A STATISTICAL ANALYSIS OF BUSINESS INTELLIGENCE ACCEPTANCE BY SMES IN THE CITY OF TSHWANE, REPUBLIC OF SOUTH AFRICA

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ABSTRACT

Business intelligence (BI) technologies have attracted attention from academics and entrepreneurs, enterprise mangers are starting to employ them to make informed decisions for proper management. While several studies have been conducted on the need for BI in small and medium enterprises (SMEs), they have concentrated on performance and adoption and give insights and approaches, suitable for large-scaled enterprises, but insufficient for SMEs.

In this study, BI acceptance is examined within South Africa's SMEs in the City of Tshwane (n= 161). Perceived benefits and challenges are analysed in their efforts to adopt BI. By classifying BI acceptance into three categories, multinomial logistic regression is used. We build a refined model on the considerations of the supported hypotheses within, technological, organizational, environmental and behavioural factors.

Supported hypotheses are aligned to a respective BI characteristic. Application of the refined model will contribute towards providing guidance to SME owner-managers in acceptance of BI.

Keywords: Business Intelligence, Acceptance, Small and Middle-Sized Enterprises, Statistical Analysis.

Journal of Economics Literature: C14, C12, C15.

INTRODUCTION

It is critical for businesses to manage and safeguard their data, information and knowledge, since these are the most important components that define and make up an organization. With the rise and dependency on real time data and advanced technology, businesses are forced to operate in highly complex and dynamic environments, whereby data overload can be one of the challenges they are likely to face (Luciano, et al., 2018). To overcome such challenges, businesses need to understand and analyse the wide range of data at their disposal. BI is one of such dynamic applications that creates competitive advantage by extracting central data, presenting and manipulating the data into information that can be used for managerial decision support by revealing areas that require consideration (Hatta, et al., 2017). Organizational transformation will come about as a result of the alignment of the business and BI strategies put in place, and performance improvement will be guaranteed (Cokins, G., 2017).

All businesses, irrespective of size, need proper information management strategies in place, because information is the driving force for an enterprises' success (Kerzner & Kerzner, 2017), and through BI, businesses can be able to make market-aware strategic decisions

(Campbell, 2014). According to Watson & Wixom (2007), due to the lack of access to information, some decisions are made based on instinctive knowledge, which in today's information age might lead to disastrous consequences, as 'gut feeling' cannot be the determining factor for strategic decision making. Proper analytical tools such as BI need to be used by all organizations.

Business intelligence systems, can enable enterprises, specifically, small, micro and medium sized enterprises (SMMEs) to overcome information asymmetry, which is one of the great challenges faced by these enterprises, due to lack of tools and strategies for information management (Hussain, et al., 2018). It is therefore imperative to identify which factors will have an influence on the acceptance of business intelligence by small and middle-sized enterprises in order to take full advantage of business intelligence tools and applications (Cokins, G., 2017).

Concerning the foregoing reasoning, and theories of technology acceptance model (TAM) (Davis 1986; Davis 1989; Davis et al. 1989) and the Technology, organization, and environment framework (TOE) framework (Tornatzky & Fleischer 1990), our study hypotheses (Table 1).

Table 1
SUGGESTED HYPOTHESES

Factor	**Characteristic**	**Hypothesis**
Technological	Relative Advantage	*H1: Relative advantage affects Business Intelligence acceptance in Tshwane SMEs*
	Complexity	*H2: Complexity affects Business Intelligence acceptance in Tshwane SMEs*
	Compatibility	*H3: Compatibility affects Business Intelligence acceptance in Tshwane SMEs*
	Observability	*H4: Observability affects Business Intelligence acceptance in Tshwane SMEs*
	Trialability	*H5: Trialability affects Business Intelligence acceptance in Tshwane SMEs*
Organizational	Organizational Competency	*H6: Organizational Competency affects Business Intelligence acceptance in Tshwane SMEs*
	Training and Education	*H7: Training and Education affects Business Intelligence acceptance in Tshwane SMEs*
	Top Management	*H8: Top Management affects Business Intelligence acceptance in Tshwane SMEs*
Technological	Competitive Pressure	*H9: Competitive Pressure affects Business Intelligence acceptance in Tshwane SMEs*
	Trading Partner Support	*H10: Trading Partner Support affects Business Intelligence acceptance in Tshwane SMEs*
Perceived Ease of Use	Perceived Ease of Use	*H11: Perceived Ease of Use affects Business Intelligence acceptance in Tshwane SMEs*
Perceived Usefulness	Perceived Usefulness	*H12: Perceived Usefulness affects Business Intelligence acceptance in Tshwane SMEs*

LITERATURE REVIEW

BI: Different authors define BI based on various factors based on their own business perspective. According to Elbashir, et al., 2008; Calof, et al., 2015, BI is a tool that can be utilised to determine external factors that affect and influence the business, hence it has been previously compared to competitive intelligence. Côrte-Real, et al. (2014); Sadok & Lesca (2009); Ghoshal & Kim (1986) define BI as an effective competitive tool, which allows important and relevant information on new technologies, customers, competitors and markets to be collected and then analysed, in order to sustain long-term competitive advantage.

In this study, BI is defined as an organization's ability to adapt all its processes and capabilities into knowledge, ultimately producing large amount of information that can lead to better business decisions as well as improved business processes and new opportunities (Kumari, 2013).

SMEs: These are catalysts for the future economy and serve as means for innovation of new products and socio-economic development (Boonsiritomachai, et al., 2014; Adeniran & Johnston, 2014). Therefore, there is a great need to accelerate their growth, information flow and competitiveness. Watson & Wixom (2007) regard SMEs as the spine of the world's economy, since they make more than 95% of all enterprises.

