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Confirmatory Factor Analysis of a Conceptual Framework for Understanding the Factors Affecting the Organisational Adoption of Big Data: The Context of Tax Administration

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Abstract

The paper validates a proposed conceptual framework for understanding factors affecting the organisational adoption of Big Data using data from a tax administration. Factors affecting organisational adoption of Big Data are categorised into innovation, organisation and environment. A quantitative research was employed to collect and analyse perceptions of members of staff in Malawi Revenue Authority's Domestic Taxes Division towards the effect of proposed factors on the organisation's adoption of Big Data. Confirmatory factor analyses were performed to analyse the data. Results showed that the conceptual framework is statistically valid for measuring factors affecting organisational adoption of Big Data. Values for several indicators of goodness of fit and all factor loadings support that the conceptual framework fitted well with the data and that it has adequate factorial validity. The paper concludes that the conceptual framework is suitable for measuring the effect of the proposed factors on organisational adoption of Big Data. However, results are limited by the use of a single tax administration of a developing country to validate the framework. Future research could assess factors affecting organisational adoption of Big Data using the validated framework and further research could repeat validation of the framework using data from the private sector.

Keywords: Big Data, Organisational Adoption, Confirmatory Factor Analysis, Conceptual Framework, Tax Administration.

1. Introduction

Using Big Data and analytics is generally considered to improve organizational performance. Kim, Trimi and Chung (2014) describe Big Data as huge volumes of both structured and unstructured data collected from various large sources. Gathering, storing, processing, accessing, and analysing of big data require complex set of technologies because of their huge volume and structural heterogeneity. According to Sheikh (2013), big data management involves the organisation, administration and governance of huge volumes of data. Big data management ensures that data is of good quality, accessible for business intelligence and analytics. The first step in big data management is an organisation's preparation and readiness to adopt big data. Despite the perceived benefits of big data, challenges such as lack of resources, capabilities, cost, security, storage of data and sustainability prevent organisations from adopting and implementing big data technologies (Demirkan & Delen, 2013; Michael & Miller, 2013).

Sun, Cegielski, Jia, and Hall (2016) developed a framework for identifying factors affecting the organisational adoption of big data based on a content analysis "of relevant papers in the business intelligence & analytics (BI&A) literature published during the period 2009–2015" (p.1). The review identified 26 factors which affect organization's adoption of big data and the factors were integrated into a single framework that would explain adoption of Big Data. However, the conceptual framework has neither been validated nor tested statistically to test its suitability for understanding factors affecting organisational adoption of Big Data. The aims of this research is to validate the conceptual framework for understanding factors affecting the organisational adoption of Big Data proposed by Sun et al. (2016) using empirical evidence from a tax administration.

The research adopted a quantitative approach using a case study of the Domestic Taxes Division in the Malawi Revenue Authority (MRA). Perceptions of employees towards how factors in the proposed conceptual framework affect the Domestic Taxes Division's intentions to adopt Big Data were collected via an online questionnaire and measured by a 4-item Likert. Malawi is one of the developing countries that are introducing technological innovations in tax administration with the objective of creating an environment necessary for Big Data technology. Among the technological innovations that have been introduced are online payment of taxes, ASYCUDA World for clearing customs, and developing of an online tax platform, the Msonkho Online, and real-time issuance of Value Added Tax (VAT) Withholding e-certificate are in progress. All these technologies have a potential of generating Big Data for the tax administration. Malawi's tax administration is relevant for this research because it represents other revenue administrations in the developing world whose efforts to adopt Big Data are affected by several challenges.

2. Theoretical and Conceptual Frameworks

The paper is based on the theoretical framework of the Diffusion of Innovation theory (DOI) and the Technology–Organization–Environment (TOE) framework. According to Rogers (2003), the DOI explains how innovation is diffused in a five-step process involving knowing the innovation, being persuaded to adopt the innovation, deciding to adopt the innovation, implementing innovation, and confirmation. The theory propagates that the intention to adopt innovation is not only dependent on an organisation's ability to acquire innovations but also individual attitudes towards innovations. Rogers (2003) contends that the rate of adopting innovation is determined by "relative advantage, compatibility, complexity, trialability, and observability" (Cited in Sun et al., 2016, p.2). An organisation adopts innovation upon considering that it offers relatively higher value-for-money than previous innovations; it is consistent and compatible with present needs; it is user-friendly; and that the organisation is committed to adopt Big Data. The TOE framework as proposed by Tornatzky and Fleischer (1990) suggests that organisations adopt technological innovations based on three contexts namely: technology, organisation and environment (Cited in Sun et al., 2016). The technological context includes equipment, processes and all their related technologies. However, perceived benefits from technology are not only derived because of the technological innovation itself, but also because of overall support from the entire organisation. In the TOE framework, the organisational context is presented resources and other features of the organisation, for example, size, structure, human capital and their skills. The environment context refers to the organisation's competitors and stakeholders, the market and regulations which govern business.

