Procedural Tool for Analysing Building Energy Performance- Structural Equation Modelling Protocol

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Abstract

Building Energy Performance assessment technique has become a new paradigm that plays a significant part in reducing world energy demand and greenhouse gas emissions. However, there exists a global proliferation of diverse models for assessing and benchmarking buildings. This paper proposes a single Building Energy Performance assessment model that considered several factors that affect office-building energy efficiency performances in two different countries. It aimed to develop a model that could identify Building Energy Performance critical factors as a new technique for aggregating energy efficiency metrics for commercial buildings. It examined the relationship and interdependency between the variables as it affects buildings' performance as a basis for developing its theoretical model. Survey questions were derived from variables obtained from existing literature using this theoretical paper proposition. A self-administered questionnaire was used to gather data from occupants of office buildings in Nigeria and the United Kingdom. Exploratory Factor Analysis and Structural Equation Modelling via Confirmatory Factor Analysis were used to analyse the explanatory power of the measured variables and their constructs. The results identified management, strategic and operational issues as critical factors that affect Building Energy Performance in both countries. It confirmed the relationships and interdependency of the study factors and developed a new strategy that gives them proper considerations in the operations and management of Building Energy. Data collected supports the theoretical model, and the measurement model fits into the conceptual model. The model gives a quantitative approach that identified critical factors for improving energy management and auditing efficiency of buildings.

Keywords: commercial buildings; climate change; energy efficiency; factor analysis; facilities management; performance assessment model

Introduction

Building Energy Performance (BEP) assessment has proven to help track and reduce energy consumption and greenhouse gases (GHGs) emission, with improved decision-making solutions for limiting their negative impacts on the global climate (Mafimisebi et al. 2018). However, despite worldwide efforts to curtain GHGs emission, global energy demand continues to increase with a corresponding increase in building stock demand. The U.S. Energy Information Administration (2017) projected that the world energy consumption could rise by 28% by the year 2040, and increase nearly 50% by the year 2050 (U.S. Energy Information Administration 2019). The building sector alone could account for about 21% of global energy consumption in 2040 (U.S. Energy Information

Administration 2017). In 2015, global energy consumption stood at 663 quadrillions Btu (U.S. Energy Information Administration 2017). The European Union (EU) building stock contributes 36% of GHGs and also accounts for 38% of CO_2 emissions compared to US's 39% energy consumption and 36% CO_2 emissions (Amasyali and El-Gohary, 2018). In Sub-Saharan Africa (SSA), energy demand increased by around 45% from 2000 to 2012, which accounts for 4% of the global energy demand despite being home to 13% of the world population (IEA 2014). The SSA primary energy consumption increased to 847 Mtoe in 2015 (IEE 2017). The rapid growth of urbanisation in SSA due to higher population growth and rural-to-urban migration (Hanif 2018) will have significant implications for CO_2 emissions, especially if the gap between potential and actual energy consumption narrowed. However, SSA could learn from past mistakes by decoupling her energy consumption and attendant CO_2 implication from economic growth and development through the adoption of sustainable energy-efficient technologies.

Global solutions for tackling climate change consequences such as mitigation and adaptation measures have not stopped the increase in building energy demand. Hence, building energy efficiency (EE) remains a crucial factor for achieving the global sustainable agenda (Mafimisebi 2017). Consequently, the uptake of BEP assessment and benchmarking has become a new paradigm for achieving building EE. Nevertheless, a universal and acceptable standard parameter for evaluation is still a dilemma due to the proliferation of assessment techniques. EE itself is not an absolute concept; therefore, it cannot be measured directly but requires a subset of indicators for its measurement (Patterson 1996). The selection of these evaluation criteria (indicators), as well as the relationship and interdependency between them, have always been challenging since several factors affect the EE performance of office buildings globally.

Different methods for aggregating metrics for energy savings and efficiency increase, as techniques for BEP assessment and benchmark, have been advanced (Wang et al. 2017). Some authors (Amasyali and El-Gohary 2018; Wilson et al. 2018) have used the quantitative energy assessment techniques (the calculation-based, measurement-based using data-driven, hybrid techniques using data-driven and the physical modelling techniques) in developing BEP assessment models. Others (Bernardo et al. 2018) uses the analytical framework techniques (environmental assessment framework, multi-criteria assessment framework) in developing decision-support tools. The global proliferation of BEP assessment tools is due to differences in climates, locations and other contextual factors. The challenge has been in, developing a universally acceptable model that could be used as a framework for managing (BEP), especially, office buildings across countries. The current paper addresses this by proposing a single energy assessment model that could take into consideration several factors that affect office BEP in two different countries. This study is part of wider research that took place between January 2015 and August 2016 in Lagos, Nigeria and Chelmsford, UK. The aim was to identify Building Energy Performance critical factors and their relationships as a new technique for aggregating energy efficiency metrics for commercial buildings. The study model helps to identify these vital factors, the relationship between them and their underlying constructs.

Literature Review

Managing Existing Building Stocks to achieve Energy Efficiency Performance

The adoption of low-zero carbon technologies, retrofit of existing buildings to low-energy buildings, and adherence to building energy efficiency (BEE) policy/ regulations have yielded meaningful results (Gram-Hanssen and Georg 2018). They are effective carbon interventions that help to improve the EE of buildings. Building maintenance often suffers a lack of adequate consideration during planning and production phases of the construction process. There is increasing emphasises on the importance of a maintenance plan as an integral part of built asset management (BAM). Maintenance plan has been confirmed that it aid the proper functioning of buildings, and secures the effectiveness and efficiency of the management of existing building stock (Jones and Sharp 2007). Hence, the need for the assessment of the energy performance of existing building stocks that could determine the effectiveness of a maintenance plan and BAM maintenance.

