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MEASURING HOUSING SATISFACTION THROUGH THE USE OF STRUCTURAL EQUATION MODELLING

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Abstract *Structural Equation Modelling (SEM) is a technique that effectively incorporates a whole range of standard multivariate analysis methods, including regression, factor analysis and analysis of variance. SEM underlies much of what sustainable human settlement (SHS) researchers do on a daily basis. SEM provides an opportunity to hypothesise models of human behaviour, and to test or confirm these models statistically. This article present how SEM can/ was used to study and to understand issues encircling SHS issues with a specific emphasis on housing satisfaction in South Africa low-income housing. Secondary research materials within and outside the field of the built environment were reviewed and in relation to the study objective. With the use of content analysis, the reviewed data were classified to meet the research objective. The researcher found that SEM using EQation modeling software (EQS) was the most appropriate technique for sustainable human settlement research studies. Because of the numerous benefits and advantages of the analysis produced by SEM through the EQS platform, such as the model estimation, and model fit attributes amongst others. The study further recommended the use of the process because of the Satorra-Bentler scaled statistics ($S – B\chi^2$), use of appropriate cut-off values for the generated model analysis / fit Indices for various required goodness-of-fit tests of SEM model as applicable.*

1. INTRODUCTION

Structural Equation Modelling (SEM) is currently the most inclusive statistical procedure in social and scientific research catering for all operations of the General Linear Modeling (GLM) group of statistics such as Analysis of Variance (ANOVA); Multivariate Analysis of Variance (MANOVA) and multiple regression [1]. Though there are many ways to describe SEM, it is most commonly thought of as a hybrid between some form of analysis of variance (ANOVA) / regression and some form of factor analysis. In general, it can be remarked that SEM allows researchers to perform multilevel regression/ANOVA on factors. SEM is conceptually used to answer any research question involving the indirect or direct observation of one or more independent variables or one or more dependent variables. However, the primary goal of SEM is to determine and validate a proposed causal process and/or model. In the current study, SEM was used to validate a conceptualized holistically integrated residential satisfaction model for public housing occupants in South Africa. Also, SEM takes a confirmatory approach to the analysis of a structural theory bearing on some phenomenon [2]. However, Dion [3] claims that SEM simultaneously estimates all coefficients in the model and, therefore, it can assess the significance and strength of a relationship in the context of the entire postulated model. Considering that the conceptualized model in the integrated residential satisfaction study for public housing occupants in South Africa consisted of exogenous variables; that had to were estimated from the endogenous variables. Hence, methods of analysis such as ANOVA could not be used as they lack a direct way of distinguishing between observed measures and the underlying constructs [1]. Likewise, in SEM, a clear distinction is made between true variance and error variance, which implies that model parameters are estimated by taking measurement error into consideration. Before SEM on the study was performed, CFA was carried out on each exogenous variable to determine best-fit for the model.

Furthermore, the choice of the software EQS, for analysis of the sustainable human settlement research was enhanced by the benefits of utilizing the Satorra-Bentler scaled statistics ($S - B\chi^2$), which provides an adjusted and a more robust measure of fit for non-normal data. This approach according to Byrne [4] is more accurate than the normal chi-square test statistics (χ^2). Likewise Kline [1] informs that EQS offers several different estimation methods for non-normal data as well, including the Robust Maximum Likelihood (RML).

EQS Version 6.2, a software package was used for the SEM analysis as it is a user-friendly software that provides a graphical user interface, which is easy to understand. EQS also enables data to be imported directly from SPSS. Other reasons why the researcher adopted EQS 6.2 and SPSS 20.0 software include: first, the software is available at the University's Postgraduate and Statistics Centre; hence, it was easier for the researcher as a postgraduate student to access the software. Second, EQS was seldom used by previous researchers as revealed from the literature to enhance conceptual understanding of residential satisfaction in subsidised low-income housing research as compared to other techniques, such as AMOS and LISREL [5]. Being a user-friendly graphically modeling interface, EQS offered for the SHS study, a wider variety of goodness-of-fit measures [5]. For SHS research, SEM provides an opportunity to hypothesise models of human behaviour, and to test or confirm these models statistically. Therefore, the aim of this paper is to present how Structural Equation Modelling technique can be used to study and to understand issues encircling SHS issues with a specific emphasis on housing satisfaction in the South Africa low-income housing.

