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BIG DATA ANALYTICS CAPABILITIES FOR IFRS 9 SUCCESS

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Research paper

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Abstract

In the aftermath of the global financial crisis, financial reporting standards have proven inadequate in providing sound governance. With financial data being heavily dependent on information systems, a new standard, IFRS 9, is being adopted. IFRS 9 could leverage recent advancements in big data analytics capabilities to improve financial compliance and assurance. While such potential is widely acknowledged, big data analytics capabilities have not yet been adequately identified and validated in the context of financial reporting compliance. In addressing such discrepancy, this study attempts to explore the relationship between a firm's capability to conduct big data analytics and their perception of IT applications leveraged for compliance with the standard. This study identifies four constituent capabilities and provides empirical validation for their interrelation with a holistic big data analytics construct. It addresses the link between capabilities and perceived IFRS 9 benefits by a range of institutional stakeholders. The findings suggest that analytics governance, analytics personnel capabilities, and Big Data characteristics have a significant influence on big data analytics capabilities. The latter was found to have a significant relationship with perceived benefits of IFRS 9. These findings hold important implications to theory and practice given the impending mass adoption of IFRS 9.

Keywords: IFRS 9, Big Data Analytics Capabilities, Structural Equation Modelling, Analytics Gov-ern-ance, Big Data characteristics

1 Introduction

Financial transactions take place every microsecond, a reality made possible by the Information Systems (IS) advancements witnessed in the past two decades. IS not only facilitate the international distribution of wealth, they are also relied upon by international regulatory bodies to ensure justice, equity and standardisation in worldwide financial markets. On January 1, 2018 a new standard profoundly reliant on the information technology (IT) capabilities of reporting entities becomes mandatory. The standard, known as International Financial Reporting Standard (IFRS) 9, was developed by the International Accounting Standards Board (IASB) to replace International Accounting Standard (IAS) 39. IAS 39, specifically its incurred credit loss model. Such model was criticised after the global financial crisis of 2007 for enforcing tight restrictions on loan loss recognition which led to an overstatement of financial instrument values (Camfferman, 2015), a factor which was regarded as exacerbating the impact of the crisis. The expected credit loss (ECL) model of IFRS 9 is a direct response to IAS 39's incurred credit loss issues. IFRS 9's ECL model requires reporting entities to use predictive modelling to identify potential credit losses associated with portfolios of financial instruments. The model includes a three-stage categorisation approach to the measurement of financial instrument impairment (BDO IFR Advisory Limited, 2014), with each stage dictating "the amount of impairment to be recognised (as well as the amount of interest revenue)" (BDO IFR Advisory Limited, 2014, p. 9).

Migration from stage to stage requires the determination that a "significant increase in credit risk" (International Accounting Standards Board, 2014, para B5.5.7) has occurred or that the financial instrument has become impaired. Stage one requires entities to predict and report at the reporting date expected credit losses associated with the first twelve-month period of a financial instrument using the gross carrying amount. Stages two and three require entities to predict and report at the reporting date expected credit losses for the lifetime of financial instruments, calculated using the gross carrying amount and amortized cost respectively. The fundamental differentiating factor between the incurred credit loss model of IAS 39 and the expected credit loss model of IFRS 9 is that the latter does not require an adverse credit event to take place for credit losses to be recognised (International Accounting Standards Board, 2014). In other words, the expected credit loss model of IFRS 9 is forward looking and is heavily dependent on predictive analytics, unlike the incurred credit loss model of its predecessor IAS 39.

Professional services firms have identified significant information systems, particularly data analytics and governance challenges associated with the implementation of IFRS 9 requirements. Deloitte (2014, 2015, 2016) for example conducted three industry surveys on financial institutions of whom are affected by the standard. They identified an increase in concern over data and governance quality with regard to the use of credit risk management systems and data for financial reporting purposes. Ernst and Young (2017) declared that the introduction of the standard "represents a large-scale transformational change for financial institutions" (p. 18) and that to comply with its requirements entities will need to ensure that IS infrastructures can handle complex analytics calculations "performed leveraging large volumes of new data" (p. 18). The accessibility to historical data for some financial instrument portfolios was another challenge identified by Moody's Analytics (2016) who also uncovered through their industry surveys "issues related to handling larger volume of calculations" (p. 28) and the quality of the data required.

Chartis Research (2016) in collaboration with PwC conducted research into the IT solutions available for entities to comply with the requirements of the standard. The report explores solutions offered by vendors such as AxiomSL, Moody's Analytics, Oracle, SAP, SAS and Wolters Kluwer Financial Services. Chartis Research (2016) also outlined a suggested IT architecture diagram which they recommend entities consult when implementing their IFRS 9 solutions. This diagram is presented in figure 1 and highlights the crucial role of data mining, analytics engines, online analytical processing (OLAP) cubes, data warehouse and operational data storage in implementing the standard. The diagram also identifies data sources used for compliance such as credit card, auto loans, treasury and core banking data assets. Important aspects also highlighted by Chartis Research (2016) include the pivotal role of operational risk mitigation, IT policy compliance, financial controls, IT governance and the internal audit function within affected entities.

