10-2019

Understanding the adoption of Cloud BI in SMEs

Daniel Ferro

Ricardo Martins

Understanding the adoption of Cloud BI in SMEs

Daniel Ferro, NOVA Information Management School (NOVA IMS), Portugal, m2016028@novaims.unl.pt

Ricardo Martins, NOVA Information Management School (NOVA IMS), Portugal, rmartins@novaims.unl.pt

Abstract

Business Intelligence (BI) systems have been largely used to support decision-making and increase competitive advantage between firms. In order to understand the adoption of BI systems in organizations, many studies have used adoption theories to support their results. However, to our knowledge, none of these studies have focused on the adoption of cloud BI solutions in small and medium enterprises (SMEs). This study aims to fill this gap in the literature and assess the determinant factors to the adoption of cloud BI in SMEs. We propose a conceptual model based on the combination of two prominent adoption theories: diffusion of innovation (DOI) theory, and the technology, organization, and environment (TOE) framework. Data collected from 203 SMEs were analysed using the partial least squares structural equation modelling (PLS-SEM) method. Results show that the variables relative advantage, compatibility and top management support are significant to the adoption of cloud BI in SMEs.

Keywords: *Business Intelligence (BI); Innovation adoption; SMEs; Technology-organization-environment (TOE) framework; Diffusion of Innovation (DOI) theory*

1. INTRODUÇÃO

Historically, BI systems have been primarily adopted by large organizations (Olszak & Ziemba, 2012). "The information systems (IS) literature has long emphasized the positive impact of information provided by business intelligence systems (BIS) on decision-making, particularly when organizations operate in highly competitive environments" (Popovič, Hackney, Coelho, & Jaklič, 2012). However, BI systems are also characterised by their complex implementation, along with high investment requirements to develop and maintain such solutions. Since many SMEs don't have a dedicated IT department, and are usually run by their owners, BI implementation isn't, at first sight, accessible to organizations of that scope (Papachristodoulou, Koutsaki, & Kirkos, 2017).

In order to overcome the technological and financial barrier for the BI implementation in SMEs, BI vendors started to look for affordable solutions to fit SMEs' needs (Papachristodoulou et al., 2017). The cloud computing technology has come up as a low-cost alternative to provide SMEs with access to BI (Horakova et al., 2013). Cloud BI started to be considered a solid alternative to increase SMEs' accessibility to BI (Carcary, Doherty, Conway, & McLaughlin, 2014; Gupta, Seetharaman, & Raj, 2013; Sang, Xu & de Vriezeaper, 2016; Tutunea & Rus, 2012).

In the wide field of IS/IT, it's a common practice to use adoption theories to support studies on new technologies adoption (El-Masri & Tarhini, 2017; Sharma, Al-Badi, Govindaluri, & Al-Kharusi, 2016). In the context of BI, adoption studies have mainly focused their contributions on large organizations (Puklavec, Oliveira & Popovic, 2018). To our knowledge, no contributions using IS theories have yet been made to understand the adoption of cloud BI systems in SMEs. According to Olszak, (2016), the measurement and assessment of BI development should be based on proven and scientific theories.

Our research aims to fill this gap in the literature. Since cloud BI has been largely coined by several authors as an alternative for outsourcing data analysis and processes in the cloud (Mazón, Garrigós, Daniel, & Trujillo, 2012), our study can provide important findings to the research community as well as to contribute to the future of cloud BI in SMEs. To conduct our research, we use a combination of the diffusion of innovation (DOI) theory and the technology-organization-environment (TOE) framework.

2. Theories and literature review

2.1. Cloud BI and sme's

Existing literature shows that current BI solutions and tools are mostly designed to fit large companies' needs Sang, Xu & de Vriezeaper, 2016). The implementation and integration process of such solutions often take time and requires high investments and maintenance costs (Horakova et al., 2013). Since SMEs usually suffer from tight budgets, less technological knowledge and dedicated staff, traditional BI solutions are almost unreachable to these companies (Sang, Xu & de Vriezeaper, 2016; Solberg Søilen & Hasslinger, 2012).

With the perceived value of BI tools by SMEs and the evolution of technology in recent years, BI vendors started to design applications and tools that would fit SMEs' needs. Such solutions are offered in the cloud and provide SMEs with many benefits and exciting future opportunities (Papachristodoulou et al., 2017). Many authors consider cloud BI as a viable alternative for SMEs (Guarda, Manuel Pinto, Filipe Augusto, & Maria Silva, 2013; Papachristodoulou et al., 2017; Sang, Xu & de Vriezeaper, 2016).

The benefits are many, and it includes low entry costs, quick implementation, ease of use, flexible payment models (Horakova et al., 2013), with no maintenance required (Abadi, 2010), scalability, and variety of features presented (Agarwal, 2011; Sang, Xu & de Vriezeaper, 2016).

2.2. TOE

The TOE framework was developed by Depietro et al. (1990). The framework is a firm-level theory that examines three elements (Technological, Organizational, and Environmental context) that influence innovation adoption. The organizational factor includes organizational aspects such as size, centralization, formalization, quality of human resources, amount of slack resources and managerial structure. The technological factor is comprised of internal and external technology that are relevant to the organization and available for possible adoption. The environmental factor includes market elements, competitors, accessibility to resources and the regulatory environment (Chong, Ooi, Lin, & Tang, 2009; Oliveira & Martins, 2011; Oliveira, Thomas, & Espadanal, 2014; Yang, Sun, Zhang, & Wang, 2015)

2.3. DOI

The DOI theory was formulated by Rogers, (2003), and it's based on five factors to explain innovation adoption: Relative Advantage, Compatibility, Complexity, Observability, and Trialability. Relative advantage refers to the extent to which an innovation is better than the idea it supersedes. Compatibility refers to the degree to which an innovation can be assimilated into the existing business processes, practices, and value systems. Complexity is associated with the difficulty to use the innovation. Observability, to the extent to which the innovation is visible to others. Finally, trialability refers to the ease of experimenting with the innovation (Lin & Chen, 2012; Oliveira & Martins, 2011; Wang, Li, Li & Zhang, 2016).