2. THE SEM PROCESS

There is no universally agreed SEM process, but SEM scholars such as Bollen [6] and McDonald and Ho [7] stated that SEM applications should typically follow a five-step process. This include: model specification stage; model identification stage; model estimation stage; model evaluation stage and model re-specification. While these processes are vital, but in the present study, the process culminated at the fourth step as the study objective was achieved. Hence, there was no need for re-specification of the model. The subsequent sections of the paper details, the process followed to achieve the study's objective.

2.1 Model specification stage

The current study was aimed to build a conceptual residential satisfaction model that is centered on the subsidised low-income housing scheme. The theoretical, conceptual framework for the current research builds on the work of Marans and Rodger [8] and Marans and Sprecklemeyer [9] models of satisfactions. Marans and Rodger [8] conceptualized that an individual's overall satisfaction with housing depends on their perception of the various neighbourhood characteristics and their assessment of them. Marans and Rodgers's [8] model also conceptualized that both the perpetual evaluative process and the overall satisfaction level are related to the residents' characteristics, such as social class, housing status amongst others). Similarly, Marans and Sprecklemeyer [9] determined that residents' satisfaction is a function of the physical environment through one's perception and beliefs of the physical environment. In this particular model, housing satisfaction was derived as a result of an integrated relationship between the environment and the human perception of beliefs. The three basic components of the model were: the physical environment, the perception and attitude of residents toward their housing environment and residents' satisfaction. Based on the fundamental underpinning of these two models, and the incorporated theoretical perspectives, which has been adopted in other similar studies, they were, therefore, useful for conceptualizing the present study as a variety of satisfaction studies with urban housing living being conceptualized were within the broad theoretical framework.

Therefore, the conceptual framework for the study that used SEM as the analysis tool was primarily based on the approach used by Marans and Rodger [8]; when they view residential satisfaction as a criterion of evaluation of residential quality and, at the same time, as a variable predicting certain behaviour. In this regard, residential satisfaction was treated as a criterion variable and, therefore, as a dependent variable. The approach had also been used by Galster and Hesser [10], Cutter [11] and Weidemann and Anderson [12]. Based on the fundamental factors and constructs associated with all the previous models of residential satisfaction, the study model studied the relationship of the dwelling unit; neighbourhood and environmental features; services provided by government; building quality; which are the essential variables that have been measured in a majority of the previous studies, with the inclusive consideration of the impact of needs and expectations, and beneficiaries participation; which were classified as the study's exogenous variables and their role in predicting overall beneficiary residential satisfaction, which is the endogenous variable. These in turn, was assume to predict the beneficiaries' satisfaction towards the housing stocks, behaviour to maintain the housing stocks and their overall responsibility in the low-income neighbourhood, or likelihood to move and eventually place attachment through the SEM analysis.

Therefore, conceptual model theorized that residential satisfaction is established by the relationship that exists between the exogenous variables, which include the basic elements by which the subjective and objective measurements are linked. These variables were identified from the review of literature and the first phase of data collection for the study via a Delphi Survey; were considered the major determinants of residential satisfaction in subsidised low-income housing. These were adapted to fit with the peculiar housing and other socio-economic characteristics of the South African society. Hence, it was envisaged that the combination of the objective and subjective measures will then produce a measure of residential satisfaction for the housing beneficiaries.