Barriers and Drivers

The issue of barriers and drivers to improving existing BEP, which often confronts owner and facilities managers have been expounded in extant literature. The problems of initial capital cost for purchase and installation of EE technologies, difficulties in securing finance, information barrier and transaction cost, low and subsidised energy price, lack of access to funding, long payback period etc., have been identified (Gliedt and Hoicka 2015; Wang et al. 2016). Also, the absence of regulatory framework, energy codes and management policy, etc., are well-known barriers (Wang et al. 2016; Strachan and Banfill 2017). The issues of inadequate human and institutional capacities to support management decisions, management lack of interest on energy efficiency, none availability of energy use and consumption data, lack of technical skills for identifying, developing and implementing EE measures etc., (McKanea et al. 2017) are also identified as barriers to BEP.

Tracking and monitoring the impacts of identifiable EE barriers and drivers is prerequisite for a BEP assessment model. Gliedt and Hoicka (2015) suggested that the organisation's emphasis on benefits of energy upgrades, increase knowledge and access to information, and access to funding are ways of overcoming barriers within an organisation decision-making process. Their study confirmed that energy prices, internal leadership, internal fund availability for EE projects, and integration of renewable energy into organisation strategic plan with an elevated level of internal organisation knowledge of EE options are drivers for undertaking energy upgrade. Wang et al. (2016) found that saving on operational energy costs, improving public image, financial rewards from governments, and building reputation with governments are incentives and benefits for EE performance of public facilities in China.

Management Policy

Nowadays, energy management policy has become critical in achieving improved BEP. The practices of strategic energy management (SEM) such as developing an organisation's policy on EE, establishing of building operations and maintenance plan, developing and enforcing policies on energy-efficient purchasing, and engaging occupants on EE (Abdel-Azim et al. 2017) have gradually become part of sustainable management policy. Extant literature stressed organisations' uptake of environmental and energy management standards (Kanneganti et al. 2017) including ISO 9001: Quality Management systems (Kasperavičiūtė-Černiauskienė and Serafinas 2018) as concrete commitments towards sustainable management of office BEP (Mafimisebi et al. 2018). Hence, this paper considers management policy as an integral part of the BEP model that could help to monitor and measure BEP at the strategic, tactical and operational level in the organisation.

Operations Management

The use of facilities management (FM) operational and maintenance techniques such as: benchmarking for decision-making, energy audit and retrofit, re-commissioning, proactive maintenance techniques, rating system and certification, and comfort-setting etc., are crucial to improving BEP (Min et al. 2016). Energy audit often involves physical walk-through inspection for identifying energy saving potentials in buildings. It is distinct from an energy assessment that consists of the computation of actual or modelled building energy used. While an assessment could be in the form of simulation-based thermal modelling of different retrofit measures (Iman et al. 2017); calculation of design energy use in a building; and mining of a building actual energy consumption via metering. Building energy benchmarking involves the comparison of the actual energy performance of two or more building types using predetermined measurement metrics. Benchmarking could be single-criterion based using the traditional energy used intensity that considers only the energy effect of floor size, or multi-criteria decision-making (MCDM) using multi-criteria modelling techniques (Wang et al. 2017).

Strategy for Driving Building Energy Performance

Already identified contemporary EE factors in existing literature underpin the need for the adoptions of sub-set of strategic drivers for improving BEP. Past study (Mafimisebi 2017) has highlighted the importance of reducing energy consumption and its negative environmental impact, thereby enhancing the vitality of people at the workplace, and call for organisations to make strategic facilities management (SFM) an integral part of organisation's Sustainability Policy. The Performance Metrics (PMs) are subset objectives used for measuring the energy performance of each case study building while the Key Performance Indicators (KPIs) are standardised whole-building analysis metrics used for comparing and benchmarking across case-study buildings (O'Brien et al. 2017). These definitions are in line with O'Brien et al. (2017) articulation of PMs in their study of building performance metrics using occupant's building interactions. A recent study (Mafimisebi et al. 2018), affirmed how the adoption of PMs and KPIs helped to improve BEP and resulted in energy savings. However, PM (BEU) and KPI (BEU intensity) come with disadvantages as both do not take account of operational issues like comfort environment and occupancy hours. Hence, a combination of the structural modelling procedure and standardised assessment PMs and KPIs is advanced in this paper.

Existing Building Energy Performance Assessment Models

Primarily, existing BEP assessment models could be used for classification, diagnosis and intervention purposes based on different techniques. These assessment techniques are well expounded in extant literature (Wang et al. 2012). Some of the popular assessment techniques include: building environmental assessment, building energy certification, whole building benchmarking, hierarchy assessment and diagnosis using various energy quantification methods (calculations, weighting, and rating) (Mattoni et al. 2018). Quantification methods such as simple calculation, dynamic simulation, measured energy data from existing buildings, asset rating, operational rating, hybrid approach (calculation-based asset rating), etc., could be based on single-criteria or multi-criteria-based performance metrics (PMs) / or key performance indicators (KPIs) as expounded in Wang et al. (2017) study that developed a quantitative multi-criterion benchmarking procedure for rational decision-making in building energy retrofit.