3. CONCEPTUAL MODEL AND HYPOTHESES

3.1. Combining TOE and DOI

According to Oliveira & Martins, (2011), the combination of DOI and TOE is applicable for the study of IT adoption at the firm level. The table 1 shows some examples of the constructs used in previous empirical studies in the IT/IS literature combining DOI and TOE. The conceptual model is presented in Figure 1.

ARTICLE	RA	COMP	CX	TR	COST	TMS	SC	PC	CP	GS
(Kumar, Samalia, & Verma, 2017)	x					x	x	x	x	
(Puklavec, Oliveira & Popovic, 2018)					x	x				
(Hatta, Miskon, & Abdullah, 2017)	x		x							
(Sun, Cegielski, Jia, & Hall, 2018)	x	x	x	x	x	x	x	x	x	x
(AL-Shboul, 2018)	x	x	x	x		x	x		x	x
(Oliveira et al., 2014)	x			x	x	x	x		x	x
(B. Lin & Raman, 2009)	x	x	x			x				

Table 1 – Independent variables of past studies using TOE and DOI (RA=Relative Advantage, COMP=Compatibility, CX=Complexity, TR=Technology Readiness, COST=Cost Reduction, SC=Security Concerns, PC=Privacy Concerns, TMS=Top Management Support, CP=Competitive Pressure, GS=Government Support)

3.2. Innovation diffusion context

Relative advantage is described as “the degree to which an innovation is perceived as better than the idea it supersedes” (Rogers, 2003). Perceived relative advantage also helps to promote the continuous use of an innovation (Li, Troutt, Brandyberry, & Wang, 2011). Prior studies have acknowledged the importance of relative advantage as a determinant factor for driving technology adoption (Gangwar & Date, 2015; Yeng, Osman, Nizam, Abdullah, & Jin, 2016). Accordingly, the following hypothesis is proposed:

- **Hypothesis 1**: Relative advantage has a positive effect on the adoption of cloud BI by SMEs.

Rogers, (2003) defines compatibility as “the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters”. Yang et al., (2015) states that compatibility plays a significant role in the adoption of SaaS solutions, and that providers should adapt their systems to individual customers’ needs. Puklavec et al., (2014) identifies that large organizations’ BI systems have more functionalities and are generally more complex, and that is why SMEs need a different type of BI. Therefore, we propose the following hypothesis:

- **Hypothesis 2:** Compatibility has a positive effect on the adoption of cloud BI by SMEs.

Rogers, (2003) defines complexity as the “degree to which an innovation is perceived as difficult to understand and use”. The complexity of an innovation increases the implementation risk and can be negatively associated to the adoption of IS innovations (Premkumar & Roberts, 1999). A recent study made by Choi et al., (2018) argues that technical complexity is considered to be one of the most critical risks on the cloud computing innovation and diffusion process. Therefore, we propose the following hypothesis:

- **Hypothesis 3**: Complexity has a negative effect on the adoption of cloud BI by SMEs.

3.3. Technological context

Technology readiness can be seen as the degree of internal IT expertise and technological infrastructure within an organization (Sun et al., 2018). According to Yeoh & Koronios, (2010), BI systems, like ERP systems, comprise more than the simple purchase of software and hardware; it requires IT resources and infrastructure. Accordingly, the following hypothesis is proposed:

- **Hypothesis 4**: Technology readiness has a positive effect on the adoption of cloud BI by SMEs.

The cost of IT/IS is still a big obstacle that prevents adoption among SMEs (Premkumar & Roberts, 1999). One of the biggest advantages for SMEs when moving to the cloud is related to the cost-reduction benefit of this technology (Gupta et al., 2013). Accordingly, the following hypothesis is proposed:

- **Hypothesis 5**: Cost reduction has a positive effect on the adoption of cloud BI by SMEs.

Many past researches have addressed the issues around security and privacy in cloud-computing environments. Gutierrez, Boukrami, & Lumsden, (2015) acknowledged the fact that many organizations have hold back on the adoption of cloud services due to security and data ownership issues. A recent study made by Senyo, Addae, & Boateng, (2018) also presents some concerns around security and privacy in the cloud environment. Accordingly, the following hypothesis is proposed:

- **Hypothesis 6**: Security and privacy concerns have a negative effect on the adoption of cloud BI by SMEs.

3.4. Organizational context

Top management support is considered to be the most significant variable in IS innovation adoption (Ramdani, Kawalek, & Lorenzo, 2009). Y.-S. Wang et al., (2016) argued that top management support has a positive effect on hotels' adoption of Mobile reservation systems. Accordingly, the following hypothesis is proposed:

- **Hypothesis 7**: Top management support has a positive effect on the adoption of cloud BI by SMEs.

3.5. Environmental context

Competitive pressure refers to the "level of pressure felt by the enterprise from other external partners such as competitors in the industry" (AL-Shboul, 2018). According to K. Zhu, Dong, Xu, & Kraemer, (2006), the use of e-business by organizations is more likely to be driven when there is existing pressure from competitors. Therefore, the following hypothesis is proposed:

- **Hypothesis 8**: Competitive pressure has a positive effect on the adoption of cloud BI by SMEs.

Government support refers to the rules, regulations, instructions, policies and initiatives that support a new technology adoption (AL-Shboul, 2018). Hwang et al., (2004) argued that government policies had a positive impact on the adoption of data warehouse technology by Twainian banks. It is known that the government plays a key role in innovations that demand resources and present a high level of uncertainty (Bonzanini, Dutra, Barcellos, & Marques, 2016). Therefore, the following hypothesis is proposed:

- **Hypothesis 9**: Government support has a positive effect on the adoption of cloud BI by SMEs.

