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Multi-Criteria Data Evaluation Strategy for Development Scales: An Example Study

Abayomi Ibiyemi[1], Olayinka Ogungbemi[2], Martins Adenipekun[3]
[123]Department of Estate Management and Valuation, School of Environmental Studies, Lagos State Polytechnic, Lagos, Nigeria.
Corresponding Author: Abayomi Ibiyemi, yomi1004@googlemail.com

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Abstract

This study illustrates checks using data from the sustainability and Appraisers' scale designed to make causal analysis between perceived industrial sustainability benefits and Appraisers' support. It obtained questionnaire responses from 267 Real Estate Appraisers. The study objectives are to assess the pattern and extent of the missing data; the assumptions of the multivariate normality with the bootstrap resampling; the consistencies of the slopes of change, and identify the costs that may arise from poor data quality. The work also investigates convergent, discriminant, cross boundary validities and highlights their relevance to the validity of research findings. The missing values at <10%; the normality assumption holds for the SUP, BPG, BLR constructs. Bollen-Stine bootstrap analysis could not validate the normality models for BQL, BCS, BHBV; 60 of the 109 slopes of change are consistent (p>.05). The factor loadings reliably represent the unobserved variables (p>.35) and there is sufficient evidence for convergent and discriminant validities, but cross boundary validity is not proven. Nevertheless, with appropriate data transformation, there could be no necessity for further data collection, nor a new survey of data. The study contributes to the accuracy of assessments and the interpretability of scores for testing theories.

Keywords: Data exploration, sustainability, real estate appraisers, evaluation, benefits.

Introduction

Data quality documentation plays a critical role in many standards due to the realization that an understanding of quality is essential to the efficient use of survey data. Despite the importance of having correct and adequate data, the current literature agrees that poor quality data constitute a significant cost factor for many companies. Good quality data are fit for their intended uses in operations, decision making and planning (Redman, 2008). Curry, Freitas & Rain (2010) implies that the data correctly represent the real-world construct to which it refers and the totality of features and characteristics of data that bears on its ability to satisfy a given purpose. ISO 9000 (2015) supporting the views, explains that the degree to which a set of characteristics of data fulfills requirements represents its quality status. The ISO9000 lists the data quality characteristics as completeness, regarding normality, factor structure and validity, accuracy, consistency, availability and timeliness. Furthermore, apart from the

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theoretical definitions, as the data volume increases, the question of internal consistency within the data becomes significant, regardless of fitness for use for any particular external purpose. People's views on data quality can often be in disagreement, even when discussing the same set of data used for the same purpose. As of fact, theories indicate that there are inconsistent guidelines for the item development and analysis procedure. For instance, it is not clear what guidelines, researchers use to: (a) define the theoretical constructs to be measured, (b) generate an item pool (c) assess the quality of the items, revise or withdraw items from the scale or examine the robustness of the scale scores. Available guidelines that exist seem not to be consistent in use, and the relationship between the use of one recommendation over another and a more beneficial product in the shape of more valid test scores has to be proven. Establishing research-based guidelines in these areas can help to ensure that the scale development process should result in products that provide quality scores. Robustness and reliability are two underlying factors in the evaluation of a measurement instrument that engender psychological outcomes of interest, as a base for further data collection or research replications (Tavakol & Dennick, 2011). Scale development compels the perception of people and their processes in a manner that helps both theory and development. The purpose of scale development and validity is to make a theory of human needs understandable and operational for development. New reality and challenges compel researchers to adopt transdisciplinary approaches. Even so, Curry, Freitas & Riain (2010) emphasize that in practice, data quality is a concern for professionals. Problems arise with data quality from inconsistencies and data handling. Stakeholders, scientists and researchers are starting to participate within data creation communities to improve the quality of their daily data.

Curry, Freitas & Riain (2010) insist that the grounds for the proper orientation arise because professionals are rarely analysing a particular problem, but instead, a web of complicated matters that might be intractable through the application of general policies. The social science phenomena have abstract concepts or theoretical constructs, the measurements of which tie in with the operationalisation of the constructs in defined variables, and the development and application of tests to measure the variables. For instance, cost savings as a construct may be operationalised as water conservation, energy efficiency, and lower service maintenance costs. As sustainability research involves a substantial level of subjectivity in assessment and other possible sources of error, control for known sources and report for reliability and validity of measurements are employed. The identification, testing of assumptions, convergent and divergent validities seems not to have been considered adequately in the existing sustainability literature. This article fills the theoretical gap by addressing these limitations.

It explores the theoretical questions concerning: (I) The pattern of missing data, their location, and how extensive are they? (II) The assumptions of the multivariate normality with probable bootstrap resampling? (III) The consistencies of the slopes of change, and the factor loadings (IV) Convergent, discriminant, and cross boundary validities? (V) Costs involved in poor data quality? The research questions (I) – (IV) above are asked to prompt the evaluation of the quality of data based on the specified parameters. The exploration is a significant function of finding the desirable attributes of data. The assessments underline the extent to which the results of research findings support theory testing, planning and decision making. Also, the practical understanding about the interpretability of scores as a ground for resurvey or further data collection implies that poor data quality could generate private and social costs.

Operational Definition of Terms

Real Estate Appraisers - Real estate appraisers bearing full registration status with the Registration Board of Appraisers, and those in the final stages of complete registration.

Data exploration: The approach to analysing and summarizing the main characteristics relating to the distribution of data, missing values, factor loadings, the convergence of two different measurement procedures, differences from other constructs in the study, and cross boundary validities.

Review of Literature

Missing Values

Missing data occurs when a variable of observation has no data value. They are a common occurrence and can have a significant effect on the inferences and outcomes. IBM (2011) iterates that there are two sets of methods for handling missing values: (1) The Multiple Imputation methods that provide analysis of patterns of missing data. That is, the production of multiple versions of the dataset, each containing its set of imputed values. The execution of the statistical analyses, the parameter estimates for all of the imputed datasets is pooled, allowing estimates that are more accurate than they would be with only one imputation. (2) The missing value analysis provides a slightly different set of descriptive tools for analyzing missing data (especially the Little's MCAR test) and includes a variety of single imputation methods. Multiple imputations are conceived to be superior to single imputations (IBM, 2013). Gaskins (2012) summarizes that missing values can be handled list wise, pair wise, or replaced with mean, or median for continuous and interval, including the Likert scale responses.

