.g. loss of intellectual property) the benefits associated with allowing people external to the R&D unit both inside and outside the company to assist with all aspects of the innovation process were too great. Organizations have found that with the speed of change and the need for faster and better innovation, it was beneficial to allow other people to have a role in generating ideas, evaluating them and even helping with commercialization. Given the complexity and volume around data and intelligence, it is clear that similar to open innovation, it is time to for CI to consider opening up all phases of the intelligence process to deal with similar challenges: the need for quicker intelligence, the need to cope with frequent environmental change, and the need to deal with the complexity posed by big data. The following discussion explores how this would work by going through some of the elements of the traditional intelligence wheel.

In looking at open intelligence, some of the language of open innovation from Hansen and Birkinshaw can be related to CI:

- In-house: This will refer to the traditional model of intelligence where most aspects of the intelligence process are done within the CI unit;
- Cross- Pollination: This will refer to supplementing the in-house CI unit with input from others and other units

Table 1 Hansen and Birkinshaw innovation value chain.

	IDEA GENERATION			CONVERSION		DIFFUSION
	IN-HOUSE Creation within a unit	CROSS-POLLINATION Collaboration across units	EXTERNAL Collaboration with parties outside the firm	SELECTION Screening and initial funding	DEVELOPMENT Movement from idea to first result	SPREAD Dissemination across the organization
KEY QUESTIONS	Do people in our unit create good ideas on their own?	Do we create good ideas by working across the company?	Do we source enough good ideas from outside the firm?	Are we good at screening and funding new ideas?	Are we good at turning ideas into viable products, busi-nesses, and best practices?	Are we good at diffusing developed ideas across the company?

of the organization to assist in all aspects of intelligence development;
- External: This will refer to supplementing both in-house and cross-pollination with people outside the organization such as key customers, suppliers, experts, and other stakeholders to assist with intelligence development.

8. INTELLIGENCE PLANNING

There are many aspects of intelligence planning that could be discussed that could benefit from open intelligence but for the purposes of a basic exploration of the concept we will look at one: intelligence topic generation. Intelligence topics are traditionally developed by the person responsible for intelligence based either on their understanding of management needs or through direct consultation with management. We call this the traditional in-house approach to topic development. In CI, we talk about it in terms of "what is keeping the CEO up at night", "what key decisions are being made". Cross-pollination (opening up the process to units outside intelligence) would involve allowing others in the organization to contribute to the intelligence topic generation process. Personnel in R&D, for example, understand the technical environment well and might have some interesting perspectives on what topics need to be investigated. Those in maintenance or service may have ideas based on the complaints and problems that customers are having. Taking an external perspective (fully open), imagine if customers, suppliers, and other stakeholders—possibly even including competitors—provide input on the intelligence topic selection process. Nan Bulger, in a 2015 article, wrote about integrated intelligence and said that the purpose of intelligence is to "help your customers' compete in the market and help your customers make money". If the purpose is to make customers more competitive (a business to business objective – B2B) or simply to satisfy customers (both B2B and more traditional consumer markets), then would it not make sense to ask them what topics are most relevant to them? Or perhaps show customers suggested intelligence topics and ask them which one would result in intelligence that would help them better position themselves with their customers?

It's not just idea generation of topics that could be done in an open intelligence approach, topic selection could also be done this way. We can envision a Delphi approach where people from outside the CI function rank the intelligence topics, thereby helping the intelligence team determine which ones are more relevant to other units of the organization and to key stakeholders.

9. COLLECTION

Open intelligence applied to collection is something that on the surface CI already does very well. The profession understands the importance of gathering information from broad sources both within and outside the organization. They get the need for diverse sources of information but there are a few aspects of collection that we want to bring up in the context of open intelligence. To what extent is information being entered into the intelligence system from other units of the organization (cross-pollination)? From outside the organization (external)? This is not about where information comes from but who is providing it. In an open intelligence environment, information is being directly entered into the system by stakeholders and by people in other parts of the organization. Open intelligence also requires that CI practitioners extend collection sources to recognize data variety – to what extent (where relevant) is online video, social media, and so forth being integrated into intelligence efforts? How is the internet of things figuring into collection plans? Imagine what could happen if organizations addressed variety, velocity and volume. This no doubt will require the use of technology but given rates of change and increased data (and data complexity) this will be needed. One thing to consider is that, in the big data world, 80% of what is available is unstructured or semi-structured (text, images, and sound). Therefore, some form of unstructured data technology will become important.