Materials and Methods

Materials

This paper used the BEP framework as an assessment model to explain the role of management, strategic and operational factors that affect office BEP. The framework combined the BAM decision-making model (Jones and Sharp 2007) required to identify BEE needs, establish cause, development of solutions and evaluation of solutions. It also includes the Mckinsey 7-S framework model (McGrath and Bates 2013) as a new technique for integrating EE and BEP into the key dimensions of organisations. It advocated that organisations should focus on BEP as central attitudes and beliefs in putting climate change at the core of the business and stemming the consequences of climate change.

Extant literature reviewed in this paper has identified EE drivers, barriers and decision-support solutions, and the several issues affecting BEP in Nigeria and the UK, hence the need for developing a new BEP. The premise is that occupants are the centre of buildings' energy use and global CO_2 emissions. Despite the increasing innovations in EE policy, building management systems and renewable energy technologies, there is an increase in global energy demand and CO_2 emissions. One of the reseasons is that the focus of organisations' management often shifts away from the management of these interventions installed in commercial buildings. Having a BEP model as a tool is not enough as an operational-based model. There should be an internalised EE strategy that can drive management policies and operational EE interventions (for monitoring and control) (Mafimisebi et al. 2018). Consequently, this study proposes a BEP model (Figure 1) based on the management technique that enables organisations to have building energy efficiency (BEE) and BEP as commonly shared values among management. The BEP model simplified BEE assessment and management for integrating global advancements in reducing energy demand.

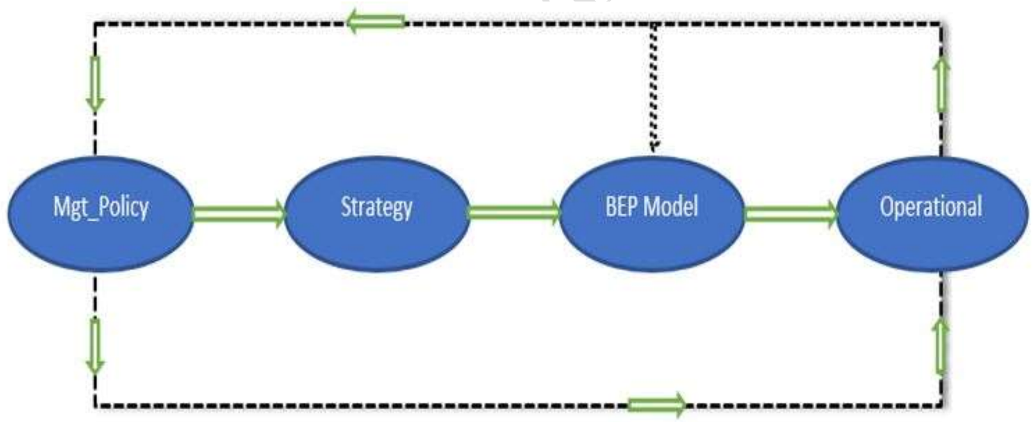

Figure 1: Conceptual Model for BEP

In the BEP model (Figure 1), the management policy represents the organisation's plan as strategy actions for achieving BEP improvement. This paper argues that strategic sustainability policy (SSP), strategic facilities management (SFM) and strategic energy management (SEM) policies are the critical measurable indicators of organisation commitment to EE and climate change challenges. Hence, these policies should be part of the core management policy of the organisation. The strategic drivers are the dedicated internal structure and specialised staff for the organisations' BEP. The premise is that interventions such as standardised energy performance metrics (PMs) and key indicators (KPIs), installed renewable energy technologies (RETOs, building energy technologies (BEMTechs), SEM (staffing), and combined SSP and SFM is vital for driving BEP improvement; while the regular energy assessment, audit and the use of energy modelling techniques underpin the success of an operational energy management process. Also, this study has identified that policy framework, operational process, sustainable building management underpinned by the built asset management policy, common EE barriers and/ drivers, available low-zero carbon solutions and climate as the critical factors that determine office BEP, hence, indicators for the BEP sub-model.

Often time, the choice of these techniques and their implementation are fragmented. The best path to maximise utilised data (quantitative and qualitative) across countries, is to combine the central BEP sub-model data with other sub-models' data (policy, strategy, and operational procedure) as a single measurement model. Here, the four constructs and their indicators (as sub-models) were merged to form a unique 4-factor measurement model. The merger helps to achieve BEP improvement, and this aligned with the Shewhart's plan-do-check-act model (McGrath and Bates 2013). It allows the strategic drivers (dedicated specialist staff) to anticipate and tackle energy use problems using results from BEP model and the operational management process. The aim is to determine if identified management, operational and strategic drivers for improving BEP fit into a structural equation measurement model and thus, ascertain if the constructs and their indicators (measurement model) fit the theoretical model.

Methods

This paper formed part of a broader research project on the development of a BEP assessment model based on its framework measured variables. It adopted the quantitative approach embedded with the multiple-case technique of inquiry as to its research design. The reason being that the circumstance of BEP across countries involves more variables of interest than the data points, and researchers have no control over these circumstances, unlike a laboratory experiment with few variables. Hence, the need for the adaptation of multiple sources of evidence and prior development of a theoretical proposition to guide data collection and analysis (Yin, 2014) in this paper. This study employed a literature review of the identifiable factors influencing BEP globally. The strategy of inquiry helped in obtaining prior knowledge and an in-depth investigation into case buildings' occupants, owners, and facilities managers (FMs) perceptions of office BEP, organisation's policy, and EE programmes. Also, the survey is limited to contemporary variables and not historical phenomenon (actual energy used data), hence these factors aid in accounting for variances in the heterogeneous nature of the study, and in collecting data from multiple sources in Nigeria and the UK.