2.2 Model identification stage

Before proceeding to the model estimation and evaluation stages, for any SEM study, it is critical to determine whether the postulated model could be analysed or not. Model complexity is determined by establishing whether a model is just-identified, under-identified or over-identified. A just-identified model is one, in which there is a one-to-one correspondence between the data and the structural parameters. That is, the number of data variances and covariance should be equivalent to the number of parameters to be estimated as postulated b Byrne [4]. Further, Byrne [4] informs that despite the capability of any model to yield a unique solution for all parameters, the just-identified model is not scientifically interesting because it has no degree of freedom and, therefore, can never be rejected. While, an over-identified model is one, in which the number of estimable parameters is less than the number of observations. Accordingly, an over-identified model according to Byrne [4] is desirable as it will result in a positive degree of freedom that allows for rejection of the model, therefore, rendering it to be of scientific use. Finally, the under-identified model is one, in which the number of parameters to be estimated exceeds the number of variables and covariances. As a result, there can be an infinite number of solution, and, therefore, defeats the purpose of the analysis [1] [4]. In summation, Kline [1] defined that for a model to be analysed, there has to be at least as many observations as the parameters to be estimated, meaning that the degree of freedom (df) should be greater than zero ($df \geq 0$). Therefore, the current study model was over-identified because there were 84 indicators for both the exogenous and the endogenous variable. While there were 3570 data points (meaning, 84 variances and 3486 covariances). The errors were uncorrelated, and each indicator loads on only one factor. In addition, the covariance between the factors was not zero. Hence, the sustainable human settlement research hypothesised model was said to be identified.

2.3 Model estimation stage

It is important to estimate a SEM model, with a factor structure, at one-time point and then test if the factor structure, that is, the measurement model, remains the same across time points. Hence, Ullman [13] informs that model estimates for SEM path coefficients and their standard errors are generated under the inherent postulation that the model fit is excellent. If the model fit is very close, then the estimates and standard errors may be taken seriously, and individual significance tests on parameters (path coefficients, variances, and covariances) may be performed.

For the current study, an examination of the degree of freedom of the postulated model revealed that the model was over-identified. That is; the least value for the degree of freedom was found to be two within the residential satisfaction manifest constructs. Likewise, all values of *df* for the model constructs were positive and, therefore, indicative of an over-identification of the measurement models. After the screening process was completed, it was established that the data for the study was non-normal with the lowest Mardia's Coefficient of 13.1652 (residential satisfaction) and the highest Mardia's Coefficient of 56.0118 (beneficiary's participation). The non-normality of the data influenced the choice and use of the Robust Maximum Likelihood (*RML*) Estimation Method. The RML gives several robust fit indices [14]. Byrne [4] suggests that one of the outputs from the RML Estimation Method is the robust chi-square statistics (χ^2) referred to as the Satorra-Bentler Scaled Statistics ($S - B\chi^2$) and robust standard error, which are corrected for non-normality in large samples, as the case of the present study; with the sample size being 751. SEM software, EQS Version 6.2 was used in part, due to the ability of the programme to adjust standard errors for the non-normality of the data. Furthermore, the covariance matrix method was the chosen in-put matrix for the analysis/estimation in the residential satisfaction study. The analysis strategy adopted to examine the hypothesized model was firstly used to estimate the measurement part of the model and after that, to analyse the measurement and structural parts of the model respectively. Likewise, the results from the analysis were reported in the same manner namely, results from the measurement model analysis referred to as the Confirmatory Factor Analysis (CFA) were presented first and thereafter, the results from the analysis for the entire structural model referred to as the full latent variable model (FV) were presented.

2.4 Model evaluation stage

Evaluation of the hypothesised residential satisfaction model was the next step after the pre-analysis conditions, selection of the input matrix of the data and the model estimation stages were determined. The following fit indices identified from Hu and Bentler [15]; Boomsma [16]; Kline [1]; Streiner [17]; and Hooper, Coughlan and Mullen [18] were used to determined model fit. These statistics parameters relied on were:

- Chi-square values χ^2;
- Satorra-Bentler Scaled Chi-square ($S - B\chi^2$);
- Bentler Comparative Fit Index (CFI);

- Standardised Root Mean Square Residual (SRMR);
- Goodness of Fit Index (GFI);
- Root Mean Square Error of Approximation (RMSEA); and
- Root Mean Square Error of Approximation with its 90% confidence interval (RMSEA @ 90% CI).

