Exploring business intelligence and its depth of maturity in Thai SMEs

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Exploring business intelligence and its depth of maturity in Thai SMEs

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Abstract: Increased complexities in making effective and timely business decisions in highly competitive markets have driven organisations worldwide to adopt business intelligence (BI) technologies. Large enterprises have reached a mature stage of BI adoption while small- and medium-sized enterprises (SMEs) still lag behind—despite organisations of all sizes can benefit from the use of this technology to aggregate, manage and analyse data for assisting decision-making that enhances profitability. This study proposes a BI maturity model for SMEs that distinguishes different levels of BI maturity and identifies the factors that currently impact their levels of BI adoption. The proposed model is empirically tested using survey data from 427 SMEs and analysed using multinomial logistic regression. Results indicate that BI adoption in Thai SMEs is still at an initial stage, with the majority being classified in the lowest level of BI maturity. Significant factors that impact the levels of BI adoption are relative advantage, complexity, organisational resource availability, competitive pressure, vendor selection and owner-managers' innovativeness. Results from the study can be used by government agencies to develop strategies to increase the rate of BI adoption among SMEs. IT vendors also can use the results to determine which SMEs they should target.

ABOUT THE AUTHORS

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PUBLIC INTEREST STATEMENT

Business intelligence (BI) is today a key information system (IS) for many enterprises globally. BI supports enterprises through better decision-making by faster access to more reliable information. BI helps grow the quality of client relationships, increase income and rationalise non-IT expenses. Large organisations recognising the competitive advantage gained from BI were the first to implement BI and BI has become an important and integral part of enterprise decision support. SMEs still underestimate the value of BI and limit BI capabilities to basic administrative tasks. BI systems have become more affordable and represent an opportunity for Thai SMEs to gain competitive advantage through better decision-making. This study explored Thai SMEs' current BI adoption levels and identified factors impacting BI adoption levels. The study's findings and proposal of a new BI adoption framework will help Thai Government agencies and technology suppliers develop strategies to encourage higher levels of BI adoption for Thai SMEs.

1. Introduction

For over two decades, research into business intelligence (BI) has become increasingly significant in supporting the industry. For instance, Gartner's survey of 2,053 IT chiefs in 41 countries found that BI is a first priority in technological investment (Gartner, 2013). The International Data Corporation reported that worldwide investments in BI are significant and growing, having increased from US$10.53 billion in 2011 to US$11.35 billion in 2012, and estimated to reach US$17.1 billion by 2016 (IDC, 2013). Implementation of BI technology to support businesses has grown due to its increasing affordability (Chaudhuri, Dayal, & Narasayya, 2011) and the desire among organisations to make decisions in a timely manner (Habjan & Popovic, 2007). This demand for BI is not restricted to firm size, even though it has normally been associated with larger firms (Gäre & Melin, 2011) reaching BI maturity (O'Brien & Kok, 2006). Indeed, although small- and medium-sized enterprises (SMEs) now have as much need for BI as large companies (Cheung & Li, 2012), their adoption rates still lag behind. This low rate of adoption could in fact reduce the ability of SMEs to compete with larger organisations and loss of competitive advantage.

However, despite the benefits of adopting BI by SMEs are known and attempts made to provide commercially relevant BI systems, many SMEs remain reluctant to use this technology (Grabova, Darmont, Chauchat, & Zolotaryova, 2010). Furthermore, as research in this area remains sparse, there is insufficient knowledge in understanding the adoption of BI by SMEs. Additionally, the majority of such studies have been conducted for specific countries such as Australia (Elbashir, Collier, & Davern, 2008), Northern Ireland (Hill & Scott, 2004) and United States (Ramamurthy, Sen, & Sinha, 2008), with very few exploring the situation of BI in Thailand—despite rapid growth of IT spending in this country. The International Data Corporation reported that Thailand in 2015 was estimated to increase IT spending by 10.6% to US$13.4 billion (Pornwasin, 2015), whereas IT spending in Europe would increase by less than 1% (IDC, 2015). These spending trends make it crucial to further understand IT and BI implementation in Thailand.

There are two main objectives of this study. The first objective is to investigate the current state of BI adoption by four main types of Thai SMEs including manufacturing, service, wholesale and retail. In order to identify the current BI adoption state, this study is based on the concept of maturity model to classify organisations into different BI levels. The second objective is to identify the factors that influence such adoption. Rather than viewing BI adoption as a dichotomous decision to adopt or not adopt, this study has developed a maturity model to depict the stages of BI adoption on a scale from low level to high level. To explore the important factors that influence the levels of BI adoption, this study is based on the "Diffusion of Innovation" theory (Rogers, 1983), technology–organisation–environment (TOE) framework (Tornatzky & Fleischer, 1990) and the IS integration model (Thong, 1999). Clearly, recognising the factors that influence levels of BI adoption will be useful in suggesting strategies to overcome the constraints that inhibit adoption. This line of inquiry benefits both researchers and practitioners.

2. Theoretical background

2.1. Business intelligence

BI is defined differently in various fields according to interpretation and context (Niu, Lu, & Zhang, 2009). However, although there is no commonly agreed definition of BI, existing definitions share two common characteristics. The first is the fundamental aspect of BI which includes collecting, storing, analysing and delivering information available both internally and externally. The second is the aim of BI, which is to support the strategic decision-making process of the firm.

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2.2. Adoption of innovation theory

The adoption of BI in SMEs can be viewed from the perspective of innovation (Igartua, Garrigós, & Hervas-Oliver, 2010). Damanpour and Evan (1984) defined an innovation as any idea, practice or object that the adopting individual or organisation regards as new. Although a wide variety of theoretical models have been used to explore the adoption of innovations, this study employs a multiple perspective framework based on three related theoretical frameworks as the basic foundation for development of a conceptual model: diffusion of innovation theory (DOI), TOE framework and the IS integration model.

DOI was developed by Rogers (1983) with the initial aim of describing the elements that impact the process of innovation diffusion and adoption. This theory posits that potential adopters evaluate an innovation based on their perceptions, and will make a decision to accept the innovation if they perceive that it exhibits one or more of five general factors, being relative advantage, complexity, compatibility, trialability and observability. Of these factors, relative advantage, complexity and compatibility have provided the most consistent explanation for the adoption of ISs (Tornatzky & Klein, 1982). According to the review of literature by Jeyaraj, Rottman and Lacity (2006), DOI has been the most often cited work dealing with innovation adoption, as can be observed in numerous studies. However, DOI has been criticised as it is biased towards the technological component of the adoption process (Fichman, 2000). Even when technological superiority is assured, it does not guarantee the adoption of IT innovation by organisations. This is because other social, organisational and individual factors may impact IT adoption (Segal, 1994).

The TOE framework, proposed by Tornatzky and Fleischer (1990), combines innovation characteristics with other elements. This framework can be viewed as an extension to the DOI theory to strengthen what has been generally neglected, namely organisation and environment circumstances which add both opportunities and constraints to the technology adoption decision (Zhu, Dong, Xu, & Kraemer, 2006). To facilitate an understanding of innovation adoption in organisations, several studies have adopted TOE in combination with DOI to examine the impact of relevant organisational and environmental characteristics including variables such as competitive pressure, selection of vendors, absorptive capacity and organisational resource availability (Chong, 2008; Ghobakhloo, Arias-Aranda, & Benitez-Amado, 2011; Ifinedo, 2011; Tan & Lin, 2012).