Previously, BI solutions and tools had mostly aimed at large organisations, whilst inaccessible and insufficient for SMEs (Grabova, et al., 2010). As such, SMEs possessed fewer alternative BI solutions (Guarda, et al., 2013). However, in today's highly competitive business environment, SMEs now have their own tailor-fitted solutions. Unfortunately, they are still not making use of these tailored solutions to improve their socio-economic performance (Campbell, 2014).The potential of BI in SMEs is to improve or transform data management whilst, increasing profitability, competitive advantage and creating improved business processes (Guarda, et al., 2013; Kumari, 2013; Lloyd, 2011).

Different countries define SMMEs in various ways, based on factors such as size, gross turnover or industry. The Table 2 shows SMMEs characteristics and categories in a South African context.

Table 2
SMALL, MEDIUM & MICRO ENTERPRISES' DEFINITIONS BY THE NATIONAL SMALL BUSINESS ACT

Enterprise Size	Number of Employees	Annual Turnover (S.A Rand)	Gross Assets, Excluding Fixed Property
Medium	Fewer than 100 to 200, depending on Industry	Less than R4 million to R50m depending on industry	Less than R2m to R18m depending on industry
Small	Fewer than 50	Less than 2 million to R25m depending on industry	Less than R2m to R4.5m depending on industry
Very Small	Fewer than 10 to 20, depending on Industry	Less than R200 000 to R500 000 depending on industry	Less than R150 000 to R500 000 depending on industry
Micro	Fewer than 5	Less than R150 000	Less than R100 000

Acceptance of BI by SMEs

Some of the most basic characteristics of a BI tool is that it has the ability to collect data from diverse sources, also has advanced analytical methods, and it is able to support multiple user demands (Wu, et al., 2014). Such capabilities are likely to lead to acceptance of BI by any enterprise that has a desire to improve its profitability and sustain its growth.

The South African government has made SMEs a priority because of their employment potential, due to the high unemployment rate in the country (Amra, et al., 2013). In an attempt for SMEs to function at their highest potential, the utilisation of BI tools is a necessity. These BI tools are characterised based on their method of information delivery, reporting capabilities and statistical, ad-hoc or predictive analysis (Wu, et al., 2014). According to Johnson (2016), with the right BI tool, integrating numerous dissimilar business and financial systems is an attainable task, since it helps provide a consolidated view of the enterprises performance.

Current situation of SMEs in South Africa

In South Africa, SMEs face a number of challenges, from accessing credit to complexity of technology adoption (Adeniran & Johnston, 2014; Mahembe, 2011; Ponelis & Britz, 2011). Due to their important role when in a country's economy, SMEs are now government's main developmental focus. With an unemployment rate of 24.5%, small businesses can help leverage employment creation (Olawale & Garwe, 2010).

The National Small Business Act together with various policies and programmes have been initiated and implemented to support SMEs. This support from government is because SMEs are considered as the driving force towards the growth of the economy, and that their role in job creation is great (Amra, et al., 2013). This has led them to be a priority for the South African government that has established the department of Small business Development to handle SME development.

In South Africa, a majority of new SMEs do not grow. There is a failure rate of 75%, which makes it among the highest in the world (Chimucheka, 2013; Olawale & Garwe, 2010). Most SMEs fail within their first two years of operation. The two main reasons for new firm failure is the lack of training or education, and the lack of financial support (Chimucheka, 2013).

For SMEs to grow in size, turnover and create an even greater competitive advantage against their challengers; it is essential that they utilize ICT tools in their data processing to inform their strategic planning and decision making processes. (Ponelis & Britz, 2011).

RESEARCH MODEL

In summary, based on the theories of technology acceptance model (TAM) (Davis 1986, Davis 1989, Davis et al. 1989) and the Technology, organization, and environment framework (TOE) framework (Tornatzky and Fleischer 1990). The following factors are evaluated for use in the refined model of the study.

Technological Characteristics

Relative advantage: Relative advantage according to Rogers (1995) is the degree to which an innovation is deemed as being better than the current systems available; cited as a key driver for adoption. (Ngai, et al., 2008; Roca, et al., 2006; Amoako-Gyampah & Salam, 2004) did studies that identified the advantages of BI technology to enterprises. Regardless of the benefits BI brings, some authors have argued that some BI vendors are not able to clarify its benefits to its stakeholders; hence, customers are likely not to adopt BI applications (Hasan et al., 2016).

Complexity: This, according to Rogers (1995), is determined by the degree to which an innovation is perceived as being difficult to use and understand. Studies by Al-Mamary et al., 2014; Azvine et al., 2005 cite complexity as one of the innovation adoption barriers and Hwang et al., (2004) echoed the above sentiments when they mentioned that the less complex a technology is, the higher the adoption probability of the technology. With the intense issue of complexity of BI applications, resistance to change, and social influence, according to Al-Somali et al., (2009), there has been a bit of resistance to the adoption of BI and this is likely to hinder acceptance from organizations that are considering the utilisation of BI.

Compatibility: Rogers (1995) states that the degree to which an innovation is perceived as being consistent with the enterprises existing values, past experiences and the needs of the possible adopters is known as compatibility. Not all systems used can be compatible with BI systems, this is likely to cost a business a lot in terms of time, and resources needed to migrate and integrate its data. These compatibility related issues according to (Gefen, 2004), are some of the issues that are likely to become adoption barriers (Khan, et al., 2010; Ramamurthy, et al., 2008). For the case of SMEs, where availability of funds is a challenge, they are less likely to accept such an innovation.

Trialability: Trialability is the extent to which potential adopters are awarded an opportunity to experiment with a particular innovation. A number of studies have established that the adoption of IT technology can be influenced by the trialability of the innovation, such as e-learning, (Lee, et al., 2011), e-business (Lin & Lee, 2005) healthcare sector (Nath, et al., 2016). In a study by (Jon, et al., 2001), it was discovered that in the case of SMEs, trialability is one of the significant influencers of electronic commerce. In another study of SMEs by Boumediene & Kawalek, 2008 it was found out that the adoption of systems such as CRM, ERP and electronic procurement are impacted on by trialability.