3.6. Control variables

Industry and Firm size are used as control variables to assess data variation that is not explained by the other variables of the research model. The use of control variables is a common practice in IS studies (Cho & Chan, 2015; Kim, Jang, & Yang, 2017; Puklavec, Oliveira & Popovic, 2018).

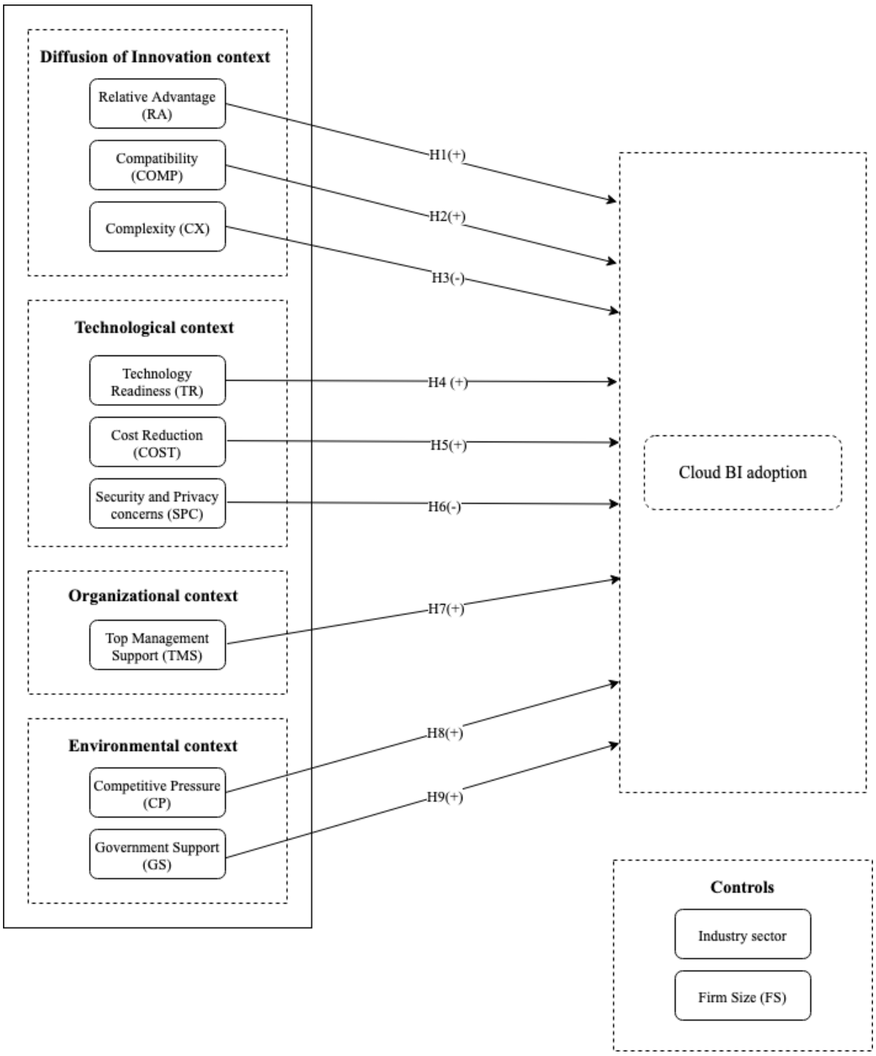


Figure 1 - Conceptual model

4. Methodology

4.1. Measurement

In order to test the conceptual model, a questionnaire survey method was used. The constructs were based on past literature studies (see Table 2). Participants responded to each question on a seven-point Likert scale ranging from “strongly disagree” to “strongly agree”.

CONSTRUCTS	MEASUREMENT ITEMS	SOURCE
Relative Advantage	RA1 - Cloud BI allows companies to make the right decisions and to take the right actions. RA2 - Cloud BI enables to perform decisions and actions more quickly. RA3 - Cloud BI gives greater control over a business.	(Puklavec, Oliveira & Popovic, 2018)
Compatibility	Comp1. Using cloud BI is compatible with all aspects of my work. Comp2. I think that using cloud BI fits well with the way I like to work. Comp3. Using cloud BI fits with my work style.	(Jaklič, Grubliešič, & Popovič, 2018)
Complexity	CX1 – Cloud BI services are easy to integrate with existing processes. CX2 – Confidence levels in cloud BI influence adoption decision. CX3 – Cloud BI is easy to use and manageable.	(Gutierrez et al., 2015)
Technology Readiness	TR1. Our employees are well-trained and educated towards the importance of cloud BI. TR2. Existing technology supports cloud BI adoption. TR3. Cloud BI adoption is perceived as being both useful and easy to use.	Adapted from Gutierrez et al., (2015)
Cost reduction	Cost1. Cloud BI is more cost effective than other types of technologies. Cost2. Organizations can avoid unnecessary cost and time by using cloud BI solutions. Cost3. Cloud BI solutions save time and effort.	(Chong & Chan, 2012)
Top Management Support	TMS1 - Our management actively participates in establishing a vision and formulating strategies for utilizing cloud BI solutions. TMS2 - Our management communicates its support for the use of cloud BI solutions. TMS3 - Our management is likely to take risk involves in implementing cloud BI solutions.	(Puklavec, Oliveira & Popovic, 2018)
Security and Privacy concerns	SPC1. The confidentiality and security of your business data are not guaranteed when adopting cloud BI solutions. SPC2. In case of damage, present liability law is still unclear about who will bear the damage. SPC3. The cloud BI provider will exploit contractual loopholes (i.e., incomplete contracting) to the detriment of your company.	(Benlian & Hess, 2011)
Competitive Pressure	CP1 – cloud BI would allow stronger competitive pressure advantage. CP2 – cloud BI would increase the ability to outperform the competition. CP3 – cloud BI would allow generation of higher profits.	(Gutierrez et al., 2015)
Government support	GS1. We believe that effective laws can protect the privacy of customers. GS2. We believe that our law environment is advantageous to the adoption of cloud BI solutions. GS3. Our government has expressed the determination to support the development of cloud BI solutions.	adapted from (Hung, Chang, Lin, & Hsiao, 2014)
Cloud BI adoption	CloudBIa1. My company invests resources in cloud BI. CloudBIa2. Business activities in our company require the use of cloud BI. CloudBIa3. Functional areas in my company require the use of cloud BI.	(Martins, Oliveira, & Thomas, 2016)