Assumptions of multivariate normality and bootstrapping

Statistical errors are fundamental in the scientific literature, and about 50% of the published articles have at least one error (Curran-Everett & Benos, 2004). Ghasemi & Zahediast (2012) stress that the assumption of normality need to be checked in many parametric statistical procedures because their validity devolves on it. Multivariate normality is one of the key assumptions in multivariate data analysis. In statistical

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modeling, it is frequently crucial to verify if the data at hand fulfill the underlying distributional assumptions, if not precisely, at least, approximately (Ramzan, Zahid, & Ramzan, 2013). Many a time such an examination may be demanded for the residuals after fitting various models. When the data is pre-examined, it could often reduce the burden of searching for procedures that are robust to departure from multivariate normality.

Normality of data concerns to the situation where the data is from a population that has a normal distribution (Field, 2009). The distribution is the most significant and the most frequently used distributions in both the theory and application of statistics. With large sample sizes (> 30 or 40). Pallant (2007) and Ibiyemi (2009) submit that the violation of the normality assumption may not cause significant problems (Pallant, 2007: Ibiyemi, 2009). The logical implication of this assertion is that parametric procedures might apply even when the data is a non-normal distributed (Elliott & Woodward, 2007). For samples consisting of hundreds of observations, the distribution of the data may be disregarded (Altman & Bland, 1995). The central limit theorem states that: (a) if the sample data are close to normal, then the distribution of the sample should be normal; (b) in large samples (> 30 or 40), the sampling distribution tends to be normal, irrespective of the form of the data (Elliott & Woodward, 2007; Field, 2009); and (c) means of random samples from any distribution will themselves give nascence to a normal distribution (Altman & Bland, 1995). Elliott & Woodward (2007) reckon true normality to be a myth. Normality can be observed visually by using normal plots, or by the Kolmogorov-Smirnov and Shapiro-Wilk significance tests. The tests compare the scores in the sample to a normally distributed set of scores with the same mean and standard deviation, hypothesizing that distribution of the sampleis normal. The distribution is accepted to be non-normal if the test is significant, (Altman & Bland, 1995: Field, 2009; Oztuna, Elhan & Tuccar, 2006). Elliott & Woodward (2007) summed that it is important to ascertain whether the data show a grave deviation from normality. Feller (1968) utilized the symbol ϕ (x) for P (x) in the normality equation, but then flipped to η(x). The normal distribution, an approximation to the binomial distribution was previously used by Laplace in 1783 to evaluate measurement errors and by Gauss in 1809 in the analysis of astronomical data (Havil, 2003). Havil (2003) spot lit that several factors can cause the data to appear non-normal, such as (1) The data coming from two or more different sources. This type of data could often have a multi-modal distribution. It can be solved by identifying the reason for the multiple sets of data and analyzing the data separately. (2) The data from an unstable process. This type of data is difficult if not impossible to analysebecause the results of the analysis will have no validity due to the changing nature of the process. Ibiyemi (2009) mentioned an example that particle counts are non-normal by the changing character of the particle generation process. Such data can be handled using transformations. Statistical methods rely on various assumptions to uphold them. Otherwise, inferences and interpretations based on the models could become less valid (Havil, 2003; Ibiyemi, 2009). The normality tests supplement the graphical assessment of normality (Elliott &

Woodward, 2007). The other major criteria for the evaluation of normality includes the Kolmogorov-Smirnov (K-S) test (Oztuna, Elhan & Tuccar 2006), Lilliefors corrected K-S method, Anderson-Darling test, Shapiro-Wilk test, Anscombe-Glynn kurtosis test, Cramer-von Mises test, D'Agostino skewness test, D'Agostino-Pearson omnibus test, and the Jarque-Bera test (Peat & Barton, 2005; Oztuna, Elhan & Tuccar 2006).The Kolmogorov-Smirnov test is commonly in use (Thode, 2002. For small sample sizes, normality tests have less power for not accepting the null hypothesis. Thus, small samples often pass normality tests (Oztuna, Elhan & Tuccar 2006). For large sample sizes, significant results would be inferred even in the event of a minor deviation from normality. Although this small variation will not bear on the outcome of a parametric test (Oztuna, Elhan & Tuccar 2006; Field, 2009). The K-S tests the empirical distribution function (EDF) to contrast the theoretical cumulative distribution function of the test distribution. However, a limitation of the K-S test is its high sensitivity to extreme values; the Lilliefors correction renders this test less conservative (Peat & Barton, 2005). K-S test has low power, and it may notbe actively considered for testing normality (Thode, 2002). Even so, it is not recommended when parameters are estimated from the data, regardless of sample size (Steinskog, 2007). The Shapiro-Wilk test uses the correlation between the data and the corresponding normal scores (Peat & Barton, 2005). It offers fuller power than the K-S test even after the Lilliefors correction (Steinskog, 2007). Amos employs the coefficient of multivariate kurtosis to assess normality (Bryne, 2010; Hu, 2010)

Bootstrapping resamples and creates a sampling distribution that decreases the p-value (by increasing the t-statistic) to estimate standard errors and the confidence intervals. Resampling can be used to validate the multivariate normality where the assumption is not met (Efron & Tibshirani, 1993; Gaskins, 2012). Hu (2010) catalogued bootstrapping uses as follows: (1) To confirm the mediation effect due to its accuracy level for computing confidence intervals for mediation effect particularly when the mediation effect is nonzero (2). As an aid to non-normal data. The assumption of structural equation modeling (SEM) is that data has a multivariate normal distribution.

The resampling method has more accurate Type I error rates and power than a single sample method that assumes a normal distribution. Bootstrapping can deal with the measurement error problem while allowing researchers to assess the stability of parameter estimates. AMOS uses the Bollen-Stine model to validate the distribution (IBM, 2013)

Linearity of Data

Linearity infers the consistency of the slope of change that represents the relationship between an independent variable, IV and a dependent variable, DV (Gaskins, 2012). The radically inconsistent relationship between the IV and the DV could impinge on causal modeling. A widely used test for linearity is the deviation from linearity test available in the ANOVA test in SPSS. If the Sig value for Deviation from Linearity (DFL)

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is less than 0.05, the relationship between IV and DV is not linear, and thus is problematic. However, issues of linearity can be fixed by removing outliers if the significance is borderline, or through transforming the data. Gaskins (2012) advised the use of OLS linear regression between each IV>DV pair should the DFL test produce odd results. If the sig.value is less than 0.05 in the OLS test; then the relationship can be considered "sufficiently" linear. Curve-linear regression or curve estimation may also be employed to see if the relationship is more linear than non-linear.