The decision on model fit indices was based on the proposal by Hu and Bentler [15] two-index strategy of incremental and absolute fit indexes because they perform superiorly to a single index presentation strategy. Hu and Bentler [15] suggested therefore that the maximum likelihood based SRMR and a supplemental fit index such as CFI or RMSEA, would result in minimum Type I (the probability of rejecting the null hypothesis when it is true) and a Type II Error (the probability of accepting the null hypothesis when it is false). The fit indexes χ^2, CFI, and ($S - B\chi^2$) belong to the Incremental or Comparative fit indexes, which are a group of indices that do not use the chi-square in its raw form but compare the chi-square value to a baseline model [18]. While the SRMR and RMSEA belong to the absolute fit indexes. These are fit indices, which determine how well a priori model fits the sample data [7] and demonstrates, which proposed model has the most superior fit.

Table 1: Cut-off criteria of fit statistics

Statistics	Cut-off criteria
Chi-square - $\chi 2$	Ratio $\chi 2$ to df ≤ 2 or 3 with an insignificant p value ($p > 0.05$)
Bentler Comparative Fit Index (CFI)	Value should be ≥ 0.95 for good fit
Standardised Root Mean Square Residual (SRMR)	The value should be ≤ 0.08 A value of 0.1 is also acceptable
Root Mean Square Error of Approximation (RMSEA)	Value should be < 0.05 for good fit Values < and 0.08 indicate a reasonable error of approximation Values of > 0.10 suggests a poor fit
Root Mean Square Error of Approximation with its 90% confidence interval (RMSEA @ 90% CI)	Values to be < 0.06 to 0.08 with confidence interval
Goodness of Fit Index (GFI)	Should be > 0.90

Sources: (Joreskog & Sorbom [19]; Hu & Bentler [15]; Kline [1]; Byrne [4]; Bartholomew et al. [14]; Schreiber et al. [20]; Dion [3]; Hooper et al.[18]

Further, additional fit index (Goodness of Fit Index - GFI) was adopted by the researcher for a more stringent measure to evaluate the overall model fit for the study. This follows the work of Tong [5]. According to Tong [5] and Kassim [21], the GFI is an important measure of absolute fit. It refers to the percent of observed covariances implied by the model [22]. Garson [22] and Tong [5] together inform that GFI should be equal to or greater than

0.90 for a parsimonious model [22] [5] which coincides with the current study. Also, researchers such as Joreskog and Sorbom [19] and Schumacker and Lomax [23] suggest that acceptable GFI value should be closer to 0.95.

These measures (χ^2; CFI; $S - B\chi^2$; SRMR; RMSEA; RMSEA @ 90% CI; and GFI) as adopted, provide the most fundamental indication of how well the proposed theory fits the data. Unlike incremental fit indices, their calculation does not rely on comparison with a baseline model but is instead a measure of how well the model fits in comparison to no model at all [19] [18]. The adopted cut-off values for the above fit indices used to determine the model are as tabulated in Table 1. Thereafter, the statistical significance of parameter estimates were likewise determined followed by the process of estimation of the model through confirmatory factor analysis.

2.4.1 Statistical significance of parameter estimates

The statistical significance of parameter estimates for the study was established by examining the ration output of the parameter estimate divided by its standard error (therefore analogous of *Z-values*) and tests that the estimate is statistically different from zero [4] [20]. Hence, based on an alpha (α) level of 0.05, the test statistics for the priori model were all greater than 1.96 ($Z > \pm 1.96$), meaning, the estimate = 0.00 and as such the hypothesis could not be rejected.

Also, the average absolute residual values, both unstandardized and standardized average absolute residual matrix values for the model were examined for consistencies. The result of the examination revealed that all the absolute residual values and the average off-diagonal absolute residuals, both unstandardized and standardized, were close to zero.