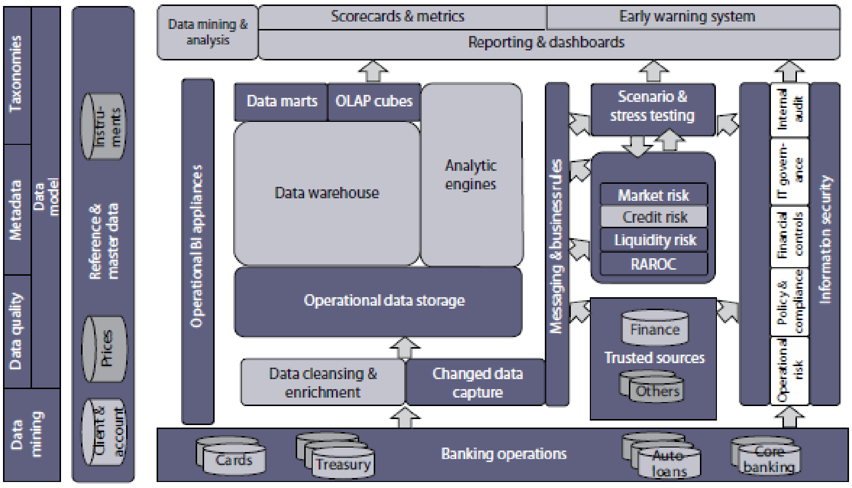

Figure 1: IFRS 9 Information Systems Architecture Diagram (Chartis Research, 2016)

The ECL model introduced by IFRS 9 will require affected entities to leverage IT solutions that facilitate the analysis of extensive and constantly changing financial data sets. A specific capability which this is associated with is the capability of the affected entities to conduct big data analytics, a concept defined by Akter et al. (2016) as “the competence to provide business insights using data management, infrastructure (technology) and talent (personnel) capability to transform business into a competitive force” (p. 114). Whilst extant literature has examined the relationship between IFRS standard evolution and the information systems of affected entities (Taipaleenmaki and Ikaheimo, 2013; Firoz et al., 2011; Grabski et al., 2011) no studies to the best of the authors’ knowledge have specifically explored the concept of big data analytics capabilities in the context of financial reporting compliance. As such, the objective of this study is to examine constituent big data analytics capabilities in relation to the success of IFRS 9 adoption.

The following section will explore extant academic literature on IFRS and big data analytics capability as well as a development of this study’s hypotheses. Section 3 will introduce the survey questionnaire method utilised to test the hypotheses and the findings of which will be explore in Section 4. Section 5 will discuss these findings and how they contribute to the body of knowledge and will conclude with a discussion of its limitations and future implications.

2 Literature Review and Hypotheses Development

IFRS Adoption Literature

Uniformity of accounting standards has been a major agenda item for accounting practice for over a century. A key focal point for IFRS research is on harmonisation, which is achieved by “setting limits to the difference between financial reports” (Van der Tas, 1988, p. 158). Harmonising financial reports can refer to either the “degree of disclosure or the accounting method to be applied” (Van der Tas, 1988, p. 158). Chand and Patel (2008, p.85) stated that “… factors (such as culture, professional experience and type of standards) impact on the interpretation and application of accounting standards". Soderstrom and Sun (2007) for example reviewed the adoption of IFRS and its impact on accounting quality, finding that literature demonstrates a positive impact of IFRS adoption. Ramanna (2013) studied the international politics of IFRS harmonisation, identifying political considerations for IFRS. Daske et al. (2008) explored the economic consequences of IFRS adoption, identifying statistically significant increases in market liquidity for firms that mandatorily adopt IFRS (p. 1131). Larson and Street (2004) examined the progress and impediments with IFRS adoption, finding issues including the perceived complicated nature of IFRS standards.

There have also been several studies specifically on IFRS 9. Onali and Ginesti (2014) for instance examined market reaction to IFRS 9 adoption events across Europe. In another study, Bischof and Daske (2016) investigated the three criterions stipulated by EU regulation before IFRS standards become binding for EU firms. Knežević, Pavlović, and Vukadinović (2015) compared both IAS 39 and IFRS 9, exploring differences between their credit loss models. Bernhardt, Erlinger, and Unterrainer (2016) summarised the criticism of IAS 39 and discussed IFRS 9's changes from the risk management perspective. Shields (2014) studied the impact of comment letter lobbying on IASB standard setting by focusing on the development of IFRS 9. Mawanane-Hewa (2016) also explored IASB lobbying, with a focus on the extent of interest group influence on IFRS 9 ECL modelling development. Novotny-Farkas (2016) examined the interaction of the ECL approach of IFRS 9 on supervisory rules and the three pillars of bank regulation.