Survey Design

The survey design involved the use of a questionnaire administered to respondents through the online survey-monkey platform. The online questionnaire survey helps to acquire data on the critical factors influencing BEP derived from the extensive literature review. The choice of the online self-administered survey ensures neutrality and reliability of the data collected. The web-based self-administered questionnaire helps remove respondents' conscious reaction, which could be a source of bias associated with questionnaire administration (Choi and Pak, 2005). Braekman *et al.* (2019) also confirmed that an online self-administered questionnaire increases the chances of getting more response than other techniques. In this study, to reduce non-response bias and achieve easy access in the survey administration, the occupants of case buildings are chosen as the participants. The elimination of restricted access to participants, reduction of non-response bias and conscious reaction from respondents, increased the accuracy of the measurement technique. Furthermore, this study used the 5-point Likert Scale as a measure used to rank respondents' perceptions for each factor, which allows several responses to the same questions (Meng et al. 2019). Thus, the findings reported in this paper can be applied to related research and phenomenon known to be applicable at a general level.

Case-study buildings are selected to achieve the same sampling frame and replication logic using the model presented in this paper. This study adopted a convenience survey and snowballing technique as a method for identifying participating organisations, workers and students. First, the issue of access to participants in commercial buildings in two geographical locations was complicated; hence, Nigeria and the United Kingdom were chosen based on a convenience survey. Another difficulty encountered was getting homogenous case buildings as samples in the same location. In overcoming this challenge, the selection of study case-study buildings was based on purposive sampling technique, and criteria such as access to participants, the same location but different climate zone, building typology, size and year of construction and building operational sustainability, occupancy and energy consumption were the basis for selecting sampled case buildings. In achieving these criteria, this study used five selected buildings in Lagos, Nigeria and another five in Chelmsford, the UK for the survey. The Nigeria buildings were mainly office buildings used for commercial purpose while the UK buildings were educational buildings used for offices and lecture purposes. Although this gives heterogeneous case buildings for the study, this paper model provides a replication logic for the survey in collecting the same data in two countries.

Survey Technique

Participants in the survey were occupants of five case buildings each in Nigeria and the UK, and in ensuring validity, sampled case buildings were of the same office building stock in both countries. The occupancy criteria are that the participants must be a staff of the organisation, staff (scholars) and students of the University within the case-study buildings and with good experience of the case building for at least a year. The staff of organisations, students and scholars of the University, make a category of the respondents as employees representing the perspective of users (occupants) of the sampled buildings. Also, the Owners/ chief executive officers (CEOs) sampled represented the commercial building owner's perspective. While the FMs / Maintenance managers (Mgrs) participation serve as a professional view on BEP. These factors informed the demographic and the sample size obtained from this study survey. The current paper used the snowballing sampling method for identifying participating organisations, workers and students within the selected case-study buildings. A formal letter of introduction and consent form were sent to the Owners/ CEOs and FMs/ Mgrs of the organisations within case buildings. The CEOs and the FMs sent emails to staff and students within case-building seeking voluntary participation, which eventually determined the response rate the sampled size of this paper survey, as illustrated in Table 1.

Table 1: Respondents in the Online Survey	
Countries	Nigeria & the United Kingdom
No of Case Buildings	10
Building Typology	Office/ Educational
No of Staff/ Students/scholars	149
Owners/ CEOs	11
FMs/ Maintenance Managers	13
Sample Size	180
Response	120
Rate of Response	67%

Also, some of the sampled case-study buildings have more than one organisation and FMs/ Mgrs responsible for each case building. Consequently, the number of organisations within a case-study building and that of FMs/ Mgrs accountable for the building determined the FMs/ Mgrs and Owners/ CEO sampled in the survey reported in this paper.

Structural Equation Modelling Protocol

This paper used the SEQM technique in analysing BEP in Nigeria and the UK. The SEQM has the advantage of capturing errors in observed variables (endogenous and exogenous), which traditional regression technique cannot do. Extant literature (Moshagen and Auerswald, 2018) has expounded on the standard protocol for the SEQM. The procedure adopted in this paper involves a three-step approach, namely: data screening, a factor reduction process using exploratory factor analysis (EFA) with IBM SPSS22; and IBM AMOS 23 for performing the SEQM via the maximum likelihood (ML) estimation method. The steps below are engaged in fulfilling SEQM protocol.

Step 1: Data Screening and Missing Values

The first step was the screening of the dataset from 120 respondents for missing data. According to Hartwell et al. (2019), the missingness of data should be explored in ascertaining its pattern. Hence, this study used the IBM SPSS 22 for patterns analysis to determine whether it is systematic or random using multiple imputations (Hartwell et al. 2019).