Reliability of factor loadings

Each unstandardised regression coefficient represents the amount of change in the dependent or mediating variable for each one unit change in the variable predicting it. Whereas, standardized regression coefficients link the predictors to the dependent variable, and the R2 value for the dependent variable appears above its rectangle in path diagrams. The standardized regression weights are less sensitive to model constraints. They represent the measure of change in the dependent variable that is attributable to a single standard deviation unit's worth of change in the predictor variable (UniTexas, 2012). A range of factor loadings from .3 (sample size ≥350) to .75, .70, .65, .60, .55, .50, .45, .40 for sample sizes, 50, 60, 70, 85, 100, 120, 150, 200, and 250 respectively was highlighted by Gaskins (2012)

Convergent, discriminant, and cross boundary validities

Campbell and Fiske (1959) established that convergent validity concerns with demonstrating that the initial measure of a construct harmonizes with another different measure of the same construct. For example, in addition to fashioning a survey-questionnaire-based measure of job routine, a researcher could make use of observers to rate the characteristics of jobs in order to differentiate between degrees of routineness in jobs in the firm. Convergent validity entails that the variables within a single factor are highly correlated, which is evident from the factor loadings. Convergent validity would imply demonstrating a convergence between the two measures. Many of the examples of convergent validation that have appeared since Campbell and Fiske (1959) have engaged different questionnaire research instruments. Amos compares composite reliability (CR), and the average variance extracted (AVE) to report convergent validity (IBM, 2011). By implication, convergent validity tests that concepts within a factor, that are expected to be related be, in fact, related. Discriminant (divergent) validity conjectures whether concepts or constructs that are supposed to be unrelated in a study are, in fact, not related. Satisfactory evaluation of discriminant validity exhibits that a test of concepts in a factor is less (not highly) correlated with other factors designed to measure theoretically different concepts. Bryman & Crammer (2003) considered researchers that are developing a new scale designed to measure the Factor-Narcissism: The objective is to show discriminant validity with a scale measuring another Factor-Self-esteem, all within a study. Narcissism and self-esteem are different concepts, and therefore, it is important that the researchers demonstrate that their new scale assesses Narcissism as different from, and unrelated to self-esteem. Discriminant validity is evaluated by comparing the shared variance (squared correlation) between each pair of constructs against the average of the AVEs of the constructs (Bove et al., 2009; Hassan et al., 2007; Walsh, Beatty and Shiu, 2009). Discriminant validity exists if the output value is less than 0.85 (John & Bennet-Martinez, 2000: Domino & Domino, 2006). Amos compares MSV and AVE, and ASV and AVE to report discriminant validity (IBM, 2013). Cross boundary validity tests whether the same questionnaire constructs hold beyond the region of study by engaging the factor invariance and constraining the circles in a structural regression model (Reisinger & Mavondo, 2007).

Benefits and Support systems for industrial sustainability

Addae-Dapaah, Liow, Hiang, & Neo Yen Shi (2009) classified sustainability benefits into economic, social, and environmental. Wasiluk (2007) posits that sustainability uptake increases property value by lowering running costs and risks, boosting gains in productivity, scaling down construction cost, and drawing-in financial incentives. Shiers (2000) reaffirmed that green building renders a healthier working environment and improved indoor air quality. Green buildings and sustainability offer a lower degree of environmental risk by functioning to minimize the environmental footprints of the real estate industry on the surroundings. The use of natural resources and appropriate management of the building stock contribute to conserving the scarce resources, reduce energy consumption, and improve environmental quality (Roper and Beard, 2006). Gloet (2006) developed a framework linking knowledge management (KM) and human resources management (HRM) and then applied it to the development of leadership and administrative capabilities to support sustainability. The study findings provided a means by which to promote sustainability through effective KM and HRM linkages. Gloet evoked means by which organizations can build up leadership and management capabilities to support sustainability across business, environmental and social justice contexts. Petrini & Pozzeboh (2009) suggested that BI has an important part to play in helping organizations implement financial support and monitor sustainable practices. Besides, they ascertained that researching how the management of sustainability in organizations can be backed up by business intelligence (BI) systems. The work offers a conceptual model that tries to hold up the operation of integration of socio-environmental indicators into an organizational scheme for sustainability. Barrios & Trejo (2003) and Glantz (2001) have formulated a framework for understanding the effectiveness of systems that link knowledge to action for sustainability by exploring the implications of that framework for research and practice. They present that science, technology, and education can make essential contributions to sustainability across a broad range of places and problems. Unless that contribution increases, it seems unlikely that the transition to sustainability could be either fast or far enough to prevent significant degradation of human life and the earth system. Cash et al. (2003) advised the creation of bridges across spatial scales so that the location-specific demands and knowledge central to sustainability can link with relevant national and international level research and development. Individual campaigns in research, innovation, monitoring, and assessment can contribute to sustainability. However, the full utility of such independent contributions devolves on developing integrated knowledge systems, a lesson already learned in agriculture, defense, and health sectors, but overleaped elsewhere.

The literature collects at the point of satisfactory theoretical understanding of the concept of missing values and the other specified parameters including the methods required to account for them. However, evidence from theory does not seem to support their consistent applications to field data before commencing the main analysis. This highlight is particularly evident in causal theories relating to sustainability studies.

Methodology

The research adopts the survey approach. The survey research offered the scope for a broad representative sampling of real estate appraisers from where reliable information are extracted about perceived benefits of industrial sustainability and their support for integration into real estate valuation. Interviews and observations have limited scope in this scheme. The secondary information is gathered from related literature sources. To address the first objective, a randomly selected pilot sample size of 46 Appraisers was first taken from the survey population across three cities (Lagos, Abuja, and Port Harcourt) for the purpose of reliability testing. The questionnaire was adjusted accordingly to reflect the outcome of face and content validity tests. The three cities are representative of the Nigerian real estate appraisers' clusters (Falade, 2005; Ibiyemi & Tella, 2013).Over 70% of registered estate firms have either their principal offices or branch offices in at least one of the three cities covered by the study. The distribution of offices comprises 52% in Lagos, 13% in Port Harcourt, and 7% in Abuja. (Babawale & Oyalowo, 2011). There are 28% in other areas.The primary data for exploration is from the reliability-tested questionnaire (Exhibit 1, Appendix A) which was retrieved from 267 randomly selected real estate appraisers distributed as follows: Lagos (102), Port-Harcourt (76) and Abuja (89).Theresponse rate is approximately41%. The 2009 Register of Appraisers is the sampling frame.
According to Hair, Anderson, Black, and Tatham (1998), the sample size five to ten times as many observations as there are variables to be analyzed, is acceptable. As in Exhibit 2 post, there is a total of 26 items on benefits and support scales in the questionnaire, and a ten-to-one ratio gives a minimum sample size of 260. The sample size was also established, based on the criterion of at least 200 subjects' observations by Boomsma & Hoogland (2012).