Studies have also examined the relationship between IFRS adoption and the information systems of affected entities. For instance, Taipaleenmäki and Ikäheimo (2013) explored how the harmonisation of financial reporting standards influence a convergence of management and financial accounting. They point out that managerial accounting generation of fair values for financial accounting purposes required under IFRS is facilitated by IT, which makes "calculation and information transfer easier and faster" (p. 331). Firoz, Ansari, and Akhtar (2011) explore the impact of IFRS adoption on the Indian banking industry. They note that IFRS adoption "is expected to have wide-ranging effects at different levels of the IT systems architecture" (p. 279). Grabski, Leech, and Aronson (2011) suggest that the need to prepare financial statements which adhere with the requirements of IFRS "has resulted in the need to modify and extend the ERP system" (p. 59). Nevertheless, to the authors' knowledge, no study has yet examined the relationship between big data analytics capabilities and the success of IFRS 9 adoption.

Big Data Analytics Capabilities and Hypotheses Development

The concept of big data analytics capability is a derived from IT capability, which Bharadwaj (2000) defines as the ability of a firm to "mobilize and deploy IT-based resources in combination or co-present with other resources and capabilities" (p. 171). Kim et al. (2012) studied IT capability through the lens of sociomaterialism seeking to identify how IT capability strengthens firm performance. Their study introduces three IT capability dimensions: infrastructure, personnel and management capabilities. They determined that extant literature in IT capability took advantage of the resource-based view to define IT capability elements. Kim et al. (2012) cite Barney (1991), Bhatt and Grover (2005), Chen and Wu (2011), Godfrey and Hill (1995) and Grant (1991) when stating that IT capability literature generally refers to physical, human and organizational elements which they term infrastructure, IT skills or knowledge and relationship infrastructure respectively. An outcome of their IT capability analysis was the proposal of an IT capability model comprising of the capability variables IT infrastructure capability, IT personnel capability and IT management capability.

Big data analytics capability is specifically concerned with capability of firms to leverage big data analytics to achieve strategic objectives. Akter et al. (2016) define big data analytics as "the distinctive capability of firms in setting the optimal price, detecting quality problems, deciding the lowest possible level of inventory and identifying loyal and profitable customers in the big data environment" (p. 113 – 114). Fosso et al. (2017) provide an alternate definition of big data analytics more closely aligned with the fundamentals of big data. They define big data analytics as "a holistic approach to managing, processing and analysing the 5 V data-related dimensions (i.e., volume, variety, velocity, veracity and value) to create actionable ideas for delivering sustained value, measuring performance and establishing competitive advantages" (p. 365). Techniques used to analyse big data sets have been drawn from "several disciplines, including statistics, computer science, applied mathematics, and economics" (George et al., 2014, p. 6).

Using Kim et al.'s (2012) IT capability research model as a catalyst, Akter et al. (2016) developed a research model to measure big data analytics capability. Their model features 11 variables, categorised into three capabilities: big data analytics management, big data analytics technology and big data analytics talent. Big data analytics management capability refers to the importance of "ensuring that solid business decisions are made applying proper management framework" (Akter et al., 2016, p. 118) when managing big data analytics. Big data analytics technology capability "refers to the flexibility of the big data analytics platform … in relation to enabling data scientists to quickly develop, deploy, and support a firm's resources." (Akter et al., p. 119). Big data talent capability is defined as the analytics professional's ability "to perform assigned tasks in the big data environment" (Akter et al., 2016, p. 119).

Fosso et al. (2017) also devised a big data analytics capability research model, which features big data analytics capability as "a third-order, hierarchical model manifested in three second-order constructs" (p. 358). These constructs are big data analytics infrastructure flexibility, big data analytics management capabilities and big data analytics personnel expertise capability. Big data analytics infrastructure capability refers to the infrastructure of the big data analytics environment, and its ability "to enable the BDA staff to quickly develop, deploy, and support necessary system components for a firm" (Fosso et al., 2017, p. 358). Big data management capability refers to the ability of the big data analytics unit to "manage IT resources in accordance with business needs and priorities" (p. 358) in a structured manner. Big data analytics personnel capability "refers to the big data analytics staff's professional ability (e.g., skills or knowledge) to undertake assigned tasks" (p. 358).