Step 2: Model Fitness and Reliability Assessment

In the second step, this study test how the processed data fit the intended model and its reliability. This paper used the Kaiser-Meyer-Olkin (KMO) measure for the adequacy of the sample and Bartlett's test of Sphericity to test the study's factors (Chan et al. 2010). A KMO statistics value ranges between 0 and 1.0. The acceptable value for KMO is a threshold higher than 0.50, which could confirm the pattern of variables correlation and if intended EFA will yield a good result (Shi et al. 2016). While Bartlett's test of Sphericity helps to examine associations among the observed variables and confirm if EFA is appropriate for the proposed model (Chan et al. 2010).

Step 3: Exploratory Factor Analysis

The next step is the subjection of the study variables to exploratory factor analysis (EFA). This paper used EFA to examine the relations between the observed variables and the underlying constructs. As recommended by Chou et al. (2015), Cronbach's alpha co-efficiency was used to measure the observed variables' internal consistency and reliability, including the average correlation for measured variables under each construct using identified pattern matrix. A conservative limit of equal to or greater than 0.70 is reliable. Hence, a Cronbach's alpha value higher than 0.70 is an excellent reliability scale.

Step 4: Test for Model Factorial Validity

The study further performed the test for model factorial validity for all variables as the fourth step. The assumption that all measured items should be related was tested to know if there is a relationship among measured variables under a given construct. The average variance extracted (AVE) and composite reliability (CR) were used in proving convergent validity (Chou et al. 2015). The AVE measures the variance captured by a construct about the variance due to measurement error. It is derived as the mean extracted variance of the indicator loadings for a construct, which summaries the index of convergence. This study used the CR in measuring the overall internal consistency of indicators to a construct, as it indicates the reliability of a collection of heterogeneous but similar variables. While the factor loading (FL) shows the correlation between the measured items and their underlying construct. According to Chou et al. (2015), a good FL estimate ranges from 0.50 to 1.0, and a variance of 0.50 or higher indicates satisfactory convergence. Also, this paper used discriminant validity to ensures that those factors that are not supposed to be associated, are not associated and that there is no problem of cross-loading (Lowry et al. 2015).

Step 5: Confirmatory factor analysis- Model Fit Test

The fifth step was the confirmatory factor analysis (CFA) used in testing model fits. The CFA helps to examine models' specification and modification in improving their fits to the collected data (Tarka 2018). Model fit criteria and validation tests were performed on the single-factor and four-factor measurement models in meeting requirement for CFA procedure. The result presented in this paper was obtained using the Normalised Chi-Square (CMIN/DF), CFI (Comparative Fit Index), GFI (Goodness of Fit), RMSEA (Root-mean-square error of approximation), IFI (Increment Fit Index), TLI (Trucker Lewis Index), and standardised RMR (Root-square-mean error) as a range of selected fits based on best practice across previous studies (Moshagen and Auerswald 2018; Li 2019).

Step 6: Confirmatory factor analysis- Cross-Validation

As the final step, this study used CFA to cross-check the four-factor measurement model constructs and factors' consistency with the EFA result based on collected data, factor loading, correlation, square multiple-correlation, reliability and validity (Ibid).

Results and Discussion

This paper presents the analyses of the results based on the screened data, descriptive statistics and the EFA for measurement model identification and specification. The report also includes CFA for the structural model modification and specification that examines the factors' structure in the hypothesised measurement model and the final cross-checking of EFA with the CFA results.

Screened Data

The data screening used multiple imputation process in dealing with missing data to ensure reliability, increase validity and internal consistency for analysed data. This study replaced missing data by the most frequently observed data using the IBM SPSS algorithm. The Markov Chain Monte Carlo method (MCMC) estimation formed the basis of convergence for replacing the missing values with simple means (Armstrong and Overton 1977), and just as suggested by Kim et al. (2019), its model forms the criterion of the central trend. The study performed a twenty-five iteration in achieving the best fit for all the missing values in the 120 samples size. However, the twenty-five iterations used in the best fit is more than the typical five iterations recommended for multiple imputation process. Kim et al. (2019), observed that this anomaly could be due to complication association between data in the dataset.

Furthermore, based on Armstrong and Overton (1977) recommendation, this study also tested the hypothesis that the study's data are not missing at random using the MCAR test. The result with five imputations indicated the little's MCAR test Chi-Square of ~ 1539.455 at p-value~ 0.182 significance level through the expectation maximisation algorithm. The MCAR test recorded a non-significant p-value higher than 0.050 significance level. The missing values indicated minor tenancy showed that all missing values are missing at random (Armstrong and Overton 1977; Sen et al. 2015).

Descriptive statistics

The descriptive statistics result indicates that all study variables' kurtosis values range from -0.127 to +3.398, but less than 7.0 in absolute value. The variables skewness also lies between -2 and +2, and are negatively skewed ~ value ranges from -0.180 to -1.219. According to Byrne (2010), the standard rule of thumb is that skewness value should be within -2 to +2 range, and absolute kurtosis should be less than 7.0 for the endogenous variable normality test to be acceptable. The current study endogenous variables normality is accepted as the variables absolute kurtosis is less than 7, and the value of skewness was between -2 and +2 (Byrne 2010). The endogenous variables in this study fulfilled the normality test. Hence they are acceptable. Also, the study performed a test for the assumption of multicollinearity using variance inflation factors (VIF) for detecting the severity of variables' multicollinearity. The multicollinearity test helps to look at the extent to which other variables in the equation can explain an explanatory variable. Although, it is difficult for explanatory variables to be uncorrelated, however, their VIF should be within the acceptable threshold (1.000-5.000). The VIF result shows values between 2.324 and 3.740, confirming that this study variable satisfied the assumption of multicollinearity (Lallmahamood 2007).