Observability: It is the degree to which potential adopters of an innovation are able to perceive the results of using an innovation from users who have already adopted it (Rogers, 1995). Closely linked to trialability, observability has been named as an attribute that has a huge impact on innovation adoption. Lippert & Govindarajulu, (2006) mention that if the outcome of an innovation is visible, it can change potential adopter's perception hence inspiring them to communicate about it to contemporaries. In a survey done in an SME in Indonesia, the results showed that observability is an important attribute in the adoption of electronic commerce (Rahayu & Day, 2015; Awiagah, et al., 2015; Awa, et al., 2012).

Organisational Characteristics

Organisation competency: Competency of an organization, is the availability and accessibility of required resources that enhance acceptance and adoption (Ma & Ye, 2015). A number of studies have acknowledged that the availability of resources can be utilised as a determinant for the organisation to accept or reject an innovation (Hasan, et al., 2016; Rym, et al., 2013; Awa, et al., 2012). Resources such as skills, technology and money are some of the metrics, which can be considered in this respect (Guarda, et al., 2013). As a result of the complexity of BI technology, an enterprise will need financial resources as well as highly skilled workers (Guarda, et al., 2013).

Training and education: O'Brien & Kok, (2006) conducted a study on telecommunication firms in South Africa and found that many organisations were not utilising BI to its full potential due to staff's lack of knowledge, shortage of technical skills, and lack of training. In their study Al-Mamary et al., (2014) discovered that computer self-efficacy is closely linked to perceived usefulness of any innovation. If an individual is confident in their skills and abilities, they are likely to, not only accept an innovation but also to increase their knowledge through training and skills development.

Top Management Support: This is one of the best predictors of organizational adoption (Khan, et al., 2010). The involvement and level of support by management in operational processes enables for better process implementation since they are able to closely monitor daily operations (Dawson & Van Belle, 2013; Hofstede, et al., 1990). In SMEs, management is usually the owner themselves, and this highly centralised structure makes the owner the sole decision maker, who has the direct impact on all decision-making processes including daily as well as future investments (Zeng, et al., 2007; Thong, 1999). For SMEs the entire decision making process depends on the owner's experiential knowledge, which is fed by their judgement, prior knowledge and personal experience (Carson & Gilmore, 2000).The understanding of IT technologies by the owner-manager will lead to the possible adoption and successful implementation of any innovation (Rahman, et al., 2016).

Environmental Characteristics

Some studies demonstrate that environmental factors should be examined before adopting any type of technology, because the selection of good vendors and the effectiveness of the enterprise have an impact on the success of innovation adoption (Lee, et al., 2011).

Competitive pressure: This can be described as the external competitors who are one of the key drivers of the adoption of new technology (Obeidat, 2016; Imran & Tanveer, 2015). Dawson and Van Belle, (2013) mention that it is important for SMEs to be aware of their surrounding competitors as well as their intelligence capabilities by acquiring innovative technology (Voicu, et al., 2009). The degree of competitive pressure an organisation is facing will determine its technology adoption likelihood (Gutierrez, et al., 2015).

Trading partner support: Selecting the right vendor is one of the significant environmental factors that affect technology adoption besides the commonly mentioned competitive pressure. Vendors play a critical role, as they are the ones liable for providing technical support to their customers, hardware requirements, software upgrades, and user training (Ma & Ye, 2015). Since BI is not like most enterprise IT systems, it needs to be uniquely modified and configured to suit an enterprise's specific needs and not just implemented as the total package (Campbell, 2014). Smaller sized enterprises are more likely to outsource such solutions because of absence of skilled resources within the business, and as a result of the relationships between vendor selection and IT adoption (Guarda, et al., 2013; Kumari, 2013), careful consideration must be taken during such a process.

Behavioural Characteristics

PEOU: The most commonly adopted acceptance model, TAM, posits that there are two beliefs Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which are the key determinants of a user's attitude (AT) towards using a new technology (Davis 1986; Davis 1989; Davis, et al., 1989). The PEOU of any form of technology has been said to be one of the predictors of a person's behaviour (Ma & Ye, 2015), because it is the degree to which a user believes that through the use of a system there will be less mental and physical effort required (Davis, et al., 1989). In a study on e-learning, (Rym, et al., 2013; Islam, et al., 2014), online banking (Al-Somali, et al., 2009) it was discovered that an individual's computer self-efficacy has a positive effect on the PEOU of a system.

PU: The PU of a system is the user's belief that the system will assist them in performing their job better. It is the degree to which a person has confidence that the technology will assist them in improving their job performance, while PEOU is the degree to which a person believes that using a particular system would be free of effort (Islam, et al., 2014; Ma & Ye, 2015). Al-Somali, et al., 2009 discovered that factors such as age, education, PEOU, resistance to change, gender and PU contribute to an individual's attitude towards online banking. Venkatesh & Davis, (2000) accentuated that factors such as an individual's personality traits, past experiences and demographic characteristics have an effect on their attitude towards behavioural intensions, and when it comes to organizational performance it can be affected either negatively or positively (Al-Mamary, et al., 2014).

RESEARCH METHODOLOGY

Sampling Procedure

In this work, the population of interest was quite large and therefore, the sampling procedures and considerations were of importance because reasonable conclusions have to be stated that reflect SMEs characteristics. The sample organizations that formed part of the study were carefully chosen in order to have a suitable list of organizations. A number of steps were followed during this stage. Firstly, the target population that would be most suitable in achieving the objectives and aims of this study was identified. Secondly, the sample size was selected based on a sample frame that consisted of all registered SMEs in the area of interest. Lastly, a suitable formula was employed to determine the sample size for possible enumeration and data collection.

Sample Size

To calculate the sample size, this study adopted the proportional stratified statistical formula by Yamane (1967), which uses a confidence level of 95%.