In the context of this study, big data analytics capability is defined as the capability of international entities affected by requirements introduced by IFRS 9 to leverage big data analytics in their compliance efforts. The concept is to be measured by four multidimensional constructs adapted from Akter et al. (2016) and Fosso et al. (2017). These are analytics planning, analytics governance (Akter et al. 2016), analytics personnel capabilities (Akter et al., 2016, Fosso et al., 2017) and big data characteristics (Fosso et al. 2017). Like the capability constructs adapted by Kim et al. (2012) in their IT capability model, the constructs examined in this study are distinct but interdependent. Together they explore the ability of entities affected by the standard to plan and govern the implementation of big data analytics for IFRS 9 purposes. Furthermore, the constructs also explore the capability of affected entity's human resources and IT infrastructures to support the implementation and continued use of big data analytics. The remainder of this section will define each construct, introduce the concept of perceived benefits of IFRS 9 applications and develop the corresponding hypotheses.

Analytics planning refers to the ability of the function within an entity affected by IFRS 9 to determine how big data models can improve compliance with the standard. Akter et al. (2016) use Amazon's implementation of a predictive analytics technique termed collaborative filtering to recommend additional products to consumers based upon consumer data. In the context of IFRS 9 implementation, the ability to determine how predictive modelling using big data methodologies to efficiently and economically predict the credit loss required for compliance with the ECL model component of IFRS 9 reflects the level of big data planning within an effected entity. Thus, we hypothesize that:

Hypothesis 1: Analytics Planning positively affects Big Data Analytics Capabilities in IFRS 9 adoption.

Analytics governance refers to the ability of the entity affected by the standard to "manage IT resources in accordance with business needs and priorities" (Fosso et al., 2017, p. 358). Akter et al. (2016) refer to analytics governance as analytics control, and provide examples of its realisation such as "proper commitment and utilization of resources, including budgets and human resources" (p. 119). They again refer to Amazon for an example of the concept in practice, referring to controlling functions within the firm that evaluate big data analytics proposals, plans, performance expectation management and performance monitoring of the big data analytics unit. Again, in the context of IFRS 9, this construct reflects the degree to which entities impacted by the standard are capable of governing and controlling their big data analytics function with respect to ensuring that big data analytics methodologies are leveraged in a manner that ensures the entity is in a position to comply with the standard's requirements. Thus, we hypothesize that:

Hypothesis 2: Analytics Governance positively affects Big Data Analytics Capabilities in IFRS 9 adoption.

Analytics personnel capabilities, is derived from Akter et al.'s (2016) big data analytics talent capability construct and Fosso et al.'s (2017) big data analytics personnel expertise capability construct. The construct refers to the professional ability of analytics personnel (skills and knowledge) to perform IFRS 9 related analytical tasks in a big data environment (Akter et al., 2016, p. 119). Akter et al. (2016) explore four pillars of talent capability, including "technical knowledge, technology management knowledge, business knowledge and relational knowledge" (Akter et al., 2016, p. 18). Technical knowledge reflects the "knowledge about technical elements, including operational systems, statistics, programming languages, and database management systems" (Akter et al., 2016, p. 120). Technology knowledge refers to the understanding of resources required to realise the potential of big data analytics. Examples of technology knowledge include the use of visualisation and reporting solutions to understand trends and allocate big data resources appropriately. Business knowledge refers to "the understanding of various business functions and the business environment" (Akter et al., 2016, p. 120). This enables those in the big data analytics function to respond to stakeholder's expectation and ensure that their efforts align with strategic and operational objectives of their firms. Finally, relational knowledge refers to "the ability of analytics professionals to communicate and work with people from other business functions" (Akter et al., 2016). Thus, we hypothesize that:

Hypothesis 3: Analytics Personnel Capabilities positively affects Big Data Analytics Capabilities in IFRS 9 adoption.

Big data characteristics refers to the big data characteristics of the information systems which could be leveraged to enable big data analytics capabilities for entities affected by IFRS 9. This construct is motivated by Fosso et al.'s (2017) inclusion of big data analytics infrastructure capabilities to measure big data analytics capabilities and Fosso et al.'s (2015) systematic literature review of big data literature. Big data analytics infrastructure capability refers to the infrastructure of the big data analytics environment, and its ability "to enable the BDA staff to quickly develop, deploy, and support necessary system components for a firm" (Fosso et al., 2017, p. 358). The measurement items used for the construct have been developed to explore to what degree the information systems of entities affected by IFRS 9 facilitate the 5 'V's of big data. Meijer (2012) summarises the first 3 'V's: volume, velocity and variety. Volume refers to the amount of data stored; velocity relates to the rapid time associated with generation and collection of data and variety relates to the array of different data types, ranging from “SQL-style relational tuples with foreign/primary key relationships to coSQL-style objects or graphs” (p. 66). Gandomi and Haider (2015) explore the two additional ‘V’s of big data, veracity and variability. Veracity “represents the unreliability inherent in some sources of data. For example, customer sentiments in social media are uncertain, since they entail human judgement” (Gandomi and Haider, 2015, p.139) and variability “refers to the variation in data flow rates” (p. 66). Thus, we hypothesize that:

Hypothesis 4: Big Data Characteristics positively affects Big Data Analytics Capabilities in IFRS 9 adoption.