10. ANALYSIS

The traditional view of analysis has the person responsible for intelligence applying any one of several dozen formal analytical techniques to information that has been gathered. This is a straightforward and logical process that fits with the in-house view of intelligence. We have added to this in the earlier section in mentioning some online/technological analytical tools but it's still conceptually about the CI unit engaging in the analysis and then sending the results with recommendations off to the decision makers. A few things that we have seen over the past several years have caused us to question whether this should be changed to incorporate the open intelligence approach. The first was a presentation by Johan Van Zyl, CEO of Toyota Europe NV/South Africa on the Toyota South Africa intelligence system. During the presentation, he talked about how the client for the intelligence joins with the intelligence team during the analysis phase. This provides the intelligence team with client insights and perspectives on the data. We have also seen various foresight initiatives where experts from around the world were invited to provide analytical input either as part of expert panels or in Delphi approaches to help organizations make sense of complex environments. Volkswagen provides a very interesting open innovation example in this respect. They set up a virtual exchange where participants from throughout the company received play money that they could "bet" on what they thought were the better ideas. Whichever idea attracted the most "virtual money" on the exchange was the one selected.

There are two aspects then to think about in applying an open intelligence approach to analysis. The first is who do you open the analysis process up to (i.e., who is invited in)? And the second is the kind of analytical techniques you use to integrate broader involvement. An in-house approach (like in open innovation – so call this closed) involves only having the intelligence unit doing the analysis. Cross-pollination would involve allowing others inside the organization to participate in the analysis process and external would require inviting in outside experts, stakeholders and others. For cross-pollination and external initiatives, traditional analytical techniques would be combined with techniques such as Delphi and expert group approaches. The foresight field has a lot of techniques that should be used that integrate broad groups in the analysis function.

A final aspect of analysis that ties in with the concept of rapidity of change is the frequency of analysis. As mentioned in the collection section, organizations will need to refresh and reanalyze their data on a frequent basis. Automated analytical approaches (software and other online tools) will become more important in addressing the need for more frequent data refresh rates, broader data types, and the need for more frequent analysis.

11. COMMUNICATION

Traditionally, intelligence is given to the client after being developed by the intelligence unit. There are variations in this approach with some suggesting providing the analysis but not the recommendations (the true intelligence) to other managers in the organization and in some cases making the non-sensitive information gathered for intelligence available more broadly throughout the organization. But, generally, it's about targeted intelligence being developed and given its sensitivity being provided to those with the authority and requirement to receive it - "a need to know basis only". The open innovation groups have discussed at great length the sensitivity and concerns with sharing intellectual property more broadly than just in-house (in the R&D unit) but have generally concluded that despite the risk the potential benefits are big. Similarly, for intelligence, there will have to be discussions around how broadly intelligence should be communicated. Under the cross-pollination approach, intelligence results could be shared with others in the organization (besides the client) but perhaps only those who have appropriate security clearance levels. Under an external approach (full open intelligence) the intelligence would be shared with trusted stakeholders outside the organization. This certainly is done within the government intelligence environment (within the five eyes community for example – Australia, Canada, New Zealand, the United Kingdom and the United States) and it might make sense to share intelligence findings with key customers or suppliers to get their perspective on the intelligence. Again, this fits with the integrated intelligence concept but more importantly provides an additional level of validation on intelligence results and helps provide unique perspectives on it as well.

12. IDEAS FROM ANALYTICS AND IT TO ENHANCE THIS NEW APPROACH

To a certain extent, the analytics field has proposed IT-related solutions to address some of the problems described in this article. IT systems enable organizations to expand geographies, shift time zones, and build linkages among people (e.g., collaborative groupware) that enable the rapid transfer of knowledge across boundaries (Dodgson et al., 2006).