The modern tax administration can no longer resist the transformative abilities of big data and analytics as it is becoming increasingly clear that there is value in big data. Tax administration is data-intensive as it generates and collects huge quantities of data through its activities. Revenue bodies collect data directly from taxpayers as it is declared in customs declarations, tax returns and financial statements, or through arrangements with third parties. On several occasions, more information is obtained through tax audits and investigation activities. Such data could be classified into two broad categories, structured and unstructured where the former refers to data provided by taxpayers according to specifications of the tax law and the former lacks any pattern because it is collected randomly from different sources. Sun et al. (2016) argue that data create business value which helps organisations to grow. However, before the advent of technologies, tax administrations could not derive business value from data because of its huge volume but recently there has been a change due to the emergence of Big Data. Due to competition for markets, organisations are forced to adopt Big Data technologies to enable them have relevance and competitive advantage. Brock and Khan (2017) contend that enterprises which are data-driven and invest in Big Data technologies derive more benefits. Specifically for tax administrations, Big Data offers an opportunity to derive business value from data, improve services for taxpayers and manage tax risks (Gray, 2015). Therefore, Big Data could be considered as a strategic innovation capable of transforming business of a tax administration through data analytics which reveal useful information for effective decision-making.

Sun et al. (2016) used the TOE framework to identify 26 factors which affect organisational adoption of Big Data and categorised them into innovation characteristics, organisational characteristics and environment characteristics. The characteristics of each category are as follows: innovation (relative advantage, cost of adoption, complexity, compatibility, observability and trialability); organisation (human resource, technology resource, management support, technology readiness, organisation's information and technology (IT) structure, decision making culture, business strategy orientation, business resources, change efficacy, information systems (IS) strategy orientation); and environment (security privacy ethics, trading partner readiness, regulatory environment, uncertainty risk concern, institutional based trust, competitive pressure, market turbulence, IS fashion). Table 1 summaries the description of each characteristic which affect organisational adoption of Big Data. However, there is no empirical research which has validated the conceptual framework proposed by Sun et al. (2016), therefore this paper addresses this research-gap. Based on the conceptual framework, the adoption of Big Data could be explained by the equation, $Y = \alpha 0 + \beta 1X1 + \beta 2X2 + \beta 3\ X3 + u$… where, adoption of Big Data denoted Y is the sum of constant factors ($\alpha 0$), technological context ($\beta 1X1$), organisational context ($\beta 2X2$), and environmental context ($\beta 3X3$) and an error (u).

3. Methodology

3.1 Participants

Participants to the survey were members of staff in the MRA's Domestic Taxes Division who were randomly selected to take part in the survey. The minimum sample size for validating the model was computed based on the requirements of the Structural Equation Modeling (SEM) techniques which employed in this research. MRA's Human Capital and Organisational Development Division indicated that the Domestic Taxes Division had 473 members of staff. A priori power analysis for SEM that was calculated using software developed by Soper (2017) suggested 119 as the minimum sample size in order to have 80% power for detecting a medium-sized effect when employing .05 criterion of statistical significance (Cohen, 1988; Durlak, 2009; Lakens, 2013). To account for potential non-responses, the survey questionnaire was sent to all 473 members of staff via email and 244 responded representing 51.6% response rate. Participants comprised of 62.7% males and 37.3% females and the majority, 68.9%, were in the age-group, 31 to 45 years old. In terms of level of education, majority of participants (54.5%) were educated up to undergraduate level. The greatest proportion of the participants (33.2%) were from the Small Taxpayers' offices of the Domestic Taxes Division and the least were from Medium Taxpayers' offices (17.6%) and the rest were from Large Taxpayers' Office and the Head Office. In terms of functions of participants in tax administration, the greatest proportion of participants were from Tax Audit (25.4%) and the rest were from Tax Register, Taxpayer Service, Technical and Appeals, Compliance Risk Management, Business Analysis & Data Analytics, Return and Payment Processing, Collection and Filing Enforcement, Electronic Fiscal Devices, Tax Audit, Msonkho Online (Integrated Tax Administration System) and Overall Leadership.