Big Data Analytics Capabilities and Perceived Benefits. It is expected that entities affected by changes introduced by IFRS 9 will need to leverage big data analytics to comply with the standard. An IFRS 9 IT architecture diagram proposed by Chartis Research (2016, p. 29) identifies the use of big data artefacts, such as data marts, online analytical processing cubes and data warehouses as sources for IFRS 9 applications, such as early warning systems and dashboards. Commentary on the standard’s implementation by professional services firms and professional bodies has also highlighted the importance of predictive analytics on large sets of financial data (Deloitte, 2014, 2015, 2016; Ernst and Young, 2016, 2017, Moody’s Analytics, 2016, Global Public Policy Committee, 2016, European Banking Authority, 2016, 2017). A high degree of big data analytics capability within an affected entity may positively affect the intention of industry actors within the affected organisations to use IFRS 9 analytics applications for compliance. Thus, the following hypothesis is proposed:

Hypothesis 5: Big Data Analytics Capabilities positively affects Perceived Benefits of IFRS 9 adoption.

The research methodology will be discussed in the next section.

3 Methodology

This paper adopts a quantitative research approach. Empirical data was collected using a survey method during July and September of 2017. The survey questionnaires were distributed to industry professionals involved with IFRS 9 implementation projects in international entities. To identify the participants, we explored online portals of IFRS 9 professionals and found two active LinkedIn groups. These groups are called the ‘IFRS 9 Implementation Group’ and the ‘IFRS 9 and CECL Modelling’ group. These groups formed an online meeting place for professionals involved in IFRS 9 implementation efforts to share advice and discuss progress. Table 1 provides an overview of the LinkedIn groups leveraged for the survey questionnaire distribution.

Table 1: Summary of LinkedIn Groups Used for Sampling

Group Name	Description	Members	Group URL
IFRS 9 Implementation Group	The purpose of the group is to discuss practical challenges of implementing IFRS 9 without touching on confidential and or sensitive information.	1,490	https://linkedin.com/groups/8191086
IFRS 9 and CECL Modelling	A LinkedIn group dedicated to the discussion of IFRS 9 / CECL modelling issues. For further resources (papers / glossary etc.) check the website www.openriskmanual.org	754	https://linkedin.com/groups/8540200

A list of group members was extracted from the LinkedIn group pages and combined into a Microsoft Excel worksheet, which was then used by a macro which invited each group member to become a connection with one of the authors. LinkedIn permits a 300-character message to be sent with a connection invitation request. This message was leveraged to provide an invitation to participate in the survey questionnaire which was hosted online using Qualtrics (2017). A total of 2,192 connection invitation requests were sent to these group members inviting them to participate in the survey questionnaire. A seven-point Likert scale was utilised to measure the industry professional's attitudes towards information systems success factors and organisational big data analytics capabilities in IFRS 9 adoption. There were 113 responses received through Qualtrics, equating to a response rate of 5.16%.

Responses to the survey questionnaire were analysed using Structural Equational Modelling Partial Least Squares (SEM-PLS), which does not require multivariate distribution and independent observations (Chin and Newsted, 1999) and can operate efficiently with small sample sizes (Hair et al., 2014, Reinartz et al., 2009). Furthermore, the complexity of a structural model has little impact on the sample size required for SEM-PLS (Hair et al., 2014). Hair et al. (2014) recommend the use of the software package G*Power (Faul, Erdfelder, Lang, and Buchner, 2007) to calculate the required minimum sample size for SEM-PLS analysis. Ringle et al. (2014) supports this recommendation, proposing that researchers should use as input parameters an effect size f^2 of 0.15; an α error probability of 0.05, a power $(1 - \beta)$ error probability of 0.80 and the number of predictors equal to 4. Accordingly, G*Power recommended a minimum sample size of 85. SmartPLS Version 3 (Ringle, Wende, and Becker, 2015) was used to operationalise this study's SEM-PLS model, testing for the reliability and validity of the survey instrument as well as the reliability and validity of the measurement items and constructs. Hair et al. (2014) recommend that researchers assess their response data set for suspicious responses or missing values. Of the 113 responses, 5 responses contained missing values and 1 was deemed suspicious as it appeared to be a straight-line response. These 6 responses were subsequently removed.