Table 2 – Measurement items

4.2. Data

Data were collected from January to March of 2019. 1475 individuals were contacted, resulting on 203 valid answers, which corresponds to a response rate of 13.76%. The sample consisted of professionals identified with potential knowledge around cloud BI (i.e. CEOs and IS Managers), contacted via LinkedIn. The profile of the sample is shown in Tables 3, 4, 5, 6:

INDUSTRY	NUMBER	PERCENTAGE
Entertainment	6	3%
Financial	4	2%
Hospitality	11	6%
Human Resources	7	3%
Information Technology & Services	57	28%
Marketing	24	12%
Computer Software	94	46%

Table 3 - Sample characteristics: Industry

FIRM SIZE	NUMBER	PERCENTAGE
Micro (<=10)	25	12%
Small (11 – 50)	98	48%
Medium (51 – 250)	80	40%

Table 4 - Sample characteristics: Firm size

RESPONDENT'S POSITION	NUMBER	PERCENTAGE
Board member	12	6%
CEO	15	7%
IS Managers, Director IT, Head of IT	112	55%
Other department managers	64	32%

Table 5 - Sample characteristics: Respondent's position

CONTINENT	NUMBER	PERCENTAGE
South America	49	24%
North America	18	9%
Oceania	5	2%
Asia	18	9%
Europe	105	52%
Asia	8	4%

Table 6 - Sample characteristics: Continent

5. Results and discussion

The data analysis is conducted through partial least squares (PLS). According to the Kolmogorov-Smirnov's (K-S) test, data in our research model is not normally distributed ($p<0.01$). Due to the model's complexity and the relatively small sample sizes, PLS is the most appropriate path modelling technique to be used. In order to test and validate the research model, we used Smart-PLS 3 software (Ringle, Wende, & Becker, 2015). Before testing the structural model, an assessment of the measurement model was conducted.

5.1. Measurement model

An assessment of the constructs reliability is presented by examining the results of composite reliability (CR) and Cronbach's alphas (CA). As shown in Table 7, the values of composite reliability (CR) and Cronbach's alphas (CA) are above 0.7 for all constructs, thus indicating that the constructs are reliable (Chau, 1999; Straub, 1989).

Convergent validity is assessed through the average variance extracted (AVE). As seen in Table 7, the values for AVE are shown above 0.5 for all constructs. This means that each construct explains more than 50% of the variance with regard to its indicators (Bagozzi & Yi, 1988; Fornell & Larcker, 1981; Henseler, Ringle, & Sinkovics, 2009).

Indicator reliability test was based on the criterion that the loadings should be above 0.7 to support its reliability (Henseler et al., 2009). Table 8 (bold values) shows that all loadings are greater than 0.7, thus making the indicators reliable.

Discriminant validity was evaluated based on both Fornell-Larcker and cross-loadings criteria. As presented in Table 7, the square root of AVE (diagonal elements in bold) is higher than the correlations between the constructs. The cross-loading criterion calls for the factor loading to be higher than all cross-loadings (Chin, 1998). This requirement is fulfilled and shown in Table 8. Therefore, both results satisfy the construct's discriminant validity requirements.

5.2. Structural model

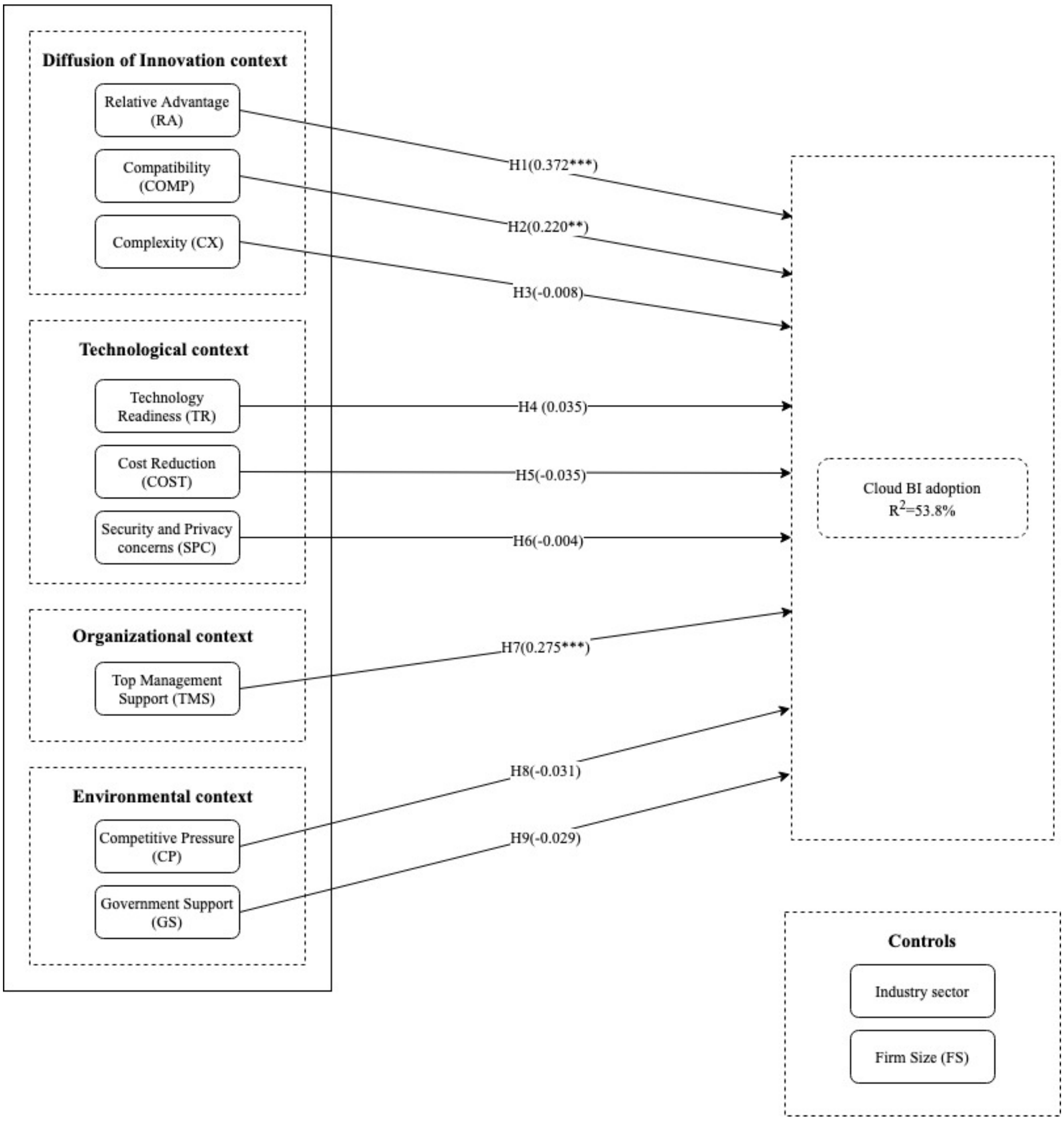
The assessment of the structural model was done by the estimation of path coefficients and through the squared multiple correlation coefficient (R^2). The PLS results are shown in Fig.5.1. The path significance levels were assessed by using the bootstrapping method with 5,000 resamples (Chin, 1998; Henseler et al., 2009). The results show that hypotheses H1, H2 and H7 were supported, meanwhile H3, H4, H5, H6, H8 and H9 were not supported.