3.2 Research Design

The research employed quantitative research approach to collect perceptions of members of staff in MRA's Domestic Taxes Division towards how factors in the proposed conceptual framework affect the Domestic Taxes Division's intentions to adopt Big Data. The research approach enabled collection of quantifiable data which was used to validate the conceptual framework for understanding factors affecting organisational adoption of Big Data as proposed by Sun et al. (2016). "Intention to adopt Big Data" was the dependent variable and the three categories of factors affecting organisation adoption of Big Data were independent variables namely: innovation, organisation and environment.

3.3 Measures

A questionnaire was specifically developed for the research based on the conceptual framework for understanding factors affecting the organisational adoption of Big Data proposed by Sun et al. (2016). The questionnaire had three constructs for assessing organisational adoption of Big Data namely: innovation characteristics, organisational characteristics and environmental characteristics. The independent variables were operationalised through their characteristics as proposed by Sun et al. (2016) as follows: innovation (relative advantage, cost of adoption, complexity, compatibility, observability and trialability); organisation (human resource, technology resource, management support, technology readiness, organisation IT structure, decision making culture, business strategy orientation, business resources, change efficacy, IS strategy orientation); and environment (security privacy ethics, trading partner readiness, regulatory environment, uncertainty risk concern, institutional based trust, competitive pressure, market turbulence, IS fashion). The dependent variable was operationalised through a 3-item measure (readiness, focus and planning) which asked participants how the Domestic Taxes Division was ready to adopt Big Data, had begun to focus on Big Data opportunities, and was planning for adoption of Big Data. For all variables, participants rated their level of agreement with how the proposed factors affect (Revenue Authority's name hidden)'s Domestic Taxes Division to adopt Big Data on a 4-item Likert scale which ranged from 1=Strongly Disagree to 4=Strongly Agree.

3.4 Procedure

Perceptions of research's participants towards factors affecting adoption of Big Data in MRA's Domestic Taxes Division were collected through an online survey via the link http://ukfa6xa9e3j2m3ai.mikecrm.com/O5ycHxj). The proposed conceptual framework for understanding factors affecting organisational adoption of Big Data was statistically validated using Structural Equation Modeling (SEM) techniques in the Analysis of Moment Structures (AMOS). SEM is a combination of a measurement model and a structural model in which the former indicates relationships between observed/measured variables and unobserved variables while the latter represents relationships between unobserved variables only and is employed to test hypotheses (Arbuckle, 2013; Shah & Goldstein, 2006). As a statistical methodology, SEM "takes a confirmatory (i.e., hypothesis-testing) approach to the analysis of a structural theory bearing on some phenomenon" (Byrne, 2010, p.3). Confirmatory Factor Analyses (CFA) were conducted to test the structure of the three-factor model for understanding factors affecting organisational adoption of Big Data.

Before performing the analyses, the data were tested for the assumption of normal distribution based on values of Skewness and Kurtosis to ensure their suitability for SEM. Therefore, the Maximum Likelihood Estimation was used to assess the level of model-fit based on the Chi-Square (χ^2), and the following fit indices: Root Mean Square Error of Approximation (RMSEA), Normed Fit Index (NFI), Comparative-Fit Index (CFI), the Tucker-Lewis Index (TLI) and Incremental Fit Indices (IFI). Indices were measured based on the following criteria: $\chi^2/df < 3$ (Hair, Black, Babin, Anderson & Tatham, 2009; Kline, 2015); GFI, TLI, CFI, IFI > .9 (Hair et al., 2009; Hooper, Coughlan & Mullen, 2008); and RMSEA< .08 (Byrne, 2016; Hair, Black, Babin & Anderson, 2013; Hooper, et al., 2008; Kline, 2015). Assessments of the measurement model for explaining organisational adoption of Big Data established validity based on the criteria, factor loading > .5; 1.96 < t-value < - 1.96; R^2 > .5 (Hair et al., 2013; Shah & Goldstein, 2006).

3.5 Results

The research validated the conceptual framework for understanding factors affecting the organisational adoption of Big Data. Statistical tests suggested that there were neither missing values nor outliers in the data set used to validate the conceptual framework. Assessment of normality confirmed that data were normally distributed as all items had values of Skewness and Kurtosis within the acceptable range of a normal distribution, -2 to +2 (Field, 2009; Gravetter & Wallnau, 2014).