Yamane's formula:

$$n = \frac{N}{1 + N\left(e\right)^2}$$

n=the sample size
N=Population size
e=the error rate of sample (the level of precision)

In this study, N represents the total population of formally registered SMEs in Gauteng, which according to a report by SEDA, amount to 306 231. The frequently used tolerable error rate of 5% will be adopted for this study. When Yamane's formula is used, the calculation will be as follows:

$$n = \frac{306231}{1 + 306231\left(0.05\right)^2}$$

n=399.725

So according to the calculation, this study ought to use a minimum sample size of 400 SMEs. However, due to the low responses to the questionnaires administered, a sample of 161 was considered in the analysis.

Data Collection

Questionnaire construction: The questionnaire employed in this work comprised of two parts; one for general questions on the respondents themselves as well as the company's profile, and the other for questions addressing possible factors driving BI acceptance.

DATA ANALYSIS

A statistical package for social scientists (SPSS 23) was used to obtain the statistical results. For instance, the respondent's demographic information was presented through descriptive statistics. For inferential purposes, a multinomial logistic regression model was used to make predictions and generalise the sample results to the population.

Measurement Model

This was accomplished in three steps; the first step was a univariate analysis, where descriptive statistics of each variable were stated. The second was a bivariate analysis, where the spearman's rank correlation was used to test for the association between the dependent and the individual independent variables. The last step involved the use of Cronbach's alpha to test the credibility of internal consistency through coefficient scores.

Convergent and Discriminant Validity

Convergent validity is confirmed when the item's associated factors load strongly through using standardised loading thus having 0.50 or more (Tables 3-8). Discriminant validity is demonstrated when one construct's measurement items lack correlation with other constructs measurement items. This is shown when each item loads stronger on its associated factors than it does on other factors.

In this work, any items that did not load strongly on the intended factors was not considered for further analysis. In addition, the main components of factor analysis were used to remove extreme discrepancies of all items through observing convergent and discriminant validity. Measurements scales were validated by assessing the four characteristics of the conceptual framework, which include technological (5 constructs), organizational (3 constructs), environmental (2 constructs), and behavioural intensions to act (2 constructs).

Technological Characteristics

For these characteristics, three validity scales for relative advantage, complexity and trialability were confirmed using convergent and discriminant validity scales. Even though the total technological characteristics are five, Table 3, two items for observability and compatibility did not load well on their particular constructs and subsequently left out for further analysis. All items have loading values 0.50 and more on their connected factors and also load more strongly on other connected factors as well. The analysis for validity was recalculated after some items were removed, which explained 73.35% of the total variation on the model.

Table 3 CONSTRUCT VALIDITY ANALYSIS FOR TECHNOLOGICAL CHARACTERISTICS					
Component	**1**	**2**	**3**	**4**	**5**
Relative Advantage 1	0.717	-0.179	-0.036	0.156	0.188
Relative Advantage 2	0.716	-0.211	0.057	0.032	0.219
Relative Advantage 3	0.742	-0.132	0.088	0.222	0.111
Relative Advantage 4	0.745	-0.129	-0.077	0.129	0.119
Complexity 1	-0.466	0.699	-0.060	-0.058	-0.137
Complexity 2	-0.519	0.698	-0.061	-0.034	-0.129
Complexity 3	-0.400	0.782	-0.039	-0.030	-0.57
Complexity 4	-0.029	0.667	0.120	-0.060	-0.221
Compatibility 2	-0.200	-0.167	0.740	-0.049	-0.019
Compatibility 3	0.280	0.171	0.709	0.101	0.060
Compatibility 4	-0.039	-0.065	0.790	0.078	0.182
Trialability 1	0.163	0.010	0.148	0.591	-0.194
Trialability 2	0.194	-0.101	0.101	0.649	-0.046
Trialability 3	0.083	-0.041	-0.022	0.798	0.119
Trialability 4	0.39	-0.038	-0.039	0.812	0.101
Observability 2	0.221	-0.075	-0.050	0.001	0.576
Observability 3	0.200	-0.019	0.200	-0.011	0.649
Observability 4	0.089	-0.159	0.060	-0.038	0.728

Environmental Characteristics

For these, competitive pressure and vendor selection were confirmed. The two factors extracted endorsed the model to collectively explicate 72.61 %. All items loaded into their projected constructs with the loading value of more than 0.50 and loading more strongly on other related factors (Table 4).

Table 4 CONSTRUCT VALIDITY ANALYSIS FOR ENVIRONMENTAL CHARACTERISTICS		
Component	**1**	**2**
Competitive Pressure 1	0.744	0.373
Competitive Pressure 2	0.797	0.168
Competitive Pressure 3	0.709	0.197
Competitive Pressure 4	0.748	0.136
Trading Partner Support 1	-0.021	0.594
Trading Partner Support 2	0.397	0.679
Trading Partner Support 3	0.369	0.741
Trading Partner Support 4	0.300	0.782

Organisational Characteristics

The Table 5 shows three factors (organization’s competency, training and education and top management) were initially extracted, however, training and education was unable to load on the intended factor, and subsequently dropped. A recalculation of the analysis of validity was done and the model collectively explained 70.01% of total variance.

Table 5 CONSTRUCT VALIDITY ANALYSIS FOR ORGANIZATIONAL CHARACTERISTICS		
Component	**1**	**2**
Organization's competency 2	0.712	0.177
Organization's competency 3	0.739	-0.138
Organization's competency 4	0.731	0.180
Training and education 1	0.091	0.789
Training and education 2	0.109	0.842
Training and education 3	0.111	0.701
Top Management	0.029	0.148
Top Management	0.112	0.168
Top Management	0.333	-0.127
Top Management	0.119	0.169

Behavioural Characteristics

Two factors (PEOU and PU) were initially extracted; however, one item, PU was unable to load on the intended factor, hence left out. A computation of the analysis of validity was done and the model collectively explained 70.03% of total variance (Table 6).