Participants were asked which job position they hold, resulting in 93 unique responses. Due to this large number, each position was manually allocated into categories relevant to the study of IFRS 9: Risk, Finance, Information Technology (IT), Audit, Consultant and Management. Some positions did not fit into these categories and as such were categorised into 'Other'. These categories were inspired by the industry analysis which makes mention of the increasing emphasis on the relationship between risk, finance and IT departments due to regulatory standards such as IFRS 9 (European Banking Authority, 2016). It was determined that a majority of respondent's positions were categorised as management (25.23%). This was closely followed by risk (22.43%), finance (22.43%) and consultancy (16.82%). Audit (3.74%) and Information Technology (3.74%) were the lowest and 5.61% were categorised as Other.

4 Results

Measurement Model Evaluation

The evaluation of a SEM measurement model involves an examination of its consistency reliability and validity (Hair et al., 2014). Internal consistency reliability is defined as "a form of reliability used to judge the consistency of results across items on the same test" (Hair et al., 2014, p. 116) and can be measured using Cronbach's (1971) alpha and composite reliability. Convergent validity is defined by Hair et al. (2014) as "the extent to which a measure correlates positively with alternative measures of the same construct" (p. 102) and can be determined through an analysis of the construct's average variance extracted (AVE) and outer loadings. Table 2 presents the PLS Loadings, T-Statistics, Significance Levels, Composite Reliability and AVE, calculated using SmartPLS's bootstrapping procedure with 5000 sub samples as recommended by Hair et al. (2014).

For a measurement model's validity to be determined, the indicator construct loadings must be greater than 0.707 (Chin, 1998), which is the case in this study. Each indicator's T-Statistic is greater than

2.54, resulting in a corresponding significance level of 99%. Both composite reliability and AVE are used to determine construct reliability. Composite reliability values between 0.70 and 0.90 are desired and deemed satisfactory (Hair et al., 2014), which again was met in this measurement model. AVE is defined as “the grand mean value of the squared loadings of the indicators associated with the construct” (Hair et al., 2014, p. 103), a must equal or exceed 0.50 (Hair et al., 2014). Meeting this criterion suggests that “on average, the construct explains more than half of the variance of its indicators” (Hair et al., 2014, p. 103). The minimum AVE requirement of 0.50 is also met in this study’s measurement model. The PLS loadings, composite reliability, AVE values and the 99% significance level of each indicator suggests that the measurement model is both valid and reliable.

Table 2: Measurement Model Statistical Analysis Results

CONSTRUCTS AND INDICATORS	PLS Loading	T - Statistics	Significance Level	Composite Reliability	AVE
ANALYTICS GOVERNANCE				0.9580	0.8520
GOVN1	0.9080	42.7350	0.01		
GOVN2	0.9130	29.6560	0.01		
GOVN3	0.9330	55.9210	0.01		
GOVN4	0.9370	83.6890	0.01		
ANALYTICS PERSONNEL CAPABILITIES				0.9650	0.9020
PERS1	0.9430	59.6350	0.01		
PERS2	0.9520	81.6600	0.01		
PERS3	0.9550	91.3310	0.01		
ANALYTICS PLANNING				0.9620	0.8640
PLAN1	0.9150	34.2220	0.01		
PLAN2	0.9430	70.4070	0.01		
PLAN3	0.9330	46.6890	0.01		
PLAN4	0.9270	43.1910	0.01		
BIG DATA CHARACTERISTICS				0.9280	0.7220
BDATA1	0.8020	17.4920	0.01		
BDATA2	0.8630	28.2490	0.01		
BDATA3	0.9070	40.8980	0.01		
BDATA4	0.8720	30.2400	0.01		
BDATA5	0.8000	17.0550	0.01		
BIG DATA ANALYTICS CAPABILITIES				0.9830	0.9500
BDAC1	0.9740	137.8360	0.01		
BDAC2	0.9740	134.2630	0.01		
BDAC3	0.9770	92.8310	0.01		
PERCEIEVED BENEFITS OF IFRS 9 APPS				0.9340	0.7390
BENEFIT1	0.8340	22.6390	0.01		
BENEFIT2	0.7880	18.2380	0.01		
BENEFIT3	0.9070	43.9750	0.01		
BENEFIT4	0.8800	32.2610	0.01		
BENEFIT5	0.8840	36.6120	0.01		

Structural Model Evaluation

The structural model "represents the relationships between constructs or latent variables that were hypothesized in the research model" (Duarte and Raposo, 2010, p. 466). An evaluation of the structural model includes an assessment of the dependent construct's coefficient of determination (R^2) (Hair et al., 2014), which are values used to determine the predictiveness of the model. R^2 values range from 0 to 1 (Hair et al., 2014) with values equal to 1 suggesting that the endogenous constructs are perfectly predicted by their linked exogenous constructs (Vatanasakdakul, 2007). Higher R^2 values in the structural model correspond to increased predictive power (Vatanasakdakul and D'Ambra, 2007).