Vol. 1, No. 1, 2016, pp. 40-67
www.ijssh.ielas.org
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However, Pallant (2011) insists on a lower limit of 300 events in medical research. The study sample size of 267 satisfies the minimum literature specifications.

The questionnaire comprises three sections: Section one concerned the demographic and professional data of the respondents. In section two, the survey sought to ascertain the respondents' knowledge about potential benefits and support for integrating sustainability into theindustrial real estate valuation. The literature-driven expectation is that Industrial Sustainability-Related Obsolescence (ISRO) could induce industries to invest in sustainability initiatives that can assure all the benefits that the respondents considered to be of importance (Ibiyemi, Adnan, & Daud, 2015). This section has 21 items. A 5-point Likert scale (1-not important, 2-not so important, 3-neutral, 4-important, 5-very important) was applied. Section three has 5 items, including 2 new concepts (s4 and s5). Scoring was on a 5-point Likert scales (1-strongly disagree, 2-disagree, 3-neutral, 4-agree, 5-strongly agree). Addae-Dapaah, Liow, Hiang, & Neo Yen Shi (2009); Babawale & Oyalowo (2011); and Ibiyemi, Adnan & Daud (2015) usedsimilar scales in their studies. The scales are considered appropriate.

Variables of study - Exhibit 2 shows the distribution of the latent and observed variables

Methods of analyses: The data presentation and reports have been structured into fiveparts as follows:

First Part: Presentation of percentage and frequency-based responses to the reliability-tested questionnaire.

Second Part: Analysis of missing value pattern, location, and extensiveness, using the multiple imputation methods in SPSS22

Third Part: Test of normality and bootstrapping for estimating the distributional properties of the observed data using AMOS22, and the test of linearity in SPSS22.

Fourth Part: Test reliability of factor loadings using the AMOS22 output for the standardized regression weights.

Fifth Part: Test of questionnaire scale for convergent, discriminant, and cross boundary validities using AMOS22 and Statistical Tools Excel Package (STEP). The scope of validity of this study coversconvergent, discriminant, and cross boundary validities. Other validities, such as construct, criterion-related, concurrent, predictive validities are not examined.Reliability analysis was carried out for internal consistencies. All the items correlated adequately in the constructs. The minimum corrected item-Total correlation = .790, and the Cronbach Alpha coefficient = .820. The data exhibits good internal consistencies at > .70 correlation matrix. The stability of the responses for the three constructs or factors was assessed to be close to .8 (Guttmann's Split-half coefficients were at .73, .76, .81 respectively)

Results and Analysis

80.9% of the respondents are real estate appraisers having full registration status with the Registration Board of Appraisers, 15.3% are in the final stages of complete registration. 3.7% did not indicate their status. 86.1% hold either Ph.D or MSc degrees; 4.9% with first degrees. 33.7% are either head of firms, managing or staff partners, 46% are university and polytechnic lecturers while 9% work for governments and private organizations. 54.6% are above 50 years old, and 91.4% have over 10 years' experience while 8.6% has under 10 years' experience. It indicates that these respondents are core professionals, having the broad experience to deliver quality responses on the subject matter. Of the 267 respondents, 19% were based in Ikeja axis, 21% in Lagos Island, 16% operated within Victoria Island-Lekki area, 10% based on the Surulere axis. These are the core cluster operation areas for Appraisers in Lagos, and Nigeria. 13% are in other parts of Lagos Metropolis. Of the remaining 34%, 9% practice in Port Harcourt and 25% in Abuja. The distribution of sampling and responses are representative for statistical analyses and inferences. Exhibit 2 shows the frequency distribution of the answers.

Exhibit 2- Frequency Distribution of the 26 variables (Factors 1-6)

Latent Variables (Factors)	Items (Observed Variables)	(Likert scales) *Frequencies*					Total
POTENTIAL BENEFITS		1	2	3	4	5	
1. High Building Value (BHBV)	o Faster tenants' lease up a2 o Valuation premium a3 o Better market distinction a4 o Higher prestige a5	39 22 18 44	25 36 35 32	13 20 7 18	136 145 153 115	53 44 54 56	266 267 267 265
2. Cost Savings (BCS)	o Water conservation b1 o Energy efficiency b2 o Lower services maintenance costs b3 o Less claims on medical costs b6	56 53 65 68	43 25 28 31	29 40 15 22	64 57 78 59	75 82 81 86	267 267 267 266
3. Lower Risks (BLR)	o Reduced waste water pollution and degradation c1 o Lower risk of unsustainable resource use c2 o Reduced liability risks c3 o Reduced health and safety risks c4	90 79 84 72	23 46 29 28	23 23 36 10	29 75 56 57	101 44 62 100	266 267 267 267
4. Productivity Gains (BPG)	o Boosts creativity d1 o Higher morale d2 o Improved employee	81 54 35	30 53 35	21 19 23	81 67 107	54 74 67	267 267 267

	productivity d3	46	43	46	62	70	267
	o Improved indoor quality for staff welfare d4	71	11	21	119	37	267
	o User satisfaction - d5						
5. Quality of Life (BQL)	o Sustainability provides the future generation needs - f1	7	-	20	101	146	267
	o Less pollution - f2	1	1	-	131	134	267
	o Fight global warming - f3	12	13	-	157	85	267
	o Minimise wastes - f4	-	24	-	164	79	267
SUPPORT							
6. Support (SUP)	o Invest in Green industrial building rating tools s1	-	-	-	147	120	267
	o Recommend green features to others s3	-	-	-	132	135	267
	o The relationship between sustainability and industrial building obsolescence s4	10	-	-	162	95	267
	o Industrial valuation to reflect sustainability s5	-	-	-	166	101	267
	o Would support the cost/ISRO approach where no market exists s7	-	-	-	153	114	267

Respondents were requested to grade the degree to which they consider each of the 21 reliability-tested variables in factors 1-5 is acontributor to potential industrial sustainability benefits. They were also asked to indicate their support for green industrial features and sustainability based on responses to the 5 items in factor 6.