The result obtained shows KMO values of 0.700 to 0.900. The adequate least KMO test is 0.50; value 0.7 and 0.80 is good, and 0.9 and above is excellent. The KMO result reveals that the variables' correlation is compact, and the EFA result will be reliable, while Bartlett's test of Sphericity result is substantial between 186.490 and 425.264 and significance at 0.000. According to Chan et al. (2010), large Bartlett's test of Sphericity reinforces the appropriateness of EFA for the study variables, and that the examined variables are reliable and proper. Likewise, the results for sampling adequacy based on EFA pattern matrix (Table 2) shows that the observed variables used in measuring each construct, all measured the same construct. The constructs obtained factor-loading of 0.737 to 0.828 that is greater than the recommended 0.700 (Sen, Roy and Pal, 2015).

Furthermore, a two-stage approach for analysing the processed data was employed. First, the study conducted an EFA to check the consistency and adequacy of observed variables with their respective constructs; then run a CFA using model fit criteria and corresponding factor analysis from the CFA to cross-validate the EFA results (Li 2019).

Table 2: Pattern Matrix for Measurement Model based on EFA

	BEP MODEL	STRAT_DRIV	OPERATIONAL	MGT. POLICY
Indicators:				
Policy.Frmwk	0.866			
Operational	0.774			
SBM.BAM	0.747			
BAR.DRI	0.743			
LZC.Solns	0.663			
Climate	0.627			
SEM_1		0.936		
BEMTechs		0.846		
PMs.KPIs		0.842		
RETOs		0.784		
SSP.SFM		0.733		
Assessment			0.977	
Energy. Audit			0.821	
Model. Use			0.657	
SFM				0.954
SSP				0.752
SEM				0.730
Sum of Factor's Loadings	4.420	4.140	2.455	2.443
Average Factors' Loadings	0.737	0.828	0.818	0.814
AVE (%) Average Variance Extracted	0.543	0.686	0.669	0.663

Exploratory Factor Analysis for Model Specification and Identification

The study reported in this paper performed the reliability and validity tests using composite and factorial validity for the 4-factor measurement model (shown in Figure 2). The EFA results indicate that the measured variables identified their constructs and are well specified, adequate convergence is also confirmed, and there is no problematic cross-loading (shown in Table 2). The Cronbach alpha coefficient for the extracted four factors: operational (0.881), managerial (0.875) BEP-Model (0.881) including the strategic driver (0.924) are higher than 0.70, which shows excellent reliability within the constructs (Li, 2019). The results of factorial validity for the convergence test using the indicators' factor loading (FL) indicates that there is adequate convergence, as most FL is higher than 0.7. Also, the factors' AVE is higher than the recommended 0.50, while the factors' average FL are likewise higher than 0.70 demonstrating excellent construct reliability (CR) (Chou et al. 2015).

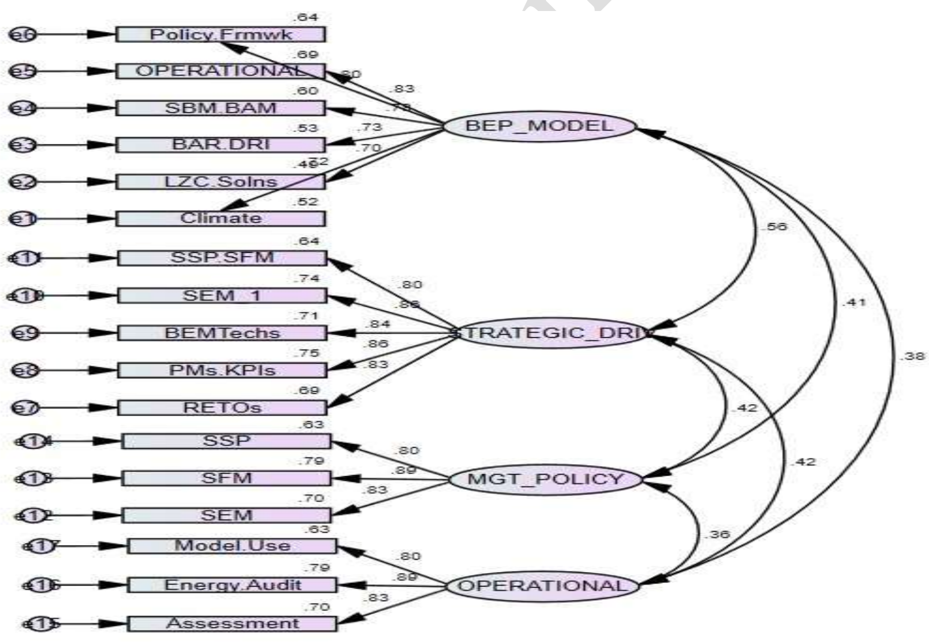

Figure 2: 4-Factor Measurement Model

The result confirms that policy framework, operational energy management, sustainable building management based on the built asset management, identifiable EE barriers and drivers, low-zero carbon solutions, and climate zone accurately measured the BEP_model as indicators (Figure 2). Likewise, strategic energy management policy, combined strategic sustainability policy/ facilities management, building energy management technologies, use of renewable energy technologies and EE performance metrics/ key performance indicators are a good measure of an organisation strategic drives for improving BEP. Additionally, dedicated EE management policies such as strategic energy management, sustainability and facilities management policies indicate that the organisation is committed to enhancing BEP while the efficacy of an organisation and BEP operations management depends on the use of a robust model, regular energy audits and assessment (Dávi et al. 2017).