CONSTRUCTS	**MEAN**	**SD**	**AVE**	**CR**	**CA**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
TR	5.57	1.52	0.751	0.900	0.834	**0.866**									
TM	5.57	1.48	0.829	0.936	0.897	0.609	**0.911**								
SP	4.58	1.52	0.718	0.884	0.807	-0.063	-0.031	**0.847**							
RA	5.00	1.49	0.871	0.953	0.926	0.521	0.465	-0.047	**0.933**						
GOV	5.10	1.49	0.679	0.863	0.771	0.357	0.392	0.007	0.233	**0.824**					
CP	4.70	1.60	0.861	0.949	0.920	0.431	0.501	-0.053	0.505	0.505	**0.928**				
COST	3.73	1.38	0.801	0.923	0.877	0.557	0.538	-0.024	0.625	0.389	0.645	**0.895**			
COMP	4.88	1.47	0.867	0.951	0.923	0.526	0.497	-0.003	0.676	0.265	0.519	0.643	**0.931**		
COMPLEX	4.08	1.51	0.728	0.889	0.813	0.408	0.398	-0.016	0.344	0.421	0.511	0.458	0.406	**0.853**	
CLOUDBIA	5.23	1.87	0.828	0.935	0.896	0.485	0.529	-0.037	0.652	0.203	0.374	0.491	0.597	0.282	**0.91**

Table 7 - Descriptive statistics, correlation matrix, and square root of AVEs

CONSTRUCTS	CLOUDBIA	COMP	CX	COST	CP	GS	RA	SPC	TM	TR
CLOUDBIA1	**0,894**	0,534	0,299	0,472	0,353	0,234	0,606	-0,004	0,554	0,494
CLOUDBIA2	**0,923**	0,532	0,256	0,439	0,330	0,173	0,576	-0,028	0,417	0,394
CLOUDBIA3	**0,913**	0,562	0,210	0,426	0,336	0,141	0,597	-0,071	0,464	0,430
CX1	0,567	**0,913**	0,328	0,573	0,404	0,162	0,604	0,005	0,409	0,469
CX2	0,520	**0,936**	0,373	0,586	0,485	0,301	0,617	-0,005	0,484	0,461
CX3	0,576	**0,945**	0,432	0,635	0,558	0,281	0,665	-0,009	0,498	0,536
COMP1	0,286	0,337	**0,898**	0,353	0,411	0,328	0,343	-0,031	0,366	0,380
COMP2	0,193	0,395	**0,766**	0,459	0,471	0,377	0,287	0,024	0,345	0,339
COMP3	0,228	0,325	**0,889**	0,387	0,445	0,391	0,244	-0,024	0,309	0,324
COST1	0,412	0,582	0,434	**0,886**	0,589	0,342	0,519	-0,004	0,501	0,494
COST2	0,390	0,547	0,391	**0,893**	0,562	0,344	0,544	-0,005	0,415	0,458
COST3	0,501	0,593	0,404	**0,906**	0,581	0,358	0,605	-0,049	0,518	0,533
CP1	0,371	0,510	0,485	0,609	**0,924**	0,450	0,434	-0,042	0,500	0,450
CP2	0,280	0,392	0,438	0,550	**0,937**	0,499	0,436	-0,058	0,417	0,350
CP3	0,374	0,519	0,488	0,624	**0,923**	0,463	0,526	-0,049	0,466	0,387
GS1	0,182	0,231	0,290	0,276	0,335	**0,835**	0,165	-0,001	0,308	0,287
GS2	0,194	0,265	0,422	0,397	0,539	**0,887**	0,246	0,011	0,374	0,348
GS3	0,100	0,121	0,332	0,278	0,356	**0,743**	0,151	0,007	0,274	0,226
RA1	0,626	0,630	0,298	0,572	0,476	0,213	**0,936**	-0,067	0,468	0,474
RA2	0,599	0,649	0,354	0,610	0,497	0,235	**0,926**	-0,065	0,412	0,487
RA3	0,601	0,614	0,311	0,569	0,442	0,204	**0,939**	0,002	0,421	0,497
SPC1	-0,032	-0,021	-0,027	-0,016	-0,101	-0,017	-0,030	**0,869**	-0,056	-0,076
SPC2	-0,037	0,006	0,016	-0,015	-0,004	0,028	-0,039	**0,886**	0,008	-0,039
SPC3	-0,023	0,008	-0,043	-0,036	-0,035	0,001	-0,055	**0,782**	-0,041	-0,047
TM1	0,471	0,392	0,380	0,475	0,456	0,366	0,379	-0,010	**0,908**	0,549
TM2	0,525	0,483	0,388	0,512	0,481	0,369	0,442	-0,053	**0,947**	0,614
TM3	0,444	0,484	0,317	0,483	0,431	0,335	0,450	-0,018	**0,876**	0,492
TR1	0,427	0,426	0,352	0,566	0,410	0,314	0,450	-0,094	0,578	**0,867**
TR2	0,412	0,434	0,267	0,424	0,334	0,243	0,429	-0,028	0,521	**0,873**
TR3	0,422	0,506	0,441	0,455	0,375	0,370	0,474	-0,040	0,482	**0,859**