2.4.2 Reliability and Validity

In detemining the score reliabilityn for the study, the internal consistency reliability measure statistics of Rho coefficient and Cronbach's [24] alpha (α) were adopted. Kline [1] and Byrne [4] theorize that the Cronbach's alpha measures the degree to which responses are consistent across all items within a single measure and if this statistics is low, the content of the items may be so heterogeneous that the total score is not the best possible unit of analysis for the measure. Hence, the acceptance of Cronbach's Alpha to measure internal homogeneity is limited. Byrne [4] further argues that the use of the Cronbach's Alpha Coefficient to judge latent variable models especially models with multi-dimensional structure is questionable because it is based on a very restrictive model that requires all factor loading and error variances to be equal. Therefore, in establishing score reliability for the study, the Rho Coefficient was relied upon more than the Cronbach's Alpha Coefficient even though it is the most common method used for assessing the reliability for a measurement scale with multi-point items [25]. The Rho coefficient provides a good estimate of internal consistency because the model that was analysed in the current study was a full latent variable mode [4].

2.4.3 Measurement Models evaluation: Confirmatory Factor Analysis

Furhtermore, Confirmatory Factor Analysis (CFA) was used to scrutinize the factor structure of the exogenous and endogenous indicator variables nfor the study. CFA in contrast to Exploratory Factor Analysis (EFA) which is simply aimed to identify the factor structure present in a set of variables; CFA is used to test an hypothesized factor structure or model and to assess its fit to the data. CFA may be viewed as a sub-model of the more general structural equation modeling (SEM) approach to analysis. However, CFA present the measurement model of the relations of indicators (observed variables) to factors (exogenous variables), as well as the correlations among the latter. CFA is generally based on a strong theoretical and/or empirical foundation that allows the analyst to specify an exact factor structure in advance. The CFA approach usually restricts which variables will load on which factors, as well as which factors will be correlated. In CFA each observed variable has an errors term, or residual, associated with it that expresses the proportion of variance in the variable that is not explained by the factors. These error terms also contain measurement error due to the lack of reliability in the observed variables. The typical research question in CFA is: Are the covariances (or correlations) among variables consistent with an hypothesized factor structure? As such, CFA is quite useful for studying the factorial validity of multi-item construct such as residential satisfaction.

Therefore, after establishing the score reliability, the construct validity was conducted to demonstrate the extent to which the constructs hypothetically relate to one another. This is also referred to as the test of measurement invariance (MI), factorial invariance or measurement equivalence between indicator variables. Measurement invariance is a very important requisite in SEM. MI attempts to verify that the factors are measuring the same underlying latent construct within the same condition. MI as used in the present study was used to ensure that all attribute related to the same set of observations in the same way. The MI for the present study was determined based on examination of the residual covariance matrix from the CFA output results, which determined the variables to be included in the full structural model.

Therefore, preliminary Confirmatory Factor Analysis (CFA) was performed to measure the dimensions of all latent variable indicators to identify which items were appropriate for each dimension. Indicator variables with an unacceptably high residual covariance matrix (*>2.58*) were dropped. Residual covariance matrix values greater than 2.58 are considered large [19] [4]. In order for a variable to be included in a CFA measurement model analysis for the study, which enables the model to be described as well-fitting, the distribution of residuals covariance matrix were symmetrical and centered around zero. This procedure was adopted as a means to ensure that the indicator variables were measuring the same latent construct. For instance, when an investigator wishes to use a given measure or set of measures to make evaluations, the validity of those comparisons depends on the assumption that the same construct is being measured. Hence, the assumption of measurement invariance is most times tested in CFA [26], so as to allow for comparison of indicator variables under the same condition.

Since this study sought to test the potential relationships among variables, a CFA using EQS

6.2 Software was applied on the indicator variables that passed the first CFA test of Residual Covariance Matrix Analysis. Further, to achieve construct validity, the measurements demonstrated convergent validity and discriminant validity. Convergent validity refers to the items purporting to measure the same construct correlates positively with one another [27] as already described above. On the other hand, the latter requires that an item does not correlate too highly with other items of different constructs [28]. In this study, the correlation matrix and inter-construct correlation were analyzed for convergent and discriminant validity. In addition, due to the absence of another external criterion against which comparison could be made of the measures, discriminant validity was also used to examine construct validity. This is because a set of variables hypothesised to measure different aspects only shows discriminant validity if their inter-correlations are not too high [1].