Missing Value Analysis

Exhibit 3. shows the summary of the missing values table. Missing values ranged from 0.4% - for BLR, BCS, BHBV to 3.7% of data for, the professional qualifications and age group of respondents. The pattern of missing values takes on a regular diagonal path, with more residents failing to respond to reduced waste water pollution and degradation, fewer claims on medical costs, and faster tenants' lease up, as in Exhibit 4, APPENDIX B. The indication is that with missing values <10% of a particular variable or respondent adequate data points would be available to run analysis, and the data could be less problematic for causal models in particular (Gaskins, 2012)

Exhibit 3 - Percentage of missing values

Variable Summary[a,b]

	Missing		Valid
	N	Percent	N
Professional qualifications of respondents	10	3.7%	257
Age group of respondents	10	3.7%	257
BLR Reduced waste water pollution and degradation c1	1	0.4%	266
BCS Less claims on medical costs b6	1	0.4%	266
BHBV Faster tenants's lease up a2	1	0.4%	266

a. Maximum number of variables shown: 25
b. Minimum percentage of missing values for variable to be included: 0.3%

Test of multivariate normality

As inExhibit5, the table has a separate row for each observed variable. A final row, labelled 'multivariate', contains the coefficient of multivariate kurtosis (Mardia, 1970, 1974*).* The critical ratios (c.r) value for multivariate kurtosis, <5 in magnitudemeets the assumption of MVN (Bryne, 2010). In this case, the c.r value is <5 for SUP (4.165), BPG (-1.014), BLR (-1.058). Hence, the normality assumption holds for the three constructs. However, since the c.r value >5, BQL (8.385), BCS (9.786), BHBV (9.348) have non-normal distributions.

Exhibit 5 - Assessment of normality (Group number 1)

Variable	min	max	skew	c.r.	kurtosis	c.r.
s1	4.000	5.000	.203	1.356	-1.959	-6.533
s3	4.000	5.000	-.022	-.150	-1.999	-6.669
s4	2.000	5.000	-1.168	-7.792	3.110	10.375
s5	4.000	5.000	.502	3.349	-1.748	-5.830
s7	4.000	5.000	.295	1.970	-1.913	-6.380
		Multivariate Kurtosis (SUP)			**4.289**	**4.165**
f1	3.000	5.000	-.786	-5.243	-.407	-1.357
f2	1.000	5.000	-1.129	-7.532	4.519	15.074
f3	1.000	5.000	-1.751	-11.681	3.302	11.015
f4	2.000	5.000	-1.261	-8.409	1.812	6.044
		Multivariate Kurtosis (BQL)			**7.111**	**8.385**
d1	1.000	5.000	-.141	-.939	-1.573	-5.248

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Variable	min		max	skew	c.r.	kurtosis	c.r.
d2	1.000		5.000	-.216	-1.444	-1.490	-4.971
d3	1.000		5.000	-.685	-4.570	-.796	-2.654
d4	1.000		5.000	-.263	-1.755	-1.283	-4.279
d5	1.000		5.000	-.517	-3.449	-1.245	-4.154
		Multivariate Kurtosis (BPG)				**-1.042**	**-1.014**
c1	1.000		5.000	-.115	-.767	-1.739	-5.800
c2	1.000		5.000	.032	.215	-1.534	-5.116
c3	1.000		5.000	-.020	-.135	-1.564	-5.217
c4	1.000		5.000	-.375	-2.504	-1.572	-5.242
		Multivariate Kurtosis (BLR)				**-.897**	**-1.058**
b1	1.000		5.000	-.255	-1.700	-1.439	-4.799
b2	1.000		5.000	-.327	-2.183	-1.403	-4.679
b3	1.000		5.000	-.422	-2.812	-1.425	-4.754
b6	1.000		5.000	-.297	-1.983	-1.527	-5.093
		Multivariate Kurtosis (BCS)				**8.299**	**9.786**
a2	1.000		5.000	-.889	-5.930	-.469	-1.565
a3	1.000		5.000	-.918	-6.125	-.127	-.422
a4	1.000		5.000	-1.085	-7.238	.276	.922
a5	1.000		5.000	-.650	-4.333	-.925	-3.084
		Multivariate Kurtosis (BHBV)				**7.928**	**9.348**

The bootstrapping (Bollen-Stine model) has been used to validate the measurement models represented by BQL, BCS, BHBV. The ML discrepancy shows that the range of chi-square values on the left, based on 1000 resamples in Exhibits 6 below, and Exhibits 7,8, in APPENDIXC. Single factor model run with BQL, BCS, BHBV reports as follows:

BHBV: The model chi-square value of 33.006 falls within the range of .099 to 39.998 (see Exhibit 6). That is, the one sample is within one of the many possibilities in the field. Notwithstanding, the Bollen-Stine Bootstrap (Default model) reports that p=.002. Since p<.05, we fail to accept the null hypothesis that the model for normality is correct.

Exhibit 6: Maximum Likelihood discrepancy (implied vs sample) (Default model) BHBV

```
        |--------------------
   .099 |***
  2.949 |********************
  5.799 |********************
  8.649 |***************
 11.498 |********
 14.348 |*****
 17.198 |**
```

International Journal of Social Sciences & Humanities
Vol. 1, No. 1, 2016, pp. 40-67
www.ijssh.ielas.org
ISSN: 2545-420X

```
N = 1000        20.048   |**
Mean = 7.337    22.898   |*
S. e. = .148    25.748   |*
                28.598   |*
                31.448   |*
                34.298   |
                37.148   |
                39.998   |*
                         |--------------------
```

BCS: The chi-squaredmodel value of 64.232 falls outside the range of many possibilities in the field (.387 to.29.258; see Exhibit 7, APPENDIXC). Also, the Bollen-Stine Bootstrap (Default model) reports that p=.001. Since p<.05, we fail to accept the null hypothesis the null hypothesis that the model for normality is correct
BQL: The model value of 314.704 falls outside the range of many possibilities in the field(.175 to.34.504; see Exhibit 8, APPENDIXC). The Bollen-Stine Bootstrap (Default model) reports that p=.001. Since p<.05, we fail to accept the null hypothesis that the model for normality is correct.

Test of Linearity

Gaskin (2012) declares that, if the sig value for Deviation from Linearity is < .05, the relationship between IV and DV is not linear, and thus is problematic. The summaries of thesig. values for deviation from linearity (see APPENDIX D, Exhibit 9) derive from the ANOVA tables. It infers that 60 slopes of change that represents the relationships between the IVs in BHBV, BCS, BQL, BLR, BPG, and the DVs in SUP are consistent since Deviation from Linearity are> .05.49slopes of change that represents the relationships between the IVs in BHBV, BCS, BQL, BLR, BPG, and the DVs in SUP are inconsistent since Deviation from Linearity is < .05.