An IS adoption model for small business was first developed by Thong (1999), for the reason that the available organisational theories or practices applicable to large organisations may not fit the SME context. Thong developed his integrated perspective model of IT adoption in SMEs to identify four contextual variables relevant to IT adoption, including owner-manager, technological, organisational and environmental characteristics. Thong found that small businesses with owner-manager who have innovativeness and IT knowledge are more likely to adopt technologies. As owner-managers have a significant impact on making IT adoption decisions, several studies conducted on SMEs have further included owner-managers' characteristics into the factors that impact technology adoption (Chang, Hung, Yen, & Lee, 2010; Fogarty & Armstrong, 2009; Ghobakhloo et al., 2011).

The above-mentioned factors that are generally crucial in the adoption of IT have been extensively examined in the literature. These factors are significant to the success of technology adoption in the organisational context. However, limited studies have focused on the factors that specifically influence BI in the particular context of SMEs. For this reason, there is a need to conduct studies that focus more on BI in SMEs. Based on the assumption that the adoption of BI in SMEs may follow similar patterns to that of general IS and IT, this study has used the above-mentioned factors and included in the initial version of the research model.

2.3. A BI maturity model

BI involves a broad range of technologies from simple to complex (Negash & Gray, 2008; Sacu & Spruit, 2010); thus, a flexible classification of BI level is desirable. This is to recognise that organisations that adopt advanced technologies tend to have characteristics that are distinct from those

Table 1. Summary of example BI maturity models					
BI maturity model	**Concentration area**				
	First level: individual	**Second level: department**	**Third level: enterprise**	**Fourth level: strategy**	**Fifth level: sustainable growth**
IEM	Operarte	Consolidate	Integrate	Optimise	Innovate
TDWI	Infant	Child	Teenager	Adult	Sage
BIDM	Predefined reporting	Department data warehouse	Enterprise-wide data warehouse	Predictive analysis	Operational BI
EBIMM	Initial	Repeatable	Defined	Qualitative	Optimising

Source: Chuach (2010), Davis et al. (2006), Eckerson (2007) and Sacu and Spruit (2010).

with relatively simple technologies (Teo, 2007). However, there is no common classification of BI level adoption among researchers. Although some researchers categorise the levels of BI in terms of solutions and technologies (Hawking, Foster, & Stein, 2008; McDonald, 2004), the majority define BI as representing not only technologies but also processes that transform data into information and then knowledge (Pirttimaki, Lonnqvist, & Karjaluoto, 2006; Wixom & Watson, 2010). Therefore, the concept of a maturity model is applied in this study to explain the different levels of BI adoption. Maturity is described as a "state of being complete, perfect or ready" or the "fullness of development" (Soanes & Stevenson, 2008, p. 906). To reach a desired state of maturity, an evolution transformation path from initial (first adoption) stage to a target stage needs to occur (Klimko, 2001).

For classifying organisations into different levels of BI, IT consulting companies have developed a variety of BI-specific maturity models such as the information evolution model (IEM) (Davis, Miller, & Russell, 2006), The Data Warehouse Institute (TDWI) (Eckerson, 2007), BI Development Model (BIDM) (Sacu & Spruit, 2010) and the Enterprise BI Maturity Model (EBIMM) (Chuach, 2010). Each model focuses on different dimensions or perspectives and have their own limitations such as being based only on technical dimensions or only on organisational dimensions (Rajteric, 2010). However, analysis of these models revealed that they also have repetitive information due to the model addressing similar concepts, despite using different designations. For example, most BI maturity models in the first level focus on the individual, while the second level focuses on department, despite using different designations. Table 1 shows the summary of a BI maturity model.

This study adopted the IEM as proposed by SAS, the leading company in business analytics software and services (Davis et al., 2006), to classify organisations into specific BI levels. The IEM model was selected as the fundamental model as it is not restricted to the technological dimensions and also focuses on the alignment between the four dimensions of infrastructure, knowledge process, human capital and culture. All four dimensions are used to classify the level of BI in organisations. However, Lahrmann, Marx, Winter and Wortmann (2010) suggested that the IEM model had limitations in addressing the analytical applications, one of the key BI components (Ranjan, 2005). Therefore, this study includes the "Application" dimension as derived from Sacu and Spruit (2010) to more comprehensively conceptualise BI and enhance the IEM model.

2.3.1. Five dimensions in BI maturity model
There are five levels defined in the proposed BI maturity model spanning across five dimensions as follows:

Infrastructure: the implementation of technologies including hardware, software and networking tools to create, store and distribute information;

Knowledge process: the role of information in corporate knowledge sharing, the role of information in decision-making and the improvement of information accuracy;

Human capital: capabilities, responsibilities, decision-making, training, enterprise goals and improvement of personnel skill sets related to technological information;

Culture: social and behavioural norms of corporate culture in relation to the information flow within an organisation; and

Application: analytic applications that organisations have adopted from using basic software programs for generating reports to advanced programs that provide predictive results.

2.3.2. Five levels in the BI maturity model

A unique feature of the BI maturity model presented in this study is the recognition of the relationships between the five dimensions. Organisations can be classified into five different levels of BI adoption from low to high levels (operate, consolidate, integrate, optimise and innovate) depending on how they are situated in relation to the five dimensions. In accordance with Davis et al. (2006) and Sacu and Spruit (2010), each dimension is given five levels of maturity in the following order:

2.3.2.1. Operate. A company in the "Operate" level is one with the most basic BI and is typically a start-up organisation. Companies at this level focus on general information for day-to-day operations. They operate in a chaotic information environment where information access and formats are not standardised. Their employees generally keep information on individual computers. They also fear organisational change. Simple software programs to generate personal reports or personalised spreadsheets are used in this type of organisation.

2.3.2.2. Consolidate. A company in the "Cconsolidate" level is one that integrates and stores information at the departmental level. The knowledge process at this level shifts from the individual to departments. Data management is well defined in each department but not across departments, leading to problems of mismatch between departments. Employees at this level work effectively in teams with rewards from contributing to departmental goals. The "Consolidate" company typically uses software programs that can keep data in standardised formats but with limited user views.

2.3.2.3. Integrate. A company in the "Integrate" level recognises the significance of defining information consistently across the organisation by integrating data and storing it in a central data warehouse. Information is well managed in a standardised approach and clearly tied to organisational goals. As a result, decision-making is from the organisational perspective. There is cooperation in managing data between employees from various departments. Employees in the integrated company accept change when it is clearly understood. The integrated company typically uses software programs that keep data in a standardised format throughout the enterprise and allow users a multidimensional view of data.

2.3.2.4. Optimise. A company in the "Optimise" level explores methods to maximise performance in a competitive context to better serve their customers. This company views the business model as extending beyond the business; thus, infrastructure is linked through internal business systems across the supply chain. At this level, the company needs to have employees with intellectual skills, including predictive analysis, to work with other colleagues to improve organisational effectiveness. Employees embrace the idea of improving incrementally, and view change as an opportunity rather than a threat. The company in the "Optimise" organisation level typically uses software programs with automated data analysis techniques to detect relationships in the data and provide predictive results.