For the discriminant validity test, the result obtained through the factor correlation matrix indicates a positive correlation between the constructs, as their FL is higher than the 0.70, therefore no problematic cross-loading. The strategic_driv has the most active association with BEP_model (0.550) and the weakest with operational (0.239).

Confirmatory Factor Analysis for the Structure of the Models

Confirmatory factor analysis was carried out to investigate the structures of the four sub-models and the measurement model (Figure 2). The CFA was carried out in two parts, first on the construct sub-models, and secondly, on the 4-factor measurement model as single-factor and four-factor tools for measuring BEP. The CFA was used to examine the models' consistency with the collected data based on the model fits the criteria explained in this paper.

The result of CFA (Table 3) based on the selected fits criteria shows a good model fit manifestation. The normalised Chi-square for the single-factor (sub-model) and the 4-factor solution models (MM) were satisfactory though most are significantly less than 0.50 p-value. Still, the 4-factor solution (MM) indicates a recursive measurement model, showing its dependent variables can forecast each other. For the single-factor solutions, the result (CMIN/DF= 0.751, GFI= 0.994, TLI= 1.010 & SRMR= 0.018) for the independent BEP sub-model with modification is deemed acceptable and fit into collected data. The operational sub-model result (CMIN/DF= 6.962, GFI= 0.963, TLI= 0.913 & SRMR= 0.040) is poor and could be improved upon. Nevertheless, the results for Mgt_Policy (CMIN/DF= 0.001, GFI= 1.000, TLI= 1.016 & SRMR= 0.000) and Strat_Driv (CMIN/DF= 0.396, GFI= 0.994, TLI= 1.014 & SRMR= 0.010) shows adequate goodness of fit without modification (Tarka 2018).

Table 3: Models' Fit Result- Single-Factor (Construct or Sub-model) & Measurement Model (MM)

Fits Criteria	Threshold	BEP. model	Operational	Mgt_Policy	Strat_Driv	MM	Remark
CMIN/DF	<3.000	0.751	6.962	0.001	0.396	1.455	Fitting
P-Value	>0.050	0.522	0.008	0.980	0.852	0.001	Fitting
CFI	>0.950	1.000	0.971	1.000	1.000	0.961	Fitting
GFI	>0.950	0.994	0.963	1.000	0.994	0.869	Fitting
RMSEA	<0.050	0.000	0.224	0.000	0.000	0.062	Fitting
PCLOSE	>0.050	0.637	0.019	0.983	0.915	0.171	Fitting
IFI	>0.900	1.002	0.971	1.005	1.007	0.962	Fitting
TLI	close to 1.000	1.010	0.913	1.016	1.014	0.954	Fitting
SRMR	Value <0.080	0.018	0.040	0.000	0.010	0.074	Fitting

The single-factor sub-models were unified to form the 4-factor measurement model as a solution tool for measuring the effectiveness of BEP improvement interventions. The result of a 4-factor solution indicates improved goodness of fit (CMIN/DF= 1.455 with a p-value less than 0.05, GFI= 0.869) while the comparative fit index: CFI (0.961), IFI (0.962), and TLI (0.954) shows a good model fit. Also, the RMSEA is 0.065 with p-value = 0.171 proved good model fit.

Validation of the Measurement Model

For validation of the new 4-factor solution model, this study used the CFA result based on factor loading (FL), composite reliability (CR), correlations squared (r^2), and AVE to cross-check the EFA result in examining the structure of the model. The result of the reliability test (0.881 to 0.924) for the 4-factor measurement model indicated that the variables under each construct are reliable and highly correlated, which support their use as reflective and interchangeable indicators. Likewise, the convergent validity result shows that the observed variables used in measuring each construct all measured the same construct. The Cronbach alpha values (factor loading- FL) for each variable under each construct exceeds the minimum loading of 0.50, and each construct composite reliability (CR) score ranges from 0.717 to 0.822; both values for FL and CR are higher than the recommended threshold of 0.70 as stated by Zhao, Pan and Chen (2018). The result obtained establishes the reliability and validity of the data collected. Also, the result for their AVE (0.513 to 0.680) is higher than 0.500, and CR shows that the structure of the 4-factor solution is compact and well specified, confirming convergent as indicated in the EFA result (Li 2019).

Table 4: Discriminant Validity for Measurement Model (MM)				
Discriminant Validity	Factor-Correlation (r)	(r^2)	AVE 1: AVE 2 (AVEs > r^2)	Validity
BEP_Model - STRAT_DRIV	0.596	0.355	0.513: 0.676	Confirmed
STRAT_DRIV - MGL_POLICY	0.442	0.195	0.676: 0.680	Confirmed
BEP_Model – OPERATIONAL	0.473	0.224	0.513: 0.680	Confirmed
STRAT_DRIV – OPERATIONAL	0.442	0.195	0.686: 0.680	Confirmed
MGL_POLICY – OPERATIONAL	0.454	0.206	0.680: 0.680	Confirmed