3.6 Scale Reliability

Internal consistency of questionnaire's constructs were measured using Cronbach's alpha coefficients which satisfied the minimum recommended limit of .6 as summarised in Table 2 (Gliem & Gliem, 2003; Hair, Black, Babin, Anderson, & Tatham, 2009; Kline, 2015). Similarly, item-total correlations were above .3 suggesting that the questionnaire had measured what it intended to measure (Brzoska & Razum, 2010; Cristobal, Flavián & Guinaliu, 2007).

4. Exploratory Factor Analysis

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .94 and Bartlett's Test of Sphericity suggested that the correlation matrix was factorable (χ^2 (435) = 9,560.16, $p < .001$). Similarly, all measures of sampling adequacy in the diagonals of the anti-image correlation supported that all items should be included in the factor analysis matrix because they exceeded .5, (Hauben, Hung & Hsieh, 2017). Finally, all communality scores were above .2 a confirmation that there was common variance between items (Child, 2006). The factor analysis employed the principal axis factoring using varimax rotations to identify factors underlying adoption of Big Data. The analysis suggested a three-factor solution whereby 81.6% of the variance was explained and the scree plot values began to level off after four factors. According to the Eigenvalues, the first factor explained 44.8% of the variance, the second factor 23.6% of the variance, and the third factor 13.1% of the variance. Table 3 shows that in the final rotated factor loading matrix there were no cross-loadings.

5. Confirmatory Factor Analysis

The twenty-nine items for the three-factor model explaining adoption of Big Data in organisations were analysed through the CFA. A chi-square difference test showed that the model violated the goodness-of-fit criterion (□2(371) = 974.9, p < .001; □2/df = 2.63). In addition, all goodness-of-fit indices also indicated a poor fit of the hypothesised model because they were not within the accepted ranges (GFI = .77, TLI = .93, CFI = .94, IFI = .94, RMSEA = .08). Model building approach was employed to modify the hypothesised model by adding more based on diagnostic information produced by CFA namely, Modifications Indices (MI) and Expected Parameter Change (EPC) values for covariances and regression weights (Shek &Yu, 2014). Table 4 summarises parameters with relatively large MI values, suggesting a covariances between items whose correlated errors were included between errors to derive an acceptable model-fit. All chi-square difference tests showed statistically significant improvement in fit between the independence and all models, M0 to M12 (p < .001). Finally, all indices supported a good fit of Model 12 to the data (□2(284) = 333.32, p < .001; □2/df = 1.17, GFI = .91, TLI = .99, CFI = .99, IFI = .99, RMSEA = .03).

Measurements of validity summarised in Table 5 suggested that Model 12 illustrated in Figure 1 satisfied criteria for assessing validity of the measurement model. Considering the satisfactory fit of Model 12 in the data, it was adopted as the final model for explaining factors affecting organisational adoption of Big Data.

6. Discussion

The aim of this paper was to validate the conceptual framework for understanding factors affecting the organisational adoption of Big Data proposed by Sun et al. (2016) using empirical evidence from a tax administration. Sun et al. (2016) proposed that there are three categories of factors which affect organisations in their efforts to adopt Big Data namely: innovation, organisation and environment. Results of the confirmatory factor analyses showed that the conceptual framework is statistically valid for measuring factors affecting organizations' efforts to adopt Big Data. Values for several indicators of goodness of fit support the conceptual framework because it fitted well with the data. In addition, all factor loadings were found to be statistically significant (p <.05), suggesting an adequate factorial validity of the conceptual framework. Therefore, the conceptual framework is suitable for measuring the effect of the proposed factors on organisational adoption of Big Data.

Confirmatory factor analyses showed that the original three-factor model did not fit the data. Instead, there were correlations between factors within each category as follows: innovation (relative advantage and cost of adoption, observability and trialabilty); organisation (human resource and technology resources, human resource and management support, IS strategy orientation and firm size, IS strategy orientation and appropriateness, firm size and appropriateness) and environment (security privacy ethics and trading partner readiness, security privacy ethics and regulatory environment, trading partner readiness and regulatory environment, uncertainity risk concern and regulatory environment, IS fashion and regulatory environment). The twelve correlations suggest that in responding to a question relating to a particular factor, participants might also consider the correlated factor, for example, in the correlation between relative advantage and cost of adoption, in considering the relative advantage of adopting Big Data participants might have considered if the investment in Big Data would bring significant monetary value to the organisation.