Figure 1 illustrates this study's structural model. The results demonstrate that the endogenous construct big data analytics capabilities has an R^2 value of 0.640. This implies that the exogenous constructs analytics planning, analytics governance, analytics personnel capabilities and big data characteristics explain 64.00% of the variance in big data analytics capabilities. Big data characteristics appears to have the highest contribution to the R^2 of big data analytics capabilities as it had the highest path coefficient at 0.365. This was followed by analytics personnel capabilities (0.317) and analytics governance (0.305). Analytics planning had a negative path coefficient at -0.022 which will be later explored. The other endogenous construct, perceived benefits of IFRS 9 applications, has an R^2 value of 0.430, which implies that the exogenous construct big data analytics capabilities explains 43.00% of the variance in perceived benefits of IFRS 9 applications.

Table 3 provides an outline of the actual effect, path coefficients, T-Statistics and significance levels for each of the relationships in the structural model. The results of this study and the evaluation of the strutural model demonstrate that analytics governance, analytics personnel capabilities and big data characteristics positively effect big data analytics capabilities with path coefficients of 0.305, 0.317 and 0.365 accordingly. These relationships are significant at the levels 0.05, 0.01 and 0.01 correspondingly. This finding helps to support hyptothesis one regarding the multidimensional nature of the concept of big data analytics capabilities. However, analytics planning's negative effect on big data analytics capabilities (and its negative path coefficient of -0.022) does not permit a full acceptance of hypothesis 1. The results also suggest that big data analytics capabilities has a positive effect on perceieved benefits of IFRS 9 applications with a path coefficient of 0.656 at signifiance level 0.01. This finding supports hypothesis 2.

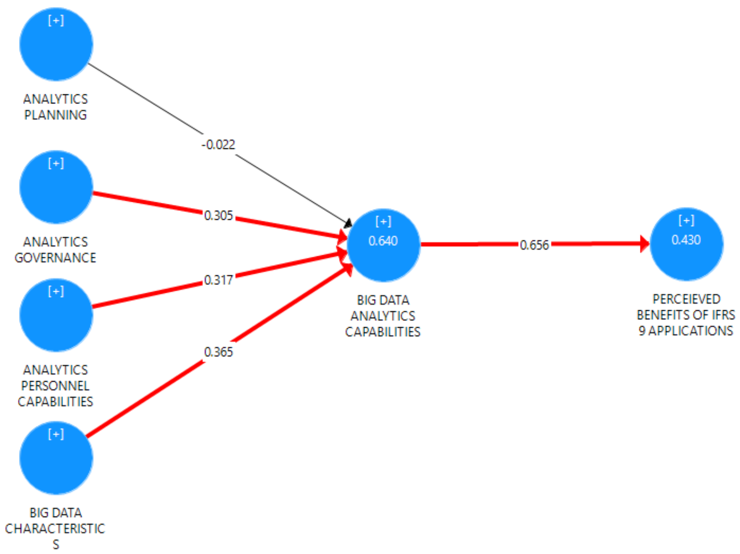

Figure 3: Structural Model SmartPLS Output

Table 3: Path Coefficient Results

Relationship	Actual Effect	Path Coefficient	T Statistics	Significance Level
H1: Analytics Planning → Big Data Analytics Capabilities	-	-0.022	0.204	Not Significant
H2: Analytics Governance → Big Data Analytics Capabilities	+	0.305	2.551	0.05
H3: Analytics Personnel Capabilities → Big Data Analytics Capabilities	+	0.317	2.804	0.01
H4: Big Data Characteristics → Big Data Analytics Capabilities	+	0.365	4.582	0.01
H5: Big Data Analytics Capabilities → Perceived Benefits of IFRS 9 Applications	+	0.656	13.803	0.01

5 Discussion and Conclusion

Hypotheses 1, 2, 3 and 4 were developed to explore whether big data analytics capabilities is a multi-dimensional construct and can be measured by the analytics planning, analytics governance, analytics personnel capabilities and big data characteristics. The results of this study indicate that big data analytics is indeed a multi-dimensional construct and can be measured by the analytics governance, analytics personnel capabilities and big data characteristics. Therefore, hypotheses 2, 3 and 4 are accepted. However, as it was determined that analytics planning did not have a significant relationship with big data analytics capabilities hypothesis 1 was not accepted.