Table 6 CONSTRUCT VALIDITY ANALYSIS FOR BEHAVIOURAL CHARACTERISTICS		
Component	**1**	**2**
Perceived ease of use 2	0.678	0.244
Perceived ease of use 3	0.711	0.074
Perceived ease of use 4	0.699	-0.051
Perceived usefulness 1	-0.235	0.660
Perceived usefulness 2	0.411	0.519
Perceived usefulness 3	0.163	0.788

Independent Variables

After convergent and discriminant validity were verified, the reliability of the constructs had to be evaluated, and this was done with the calculation of the coefficient scores using Cronbach's alpha, (Tavakol & Dennick, 2011). The values of alpha as indicated in Table 7 are above the commended value of 0.70, (Tavakol & Dennick, 2011). It was assumed that those items with a low value of alpha could have been due to a low number of questions, poor interrelatedness between items or heterogeneous constructs. However, no further examination was done to circumvent this.

Table 7 RELIABILITY ANALYSIS			
Measurement items	**Cronbach's alpha**	**Mean**	**Item**
Technological characteristics			
Relative advantage	0.831	2.847	4
Complexity	0.829	2.899	4
Compatibility	0.655	3.219	3
Trialability	0.722	3.157	4
Observability	0.665	3.363	3
Organisational characteristics			
Organization's competency	0.791	3.191	3
Training and education	0.665	3.176	3

Top management	0.717	3.158	4
Environmental characteristics			
Competitive Pressure	0.785	3.186	4
Trading Partner Support	0.716	2.668	4
Behavioural intension			
Perceived Ease of Use	0.659	3.483	3
Perceived Usefulness	0.622	3.174	3

Table 8
DEMOGRAPHIC AND ORGANIZATIONAL ANALYSIS OF RESPONDENTS

		Number	**Percentage**
Gender			
	Male	94	58%
	Female	67	42%
Age Group			
	18-25	24	15%
	26-33	32	20%
	34-41	73	45%
	42-49	29	18%
	50 & above	3	2%
Highest Education level			
	Grade 12	93	58%
	Diploma	35	22%
	Bachelor Degree	29	18%
	Master's Degree	20	1%
	Doctorate	0	0%
	Other Certification	2	1%
Position			
	Intern	3	2%
	Junior Employee	61	38%
	Supervisor/Team leader	3	2%
	Managing director / General Manager	5	3%
	Owner	89	55%
Working experience			
	Less than 1 year	7	4.5%
	1-3 Years	81	50.5%
	4-7 Years	48	30%
	8-11 Years	15	9%
	More than 12 Years	10	6%
Years of business operation			
	Less than 1 year	5	3%
	1-3 Years	63	39.2%
	4-7 Years	29	18%
	8-11 Years	56	35%
	More than 12 Years	8	4.8%
Business category			
	IT Services	26	16.2%
	Support Services	66	40.8%
	Manufacturing	8	5.1%
	Telecommunications	3	1.6%
	Retail	55	34.3%
	Wholesale	3	2%

	Other		
Areas that the organisation uses computer software / system			
	Profit forecasting	3	2%
	Market research	2	1%
	Production planning	23	14%
	Sales planning	5	3.4%
	Strategic analysis	6	3.5%
	Cash flow forecasting	2	1%
	Customer management	3	2%
	Staff planning	23	14%
	Financial accounting	43	27.1%
	Stock control	52	32%
	Marketing mix	0	0%
	Other (Please Specify)		
Company website?			
	Yes	98	60.8%
	No	63	39.2%
Computer knowledge rating			
	Beginner	14	9%
	Moderate User	92	57%
	Advanced User	55	34%
Internet Usage?			
	Yes	142	88%
	No	19	12%
Frequency of internet usage			
	Less than once a month	0	0%
	Once a month	10	6%
	Once a week	3	2%
	Once in 2 –3 days	6	4%
	Every day	142	88%

Multinomial Logistic Regression Equation

The multinomial logistic regression is utilised when response variables have two or more categories, as a result, the multinomial logistic regression model is known to be a multi equation model. These equations, however, depend on the total number of categories of outcomes minus one. A number of non-redundant logits (‘*k-1*’) can be produced if the response variable (‘*k*’) has any categories. A baseline category logit is the simplest form of logit, which compares each category to a baseline (Heeringa, et al., 2017). The coefficients for the baseline category are all zero.

If the baseline category is ‘*k*’ for the ‘i^{th}’ category, the model is:

$$Logit\left(P_{\iota}\right)=\ln\left[\frac{P(\text{category}_{\iota})}{P\left(category_{k}\right)}\right]=\alpha_{\iota 0}+\beta_{\iota I}X_{\iota}+...+\beta_{\iota n}X_{n}+\varepsilon$$

Where: i=1,2….k-1; P=probability; k=referenced category; α=a constant, equalling the value of Y when the value of X=0; β=Beta, the coefficient of independent variables which represents the slopes of the regression line. Every Beta value explains how much Y change for each one unit change in X; ε the error term, in predicting the value of Y, giving the value of X; X= independent variable (enabling factors of BI acceptance).

The above model was adopted in order to identify the impact of independent variables (enabling factors) on the dependent variables (levels of BI acceptance). The lowest level of BI acceptance (Not accept) was used as the reference category, together with two non-redundant logits, fully accept/Not accept and partially accept/Not accept.

It is through the likelihood ratio test, that the null hypothesis is used to show that the parameter values established on the dependent variable have no effects (Protassov, et al., 2002). Table 9 illustrates the outcome of the likelihood ratio test using a multinomial logistic regression. Also displayed is the verification of the null hypothesis through the comparison of the significance level of the independent variables in response to the well-defined confidence intervals.