The paper illustrates the importance of subjecting conceptual frameworks to a confirmatory factor analyses and underscores theoretical advancements regarding factors affecting adoption of Big Data as described in the Diffusion of Innovation theory and the Technology–Organization–Environment (TOE) framework. In addition, the paper is significant to both theory and practice of Big Data because it contributes a statistically validated framework for understanding factors affecting the organisational adoption of Big Data. Tax administrations in developing countries would use the validated framework to assess factors affecting their adoption of Big Data technologies. It is important for tax administrations to understand factors affecting their adoption of Big Data using validated measurements because that would enable them estimate the impact of each factor and prioritise factors requiring immediate attention for smooth adoption of Big Data.

The limitation with this research is that it is based on a single revenue administration of a developing country where the concept of Big Data is relatively new in many public sector organisations. Future research could assess factors affecting organisational adoption of Big Data using the validated conceptual framework. Considering that public sector organisations are distinct from private sector organisations because of their not-for-profit nature, future investigation could replicate the validation of the conceptual framework using data from the private sector.

Table 1 Factors Affecting Organisational Adoption of Big Data Category/Characteristics

Innovation Characteristics	**Description**
Relative advantage	Perception that characteristics of big data are being better than those of previous technologies.
Cost of adoption	Initial investment required to embrace big data
Complexity	Characteristics of big data are perceived as being difficult to understand and use
Compatibility	Extent to which characteristics of big data are consistent with the existing Information, Communication and Technology (ICT) architecture and needs
Observability	Perception towards benefits of big data after observing how other organizations use it
Trialability	Adopting big data on experimental basis and without commitment.

Organisation Characteristics	**Description**
Human resource	Adequate human resources for the adoption of big
Technology resource	Adequate technology resources for the adoption of big data.
Management support	Willingness to allocate sufficient resources and encourage adoption of big data.
Technology readiness	Adequate ICT expertise and infrastructure that can easily handle the changes triggered by the adoption of big data.
Organisation IT structure	How well-organized the IT structure is and well-suited for the adoption of big
Decision making culture	A culture of making managerial and operational decisions based on evidence. i.e. data-driven decision-making
Business strategy orientation	Availability of strategy oriented to business analytics and using big data for strategic decisions.
Business resources	Adequate business resources for the adoption
Change efficacy	Ability of members of staff to easily handle the changes triggered by the adoption of big data
IS Strategy orientation	Availability of IS strategy which prioritizes use of big data.
Firm size	Extent to which size of the organization support adoption of big data.
Appropriateness	Potential benefit from big data based on timing of its introduction.

Environment Characteristics	**Description**
Security privacy ethics	Extent to which data collection from individuals causes individuals' security, privacy concerns etc.
Trading partner readiness	Readiness of stakeholders and collaborating partners to adopt big data
Regulatory environment	Support from government regulatory agencies to adopt big data

Uncertainity risk concern	Capability of handling concerns regarding potential unexpected consequences related to
Institutional based trust	Belief that the organisation will be safe to adopt big data because it has reliable platform and trusted systems.
Competitive pressure	Extent of external threats or competition from stakeholders which can be combatted by the adoption of big data.
Market turbulence	Extent to which customers' preferences, demands and needs have changed in big data environment.
Information systems fashion	Extent to which the organisation obtains information through external communication such information-sharing arrangements with stakeholders.

Source: (Sun, S 2016)

Table 1, Cronbach's Alpha Coefficients for Constructs' Measurement Scales

Construct	No of items	Cronbach's alpha (α)
Innovation	6	.94
Organisation	12	.98
Environment	8	.97
Intention to adopt Big data	3	.87

Table 2: Factor Loadings Based on Principal Axis Factoring with Varimax Rotation (N=244)

Item	Factor 1	Factor 2	Factor 3	Measure of Sampling	Communalities
Relative advantage			.87	.9	.81
Cost of adoption			.9	.88	.84
Complexity			.85	.92	.76
Compatibility			.84	.92	.72
Observability			.8	.94	.7
Trialability			.77	.95	.65
Human resource	.89			.94	.92
Technology resource	.9			.94	.9
Management support	.91			.96	.9
Technology readiness	.93			.97	.9
Organisation IT structure	.93			.97	.9
Decision making culture	.93			.97	.92
Business strategy	.91			.97	.89
Business resources	.92			.97	.89
Change efficacy	.90			.98	.83
IS Strategy orientation	.89			.95	.87
Firm size	.89			.96	.86
Appropriateness	.86			.97	.84
Security privacy ethics		.83		.92	.77
Trading partner readiness		.85		.89	.82
Regulatory environment		.94		.9	.9
Uncertainity risk concern		.87		.93	.81
Institutional based trust		.93		.93	.9
Competitive pressure		.94		.9	.92
Market turbulence		.87		.94	.82
Information systems fashion		.93		.94	.87