2.3.2.5. Innovate. A company in the "Innovate" level seeks ways to transform its value proposition for sustainable growth. The company uses flexible systems that can manage data including structured and unstructured data. In addition to having standardised processes, the company prepares for new processes to support forthcoming new innovations. Employees at this company require expertise in advanced decision-making software to analyse new ideas that align with enterprise goals. As an

organisation that encourages novel ideas, the innovate company understands that failures are inevitable and part of the learning process. The innovate organisation typically uses software programs that allow users to generate an automated exception reporting when something unusual occurs.

2.4. Conceptual model and hypotheses

Based on the BI maturity model and three related theoretical frameworks, the proposed conceptual model is presented in Figure 1. Nine hypotheses are proposed below.

2.4.1. Relative advantage

Ifinedo (2011) found that the more organisations perceive technology as having advantage over existing practices and systems, the more the adoption of such technology will be positively encouraged. In the case of BI, the advantages of adopting this technology to support business operations are clear (Ko & Abdullaev, 2007). For example, retail companies can use BI to determine which of their products are most profitable, and where to place them in their stores (Williams & Williams, 2003). Hence, we hypothesise that:

> H1: Relative advantage of BI significantly impacts on BI adoption levels among SMEs.

2.4.2. Complexity

Complexity can present a barrier to innovation adoption (Chang et al., 2010). For example, Ramamurthy, Sen and Sinha (2008) found that lower complexities in a technology result in higher positive effects on its adoption, which infers that the high complexity of BI technology can cause employees to resist its adoption (The Economist Intelligence Unit, 2007). Voicu, Zirra and Ciocirlan (2009) confirmed that BI models are highly complicated because they integrate mathematical functions to predict trends in a firm's performance that provide solutions in a variety of situations. Hence, we hypothesise that:

> H2: Complexity of BI significantly impacts on BI adoption levels among SMEs.

Figure 1. Research model.

Source: Research study (2016).
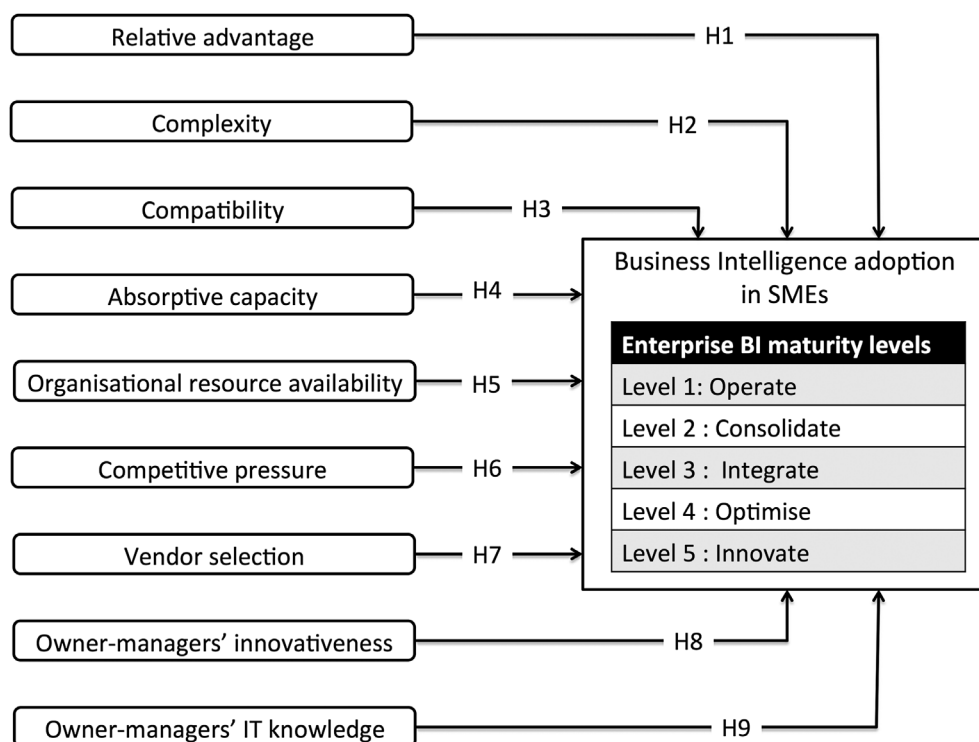
2.4.3. Compatibility

Some studies employing the compatibility factor have proven its validity in predicting technology adoption among organisations (Chang et al., 2010; Grandon & Pearson, 2004). Bajaj (2000) indicated that this factor can bring changes to the organisation by converting old data to be read on new architecture, retraining users to use and allowing IT personnel to effectively maintain software. However, if existing systems are not compatible with BI technology, it may take a significant investment of time and resources to migrate data. Hence, we hypothesise that:

H3: Compatibility of BI significantly impacts on BI adoption levels among SMEs.

2.4.4. Absorptive capacity

The absorptive capacity of an organisation has been identified as the ability of its members to use existing or pre-existing knowledge (Griffith, Sawyer, & Neale, 2003) to increase recognition of new and external information that can be applied to increase economic benefit. This capacity can be used as a predictor of the organisation's ability to adopt an innovation or not (Khalifa & Davison, 2006). However, a survey conducted on telecommunication firms by O'Brien and Kok (2006) indicated that many organisations were not fully utilising BI due to lack of knowledge, technical skills and training. Hence, we hypothesise that:

H4: Absorptive capacity significantly impacts on BI adoption levels among SMEs.

2.4.5. Organisational resource availability

Organisational resource availability has also been identified as influencing innovation adoption (Adler-Milstein & Bates, 2010; Oliveira & Martins, 2010). However, due to high complexity and cost, BI implementation is often out of reach to organisations with less financial resources and skilled workers (Sahay & Ranjan, 2008). As Chong (2008) mentioned, managers will support the adoption of a new technology when capital, human resources and organisational time to implement are available. Hence, we hypothesise that:

H5: Organisational resource availability significantly impacts on BI adoption levels among SMEs.

2.4.6. Competitive pressure

Competitive pressure tends to stimulate firms to look for new approaches to business by raising efficiency and increasing productivity for survival (Themistocleous, Irani, Kuljis, & Love, 2004). This pressure can come from either competitors or trading partners, which results in a greater intention by firms to adopt the technologies that are being used by competitors. To avoid being labelled as less receptive to change and incompatible with industry norms, some organisations adopt new technologies that are commonly used by other companies (Teo, 2007), indicating a strong relationship between the degree of competitive pressure and technology adoption (Dholakia & Kshetri, 2004; Hwang, Ku, Yen, & Cheng, 2004). Hence, we hypothesise that:

H6: Competitive pressure significantly impacts on BI adoption levels among SMEs.

2.4.7. Vendor selection

Selection of vendors is a significant factor in IT adoption as they can help facilitate adoption implementation and ongoing success (Moffett & McAdam, 2003). This is important because even when innovative enterprise systems are advanced, they may not be stable enough to meet the entire information processing needs required (Davenport, 2000). Due to BI being different from other enterprise information technologies, it requires tailored solutions to suit each particular firm and industry (Hill & Scott, 2004). Hence, we hypothesise that:

H7: Vendor selection significantly impacts on BI adoption levels among SMEs.