Table 8 - Factor Analysis



Note: Standardized coefficients. * p < 0.10; ** p < 0.05; *** p < 0.01

Figure 2 - Structural model of Cloud BI adoption

In order to understand the factors that most influence the adoption decision of SMEs towards cloud BI systems, we use a combination of the DOI theory and the TOE framework. A discussion of each strand of the research model is presented below:

5.3. Innovation diffusion

Relative advantage was found to have a positive influence on the intention to adopt cloud BI systems in SMEs. This finding is consistent with similar studies in the literature (Oliveira et al., 2014; Thong, 1999; Y.-M. Wang, Wang, & Yang, 2010).

Compatibility was also found to have significant impact on the intention to adopt cloud BI systems by SMEs. This finding contrasts with some past researches (Martins et al., 2016; Oliveira et al., 2014), but is also supported by others (AL-Shboul, 2018; Low, Chen, & Wu, 2011).

According to Thong, (1999), relative advantage and compatibility are usually identically perceived by respondents. Scholars Moore & Benbasat, (1991) state that it's very unlikely that respondents perceive the advantage of an innovation if it is not compatible with their experience or work style.

Complexity is related to the difficulty to use and manage an innovation. In our study, complexity was not seen as significant to the adoption of cloud BI systems by SMEs. This finding is inconsistent with previous studies (Oliveira et al., 2014), but it also goes in accordance with others (AL-Shboul, 2018; Low et al., 2011).

5.4. Technology context

None of the variables in the technology context were found to be statistically significant to the intention to adopt cloud BI systems by SMEs. A possible explanation for these results may be attributed to the fact that cloud BI is a relatively recent technology, and therefore, it didn't yet reach a high maturity level in this context.

5.5. Organization context

Top management support was found to be statistically significant to the intention to adopt cloud BI systems by SMEs. This finding is consistency with past studies (AL-Shboul, 2018; Chong & Chan, 2012). Top management support refers to the responsibility that managers assume when accepting the risks of innovations adoption, along with their support and communication towards adoption. This result may be supported by the fact that SMEs owners and managers are generally the ones responsible for the decision-making processes in these companies (Ahani, Rahim, & Nilashi, 2017). Therefore, the more top managers are willing to take the risks of adopting a cloud BI solution, the more likely it is for this adoption to take place.

5.6. Environment context

Similar to a study on cloud computing adoption by Oliveira et al., (2014), both competitive pressure and government support were found as not significant to cloud BI adoption in SMEs. Competitive pressure refers to the benefits achieved through the use of cloud BI systems in face of the competition. Government support refers to the laws created by the government to protect the privacy of customers and support the development of cloud BI.

6. CONCLUSION

The results of this research offer several insights to SME managers and cloud BI vendors. From the nine variables analysed in the research model, three of them (relative advantage, compatibility and top management support) were found to be significant to the adoption of cloud BI in SMEs. Therefore, if organizations perceive the impact of having a compatible environment for implementing cloud BI, an increased awareness around the advantages and benefits of such solutions, and the support and approval from top managers, the adoption of cloud BI could be potentialized.

Our research integrated the DOI theory and the TOE framework to support the main determinants logistical factors affecting the adoption of cloud BI in SMEs. However, our model suffers from some limitations. The analysis focused on the singular relationship between the dependent and independent variables. Consequently, nothing is known with regards to the interrelationships between the independent variables. Future studies should also include these internal relationships as part of the research model. Moreover, it would be interesting to evaluate all stages that determines the cloud BI diffusion process in SMEs, which includes intention, adoption, and routinization.

BIBLIOGRAPHY

Abadi, D. J. (2010). DataManagement in the Cloud: Limitations and Opportunities. Bulletin of the IEEE Computer Society Technical Commitee on Data Engineering. https://doi.org/10.1007/978-1-4419-0176-7

Agarwal, P. (2011). Continuous SCRUM: agile management of SAAS products. Proceedings of the 4th India Software Engineering Conference, 51–60. https://doi.org/http://doi.acm.org/10.1145/1953355.1953362

Ahani, A., Rahim, N. Z. A., & Nilashi, M. (2017). Forecasting social CRM adoption in SMEs: A combined SEM-neural network method. Computers in Human Behavior, 75, 560–578. https://doi.org/10.1016/j.chb.2017.05.032

AL-Shboul, M. A. (2018). Towards better understanding of determinants logistical factors in SMEs for cloud ERP adoption in developing economies. Business Process Management Journal. https://doi.org/10.1108/BPMJ-01-2018-0004

Bach, M. P., Zoroja, J., & Čeljo, A. (2017). An extension of the technology acceptance model for business intelligence systems: project management maturity perspective. International Journal of Information Systems and Project Management, 5(2), 5–21. https://doi.org/10.12821/ijispm050201

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. Journal of the Academy of Marketing Science, 16(1), 74–94.