Factor Loadings and Correlations

The standardised regression weights provide substantial factor loadings ranging from .445 to .910 [Exhibit 10 (1), Appendix C], suggesting that they are reliable indicators of their corresponding factors. The squared multiple correlations provide information about how much variance the factors account for in the observed variables. f1-f2, d1-d3, c4 have the lowest R2 of .248, .198, .273. .479, .313, .379, .245, .413, .499 respectively. The remaining R2 is>. 5 (see APPENDIX E, Exhibit 10 (2),). Finally, the highest correlation between the 6 factors .584[see APPENDIX E, Exhibit 10 (3)], and the highest covariance estimates of .476are not statistically distinguishable from zero (p<.823) [see APPENDIX E,Exhibit 10(4)]. Although the goodness of fit and the baseline comparisons are statistically different from the null model, the observed

International Journal of Social Sciences & Humanities
Vol. 1, No. 1, 2016, pp. 40-67
www.ijssh.ielas.org
ISSN: 2545-420X

variables exhibitgood factor loadings in all cases (>.35). It indicates that the 26 measurement variables significantly represent their respective unobserved constructs or factors. Also, the correlation and covariance estimates show improvement in the model fit.

Convergent and Discriminant validities

Reliability of responses is at CR>.7 is admissible. There isconvergent validity if CR>.7, CR>AVE, and AVE >.5. As in the Exhibit 11, CR>.7 for BHBV (.704); BCS (.901); BLR (.776); BPG (.719), BQL (.763); SUP (.868). CR > AVE; and AVE >.5 (in BCS and SUP only). In BHBV, BLR, BPG, BQL, AVE<. 5, but are substantially closerto.5 (.379, .468, .343, .465). Nevertheless, since CR>AVE and CR>.7 across the 6 factors, convergent validity is sufficiently established. The measures of constructs that theoretically shouldbe related to each other are, in fact, observed to be statistically related to each other. In other words, the data proves that the variables in each factor are highly correlated, and therefore, are appropriate conceptualisations.

Exhibit 11: Results of Convergent and Discriminant validity (Statistical Tools Excel Package)

	CR	**AVE**	**MSV**	**ASV**
BHBV	0.704	0.379	0.076	0.040
BCS	0.901	0.697	0.069	0.031
BLR	0.776	0.468	0.341	0.114
BPG	0.719	0.343	0.341	0.089
BQL	0.763	0.465	0.231	0.085
SUP	0.868	0.573	0.231	0.068

c.r=composite reliability; AVE=average variance extracted; MSV=maximum shared variance ASV=average shared variance

Whenever there are high construct inter-correlations, there is a need to assess discriminant validity, to have confidence in subsequent research findings (Farrell, 2009). Discriminant validity is not proven statistically unless MSV<AVE, and ASV<AVE. Exhibit 11 shows that MSV<AVE, and ASV<AVE across the 6 factors. It indicates that the measures of constructs that theoretically unrelated to each other aresignificantly notrelated. That is, there is sufficient discrimination between different constructs

Cross boundary validity

Unconstrained configural invariance (factor invariance) tests if the useability of the instrument across boundaries. The measurement model was applied without the constraints of 1 on the regression arrows while the constraints of 1 were added in the

International Journal of Social Sciences & Humanities
Vol. 1, No. 1, 2016, pp. 40-67
www.ijssh.ielas.org
ISSN: 2545-420X

circles [APPENDIX E, Exhibit 10 (5)]. The model fit is unacceptable: CMIN/df>3 (5.635), basic comparison fit indices<.9 (NFI - .604, RFI- .549, IFI - .650, TLI - .595, CFI - .640). RAMSEA>.08 (.132).

Summary and Discussion

Reliability and stability of responses are adequate. Although, reliability is confirmed, this is not a rigorous measure of convergent validity because more than 50% of the variance could still be due to an error. There are no problematic missing values. Missing values often limit overall sample size effects. However, the threshold of missing values in the observed data (<10%) might neither present bias issues for causal models nor prevent the analysis from running. If a respondent did not respond to more than 10% of the questions, his other responses might be useless for testing causality (Gaskins, 2012). Avoiding missing data is the optimal means of handling incomplete observations. Many researchers take great care in research procedures, in recruiting informants, and in developing measures. Hard as they try, however, most researchers still encounter missing information that may occur for reasons we have not anticipated. At the data collection phase, the researcher can make decisions about what data to collect, and how to monitor data collection. The scale, data distribution and the sources of the missing data are critical issues for applying the proper techniques for treating the missing data. By AVE, the convergent validity of a construct has been evaluated. BHBV, BCS and BQL partially violate the assumption of multivariate normality. Bollen-Stine bootstrapping identified the standard errors and confidence intervals, although could not validate the model as correct for normality. The large sample size (>200) further enhances the normality of SUP, BPG, and BLR (Pallant, 2007). Assuming normality in largesamples, each of the critical values shown in the table above is an observation on a standard normally distributed random variable. Even with a large sample, the table is of limited use. All it does is to quantify the departure from normality in the sample and provide a rough test of whether the departure is statistically significant. Nonetheless, to make use of this information, it could be useful to know how robust the chosen estimation method is against the departure from calculated normality. Gaskins (2012) emphasized that a departure from normality that is significant could still be small enough to be harmless. The violation of normality should not cause a problem in the study because the sample size is large enough at >200 (Pallant, 2007). With large samples, the violation of normality should have no effect on parametric statistics to the extent that ignoring the distribution of data would not be problematic. The slopes of change are consistent. Consequently, a causal model can be built on the linearity of the data. The data demonstrate a convergence: The 4 constructs in BHBV, 5 in BCS, 4 in BLR, 5 in BPG, 4 in BQL, and 5 in SUP, are significantly correlated within each of the factors. Variables measuring theoretically different concepts do not correlate with each other. That is, the variables in SUP, BPG, BLR, BHBV, BCS, and BQL, which are supposed to be unrelated, are significantly not

International Journal of Social Sciences & Humanities
Vol. 1, No. 1, 2016, pp. 40-67
www.ijssh.ielas.org
ISSN: 2545-420X

related. Therefore, the data have sufficient discrimination between the different constructs. The proof of cross boundary validity is weak, as there wide variances for cross boundary generalizations.