Table 9
LIKELIHOOD RATIO TESTS

Enabling Factors	**Model Fitting Criteria**	**Likelihood ratio tests**		
	–2 log likelihood of reduced model	**Chi-square**	**df**	**Sig.**
Intercept	268.606	9.782	2	0.008
Relative advantage	294.482	26.747	2	0.000
Complexity	340.650	74.816	2	0.000
Compatibility	270.111	2.337	2	0.310
Trialability	269.717	2.832	2	0.221
Observability	274.969	16.164	2	0.000
Competitive pressure	289.839	23.995	2	0.000
Trading partner support	282.087	14.363	2	0.001
Organisational competency	272.036	4.1926	2	0.132
Top management	296.409	38.597	2	0.000
Training and education	280.829	21.995	2	0.000
Perceived Ease of Use	275.907	8.001	2	0.038
Perceived Usefulness	263.715	4.881	2	0.073

The Chi-square statistic is the difference in –2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Hypothesis Summary

The proposed hypotheses were grounded on previous studies as well as theoretical foundations and categorised according to the characteristics that are found in the TOE and TAM models (Al-Mamary, et al., 2016). In total twelve hypotheses were suggested for testing (Table 1). Table 10 shows the study hypotheses and their summary results of all characteristics after analysis based on the study sample size, n=161:

Table 10
SUMMARY OF THE STUDY HYPOTHESES AND THEIR OUTCOMES

Hypothesis	**Characteristic**	**Result**
Technological		
H1	Relative Advantage	Supported (0.000)
H2	Complexity	Supported (0.000)
H4	Observability	Supported (0.000)
Organisational		
H7	Training and Education	Supported (0.000)
H8	Top Management	Supported (0.000)

Environmental		
H9	Competitive Pressure	Supported (0.000)
H10	Trading Partner Support	Supported (0.001)
Behavioural		
H11	Perceived Ease of Use	Supported (0.038)

Refined Research Model

In summary, with reference to the theories of technology acceptance model (TAM) (Davis, 1986; Davis, 1989; Davis, et al., 1989), the Technology, organization, and environment framework (TOE) framework (Tornatzky & Fleischer 1990) and the summary of supported hypotheses from this study, Table 10, we argue that following characteristics affect BI acceptance for SMEs. That is, technological characteristics (relative advantage, complexity and observability); Organizational (training and education, and top management); environmental (competitive pressure and trading partner support) and behavioural (perceived ease of use), Figure 1.

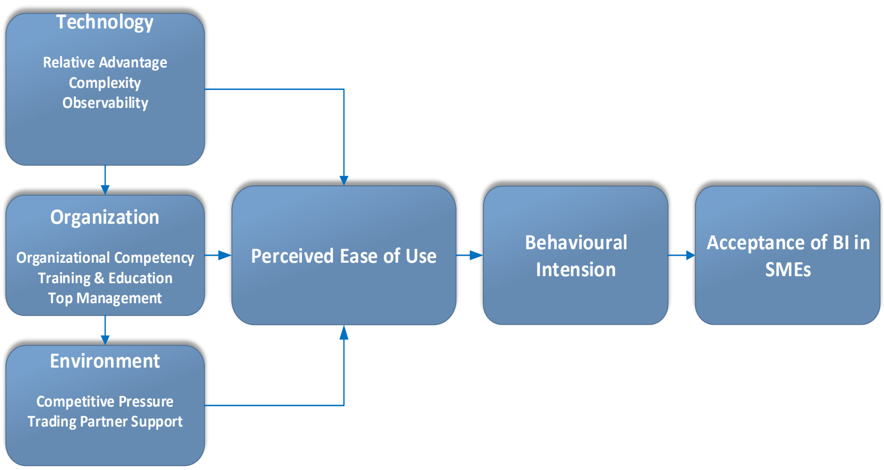

FIGURE 1
REFINED RESEARCH MODEL

STUDY RESULTS

Table 8 displays the demographic statistics relating to the respondents and the organizations. Table 9 shows the results of the multinomial logistic regression as explained by the likelihood ratio test.

In Table 10, the values in the bracket indicate the p-values for the statistically significant hypotheses at 5% level of significance. Here significance implies that there is a relation between the hypothesized variable and BI acceptance. All presented characteristics show a strong relation with BI acceptance for SMEs.

Figure 1 shows the refined model as per the supported study hypotheses. BI acceptance in SMEs has a strong relationship with all the characteristics indicated in the Table 10, save for the characteristic of PEOU whose p-value=0.038, which is interpreted as a weak relationship as compared to the rest of the characteristics with p-value=0.000.

DISCUSSION

This exploratory study examined the relationship between BI acceptance and technological, organizational, environmental and behavioural factors. The results demonstrate a strongly significant relationship between BI acceptance and the key characteristics under the said factors, Table 10. The strength of the relationship was largely the same (0.000) among technological, organisational and environmental factor characteristics. However, it differed substantially for the behavioural factor characteristic of PEOU (0.038); this could be attributed to the fact that perception is largely characterized by confounding factors that cannot readily be controlled in a given study of such a nature.

CONCLUSION

The findings of this work should be understood in light of some considerable limitations and basing solely on the scope.

Firstly, the enabling factors mentioned in this study are supported by previous studies, nevertheless a longitudinal approach could be embraced to ascertain long-term mechanisms through which BI acceptance could be affected over time. Even then, there are other factors that were not included that have a significant impact on SMEs acceptance of BI, which are internal business needs, organizational culture, government support ,and knowledge management. Therefore, this study can be used as a foundation for future research to look into other factors, such as those mentioned, with more focus on those relating to government initiatives and support.

Secondly, this study looked into the acceptance of BI without regard to the current state of adoption of BI by SMEs. Future research can look at the factors that cause SMEs to adopt a technological innovation and not accept it fully or utilise it. These enabling factors mentioned can be used as a benchmark in determining complete utilisation of BI.

Thirdly, due to database limitations encountered in this study, categorising SMEs in their various industries could be considered for further research to determine whether the category to which an SME belongs has any impact on the acceptance of BI technologies, possibly considering the four common industries; retail, manufacturing, service and wholesale.

Lastly, this study focused on the city of Tshwane, future studies, can consider looking at the entire Gauteng province, or even compare between any two provinces, or consider other countries, mainly because things are done differently in various geographical settings.

REFERENCES

Adeniran, T., & Johnston, K., (2014). ICT Utilisation within experienced South African. *The Electronic Journal of Information Systems in Developing Countries, 64*(5), 1-23.