Benlian, A., & Hess, T. (2011). Opportunities and risks of software-as-a-service: Findings from a survey of IT executives. Decision Support Systems, 52(1), 232–246. https://doi.org/10.1016/j.dss.2011.07.007

Bonzanini, M., Dutra, M., Barcellos, D., & Marques, L. (2016). The drivers for adoption of eco-innovation. Journal of Cleaner Production, 113. https://doi.org/10.1016/j.jclepro.2015.11.033

Carcary, M., Doherty, E., Conway, G., & McLaughlin, S. (2014). Cloud Computing Adoption Readiness and Benefit Realization in Irish SMEs—An Exploratory Study. Information Systems Management, 31(4), 313–327. https://doi.org/10.1080/10580530.2014.958028

Chau, P. Y. K. (1999). On the use of construct reliability in MIS research: a meta-analysis. Information & Management, 35(4), 217–227.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. Modern Methods for Business Research, 295(2), 295–336.

Cho, V., & Chan, A. (2015). An integrative framework of comparing SaaS adoption for core and non-core business operations: An empirical study on Hong Kong industries. Information Systems Frontiers, 17(3), 629–644. https://doi.org/10.1007/s10796-013-9450-9

Choi, J., Nazareth, D. L., Ngo-ye, T. L., Choi, J., Nazareth, D. L., & Ngo-ye, T. L. (2018). The Effect of Innovation Characteristics on Cloud Computing Diffusion The Effect of Innovation Characteristics on Cloud Computing Diffusion. Journal of Computer Information Systems, 58(4), 325–333. https://doi.org/10.1080/08874417.2016.1261377

Chong, A. Y. L., & Chan, F. T. S. (2012). Structural equation modeling for multi-stage analysis on Radio Frequency Identification (RFID) diffusion in the health care industry. Expert Systems with Applications, 39(10), 8645–8654. https://doi.org/10.1016/j.eswa.2012.01.201

Chong, A. Y. L., Ooi, K. B., Lin, B., & Tang, S. Y. (2009). Influence of interorganizational relationships on SMEs' e-business adoption. Internet Research, 19(3), 313–331. https://doi.org/10.1108/10662240910965379

Depietro, R., Wiarda, E., & Fleischer, M. (1990). The context for change: Organization, technology and environment. The Processes of Technological Innovation, 199(0), 151–175.

El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Educational Technology Research and Development, 65(3), 1–21. https://doi.org/10.1007/s11423-016-9508-8

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. SAGE Publications Sage CA: Los Angeles, CA.

Gangwar, H., & Date, H. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. Journal of Enterprise Information Management, (May). https://doi.org/10.1108/JEIM-08-2013-0065

Grabova, O., Darmont, J., Chauchat, J.-H., & Zolotaryova, I. (2011). Business Intelligence for Small and Middle-Sized Entreprises, 39(2), 39–50. https://doi.org/10.1145/1893173.1893180

Guarda, T. S., Manuel Pinto, Filipe Augusto, & Maria Silva, C. (2013). Business Intelligence as a Competitive Advantage for SMEs. International Journal of Trade, Economics and Finance, 4(4), 187–190. https://doi.org/10.7763/IJTEF.2013.V4.283

Gupta, P., Seetharaman, A., & Raj, J. R. (2013). The usage and adoption of cloud computing by small and medium businesses. International Journal of Information Management, 33(5), 861–874. https://doi.org/10.1016/j.ijinfomgt.2013.07.001

Gutierrez, A., Boukrami, E., & Lumsden, R. (2015). Technological, organisational and environmental factors influencing managers' decision to adopt cloud computing in the UK. Journal of Enterprise Information Management, 28(6), 788–807. https://doi.org/10.1108/JEIM-01-2015-0001

Hatta, N. N. M., Miskon, S., & Abdullah, N. S. (2017). Business Intelligence System Adoption Model for SMEs. In Pacific Asia Conference on Information Systems (PACIS) 2017 Proceedings. Retrieved from https://aisel.aisnet.org/pacis2017/192

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). Epidermal studies in some members of Andropogoneae (Poaceae). Notulae Botanicae Horti Agrobotanici Cluj-Napoca, 37(1), 59–64. https://doi.org/10.1108/S1474-7979(2009)0000020014

Horakova, M., Skalska, H., Olszak, C. M., Ziemba, E., Fitriana, R., Djatna, T., … Paraschiv, D. (2013). Business Intelligence and Implementation in a Small Enterprise. Journal of Systems Integration, 4(2), 50–62. https://doi.org/18042724

Hung, W. H., Chang, L. M., Lin, C. P., & Hsiao, C. H. (2014). E-readiness of website acceptance and implementation in SMEs. Computers in Human Behavior, 40, 44–55. https://doi.org/10.1016/j.chb.2014.07.046

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

Jaklič, J., Grublješič, T., & Popovič, A. (2018). The role of compatibility in predicting business intelligence and analytics use intentions. International Journal of Information Management, 43(June), 305–318. https://doi.org/10.1016/j.ijinfomgt.2018.08.017

Kim, S. H., Jang, S. Y., & Yang, K. H. (2017). Analysis of the Determinants of Software-as-a-Service Adoption in Small Businesses: Risks, Benefits, and Organizational and Environmental Factors. Journal of Small Business Management, 55(2), 303–325. https://doi.org/10.1111/jsbm.12304

Kumar, D., Samalia, H. V., & Verma, P. (2017). Exploring suitability of cloud computing for small and medium-sized enterprises in India. Journal of Small Business and Enterprise Development, 24(4), 814–832. https://doi.org/10.1108/JSBED-01-2017-0002

Li, X., Troutt, M. D., Brandyberry, A. A., & Wang, T. (2011). Decision Factors for the Adoption and Continued Use of Online Direct Sales Channels among SMEs. Journal of the Association for Information, (June 2014). https://doi.org/10.17705/1jais.00255

Lin, A., & Chen, N. (2012). Cloud computing as an innovation : Percepetion , attitude , and adoption. International Journal of Information Management, 32(2012), 533–540.