The total data quality costs are subsets of the summation of all involved costs. Eppler & Helfert (2004) synthesize that an optimum of overall data quality settles at a point before the maximum quality. In the end, costs caused by poor data quality and costs for assuring data quality, without early prevention, are balanced. Won & Choi, B. (2003) submits that in a first step, the non-implementation of prevention measures would make the total costs caused by poor data quality a summation of detection and repair costs. From an economic perspective, an optimum quality level should be achieved. Won & Choi, B. (2003) and Eppler & Helfert, (2004) provide a list of costs that might be involved:

1 excess labour costs
2. Higher search costs
3. Costs due to possible loss of goodwill
4. Assessment costs
5. Data re-input costs
6. Time costs of viewing irrelevant information
7. Loss of revenue
8. The costs of losing current patronages
9. The costs of losing potential new patronages
10. Higher retrieval costs
11. Higher data administration costs
12. Costs in terms of time and lost opportunity
13. Costs because of lawsuits
14. Process failure costs
15. Information scrap and rework costs.
16. Lost and missed opportunity costs
17. Costs due to increased time of delivery

If the data quality field is to make significant progress regarding its acceptance in the business world, the costs associated with poor data quality must be made more explicit, prominent, and measurable. They arematched to the cost of assuring data quality so that an optimal investment point for data quality can be approximated. A systematic method for data quality *cost-benefit analysis* can help companies determine such an optimal level of investment in data quality. However, we seem not close to the methodology for calculating the optimal level of data quality. One reason for this is the lack of overview ofall relevant data quality costs, either the costs of assuring data quality or the costs of poor dataquality. Byclassifying data quality costs, the analytical perspective that could be both systematic and instructive may be revealed.

Limitations of the Study

As with many research studies, the results are based on a limitednumeral of real estate appraisers. Firstly, while the respondents were chosen randomly from the sampling frame – Register of theBoard of Registered Appraisers - we might assert that the sampling is probabilistic, but can make no claim about possible errors of random sampling. We reckon that the data was handledproperly. Even so; it was not feasible to control missing data from the respondents. Without missing data, the research findings could have been further strengthened. Nevertheless, the sample seems relatively diverse and representative. Secondly, the sampling did not consider the clusters of Real Estate Appraisers on a regional basis, but the random selection covered the six geopolitical zones of Nigeria. Hence, it was difficult to know the extent to which these findings are generalisable.

Conclusion and Future work

The claim supports that the overall integrity of the case study data is sufficient to conclude about its useability, the needlessness of further data collection nor a new survey. The evidence for this claim abounds in the results of the findings of the specified parameters. However, the result of the cross bound validity limits the useability of the data to the region of study. Notwithstanding, an increase in sample size could enhance the significance of the results. Data quality assurance service providers can clean the data on a contract basis and consultants can advise on fixing processes or systems to avoid data quality problems in the first place. The tools which might be appropriate for improving data include some or all of the following:

1. Data profiling - initially assessing the data to understand its quality challenges
2. Data standardization - business rules engine that ensures that data conforms to quality rules
3. Monitoring - keeping track of the data quality and reporting discrepancies in the quality of data. The software can also correct automatically, the changes based on pre-defined rules.
4. Training - training costs of improving data quality know-how
5. Management and administrative costs associated with ensuring data quality.

Future work could explore common methods bias, homoscedasticity, multicollinearity, and other validities such as criterion, concurrent and predictive validities to enhance the robustness of the exploratory data studies.

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APPENDIX A

Exhibit 1 - POTENTIAL BENEFITS AND SUPPORT INSTRUMENT
Revised - (Addae-Dapaah et al., 2009) and Babawale & Oyalowo (2011)

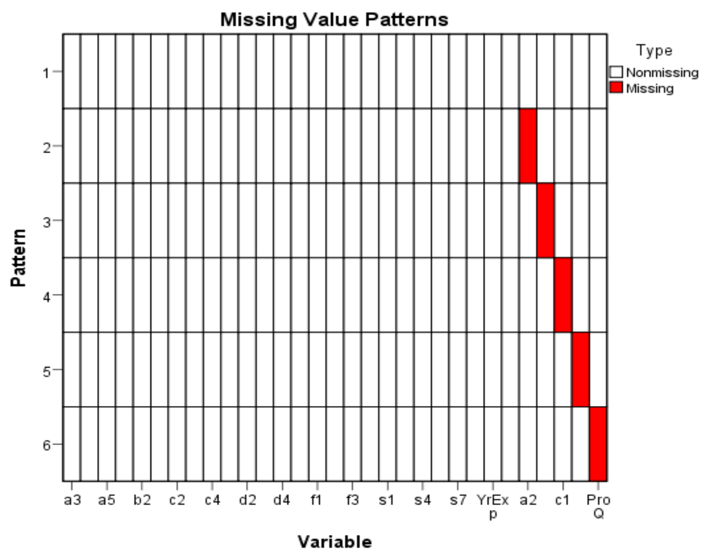
SECTION 1: Demographic profile
SECTION 2: Knowledge of Potential benefits of Green industrial Property Features and industrial sustainability
How important is each of the following benefits as an attribute of Green Industrial Building and sustainability? (Please rate the variables according to the level of importance by ticking or shading the selected box: A five-point Likert scale (1-not important, 2-not so important, 3-neutral, 4-important, 5-very important) has been used

Factors and Items					
A. High Building Value	***1 not important***	***2 not so important***	***3 neutral***	***4 important***	***5 very important***
1. To what extent can green industrial features and sustainability contribute to faster tenants' lease up					
2. Valuation premium					
3. Better market distinction					
4. Higher prestige					
B. Cost Savings					
1. Water conservation					
2. Energy efficiency					
3. Lower services maintenance costs					
4. Less claims on medical costs					
C. Lower Risks					
1. Reduced waste water pollution and degradation					
2. Lower risk of unsustainable resource use					
3. Reduced liability risks					
4. Reduced health and safety risks					
D. Productivity Gains					
1. Boosts creativity					
2. Higher morale					
3. Improved employee productivity					
4. Improved indoor quality for staff welfare					
5. User satisfaction					
E. Quality of Life					
1. Sustainability provides future generation needs					
2. Less pollution					
3. Fight global warming					
4. Minimize wastes					