3. FINDINGS

Results from the EQS outputs revealed that the robust fit indexes, CFI, GFI, SRMR and the RMSEA values and the RMSEA with 90% confidence interval met the cut-off index criteria and the parameter estimates were found to be statistically significant and reasonable. Likewise, the internal consistency and reliability analyses conducted yielded acceptable results. The Rho Coefficient of internal consistency was found to be above the minimum value of 0.70. Correspondingly, the Cronbach's Alpha was also found to be above the minimum value of 0.70. According to Kline [1], the reliability coefficient should fall between zero and 1.00. Values close to 1.00 are desired. Hence, the internal consistency and reliability was met. In addition, the indicator variables yielded high correlation values, which suggested a high degree of linear association between the indicator variables and the factors. In addition, the interfactor correlation (R^2) values were also found to be closer to the desired value of 1.00 and hence indicating that the factors explained the variance in the indicator variables. This meant that the results suggested that the indicator variables significantly predicted the factor constructs, because a majority of the measured variables were significantly associated with the factors. Lastly, the construct validity as determined by examining the magnitude of the parameter coefficients (factor loading) also revealed that the parameter coefficients (*Z-statistics*) indicated a close relation between the factors and the indicator variable. A parameter coefficient of 0.5 is interpreted as 25% of the total variance in the indicator variable being explained by the latent variable (factor). Hence, the reported parameter coefficient explained more than 25% of the variance in the indicator variable, which were indicative of an adequate fit between the indicator variables and the factors.

The postulated model, which hypothesised that overall residential satisfaction, is directly related to the influence of the exogenous variables in predicting and determining overall beneficiaries' satisfaction, fit the sample data adequately. In view of the fact that the analysis was confirmatory of the priori model, there was no need to further reestimation or re-specification / improve the structural model. Investigation of alternative models, such as the reduction of latent variables could be a matter for further studies as the current study was a confirmatory analysis of the priori. However, the Lagrange Multiplier test did not unveil significant indication of model mis-specification demanding a re-specification. Byrne [4] informs that for most models, model enhancement is purely a process that attempts to fine-tune small features of the sample and does not essentially add value to an already fitted model, like the present model. Likewise, MacCallum et al. [29] cautioned that "when an initial model fits well, it is probably unwise to modify it to achieve even better fit because modifications may simply be fitting idiosyncratic characteristics of the sample". Hence, the presented model for the study was therefore accepted with its levels of fit.

Consequently, there was no need for reestimation or respecification of the measurement models before it could be included in the full latent variable model.

4. CONCLUSION

The aim of this paper was to present how SEM technique can be used to study and to understand issues encircling SHS issues with a specific emphasis on housing satisfaction in South Africa low-income housing. Findings for the study revealed that the residual covariance estimates fell within the acceptable range; the robust fit indexes had an acceptable fit, while the RMSEA value and the RMSEA with 90% confidence interval produced a reasonable fit. All other parameter estimates were statistically significant and feasible. It was therefore, concluded that the measurement model for the residential satisfaction construct had an adequate fit to the sample data. Consequently, there was no need to improve the measurement before it could be included in the full latent variable model. Based on the findings from the SEM study using EQation modeling software (EQS), it was found that the most appropriate technique for sustainable human settlement research studies is SEM. Hence, the study recommends that this approach should always be used sustainable human settlement research studies because of the numerous benefits and advantages of the analysis produced by SEM through the EQS platform such as the model estimation, and model fit attributes amongst others. The study further recommend the use of these instrument because of the the Satorra-Bentler scaled statistics ($S - B\chi 2$) which produces a better chi-square, and because of the use of appropriate cut-off values for the generated model analysis / fit Indices for various required goodness-of-fit tests of SEM model as applicable.

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