While an IT system enables co-creation through information flows, the data are only useful to the extent that managers can generate insights that help their businesses. In a co-creation environment, different stakeholders might interpret the same data in different ways. Analytic tools, such as machine learning, can help to enable consistent interpretation of data across the co-creation ecosystem

The use of analytics in innovation however, is not well-understood (George & Lin, 2017) and we are certainly proposing an innovative approach to competitive intelligence. Nevertheless, many companies are starting to learn how best to leverage the power of these advanced technologies in generating and in implementing new ideas. George & Lin (2017) provide a framework for considering the different ways in which analytics could be integrated into innovation. The aspect most relevant to open intelligence is the role of analytics as a driver of organizational transformation. As such, analytics could influence both product and process innovation by capturing and translating data more effectively to better inform transformation decisions.

In terms of open innovation, its defining feature (relative to closed innovation) is the gathering and processing of data from external stakeholders. He and Wang (2016) argue that social media can be used for improving interaction with a wide variety of these stakeholders. In addition, it can be employed in co-creation efforts during product development. In an analysis of IT strategies and open innovation, Cui et al. (2015) suggest that outbound, inbound and coupled processes involved in open innovation can be leveraged in different ways through IT. Whereas inbound and outbound innovation tend to involve one-way flows of information, coupled processes embrace the co-creation concept in which partners and other stakeholders are involved throughout the innovation initiative.

In summary, companies can enhance the chance of open intelligence success by expanding the breadth and depth of information processing (Ciu et al, 2015). Information technologies can help to enable breadth in that these systems can gather and process information from a wide variety of sources. Analytics, however, can help with depth, leading to insights that might not have been previously considered.

13. CONCLUSIONS

Speed of change, needing to address international dimensions of business and information and increasing complexity of data (volume, variety, velocity and veracity) will require a rethink and possibly reconceptualization of how we develop intelligence. Open intelligence, our concept which is inspired by the popular and growing field of open innovation, provides an approach for addressing this challenge. However, it will require that the competitive intelligence function opens up to others inside the organization (cross-pollination) and at the most open, from others outside the organization (the external approach). Table 2 provides examples of this within planning, analysis and communication. This may make some intelligence practitioners nervous due to the potential for the intelligence to be seen by some that they do not wish to see it, but this is no worse than the potential loss of intellectual property that can arise in open innovation. Yet, many of the world's largest companies have adopted aggressive open innovation targets and established open innovation programs. It is only by harnessing the information from broader networks (open intelligence), involving a broader array of experts in analysing information (open intelligence) and sharing the intelligence with appropriate stakeholders (open intelligence) that organizations will be able to deal with the speed of change and increasing complexity of data described in this article. Even planning (including intelligence topic selection) can benefit from an open intelligence approach.

Future competitive intelligence scholarship should look at the open intelligence concept. CI researchers should look for examples in which intelligence was developed using external networks. In this article, we have provided a few examples of where open intelligence concepts were observed (e.g., Toyota South Africa) but more examples should be sought out. The concept of open intelligence appears to address the challenges we have described in this article but further development and testing of the concepts is required.

To paraphrase Henry Chesbrough, the CI unit does not have all the smart people in the world working for it, but it could. The idea in open intelligence is to get the "best minds" working for the organization's CI program as a means for addressing today's challenges but also to maximize the ability to identify and take advantage of opportunities.

Table 2 Open Intelligence – Examples within the wheel of intelligence.

	Traditional model – In house (CI unit)	*Cross pollination – across the firm*	*External*
Planning: where the topics come from	Senior management driven: "what's keeping them up at night" CI practitioner driven: "We know what's needed"	Other parts bring forward and help to select the intelligence topics – they know what key issues are from their unit's perspective	Key stakeholders have a unique perspective on the environment. What's important to them? What do they need to be competitive?
Analysis: Techniques and methods	Our unit knows how to make sense of the information. Craig Fleisher and Babette Bensoussan have shown us the techniques.	We still need Craig and Babette but let's have others from the organization help us make sense of the information. We will need group analysis approaches-exchanges, Delphi	Who are our five eyes for intelligence? Let's harness the power and insight from key customers, suppliers, other allies, experts etc. We will need group analysis approaches such as exchanges and Delphi
Communication	The intelligence is provided to the client – need to know basis	The intelligence is shared with those in the organization that could provide perspective on it and are cleared to see it.	The intelligence is shared with key people outside the organization that can provide perspective and we trust to see it

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