Al-Mamary, H.Y., Al-nashmi, M., Hassan, G.A.Y., & Shamsuddin, A., (2016). A critical review of models and theories in field of individual acceptance of technology. *International Journal of Hybrid Information Technology, 9*(6), 143-158.

Al-Mamary, Y., Shamsuddin, A., & Aziati, N. (2014). Factors affecting successful adoption of management information systems in organizations towards enhancing organizational performance. *American Journal of Systems and Software, 2*(5), 121-126.

Al-Somali, S., Gholami, R., & Clegg, B. (2009). An investigationin to the acceptance of online banking in Saudi Arabia. *Technovation, 29*(2), 130-141.

Amoako-Gyampah, K., & Salam, A. (2004). An extension of the technology acceptance model in an ERP environment. *Information & Management, 41*, 731–745.

Amra, R., Hlatshwayo, A., & McMillan, L. (2013). SMME Employment in South Africa. *In: Biennial conference of Economics Society of South Africa*, 1-22.

Awa, H., Ukoha, O., & Emecheta, B. (2012). Integrating TAM and TOE Frameworks and expanding their characteristic constructs for e-commerce adoption by SMEs. *Proceedings of Informing Science & IT Education Conference (InSITE),* 572-587.

Awiagah, R., Kang, J., & Lim, J. (2015). Factors affecting e-commerce adoption among SMEs in Ghana. *Information Development, 32*(4), 815-836.

Azvine, B., Cui, Z., & Nauck, D. (2005). Towards real-time business intelligence. *BT Technology Journal*, *23*(3), 214–225.

Boonsiritomachai, W., McGrath, M., & Burgess, S. (2014). *A research framework for the adoption of Business Intelligence by Small and Medium-sized enterprises.* Sydney, 27th Annual SEAANZ Conference Proceedings.

Boumediene, R., & Kawalek, P. (2008). *Predicting SMEs Willingness to Adopt ERP, CRM, SCM & E-Procurement Systems.* s.l., ECIS 2008 Proceedings.

Calof, J., Richards, G., & Smith, J. (2015). Foresight, competitive intelligence and business analytics tools for making industrial programmes more efficient. *Foresight and STI Governance, 9*(1), 68-81.

Campbell, H. (2014). *Business Intelligence, Cooperative Corporate Venturing relating to SMME growth in South Africa*, Johannesburg: A Master's Thesis: University of the Witwatersrand.

Carson, D., & Gilmore, A., (2000). Marketing at the Interface: Not 'What' but 'How'. *Journal of Marketing Theory and Practice, 8*(2), 1-7.

Chimucheka, T., (2013). The Impact of Entrepreneurship Education on the Establishment and Survival of Small, Micro and Medium Enterprises (SMMEs). *Journal of Economics, 4*(2), 157-168.

Cokins, G., (2017). *Strategic business management: From planning to performance*. John Wiley & Sons.

Côrte-Real, N., Ruivoa, P., & Oliveira, T. (2014). The diffusion stages of business intelligence & analytics (BI&A): A systematic mapping study. *International Conference on Health and Social Care Information Systems and Technologies, 16*, 172 –179.

Davis, F.D. (1986). A technology acceptance model for empirically testing new end-user information systems: Theory and results, Sloan School of Management, Massachusetts Institute of Technology.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly, 13*(3), 319-340.

Davis, F., Bagozzi, R., & Warshaw, P. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science, 35*(8), 982-997.

Dawson, L., & Van Belle, J. (2013). Critical success factors for business intelligence in the South African financial services sector. *SA Journal of Information Management, 15*(1), 12.

Elbashir, M.Z., Collier, P.A., & Davern, M.J. (2008). Measuring the effects of business intelligence systems: The relationship between business process and organizational performance. *International Journal of Accounting Information Systems*, *9*(3), 135-153.

Gefen, D., (2004). What Makes an ERP Implementation Relationship Worthwhile: Linking Trust Mechanisms and ERP Usefulness. *Journal of Management Information Systems, 21*(1), 263-288.

Ghoshal, S., & Kim, S. (1986). Building effective intelligence systems for competitive advantage. *Sloan Management Review, 28*(1), 49-58.

Grabova, O., Darmont, J., Chauchat, J.H., & Zolotaryova, I. (2010). Business intelligence for small and middle-sized entreprises. *ACM SIGMOD Record, 39*(2), 39-50.

Guarda, T., & Santos, M. (2013). Business Intelligence as a Competitive Advantage for small and medium sized enterprises. *International Journal of Trade, Economics and Finance, 4*(4), 176-188.

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.

Hatta, M., Natasha, N., Miskon, S., & Syed Abdullah, N. (2017). Business Intelligence System Adoption Model for SMEs.

Heeringa, S.G., West, B.T., & Berglund, PA. (2017). Applied Survey Data Analytics, 2nd Edition, Chapman and Hall/CRC, New York

Hofstede, G., Neuijen, B., Ohayv, D., & Sanders, G. (1990). Measuring organizational cultures: A qualitative and quantitative study across twenty cases. *Administrative, 35*(2), *286-316.*

Hussain, J., Salia, S., & Karim, A. (2018). Is knowledge that powerful? Financial literacy and access to finance: An analysis of enterprises in the UK. *Journal of Small Business and Enterprise Development, 25*(3), 102-117.

Imran, M., & Tanveer, A. (2015). Decision support systems: Creating value for marketing decisions in the pharmaceutical Industry. *European Journal of Business and Innovation Research, 3*(4), 46-65.

Islam, N., Azad, N., Mäntymäki, M., & Islam, S. (2014). TAM and E-learning Adoption: A Philosophical Scrutiny of TAM, Its Limitations, and Prescriptions for E-learning Adoption Research. *International Federation for Information Processing,* 164–175.

Johnson, S., (2016). *InsideINFO: News.* [Online] Available at: https://www.insideinfo.com.au/news/2016/08/16/consolidating-performance-data-bi-tools

Jon, K. Lai, L.T., Chua, K.H., & Dennis, N.C.H (2001). *Electronic commerce adoption by SMEs in Singapore.* Maui, HI, USA, Proceedings of the 34th Annual Hawaii International Conference on System Sciences.