2.4.8. Owner-managers' innovativeness

Innovativeness refers to a willingness to introduce newness and novelty through experimentation and creativity aimed at developing new products, services and processes (Zhu et al., 2006). Parasuraman (2000) found that personal innovativeness exists in certain individuals who are willing to take risks when adopting an innovation. For instance, Chang et al. (2010) found that owner-managers' innovativeness is a significant determinant of enterprise resource planning (ERP) adoption in SMEs. Hence, we hypothesise that:

> H8: Owner-managers' innovativeness significantly impacts on BI adoption levels among SMEs.

2.4.9. Owner-managers' IT knowledge

Greater owner-manager knowledge in IT can decrease the degree of uncertainty and lead to lower risk in IT adoption (Thong, 1999). This view has been reinforced by Mirchandani and Motwani (2001) who found that owner-managers' IT knowledge is a key factor highly associated with IT adoption. In agreement, Chao and Chandra (2012) reported that owner-managers have more capability in technology adoption when they are able to gain knowledge about the new technology. Hence, we hypothesise that:

> H9: Owner-managers' IT knowledge significantly impacts on BI adoption levels among SMEs.

3. Methodology

3.1. Data collection

A quantitative methodology through a survey questionnaire was employed to explore the current state of BI adoption by Thai SMEs. A self-administered questionnaire was initially developed and reviewed for content validity by five BI experts specialising in SMEs. In defining these SMEs, this study used employee numbers in line with small business research principles. Consequently, these SMEs were defined as companies with fewer than 200 employees in line with the definition by the Thailand Ministry of Industry (Brimble, Oldfield, & Monsakul, 2002) and randomly selected from a database of organisations that had submitted trade declarations to the Thai Government. Two thousand SMEs from four main industries including service, manufacturing, wholesale and retail were randomly selected. A total of 485 responses were eventually received, showing a returning rate of 24.25%. However, 58 questionnaires were excluded, where 32 respondents failed to complete the research instrument appropriately, and 26 respondents were identified as having more than 200 employees. The final number of usable responses was 427, yielding a response rate of 21.35%. The demographic characteristics of respondents are shown in Table 2.

3.2. Measurement of variables

3.2.1. Dependent variables (The levels of BI adoption)

The dependent variables in the research model are the levels of BI adoption. It is a categorical variable incorporating five groups (BI levels): operate, consolidate, integrate, optimise and innovate. The constructs and measures for classifying these levels of BI information use in enterprises were adapted from the IEM check list provided by Davis et al. (2006) and Sacu and Spruit (2010). As the model in this study classifies organisations into five levels of BI based on five dimensions of infrastructure, knowledge process, human capital, culture and application, respondents were asked five questions which represent the five dimensions. Each question had five answers representing the five levels of BI adoption. Respondents were asked to choose answers that best described their organisations. The total sum of frequencies in responses given was then used to classify each organisation into one of the five levels of BI adoption.

Table 2. Demographics of the respondents

Demographics	Categorises	n = 427	(%)
Gender	Male	257	60.2
	Female	170	39.8
Age	18–20	18	4.2
	21–30	90	21.1
	31–40	142	33.3
	41–50	117	27.4
	More than 50 years old	59	13.8
Education level	High school or equivalent	54	12.6
	Vocational or diploma	111	26.0
	Bachelor degree	160	37.5
	Master degree or higher	102	23.9
Position	Owner-manager	272	63.7
	Manager	146	34.2
	Other	9	2.1
Industry type	Manufacturing	88	20.6
	Service	100	23.4
	Wholesale	79	18.5
	Retail	160	37.5
Number of employees	Sole proprietor	12	2.8
	2–9 persons	119	27.9
	10–50 persons	142	33.3
	51–100 persons	100	23.4
	101–200 persons	54	12.6
Number of years in business	Less than 1 year	59	13.8
	1–5 years	139	32.6
	6–10 years	109	25.5
	More than 10 years	120	28.1

Source: SPSS descriptive analysis (2016).

3.2.2. Independent variables (Adopting factors)

The independent variables were measured by asking respondents to evaluate which factors impacted the levels of BI adoption in their organisations. The measurement used for analysing responses in the independent variables was developed by adapting and amalgamating measures from previous studies. The constructs of relative advantage, complexity and compatibility were adopted from Moore and Benbasat (1991), whereas absorptive capacity and organisational resource availability were adopted from Iacovou, Benbasat and Dexter (1995). The constructs of competitive pressure and vendor selection were adopted from Grandon and Pearson (2004), whereas owner-managers' innovativeness and IT knowledge were adopted from Hung, Hung, Tsai and Jiang (2010). A five-point Likert scale was used for all items, anchoring from "Strongly Agree" to "Strongly Disagree".

3.3. Measurement model evaluation

This study categorises Thai SMEs into different BI adoption levels based on five dimensions and the Spearman correlation was used to test accuracy and reliability. Using the BI maturity model, an organisation was classified into the level where the organisation possesses properties mostly similar to the description of that level in each of the dimensions. It was assumed that if respondents' organisations were ranked high in one dimension, they were also to be ranked higher in other dimensions. The Spearman correlation was used to identify the correlation between each of the dimensions.

All dimensions had positive correlation between the paired dimensions, which means that the ranks of both dimensions were moving in the same direction. Moreover, the *p*-values of all dimensions were 0.00, which was lower than the significance level of 0.05 revealing a significant association between each dimension. As all dimensions in the study model had relationships with each other, the study model had a degree of accuracy and reliability in categorising organisations into the various BI adoption levels.

Instrument reliability related with enabling factor was ascertained using Cronbach's alpha (α). The values obtained for each of the factors were as follows: relative advantage: 0.841; complexity: 0.844; compatibility: 0.665; absorptive capacity: 0.611; organisational resource availability: 0.807; competitive pressure: 0.794; vendor selection: 0.772; owner-managers' innovativeness: 0.689; and owner-manager's IT knowledge: 0.624. These values indicated that the constructs and their respective measurement items had strong internal consistency and were suitable for the study.

4. Data analysis and hypotheses testing

4.1. Data analysis

Descriptive statistics were used to explain the fundamental features of the data in regard to the proportion of BI adoption in each level. From 427 responses, 206 organisations were categorised as being at the operate level, 136 organisations at the consolidate level, 73 organisations at the integrate level, 12 organisations at the optimise level and no organisation at the innovate level. However, Israel (2009) recommended a minimum sample size of around 20% for each group when samples were categorised into sub-groups. Consequently, the two levels of BI maturity, optimise and innovate, were incorporated into a new "integrate +" level. The "integrate +" level yielded 85 organisations. The dependent variables of BI adoption are thus: operate, consolidate and integrate +.

Multinomial logistic regression was formed to test the hypotheses due to the dependent variable being the level of BI adoption, and all independent variables coming from the proposed model. Logistic regression is suitable for this situation in which the dependent variable is categorised (Hosmer, Lemeshow, & Sturdivant, 2013; Pett, 1997; Stevens, 1946). Also, as this regression requires fewer assumptions than discriminant analysis, it was more robust in the face of data conditions. Even though the multinomial logistic regression does not require any assumptions of normality, linearity and homogeneity of variance for the independent variables, it does require identification of numerical problems in multicollinearity between the independent variables. According to Hair, Black, Babin, Anderson and Tatham (2010), when numerical problems are found, the analysis should be ignored and not interpreted. In order to detect multicollinearity in this study, the standard errors for beta coefficients were identified as having no error values higher than the limit of 2.0. Therefore, no numerical problems or multicollinearity issues were found in the independent variables of this study.