SECTION 3: Willingness to support incorporation of sustainability issues into industrial assets valuation **How far is the agreement to support the following Green Industrial Building and sustainability programs if the benefits deemed to be important are provided.** Please rate the variables according to the level of agreement by ticking or shading the selected box: A five-point Likert scale (1-strongly disagree, 2-disagree, 3-neutral, 4-agree, 5-strongly agree) has been used.					
Factor and Items					
F. SUPPORT	***1 Strongly Disagree***	***2 Disagree***	***3 Neutral***	***4 Agree***	***5 Strongly Agree***
1. I would invest in Green industrial building as defined by the appropriate rating tools					
2. I would recommend green industrial buildings to others					
3. I understand that there is a relationship between sustainability and industrial building obsolescence					
4. I would recommend industrial property valuations that reflect sustainability considerations.					
5. I would support the sustainability obsolescence-cost valuation approach to industrial sustainability, where no market exists					

APPENDIX B

Exhibit 4 - Pattern of missing values



International Journal of Social Sciences & Humanities
Vol. 1, No. 1, 2016, pp. 40-67
www.ijssh.ielas.org
ISSN: 2545-420X

APPENDIX C

Exhibit 7 -ML discrepancy (implied vs sample) (Default model) BCS

```
                                |--------------------
                          .387  |***
                         2.449  |*****************
                         4.511  |********************
                         6.573  |******************
                         8.636  |************
                        10.698  |********
                        12.760  |***
N = 1000                14.822  |***
Mean = 6.483            16.885  |*
S. e. = .124            18.947  |*
                        21.009  |*
                        23.071  |*
                        25.133  |*
                        27.196  |*
                        29.258  |*
                                |--------------------
```

Exhibit 8 -ML discrepancy (implied vs sample) (Default model) BQL

```
                                |--------------------
                          .175  |***
                         2.627  |*******************
                         5.079  |*******************
                         7.531  |*************
                         9.984  |*******
                        12.436  |****
                        14.888  |**
N = 1000                17.340  |**
Mean = 6.481            19.792  |*
S. e. = .145            22.244  |*
                        24.696  |*
                        27.148  |*
                        29.600  |*
                        32.052  |*
                        34.504  |*
                                |--------------------
```

International Journal of Social Sciences & Humanities
Vol. 1, No. 1, 2016, pp. 40-67
www.ijssh.ielas.org
ISSN: 2545-420X

APPENDIX D

Exhibit 9 – Table of Sig. values for Deviation from Linearity (>.05; Linearity-NS)

Relationships	Sig. values	Relationships	Sig. values
s1→a3	.296		
s1→a5	.106	s4→c4	.365
s1→b1	.594	s4→c1	.877
s1→b2	.262	s4→f1	.086
s1→b3	.308	s4→f2	.075
s1→b6	.807	s4→b2	.055
s1→c2	.256	s4→d1	.944
s1→c4	.500	s4→d2	.796
s1→f3	.752	s4→d3	.956
s1→d1	.066	s4→d4	.125
s1→d3	.134		
s1→d4	.238	s5→a2	.059
s1→d5	.209	s5→a5	.496
		s5→d1	.080
s3→c2	.983	s5→d4	.560
s3→b1	.111	s5→d5	.075
s3→c1	.733	s5→c1	.353
s3→d1	.075	s5→c2	.298
s3→d2	.533	s5→c3	.846
s3→d3	.449		
s3→d4	.496	s7→a4	.672
s3→c3	.506	s7→a5	.549
s3→c4	.080	s7→b1	.363
		s7→c2	.235
s4→a3	.082	s7→c1	.305
s4→a5	.503	s7→d4	.567
s4→c3	.122	s7→d5	.430

APPENDIX E

Exhibit 10: **Maximum Likelihood Estimates**

1. Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
a5	<---	BHBV	.495
a4	<---	BHBV	.616
a3	<---	BHBV	.559
a2	<---	BHBV	.762
b6	<---	BCS	.739
b3	<---	BCS	.910
b2	<---	BCS	.773
b1	<---	BCS	.904
c4	<---	BLR	.526

			Estimate
c3	<---	BLR	.739
c2	<---	BLR	.743
c1	<---	BLR	.706
d5	<---	BPG	.642
d4	<---	BPG	.682
d3	<---	BPG	.526
d2	<---	BPG	.602
d1	<---	BPG	.445
f4	<---	BQL	.871
f3	<---	BQL	.809
f2	<---	BQL	.445
f1	<---	BQL	.498
s7	<---	SUP	.807
s5	<---	SUP	.891
s4	<---	SUP	.592
s3	<---	SUP	.774
s1	<---	SUP	.686

2. Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
s1	.471
s3	.599
s4	.351
s5	.793
s7	.651
f1	.248
f2	.198
f3	.654
f4	.758
d1	.198
d2	.362
d3	.277
d4	.465
d5	.413
c1	.499
c2	.552
c3	.546
c4	.277
b1	.817
b2	.597
b3	.829
b6	.546
a2	.581
a3	.313
a4	.379
a5	.245

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3. Correlations: (Group number 1 - Default model)

			Estimate
BHBV	<-->	BCS	.054
BCS	<-->	BLR	.263
BLR	<-->	BPG	.584
BPG	<-->	BQL	.234
BLR	<-->	BQL	.291
BHBV	<-->	BLR	.275
BCS	<-->	BQL	-.063
BHBV	<-->	BQL	.220
BCS	<-->	BPG	.216
SUP	<-->	BQL	.481
SUP	<-->	BPG	.032
SUP	<-->	BLR	.012
SUP	<-->	BCS	-.182
SUP	<-->	BHBV	.269
BHBV	<-->	BPG	-.010

4. Covariances: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
BHBV	<-->	BCS	.044	.060	.726	.468	
BCS	<-->	BLR	.275	.084	3.288	.001	
BLR	<-->	BPG	.476	.096	4.981	***	
BPG	<-->	BQL	.152	.053	2.878	.004	
BLR	<-->	BQL	.178	.051	3.485	***	
BHBV	<-->	BLR	.164	.056	2.932	.003	
BCS	<-->	BQL	-.052	.058	-.906	.365	
BHBV	<-->	BQL	.104	.040	2.631	.009	
BCS	<-->	BPG	.238	.086	2.755	.006	
SUP	<-->	BQL	.134	.022	6.180	***	
SUP	<-->	BPG	.012	.028	.423	.672	
SUP	<-->	BLR	.004	.026	.167	.867	
SUP	<-->	BCS	-.086	.033	-2.633	.008	
SUP	<-->	BHBV	.073	.023	3.191	.001	
BHBV	<-->	BPG	-.007	.053	-.125	.901	

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5. Path diagram (Unconstrained) for cross validity estimate