Kerzner, H., & Kerzner, H.R. (2017). *Project management: A systems approach to planning, scheduling, and controlling*. John Wiley & Sons.

Khan, A., Amin, N., & Lambrou, N. (2010). *Drivers and Barriers to Business Intelligence Adoption: A Case of Pakistan.* Abu Dhabi, UAE, European and Mediterranean Conference on Information Systems, 3-7.

Kumari, N. (2013). Business Intelligence in a Nutshell. *International Journal of Innovative Research in Computer and Communication Engineering, 1*(4), 969-974.

Lee, Y., Hsieh, Y., & Hsu, C. (2011). Adding Innovation Diffusion Theory to the Technology Acceptance Model: Supporting Employees' Intentions to use E-Learning Systems. *Educational Technology & Society, 14*(4), 124–137.

Lin, H., & Lee, G. (2005). Impact of organizational learning and knowledge management factors on ebusiness adoption. *Management Decision, 43*(2), 171-188.

Lippert, S., & Govindarajulu, C. (2006). Technological, Organizational, and Environmental Antecedents to Web Services Adoption. *Communications of the IIMA, 6*(1), 147-158.

Lloyd, J. (2011). Identifying key components of business intelligence systems and their role in managerial decision making. Eugene: *Intel Corporation*.

Luciano, M.M., Mathieu, J.E., Park, S., & Tannenbaum, S.I. (2018). A fitting approach to construct and measurement alignment: The role of big data in advancing dynamic theories. *Organizational Research Methods*, *21*(3), 592-632.

Mahembe, E. (2011). *Literature Review on Small and Medium Enterprises' Access to Credit and Support in South Africa,* Pretoria: Underhill Corporate Solutions (UCS).

Ma, L., & Ye, M. (2015). The Role of Electronic Human Resource Management in Contemporary Human Resource Management. *Open Journal of Social Sciences, 3*(4), 71-78.

Nath, N., Hu, Y., & Budge, C. (2016). Information technology and diffusion in the New Zealand public health sector. *Qualitative Research in Accounting & Management*, *13*(2), 216-251.

Ngai, E., Law, C., & Wat, F. (2008). Examining the critical success factors in the adoption of enterprise resource planning. *Computers in Industry, 59*(6), 548-564.

Obeidat, B. (2016). Exploring the Relationship between Corporate Social Responsibility, Employee Engagement, and Organizational Performance: The Case of Jordanian Mobile Telecommunication Companies. *International Journal of Communications, Network and System Sciences, 9*(9), 361-386.

O'Brien, J., & Kok, J. (2006). Business intelligence and the telecommunications industry: can business intelligence lead to higher profits? *South African Journal of Information Management, 8*(3), 1-15.

Olawale, F., & Garwe, D. (2010). Obstacles to the growth of new SMEs in South Africa: A principal component analysis approach. *African Journal of Business Management, 4*(5), 729-738.

Ponelis, S., & Britz, J. (2011). An exploratory study of business intelligence in knowledge-based South African SMEs. *In GlobDev 2011 Pre-AMCIS Workshop: ICT in Global Development,* 2-4.

Protassov, R., Van Dyk, D.A., Connors, A., Kashyap, V.L., & Siemiginowska, A. (2002). Statistics, handle with care: detecting multiple model components with the likelihood ratio test. *The Astrophysical Journal*, *571*(1), 550-545.

Rahayu, R., & Day, J. (2015). Determinant Factors of E-commerce Adoption by SMEs in Developing Country: Evidence from Indonesia. *Procedia-Social and Behavioral Sciences*, *195*, 142-150.

Rahman, A.A., Hasan, A.N., & Lahad, A.N. (2016). Issues and Challenges in Business Intelligence Case Studies. *Jurnal Teknologi*, *78*(8-2), 171-178.

Ramamurthy, K., Sen, A., & Sinha, A. (2008). Data Warehousing Infusion and Organizational Effectiveness. *IEEEE*, *38*(4), 976 - 994.

Roca, J., Chiu, C., & Martíneza, F. (2006). Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. *International Journal of Human-Computer Studies*, *64*(8), 683-696.

Rogers, E. (1995). *Diffusion of innovations.* 4 *Ed*. New York: *Free Press*.

Rym, B., Olfa, B., & Mélika, B.M. (2013). Determinants of E-Learning Acceptance: An Empirical Study in the Tunisian Context. *American Journal of Industrial and Business Management, 3*(3), 307-321.

Sadok, M., & Lesca, H. (2009). A Business Intelligence Model for SMEs Based on Tacit Knowledge. *Communications of the IBIMA, 7*(20), 2-10.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education, 2*, 53-55

Thong, J. (1999). An Integrated Model of Information Systems Adoption in Small Businesses. *Journal of Management Information Systems, 15*(4), 187-214.

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

Venkatesh, V., & Davis, F. (2000). A theoretical extension of the technology acceptance model: four longitudinal field studies. *Management Science, 46*(2), 186-204.

Voicu, V., Zirra, D., & Ciocirlan, D. (2009). *Business Intelligence Effective Solutions of Management.* Bucharest, Proceedings of the 10th WSEAS Int. Conference on MATHEMATICS and COMPUTERS in BUSINESS and ECONOMICS.

Watson, H., & Wixom, B. (2007). The Current State of Business Intelligence. *IT Systems Perspective*, *40*, 96 - 99.

Wu, X., Zhu, X., Wu, G.Q., & Ding, W., (2014). Data mining with big data. *IEEE transactions on knowledge and data engineering*, *26*(1), 97-107.

Yamane, T. (1967). Statistics, an Introductory Analysis, 2nd Ed., New York: Harper and Row.

Zeng, J., An, M., & Smith, N., (2007). Application of a fuzzy based decision-making methodology to construction project risk assessment. *International Journal of Project Management*, *25*(6), 589-600.