To assess the overall fit of the model, the difference between twice the log of likelihood (−2LL) in the base model (intercept only) and proposed model (with intercept and independent) was compared. A summary of the results obtained by fitting a linear model to the dependent variable is shown in Table 3. Results show that the full model is significant ($\chi^2 = 606.580$, df = 18, $p < 0.01$) and the pseudo-coefficients of determination for the model are relatively high (Cox and Snell 0.867; Nagelkerke 0.758 and McFadden 0.685). Model classification in Table 4 shows that 97.6% of the operate group, 83.8% of the consolidate group and 72.9% of the integrate + group were correctly classified. As a result, the overall percentage correctly predicted was 88.3%. Given that these three categories were correctly predicted, the results are impressive and fully confirm the usefulness of the model.

In order to assess relationships between the dependent variable and independent variables, results from the likelihood ratio test using multinomial logistic regression were interpreted (see Table 5). The independent variable contributed significantly to the full model (with *p*-value < 0.01 at a 99% confidence interval). Of the nine factors used in the model, six have a significant relationship with

Table 3. Model fitting summary

Model	−2 Log likelihood	χ^2	df	Sig.
Intercept only	885.916			
Final	279.335	606.580	18	.000
Pseudo-R-suare		Cox and Snell 0.867	Nagelkerke 0.758	McFadden 0.685

Source: SPSS multinomial logistic regression (2016).

Table 4. Classification accuracy

Observed	Predicted			
	Operate	Consolidate	Integrate +	(%) Correct
Operate	201	5	0	97.6
Consolidate	5	114	17	83.8
Integrate +	3	20	62	72.9
Overall percentage	48.9%	32.6%	18.5%	88.3

Source: SPSS multinomial logistic regression (2016).

Table 5. Likelihood ratio tests

Independent variables	Model fitting criteria	Likelihood ratio tests		
	−2 log likelihood of reduced model	χ^2	df	Sig.
Intercept	286.99	7.654	2	.009
Relative advantage	284.482	26.647	2	.000*
Complexity	330.650	72.816	2	.000*
Compatibility	260.111	2.277	2	.298
Absorptive capacity	283.297	3.962	2	.138
Organisational resource availability	324.591	45.256	2	.000*
Competitive pressure	310.935	31.599	2	.000*
Vendor selection	299.871	20.536	2	.000*
Owner-managers' innovativeness	268.907	9.984	2	.007*
Owner-managers' IT knowledge	283.467	4.131	2	.127

Source: SPSS multinomial logistic regression (2016).

*Represents significant level at 0.01.

the levels of BI adoption. The six were relative advantage, complexity, organisational resource availability, competitive pressure, vendor selection and owner-managers' innovativeness. Thus, support for Hypothesis H1, H2, H5, H6, H7 and H8 was provided.

Effects of the significant independent variables differentiating the levels of BI adoption can be more deeply analysed using the parameter estimates from multinomial logistic regression (see Table 6). In this study, the reference group was defined as the dependent variable group "operate" and was used to test the predicting power of the independent variables in differentiating the other two groups (both the "consolidate" and "integrate +") from the reference group. The results of two separate regressions showed that all six independent factors that found significant relationships with the levels of BI adoption could be successfully distinguished between consolidate and operate, and integrate + and operate, with the exception of organisational resource availability that could not be differentiated between consolidate and operate. Furthermore, taking into consideration the characteristics of this analysis, positive signs of β increased the odds and negative signs of β decreased the odds that an individual organisation belonged to the reference group (operate) (Hair et al., 2010).

Table 6. Parameter estimates						
Independent variables	**Consolidate vs. operate**			**Integrate + vs. operate**		
	β_1	**Sig**	**Exp(β)**	β_2	**Sig.**	**Exp(β)**
Intercept	−10.7650	.004	–	−14.432	.007	–
Relative advantage	2.591	.000**	13.339	2.236	.001**	9.357
Complexity	−2.419	.000**	.089	−4.630	.000**	.010
Compatibility	−.810	.133	.445	−.722	.245	.486
Absorptive capacity	−.882	.133	.414	−1.404	.050	.246
Organisational resource availability	−.156	.713	.856	2.098	.000**	8.147
Competitive pressure	3.029	.000**	20.682	2.709	.000**	15.011
Vendor selection	2.156	.000**	8.634	1.990	.002**	7.317
Owner-managers' innovativeness	1.381	.008**	3.980	1.452	.019*	4.273
Owner-managers' IT knowledge	−.810	.055	.445	−.647	.011	.523

Note: The reference category is operate.

Source: SPSS multinomial logistic regression (2016).

*Represents significant level at 0.05.

**Represents significant level at 0.01.

As shown in Table 6, based on both regressions, five of the six significant factors were found to be positive sign. For example, a positive β_1 of the relative advantage (2.591) indicated that organisations in the consolidate group had a higher perception of BI relative advantage than those in the operate group. Only one factor, complexity, had a negative β_1 (−2.419), indicating that these organisations in the consolidate group had a lower perception of BI complexity than those in the operate group.

5. Discussion of findings

The first main research aim of the study was to investigate the current stage of BI adoption in SMEs. Findings showed that Thai SMEs are at an early stage of BI adoption, with high numbers classified in the lowest level (operate). This is in line with previous studies that found the adoption of IT, enterprise systems by SMEs is still low in many countries. For example, a comparative analysis between SMEs and large enterprises in Germany by Struker and Gille (2010) found that the use of customer relationship management, ERP and BI systems was lower among SMEs. This result is the same in Taiwan, where ERP was at an early development for SMEs, and had not yet attained maturity stage (Chang et al., 2010). A national survey of SMEs' use of IT in the UK by Dyerson, Harindranath and Barnes (2008) revealed that although there was extensive use of IT to automate recordings of sales and processing of orders, the use of more complex technology like ERP and BI was low. The main reason for this may be due to financial and human resources not being readily available, despite SMEs often operating in chaos when managing data (Rajteric, 2010). Therefore, this low operate level in SMEs can be seen as the starting point for adoption of BI because BI applications used by organisations in this level are not complicated and do not require high IT infrastructure or knowledge to implement. The problem here is that these low BI applications may be insufficient to clean up and link the data in a meaningful way to gain benefit from information assets and improve opportunities.

Another aim of this research was to develop and test a BI maturity adoption model that can identify the levels of BI adoption in SMEs and the factors that impact these levels. Tests of reliability and validity found that the proposed research model is a good measurement tool with six of the nine factors supporting the research hypotheses. Relative advantage and complexity were significant in BI adoption, which is consistent with prior research (Ghobakhloo et al., 2011; Grandon & Pearson, 2004; Ramamurthy et al., 2008). Interestingly, results in this study also indicate that the higher the perception of relative advantage and the lower the complexity, the more likely SMEs will adopt higher levels of BI technology. As SMEs have limited resources for IT investment and BI adoption is

regarded as a risky undertaking (Hustad & Olsen, 2014), when owner-managers have relevant information and understand its advantages, their adopt decisions can be supported. Surprisingly, compatibility factor was not found to be significant in a BI adoption decision. A possible explanation for this may be that BI is not used as the main operational technology in the business, but only used to support the analysis and sharing of relevant information (Sahay & Ranjan, 2008). This would infer that the use of this technology may not require radical changes in the routine business practices.