Analytics governance has a significant positive path coefficient of 0.305 to big data analytics capabilities at significance level 0.05. Analytics personnel capabilities has a significant path coefficient of 0.317 to big data analytics capabilities at significance level 0.01. The construct of analytics governance was adapted from Akter et al.'s (2016) and Fosso et al.'s (2017) big data analytics management capability construct. The analytics personnel capabilities construct was adopted from both Akter et al.'s (2016) big data analytics talent capability and Fosso et al.'s (2017) big data analytics personnel expertise capability constructs. The significant positive relationships between analytics governance and analytics personnel capabilities with big data analytics capabilities suggest that in the context of IFRS 9 requirements implementation, industry professionals value the governance and management of IFRS 9 big data analytics alongside their peer's analytical expertise. This finding demonstrates that governance of IFRS 9 big data analytics and the skills, talent and knowledge of IFRS 9 analytics personnel are significantly important factors in organisational big data analytic capabilities. The slightly higher path coefficient of analytics personnel capabilities suggests that industry professionals prioritise the expertise of their analytics personnel over the ability of the entity to govern IFRS 9 big data analytics processes. Furthermore, big data characteristics was found to have a significant positive path coefficient of 0.656 to big data analytics capabilities at significance level 0.01. This finding suggests that in the context of IFRS 9 implementation into affected entities, professional actors perceive that the ability of their entity's information systems to facilitate analytics functions on large volumes of data, generated and captured at a rapid velocity, varying in format, flow rates and veracity is a significant factor affecting overall organisational big data capabilities.

This finding should encourage entities affected by the requirements of IFRS 9 to ensure that their analytics personnel are provided with the resources, training and skill development required to stay on top of the changes in the big data credit risk analysis landscape and that appropriate investments are made to ensure information systems leveraged to support required analytics are capable of handling the 5 'V" characteristics of big data. However, it is also of importance for affected entities to pay attention to the enhancement of governance mechanisms guiding the use of IFRS 9 related big data analytics in affected entities. Data governance has been raised as a key concern in industry analysis on IFRS 9 associated challenges (Deloitte, 2014, 2015, 2016), and this study's finding that industry professionals consider the governance of IFRS 9 data analytical processes an important factor helps to validate these concerns. This finding may promote a practical focus on the governance of data analytics activities particularly within entities affected by IFRS 9. The acceptance of hypotheses 2, 3 and 4 contributes to big data analytics capabilities literature as it confirms the association between the dimension and the constructs analytics planning, governance, analytics personnel capabilities and big data infrastructure characteristics. To date, these associations have been tested within the context of the relationship between big data analytics capabilities on firm performance (Akter et al., 2016, Fosso et al., 2017). This research contributes to big data analytics capabilities literature by extending this examination into the context of financial reporting implementations.

Organisational big data analytics capabilities has a significant relationship with intention to use IFRS 9 analytics applications at significance level 0.01 and has a positive path coefficient of 0.543. As a result, hypothesis 5 is accepted. This finding suggests that industry professionals associated with information systems utilised by entities affected by the evolution of IFRS standards perceive the ability of their entity to conduct big data analytics and governance of such analytics as an important success factor. Contextually, this finding suggests that entities with a strong organisational capability to perform big data analytics are perceived to have a higher likelihood of complying with IFRS 9. This would imply that it is in the best interest for entities affected by IFRS 9 to review their big data analytics capabilities to maximise the intended use of their IFRS 9 analytics applications.

In summary, this study has explored the concept of big data analytics capabilities in the context of IFRS 9 requirements adoption. To the authors' knowledge, this study is the first to explore the relationship between a firm's capability to conduct big data analytics and their perception of IT applications related to a new IFRS 9 standard. The key findings of this study is the determination that the capability of an entity affected by the implementation of IFRS 9 to conduct big data analytics has a positive and significant effect on their perception of IFRS 9 related applications. This study has also confirmed that the construct of big data analytics capabilities is multidimensional and can be measured using the first order constructs of analytics governance, analytics personnel capabilities and big data characteristics which were adapted from research conducted by Akter et al. (2016) and Fosso et al. (2017).

6 Limitations, Implications and Future Research

Like all studies, this study has some limitations. This study has only sought response from industry actors of whom are members of two LinkedIn groups dedicated to the implementation of IFRS 9 into international entities. As such, this study is limited in this regard. Future research should aim for a larger sample size or opt to approach entities affected by big data analytics reliant standards such as IFRS 9 directly. It would also be beneficial for the body of knowledge for future endeavours to explore whether the perceptions identified in this study change after IFRS 9 becomes mandatory for reporting periods beginning on or after January 1, 2018. Furthermore, as this study is cross sectional in nature it is limited by the fact that the hypotheses have been tested at one point in time only. Future research should seek to test this study's model in longitudinal research to explore if the results can be generalized and reliability enhanced. The low response rate also introduces epistemological contribution concerns, which future research could address by exploring alternative survey methods.

Notwithstanding, this endeavour has determined that the capability of entities affected by IFRS 9 to conduct and facilitate big data analytics has a significant positive effect on the perceived benefits of the use of applications intended for compliance purposes. This primary finding is important for both theory and practice as it highlights the critical role of big data analytics in compliance with a ground breaking regulatory evolution in international financial reporting. The study therefore provides an important theoretical foundation for a central topic in financial compliance, with global implications.

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