Note: Factor loadings <.5 are suppressed; 1 = Organisation; 2 = Environment; 3 = Innovation

Table 3, Model-fit Indices for Modified Confirmatory Factor Analysis Models

Model	Modification	χ^2	*df*	χ^2/df	GFI	IFI	TLI	CFI	RMSEA
M0	Hypothesised Model	883.43	296	2.98	.77	.94	.93	.94	.09
M1	e20 <--> e19	794.91	295	2.69	.79	.95	.94	.94	.08
M2	e17 <--> e16	709.63	294	2.41	.82	.95	.95	.95	.08
M3	e8 <--> e7	642.13	293	2.19	.83	.96	.96	.96	.07
M4	e9 <--> e7	595.27	292	2.04	.84	.97	.96	.97	.07
M5	e22 <--> e21	555.9	291	1.91	.85	.97	.97	.97	.06
M6	e21 <--> e20	513.26	290	1.77	.86	.98	.97	.98	.06
M7	e2 <--> e1	475.97	289	1.65	.87	.98	.98	.98	.05
M8	e26 <--> e21	451.38	288	1.57	.88	.98	.98	.98	.05
M9	e18 <--> e16	427.43	287	1.49	.88	.98	.98	.98	.04
M10	e18 <--> e17	368.17	286	1.29	.9	.99	.99	.99	.03
M11	e21 <--> e19	346.02	285	1.21	.9	.99	.99	.99	.03
M12	e6 <--> e5	333.32	284	1.17	.91	.99	.99	.99	.03
Criteria				< 3	> .9	> .9	> .9	> .9	< .08

Table 5, Results of the Modified Confirmatory Factor Analysis Model

Factor/Items		Factor Loading	t-value	R^2
Innovation				
INN1	Relative advantage	.87	15.24	.75
INN2	Cost of adoption	.89	15.83	.79
INN3	Complexity	.89	15.97	.8
INN4	Compatibility	.86	15.14	.74
INN5	Observability	.82	16.76	.68
INN6	Trialability	.79	Fixed	.62
Organisation				
ORG1	Human resource	.92	20.94	.84
ORG2	Technology resource	.92	21.15	.85
ORG3	Management support	.93	21.57	.87
ORG4	Technology readiness	.95	22.6	.9
ORG5	Organisation IT structure	.95	22.61	.9
ORG6	Decision making culture	.96	23.29	.92
ORG7	Business strategy	.94	22.14	.89
ORG8	Business resources	.94	22.28	.89
ORG9	Change efficacy	.91	20.4	.82
ORG10	IS Strategy orientation	.88	27.11	.77
ORG11	Firm size	.87	26.05	.76
ORG12	Appropriateness	.86	Fixed	.74
Environment				
ENV1	Security privacy ethics	.78	17.01	.61
ENV2	Trading partner readiness	.8	17.78	.63
ENV3	Regulatory environment	.9	28.37	.81
ENV4	Uncertainity risk concern	.86	21.32	.74
ENV5	Institutional based trust	.96	29.7	.91
ENV6	Competitive pressure	.97	31.7	.94
ENV7	Market turbulence	.9	24.35	.82
ENV8	Information systems fashion	.92	Fixed	.85

Note: All coefficients are statistically significant, $p < .05$; INN=Innovation, ORG=Organisation, ENV=Environment

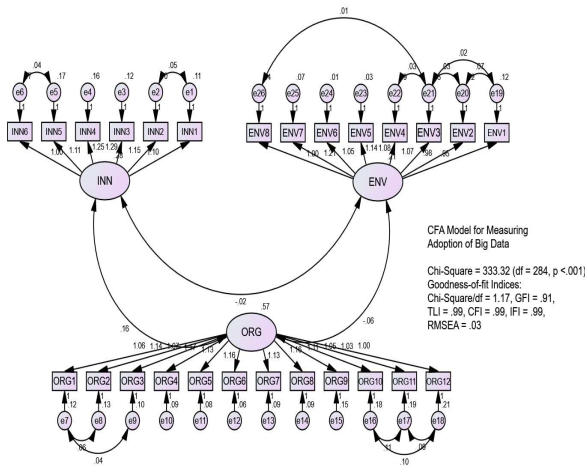

Figure 1: Confirmatory Factor Analysis Model for Understanding Organisational Adoption of Big Data

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