Organisational resource availability was found to be a significant factor influencing SMEs' BI adoption decisions. SMEs with high organisational resource availability were found to show a greater likelihood of adopting high levels of BI, whereas low organisational resource availability showed low levels of BI adoption. Insufficient financial and technological resource may force SMEs to be cautious with their investment and capital expenditure and be the reason that they adopt lower levels of BI technology. The implementation of new IT normally requires a long-term investment involving high costs in IT infrastructure. Consequently, only SMEs with adequate financial resources would regard the adoption of BI as a feasible project to undertake. Another finding was that absorptive capacity was not a significant determinant of decisions to adopt BI in participant SMEs. A possible explanation for this may be that SME owner-managers are the IT decision-makers who can ignore their organisations' absorptive capability if they regard the technology as necessary and are willing to take risks in adopting new technology (Fuller-Love, 2006).

Competitive pressure and vendor selection factors were found to have significance in the levels of BI adoption in SMEs. The results indicated that the more the firm perceives competitive pressure, the more likely it is that they will adopt higher levels of BI technology. As SMEs now face more competitive challenges due to the rapid development of IT, these pressures can signal the need to adopt advanced technologies that improve organisational performance (Beheshti, Hultman, Jung, Opoku, & Salehi-Sangari, 2007). According to Hocevar and Jaklic (2010), managers cannot maintain competitiveness by merely depending on intuition—they need accurate information-based decision-making. As SME owner-managers usually make intuitive decisions (MacGregor & Vrazalic, 2005), their strategies are based on limited essential skills that frequently fail to meet and achieve their business objectives, resulting in a loss of competitiveness (Pansiri & Temtime, 2008). As SMEs not using BI could fail to compete effectively, intense competition may positively affect their decision to utilise BI technology. In regard to the significance of vendor selection in BI adoption, a possible explanation is that SMEs focus on selecting software packages provided by vendors rather than developing their own IT systems. As there are many types of IT vendors in the business analytics market, the selection of a suitable vendor is important (Hiziroglu & Cebeci, 2013). The expertise of the IT vendor can significantly compensate for the lack of internal IT expertise, the difficulty in recruiting IT professionals and the costs of providing required IT training for employees (Thong, 1999).

In line with previous studies (Chang et al., 2010; Ghobakhloo et al., 2011), owner-managers' innovativeness was found to be significant in the levels of BI adoption. The results indicated that SMEs with highly innovative owner-managers will adopt higher levels of BI. This is supported by Fernández and Nieto (2006) who found that SMEs with innovative and non-risk-averse owners are more likely to apply distinctive and risky solutions. This is especially the case in BI, when organisations that invest in these technologies find it difficult to quantify their return on investments, as benefits of streamlining traditional activities are somewhat intangible (Hannula & Pirttimaki, 2003). For this reason, many owner-managers who lack innovativeness may see the adoption of BI as a risky investment. In this study, it is surprising to find that owner-managers' IT knowledge did not have a significant effect on SMEs' decisions to adopt BI. This can be explained by Mehrtens, Crag and Mills (2001) whose findings show that SME owners with low levels of IT knowledge seek advice from either staff with IT knowledge within their organisations or hire IT experts. In this case, owner-managers with both low and high IT knowledge can access similar information on IT adoption.

6. Limitations and further research

The findings of this study should be considered in the light of limitations that need to be acknowledged and addressed in future research. First, this study adopted a modified IEM model as the maturity model to categorise SMEs into BI levels. Use of a different maturity model may yield different results. So further research to compare the criteria in classifying BI levels is to be considered. Second, the sample for this study was drawn from SMEs of four main industries. However, as the characteristics of each industry are different, it may be of interest to examine BI adoption in specific business sectors such as service, manufacturing, wholesale and retail. This would expand the understanding of the engagement process in the adoption of BI. Third, as this study was conducted in Thailand, the results may only be generalisable to countries that have similar industrial infrastructure. Therefore, it would be of interest to conduct the same research in other countries with a different industrial infrastructure to the Thailand context.

7. Conclusion

This study explored the current BI adoption situation of Thai SMEs. The results showed that the majority of Thai SMEs were classified at the lowest level, suggesting that they are still at an early stage of BI technology adoption. This leaves ample scope for Thai SMEs to be elevated into higher levels by focusing on understanding the enabling factors of BI as a strategy. In identifying the factors that elevate BI levels in Thai SMEs, results found that high relative advantage, high organisational resource availability, high competitive pressure, high vendor selection, high owner-managers' innovativeness and low levels of complexity were all important.

By acknowledging the current stage of BI adoption and understanding the enabling factors that encourage Thai SMEs to move to higher levels, government agencies and technology suppliers can develop strategies to advance BI adoption. Initiatives that could support the use of more advanced BI could be through marketing and advertising campaigns that persuade SME owner-managers on the perceived potential advantage of using BI technologies, as well as to provide financial support and educational seminars to increase their innovativeness. IT vendors can also help advance SMEs to higher BI levels by providing their expertise for customised solutions relevant to the particular SME. Interactions between the SME and IT vendor can further benefit them in navigating the complexities of BI technology choice and implementation.

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References
Adler-Milstein, J., & Bates, D. W. (2010). Paperless healthcare: Progress and challenges of an IT-enabled healthcare system. *Business Horizons, 53*, 119–130. http://dx.doi.org/10.1016/j.bushor.2009.10.004

Bajaj, A. (2000). A study of senior information systems manager's decision models in adopting new computing architectures. *Journal of The Association for Information Systems, 1*, 1–56.

Beheshti, H. M., Hultman, M., Jung, M.-L., Opoku, R. A., & Salehi-Sangari, E. (2007). Electronic supply chain management applications by Swedish SMEs. *Enterprise Information Systems, 1*, 255–268. http://dx.doi.org/10.1080/17517570701273221

Brimble, P., Oldfield, D., & Monsakul, M. (2002). Policies for SME recovery in Thailand. In C. Harvie & B. C. Lee (Eds.), *The role of SMEs in national economies in East Asia* (pp. 202–237). Cheltenham: Edward Elgar.

Chang, S. I., Hung, S. Y., Yen, D. C., & Lee, P. J. (2010). Critical factors of ERP adoption for small–and medium–sized enterprises. *Journal of Global Information Management, 18*, 82–106. http://dx.doi.org/10.4018/JGIM

Chao, C. A., & Chandra, A. (2012). Impact of owner's knowledge of information technology (IT) on strategic alignment and IT adoption in US small firms. *Journal of Small Business and Enterprise Development, 19*, 114–131. http://dx.doi.org/10.1108/14626001211196433

Chaudhuri, S., Dayal, U., & Narasayya, V. (2011). An overview of business intelligence technology. *Communications of the ACM, 54*, 88–98. http://dx.doi.org/10.1145/1978542

Cheung, C., & Li, F. (2012). A quantitative correlation coefficient mining method for business intelligence in small and medium enterprises of trading business. *Expert Systems with Applications, 39*, 6279–6291. http://dx.doi.org/10.1016/j.eswa.2011.10.021

Chong, S. (2008). Success in electronic commerce implementation. *Journal of Enterprise Information Management, 21*, 468–492. http://dx.doi.org/10.1108/17410390810904247

Chuach, M. (2010). An Enterprise Business Intelligence Maturity Model (EBIMM): Conceptual framework. *Knowledge Creation Diffusion Utilization Journal, 12*, 303–308.