Lin, B., & Raman, M. (2009). Factors affecting the adoption level of C-commerce : an empirical study, 13–22.

Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. Industrial Management & Data Systems. https://doi.org/10.1108/02635571111161262

Martins, R., Oliveira, T., & Thomas, M. A. (2016). An empirical analysis to assess the determinants of SaaS diffusion in firms. Computers in Human Behavior, 62, 19–33. https://doi.org/10.1016/j.chb.2016.03.049

Mazón, J.-N., Garrigós, I., Daniel, F., & Trujillo, J. (2012). Introduction to the special issue of Business Intelligence and the Web. Decision Support Systems. https://doi.org/10.1016/j.dss.2011.11.007

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. Information Systems Research, 2(3), 192–222.

Oliveira, T., & Martins, M. F. (2011). Literature Review of Information Technology Adoption Models at Firm Level. Electronic Journal Information Systems Evaluation, 14(1), 110–121. https://doi.org/10.1017/CBO9781107415324.004

Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. Information and Management, 51(5), 497–510. https://doi.org/10.1016/j.im.2014.03.006

Olszak, C. M. (2016). Toward Better Understanding and Use of Business Intelligence in Organizations. Information Systems Management, 33(2), 105–123. https://doi.org/10.1080/10580530.2016.1155946

Olszak, C. M., & Ziemba, E. (2012). Critical Success Factors for Implementing Business Intelligence Systems in Small and Medium Enterprises on the Example of Upper Silesia, Poland. Interdisciplinary Journal of Information, Knowledge & Management, 7, 129–150. https://doi.org/15551229

Papachristodoulou, E., Koutsaki, M., & Kirkos, E. (2017). Business Intelligence and SMEs: Bridging the gap. Journal of Intelligence Studies in Business, 7(1), 70–78.

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. Decision Support Systems, 54(1), 729–739. https://doi.org/10.1016/j.dss.2012.08.017

Premkumar, G., & Roberts, M. (1999). Adoption of new information technologies in rural small businesses, 27.

Puklavec, B., Oliveira, T., & Popovic, A. (2014). Unpacking Business Intelligence Systems Adoption Determinants: An Exploratory Study of Small and Medium Enterprises. Economic and Business Review.

Puklavec, B., Oliveira, T., & Popovič, A. (2018). Understanding the determinants of business intelligence system adoption stages an empirical study of SMEs. Industrial Management and Data Systems, 118(1), 236–261. https://doi.org/10.1108/IMDS-05-2017-0170

Ramdani, B., Kawalek, P., & Lorenzo, O. (2009). Predicting SMEs ' adoption of enterprise systems. Journal of Enterprise Information Management. https://doi.org/10.1108/17410390910922796

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3. Boenningstedt: SmartPLS GmbH, Http://Www. Smartpls. Com.

Rogers, E. M. (2003). The diffusion of innovation 5th edition. New York: Free Press.

Sang, PGo Muan; Xu, Lai; de Vriezeaper, P. (2016). Implementing a Business Intelligence System for small and medium-sized enterprises. SQM 2016: 24th International Software Quality Management Conference, (734599), 1–13.

Senyo, P. K., Addae, E., & Boateng, R. (2018). Cloud computing research: A review of research themes, frameworks, methods and future research directions. International Journal of Information Management, 38(1), 128–139. https://doi.org/10.1016/j.ijinfomgt.2017.07.007

Sharma, S. K., Al-Badi, A. H., Govindaluri, S. M., & Al-Kharusi, M. H. (2016). Predicting motivators of cloud computing adoption: A developing country perspective. Computers in Human Behavior, 62, 61–69. https://doi.org/10.1016/j.chb.2016.03.073

Solberg Søilen, K., & Hasslinger, A. (2012). Factors shaping vendor differentiation in the Business Intelligence software industry. Journal of Intelligence Studies in Business.

Straub, D. W. (1989). Validating instruments in MIS research. MIS Quarterly, 147–169.

Sun, S., Cegielski, C. G., Jia, L., & Hall, D. J. (2018). Understanding the Factors Affecting the Organizational Adoption of Big Data. Journal of Computer Information Systems, 58(3), 193–203. https://doi.org/10.1080/08874417.2016.1222891

Thong, J. Y. L. (1999). An Integrated Model of Information Systems Adoption in Small Businesses. Journal of Management Information Systems, 15(4), 187–214. https://doi.org/10.1080/07421222.1999.11518227

Tutunea, M. F., & Rus, R. V. (2012). Business Intelligence Solutions for SME's. Procedia Economics and Finance, 3(December 2012), 865–870. https://doi.org/10.1016/S2212-5671(12)00242-0

Wang, Y.-M., Wang, Y.-S., & Yang, Y.-F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. Technological Forecasting and Social Change, 77(5), 803–815.

Wang, Y.-S., Li, H.-T., Li, C.-R., & Zhang, D.-Z. (2016). Factors affecting hotels' adoption of mobile reservation systems. Tourism Management, 53, 163–172. https://doi.org/10.1016/j.tourman.2015.09.021

Yang, Z., Sun, J., Zhang, Y., & Wang, Y. (2015). Understanding SaaS adoption from the perspective of organizational users: A tripod readiness model. Computers in Human Behavior, 45, 254–264. https://doi.org/10.1016/j.chb.2014.12.022

Yeng, K., Osman, A., Nizam, S., Abdullah, S., & Jin, Y. (2016). Relative Advantage and Competitive Pressure towards Implementation of E-commerce : Overview of Small and Medium Enterprises (SMEs). Procedia Economics and Finance, 35(October 2015), 434–443. https://doi.org/10.1016/S2212-5671(16)00054-X

Yeoh, W., & Koronios, A. (2010). Critical Succes Factors for Business Intelligence Systems. Journal of Computer Information Systems. https://doi.org/10.1080/08874417.2010.11645404

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, (October), 601–616. https://doi.org/10.1057/palgrave.ejis.3000650