This study used the Chou et al. (2015) criterion for discriminant validity as a basis for the cross-examination of the 4-factor model structure. The discriminant validity test ensures that constructs are distinct from one another and that they separately measured what they are intended to measure. The result (Table 4) indicates that each construct shared more variance with its indicators than with any other construct because the AVE of each construct is higher than the highest squared correlation (r^2) with any other construct (Chou et al. 2015). For example, the squared correlation (r^2) between BEP_model and Strat_driv (0.355) is lower than the AVEs for each construct (0.513: 0.676). Moreover, the single-factor models are also associated; the strongest correlation is between BEP_model and Strat_driv (r=0.596 & r^2=0.355 as it meets the minimum threshold of 0.500 (Ibid). Similarly, the relationship between BEP_model and Operational (r=0.473 & r^2=0.224), and that between MGL_Policy and Operational (r= 0.454 & r^2= 0.206) are equally strong. Therefore, the result confirms the existence of discriminant validity that the constructs are measuring separate variables, and there is no issue of cross-loading. Hence the 4-factor solution model could be used for measuring the effectiveness of BEP interventions.

Discussion

Existing literature (Min, Morgenstern and Marjanovic-halburd, 2016) has established that SEM, SFM, SSP influences BEP; however, they are identified individually. The congregation of these factors into different underlying constructs is one the strength of this current paper. For example, until segregated management policies (SEM, SFM, SSP) are aggregated as a core integral part of the organisation policy, it will be difficult for intended energy intervention policies to have a positive impact on BEE. Previous studies have advanced these relationships. Patterson (1996) advocates for a subset of indicators for measuring the concept of EE, but Kanneganti et al. (2017) emphasised the need for SEM as MGT policy and use of operations plan as ways of achieving EE. Other studies (Gliedt and Hoicka 2015; Dávi et al. 2017) have advocated for investment in Strategic FM, BEMTechs, RETOs, LZC to mitigate climate change, and proved that these variables are associated and impacts on BEP. Mafimisebi et al. (2018) argue that SSP.SFM underpinned the sustainable management of the organisation-built asset and improve the performance of office BEE.

Several EE drivers have been expounded in existing literature (Shaikh et al. 2017) but, their implementations as interventions for BEP have been fragmented over the years. This paper establishes through the EFA and SEQM, how an integrated subset of strategic drivers managed by dedicated staff structure in the organisation could result in improving office BEP. It can link strategic plan, method and process. Jones and Sharp (2007) also argued that benchmarking studies must be related to the strategic plan process and focus on understanding the method and process rather than just metrics, for it to be meaningful.

The use of several modelling tools, assessment techniques/ procedure, the energy audit process has been advanced as aiding improvement in BEP. Both analytical and quantitative modelling of owner decision-making has been linked to stimulating EE renovation decision (Wilson et al. 2018). However, these have yielded low impact due to fragmentation in their implementations. For example, in the current paper, the operational sub-construct indicated a poor independent fit before the merger into the 4-factor model. The resultant EFA and SEQM results showed a better fit and the need for integration of the fragmented operation energy management solutions with other critical success factors for improving BEP to maximise the desired result.

Part of the highlight of this paper is that the BEP assessment model satisfied most of the assumption and validation test procedures for EFA and SEQM. The results showed that the latent sub-construct models and the 4-factor measurement model fit into this paper's proposition. Extant literature (Wang et al. 2017; Kotireddy et al. 2018) have supported the use of multi-criteria decision-making models that consider all the contextual factors (climate zone, policy framework, an organisation sustainable building management- built asset management policy, EE barriers and drivers, low-zero carbon technology) separately as indicators of a high performing building. However, the current study model combined these identified factors and specified them, as the latent factors and the manifest variables are well lined up and identified. The new model is a 4-factor solution model with four constructs for evaluating BEP interventions.

Conclusions

This study found that corporations require innovative management strategies to achieve BEP improvement. The findings resulted in an evaluation tool that identified factors that could help indicate EE requirements, possible low-zero carbon interventions and action-based monitoring technique that will result in increasing EE. The BEP solution model could aid improved energy management and auditing efficiency for the organisation's built-asset stocks. Also, this study resulted in a tool that is based on organisation systems, dedicated BEP structure, skilled staff in EE, performing strategic EE functions and commonly shared valued that embeds the EE and environmental sustainability in combating climate change. Specifically,

- The findings proved that the measurement model fits the theoretical model. The result confirmed high correlations between observed variables of the model.

- The result confirms a strong factor-correlation among the constructs in the model. The BEP_Model- STRAT_DRIV (0.596) has the highest and BEP_Model-MGT_POLICY (0.426) has the lowest, indicating that the constructs are perfect measurements of BEP that could be used for office BEP assessment

- The SSP.SFM variable is found to be highly correlated with almost 60.0% of all observed variable, resulting as the critical underpinning variable in the overall BEP model. It helps to extend facilities management theories by depicting the crucial role of strategic drivers for improving BEP.

- The findings present a procedure for analysis of the contemporary issues that affect building energy efficiency, which serves as a tool for performing BEP assessment.

- As an innovation, this paper advanced the combination of structural modelling with standardised assessments performance metrics to derive a model that was eventually validated. The theoretical model helps harmonise several assessment tools and techniques available for addressing contentious energy performance monitoring and management in contemporary BEP discourse.

- ❖ Methodologically, this paper presented a BEP assessment procedure based on Exploratory Factor analysis and SEQM to produce a 4-Factor measurement model for office buildings across countries. Thus, it is possible to incorporate the BEP model into BIM level6 for facilities management utilisation.

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