Damanpour, F., & Evan, W. M. (1984). Organizational innovation and performance: The problem of "organizational lag". *Administrative Science Quarterly, 29*, 392–409. http://dx.doi.org/10.2307/2393031

Davenport, T. H. (2000). *Mission critical: Realising the promise of enterprise systems*. Boston, MA: Harvard Business Press.

Davis, J., Miller, G. J., & Russell, A. (2006). *Information revolution: Using the information evolution model to grow your business*. New Jersey, NJ: John Wiley & Sons.

Dholakia, R. R., & Kshetri, N. (2004). Factors impacting the adoption of the internet among SMEs. *Small Business Economics, 23*, 311–322. http://dx.doi.org/10.1023/B:SBEJ.0000032036.90353.1f

Dyerson, R., Harindranath, G., & Barnes, D. (2008). National survey of SMEs' use of IT in four sectors. *Paper presented at the 2nd European Conference on Information Management and Evaluation*, Montpellier.

Eckerson, W. (2007). Predictive analytics–extending the value of your data warehousing investment. *The Data Warehousing Institute*. Retrieved November 27, 2013, from http://www.teradata.com/t/assets/0/206/308/35d4edc6-3408-4cbd-8946-a803e49d8288.pdf

Elbashir, M., Collier, P. A., & Davern, M. (2008). Measuring the effects of business intelligence systems: The relationship between business process and organizational performance. *International Journal of Accounting Information Systems, 9*, 135–153. http://dx.doi.org/10.1016/j.accinf.2008.03.001

Fernández, Z., & Nieto, M. J. (2006). Impact of ownership on the international involvement of SMEs. *Journal of International Business Studies, 37*, 340–351. http://dx.doi.org/10.1057/palgrave.jibs.8400196

Fichman, R. G. (2000). The diffusion and assimilation of information technology innovations. In R. W. Zmud (Ed.), *Framing the domains of IT management: Projecting the future through the past* (pp. 105–127). Cincinnati, OH: Pinnaflex Publishing.

Fogarty, G. J., & Armstrong, B. (2009). Modelling the interactions among factors that influence successful computerisation of small businesses. *Australasian Journal of Information Systems, 15*, 73–89.

Fuller-Love, N. (2006). Management development in small firms. *International Journal of Management Reviews, 8*, 175–190. http://dx.doi.org/10.1111/ijmr.2006.8.issue-3

Gäre, K., & Melin, U. (2011). SMEs need formative infrastructure for business transformation. *Journal of Enterprise Information Management, 24*, 520–533. http://dx.doi.org/10.1108/17410391111166558

Gartner. (2013). *Gartner executive program survey of more than 2,000 CIOs shows digital technologies are top priorities in 2013*. Retrieved from http://www.gartner.com/newsroom/id/2304615

Ghobakhloo, M., Arias-Aranda, D., & Benitez-Amado, J. (2011). Adoption of e-commerce applications in SMEs. *Industrial Management & Data Systems, 111*, 1238–1269.

Grabova, O., Darmont, J., Chauchat, J.-H., & Zolotaryova, I. (2010). Business intelligence for small and middle-sized entreprises. *ACM SIGMOD Record, 39*, 39–50. http://dx.doi.org/10.1145/1893173

Grandon, E. E., & Pearson, J. M. (2004). Electronic commerce adoption: An empirical study of small and medium US businesses. *Information & Management, 42*, 197–216.

Griffith, T. L., Sawyer, J. E., & Neale, M. A. (2003). Virtualness and knowledge in teams: Managing the love triangle of organisations, individuals, and information technology. *MIS Quarterly, 27*, 265–287.

Habjan, A., & Popovic, A. (2007). Achieving business process change with improved business intelligence systems: A case of Slovenian company. *Paper presented at the the 7th WSEAS International Conference on Applied Computer Science, Venice*.

Hair, J. F., Black, W. C., Babin, B. Y. A., Anderson, R. E., & Tatham, R. L. (2010). *Multivariate data analysis: A global perspective* (5th ed.). Englewood Cliffs, NJ: Pearson Prentice Hall.

Hannula, M., & Pirttimaki, V. (2003). Business intelligence empirical study on the top 50 Finnish companies. *Journal of American Academy of Business, 2*, 593–599.

Hawking, P., Foster, S., & Stein, A. (2008). The adoption and use of business intelligence solutions in Australia. *International Journal of Intelligent Systems Technologies and Applications, 4*, 327–340. http://dx.doi.org/10.1504/IJISTA.2008.017276

Hill, J., & Scott, T. (2004). A consideration of the roles of business intelligence and e-business in management and marketing decision making in knowledge based and high-tech start-ups. *Qualitative Market Research: An International Journal, 7*, 48–57. http://dx.doi.org/10.1108/13522750410512877

Hiziroglu, A., & Cebeci, H. İ. (2013). A conceptual framework of a cloud-based customer analytics tool for retail SMEs. *Paper presented at the the 13th European Conference in Technology and Society (eurotecs' 13), Bosnia.*

Hocevar, B., & Jaklic, J. (2010). Assessing benefits of business intelligence systems—A case study. *Journal of Management, 15*, 87–119.

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd ed.). New York, NY: Wiley. http://dx.doi.org/10.1002/9781118548387

Hung, S. Y., Hung, W. H., Tsai, C. A., & Jiang, S. C. (2010). Critical factors of hospital adoption on CRM system: Organizational and information system perspectives. *Decision Support Systems, 48*, 592–603. http://dx.doi.org/10.1016/j.dss.2009.11.009

Hustad, E., & Olsen, D. H. (2014). *ERP implementation in an SME: A failure case information systems for small and medium-sized enterprises* (pp. 213–228). Berlin: Springer.

Hwang, H. G., Ku, C. Y., Yen, D. V., & Cheng, C. C. (2004). Critical factors influencing the adoption of data warehouse technology: A study of the banking industry in Taiwan. *Decision Support Systems, 37*(1), 1–21. http://dx.doi.org/10.1016/S0167-9236(02)00191-4

Iacovou, C. L., Benbasat, I., & Dexter, A. S. (1995). Electronic data interchange and small organizations: Adoption and impact of technology. *MIS Quarterly, 19*, 465–485. http://dx.doi.org/10.2307/249629

IDC. (2013). *Worldwide business analytics software 2013–2017 forecast and 2012 vendor shares*. Retrieved from https://www.idc.com/getdoc.jsp?containerId=241689

IDC. (2015). *IDC predictions 2015: Accelerating innovation—and growth*. Retrieved from https://www.idc.com/research/viewtoc.jsp?containerId=252700

Ifinedo, P. (2011). An empirical analysis of factors influencing Internet/e-business technologies adoption by SMEs in Canada. *International Journal of Information Technology & Decision Making, 10*, 731–766.

Igartua, J. I., Garrigós, J. A., & Hervas-Oliver, J. L. (2010). How innovation management techniques support an open innovation strategy. *Research-Technology Management, 53*, 41–52.

Israel, D. (2009). *Data analysis in business research: A step-by-step nonparametric approach*. California, CA: SAGE Publications.

Jeyaraj, A., Rottman, J. W., & Lacity, M. C. (2006). A review of the predictors, linkages, and biases in IT innovation adoption research. *Journal of Information Technology, 21*(1), 1–23.

Khalifa, M., & Davison, M. (2006). SME adoption of IT: The case of electronic trading systems. *IEEE Transactions on Engineering Management, 53*, 275–284. http://dx.doi.org/10.1109/TEM.2006.872251

Klimko, G. (2001, 8–9 November). Knowledge management and maturity models: Building common understanding. *Paper presented at the the 2nd European Conference on Knowledge Management, Bled.*

Ko, S., & Abdullaev, S. (2007, 26–29 August). A study on the aspects of successful business intelligence system development. *Paper presented at the the International Conference on Computational Science, Kuala Lumpur.*

Lahrmann, G., Marx, F., Winter, R., & Wortmann, F. (2010, 8–9 October). Business intelligence maturity models: an overview. *Paper presented at the the 7th Conference of the Italian Chapter of AIS, Naples.*

MacGregor, R. C., & Vrazalic, L. (2005). The effects of strategic alliance membership on the disadvantages of electronic commerce adoption. *Journal of Global Information Management, 13*, 1–19. http://dx.doi.org/10.4018/JGIM

McDonald, K. (2004). Is SAP the right infrastructure for your enterprise analytics'. *Paper presented at the the American SAP User Group Conference, Atlanta, GA.*

Mehrtens, J., Cragg, P. B., & Mills, A. M. (2001). A model of Internet adoption by SMEs. *Information & Management, 39*, 165–176.

Mirchandani, D. A., & Motwani, J. (2001). Understanding small business electronic commerce adoption: An empirical analysis. *Journal of Computer Information Systems, 41*, 70–73.

Moffett, S., & McAdam, R. (2003). Contributing and enabling technologies for knowledge management. *International Journal of Information Technology and Management, 2*, 31–49. http://dx.doi.org/10.1504/IJITM.2003.002447

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*, 192–222. http://dx.doi.org/10.1287/isre.2.3.192

Negash, S., & Gray, P. (2008). *Handbook on decision support systems 2*. Berlin: Springer. http://dx.doi.org/10.1007/978-3-540-48716-6

Niu, L., Lu, J., & Zhang, G. (2009). *Cognition-driven decision support for business intelligence–Models, techniques, systems and applications*. Berlin: Springer. http://dx.doi.org/10.1007/978-3-642-03208-0

O'Brien, J., & Kok, J. A. (2006). Business intelligence and the telecommunications industry: Can business intelligence lead to higher profits? *South African Journal of Information Management, 8*(3), 1–20.

Oliveira, T., & Martins, M. F. (2010). Understanding e-business adoption across industries in European countries. *Industrial Management & Data Systems, 110*, 1337–1354.

Pansiri, J., & Temtime, Z. T. (2008). Assessing managerial skills in SMEs for capacity building. *Journal of Management Development, 27*, 251–260. http://dx.doi.org/10.1108/02621710810849362

Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*, 307–320. http://dx.doi.org/10.1177/109467050024001

Pett, M. A. (1997). *Nonparametric statistics in health care research: Statistics for small samples and unusual distributions*. Thousand Oaks, CA: Sage.

Pirttimaki, V., Lonnqvist, A., & Karjaluoto, A. (2006). Measurement of business intelligence in a finnish telecommunications company. *Electronic Journal of Knowledge Management, 4*, 83–90.

Pornwasin, A. (2015, 28, November). IT spending to rise 10.6% in 2015, IDC predicts. *The Nation*. Retrieved from http://www.nationmultimedia.com/business/IT-spending-to-rise-10-6-in-2015-IDC-predicts-30248712.html

Rajteric, I. H. (2010). Overview of business intelligence maturity models. *Management, 15*, 47–67.

Ramamurthy, K., Sen, A., & Sinha, A. P. (2008). An empirical investigation of the key determinants of data warehouse adoption. *Decision Support Systems, 44*, 817–841. doi: http://dx.doi.org/10.1016/j.dss.2007.10.006

Ranjan, J. (2005). Business intelligence: Concepts, components, techniques and benefits. *Journal of Theoretical and Applied Information Technology, 9*, 600–607.

Rogers, E. M. (1983). *Diffusion of innovation* (3rd ed.). New York, NY: Free Press.

Sacu, C., & Spruit, M. (2010). BIDM: The business intelligence development model. Paper presented at the the 12th International Conference on Enterprise Information Systems, Funchal.

Sahay, B. S., & Ranjan, J. (2008). Real time business intelligence in supply chain analytics. *Information Management & Computer Security, 16*, 28–48.

Segal, H. P. (1994). *Future imperfect: The mixed blessings of technology in America*. Amherst, MA: University of Massachusetts Press.

Soanes, C., & Stevenson, A. (2008). *Concise Oxford English dictionary* (11th ed.). New York, NY: Oxford University Press.

Stevens, S. S. (1946). On the theory of scales of measurement. *Science, 103*, 677–680. http://dx.doi.org/10.1126/science.103.2684.677

Struker, J., & Gille, D. (2010). RFID adoption and the role of organisational size. *Business Process Management Journal, 16*, 972–990.

Tan, M., & Lin, T. T. (2012). Exploring organizational adoption of cloud computing in Singapore. Paper presented at the the 19th ITS Biennial Conference, Bangkok.

Teo, T. S. (2007). Organizational characteristics, modes of internet adoption and their impact. *Journal of Global Information Management, 15*, 91–117. http://dx.doi.org/10.4018/JGIM

The Economist Intelligence Unit. (2007). *Business intelligence: Putting enterprise data to work*. Retrieved from http://www.eiu.com/report_dl.asp?mode=fi&fi=252823010.PDF&rf=0

Themistocleous, M., Irani, Z., Kuljis, J., & Love, P. E. D. (2004). Extending the information system lifecycle through enterprise application integration: A case study experience. *Paper presented at the the 37th Annual Hawaii International Conference, Hawaii.*

Thong, J. (1999). An integrated model of information systems adoption in small businesses. *Journal of Management Information Systems, 15*, 187–214. http://dx.doi.org/10.1080/07421222.1999.11518227

Tornatzky, L. G., & Fleischer, M. (1990). *The process of technology innovation*. Massachusetts, MA: Lexington Books.

Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on Engineering Management, 29*, 28–45. http://dx.doi.org/10.1109/TEM.1982.6447463

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Voicu, V., Zirra, D., & Ciocirlan, D. (2009). Business intelligence effective solutions of management. *Paper presented at the the 10th WSEAS international conference on Mathematics and computers in business and economics, Prague.*

Williams, S., & Williams, N. (2003). The business value of business intelligence. *Business Intelligence Journal, 8,* 30–39.

Wixom, B. H., & Watson, H. J. (2010). The BI-based organization. *International Journal of Business Intelligence Research, 1,* 13–28. http://dx.doi.org/10.4018/IJBIR

Zhu, K., Dong, S., Xu, S. X., & Kraemer, K. L. (2006). Innovation diffusion in global contexts: Determinants of post-adoption digital transformation of European companies. *European Journal of Information Systems, 15,* 601–616. http://dx.doi.org/10.1057/palgrave.ejis.3000650

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