Engineering Journal issn: 0125-8281

Article

The Impact of Building Façade Reflectivity on Pedestrian Visual Comfort with the Application of Bayesian Structural Equation Modeling

Norishahaini Mohamed Ishak[1,*] **, Hashem Salarzadeh Jenatabadi**[2]**,**
Siti Nurul Ainun Mohd. Mustafa[3]**, and Jamalunlaili Abdullah**[1,2]

1 Faculty of Architecture, Planning and Surveying, Universiti Teknologi MARA Shah Alam, Malaysia
2 Faculty of Science, University Malaya, Malaysia
3 Faculty of Architecture, Planning and Surveying, Universiti Teknologi MARA Sarawak, Malaysia
*E-mail: norish@uitm.edu.my (Corresponding author)

Abstract. The rapid urban development promotes the need for skyscrapers, which vastly adopt a modern architecture design using reflective materials on the façade of the building, particularly for the aesthetic purpose. Nevertheless, outdoor glare or reflected daylight from a highly reflective building façade may cause visual and thermal discomforts for the residents in the neighborhood buildings and outdoor pedestrians. This might cause uncomfortable glare for individuals outside the building. The amount of glare will be higher as a result of greater solar radiation obtained all year round in tropical countries. Regression and presently structural equation modeling are the best-known statistical modeling in approximating the connection between building facade reflectivity and pedestrian's visual performance. Nevertheless, those methodologies have their own limitations. The primary aim of this research is to compare the effect of building facade reflectivity on pedestrian visual comfort by using four core statistical approximation approaches which include regression, partial least square, structural equation modeling with maximum likelihood estimator, and structural equation modeling with Bayesian estimator. The present study introduces a novel as well as practical modeling and predicting concepts for investigators and specialists in the building façade reflectivity study field.

Keywords: Glare, structural equation modeling, Bayesian predictor, maximum likelihood predictor, building façade reflectivity.

ENGINEERING JOURNAL Volume 25 Issue 1
Received 9 June 2020
Accepted 25 November 2020
Published 31 January 2021
Online at https://engj.org/
DOI:10.4186/ej.2021.25.1.211

This article is based on the presentation at the 4th International Conference on Research Methodology for Built Environment and Engineering 2019 (ICRMBEE 2019) in Bangkok, Thailand, 24th-25th April 2019.

DOI:10.4186/ej.2021.25.1.211

1. Introduction

The desires to recognize the properties and features of structure materials is very essential as it has an indirect and direct influence on the environment in the city. The occurrence of light on a surface of a structure causes it to be emitted, absorbed and reflected concurrently. The exterior fragments of the structure either horizontal or vertical have the greatest part to be exposed by solar radiation. The roughness of the surface significantly will be identified when the reflected element is in a diffusive or specular manner. Upon the source of light is being reflected, it has a visual or thermal implication towards the pedestrian comfort_[1-4]. The quantity of light being immersed (albedo) by other means has particularly affected the temperature of the surface of a building and hence increases the consumption of energy for air-conditioning the building which later promotes the issue of urban heat island effect [5-7].

During the last ten years, glass and metal have been chosen as façade finishes for skyscraper building in numerous cities worldwide. Apart from the physical characteristics of these reflective materials, the use of glass from the floor-to the ceiling on the façade happens to be a famous concept in modern construction. The disagreement is that it caters to abundant sunlight and visual contact with the outdoors along with the aesthetic viewpoint. Nevertheless, there is a great environmental impact to all that attraction; increased consumption of energy to counter the heat gain from solar and glare issues for both outdoor and indoor environments. Besides, with greater glazing as well as reflective surfaces, outdoor and indoor glare might cause a problem to the surrounding atmosphere [8-12].

2. Outdoor Glare in Urban Setting

The high number of solar reflective buildings throughout dense urban developments not only alter the microclimate of the surrounding area. Nonetheless, it could also create the problem of outdoor glare. Technically, the large reflective facade is beneficial in retaining sufficient daylight into the indoor space, but the dweller from the outdoor like motorists and pedestrians will suffer visual and thermal discomforts. The reflected glare or light from vertical sides is most clearly on the sheltered side of high-rise buildings, where the daylight is reflected from the un-sheltered light tones wall areas [13-15]. Likewise, convex and concave facades are probable to be great of a problem, as it could reflect upper angle daylight to ground areas and surrounding buildings. It is apparent that the big surfaces of reflecting substances are more probably to result in glare issues than small spaces [16, 17]. An astonishing case study that demonstrates this failure in architecture is the Walt Disney Hall Concert (WDHC) structure [18]. The shimmering façade formed of stainless steel caused the residence, drivers, and pedestrians nearby a major reflected heat and glare discomfort. Subsequently, even a refurbishment work was completed on the stainless-steel facade; the reflected glow still obtains a threat to the environment in surrounding.

The glare from indoors has obtained much consideration from the study scholar rather than the glare from the outdoor. There remains no authorized methodology in identifying the effect of the glare from outdoor in the city setting significantly affecting the dwellers from the outdoor. Several guides could be chased to identify the measure of the glare associated issue in building, for instance, the Daylight Glare Index (DGI) or Daylight Glare Probability (DGP). Thus, any on-site measurement that surpasses the permissible index will be easily examined in the model.

Dissimilar to glare from the outdoor, it remains to be discovered on the effect towards the environment in surrounding. The research on the human subject has been conducted to certify the existence of glare from outdoor issues, and however, the framework is still to be rectified [22]. Identical research has been conducted to study the impact of building façade reflectivity on outdoor visual comfort in the tropical environment [23]. The solar reflectivity research utilizing simulation softwares like Computational Fluid Dynamic (CFD) has been imposed to examine the effect of anticipated glare from the source structure [24]. Additionally, this device affirmed that it precisely forecasts the pathway of reflected light, intensity, and related temperature rise. Nonetheless, it might need a long procedure and require a powerful computer to operate it. Another lacking info in this device is the effect of dwellers' visual comfort from the outdoors.

Building materials have turned increasingly flexible and diverse with regards to their texture, colours and shapes. The strong reflective finished application for facade (e.g. glass or metal claddings) is now a well-known concept for tall buildings in the city of Kuala Lumpur (Fig. 1). Nevertheless, those reflective substances contribute to a rising number of reports related to the problem of reflected glare from outdoors. From the perspective of Malaysia's structure regulation on sunlight reflectance of substances used on architecture exterior, it remains to be imposed. Conceivably, there are no guidelines on the building façade reflectance, particularly through the construction or design procedure. For instance, Singapore has imposed that the sunlight reflectance of substances applied on architecture exterior, from compliance to be 20% and below. It is also stated that the external part of a structure must be projected and formed so that any sunlight reflection off the structure's external area does not damage the amenity to the dwellers and other structures in the neighborhoods. Hence, this research aims to assess the effect of reflective building façade glare on pedestrians' visual comfort in the city of Kuala Lumpur.

Fig. 1. Outdoor glare from reflective building façade.

3. Why Bayesian SEM

Regression modelling, factor analysis, and correlation analysis are the most familiar statistical techniques used to analyze road users' glare. Nevertheless, for the purpose of estimating the dependent or output variables, there are some concerns when using regression analysis. The multicollinearity of independent variables is the main preventable issue of regression analysis. Furthermore, this issue has an effect on separate predictors but no impact on predictive power.

In recent decades, in engineering and other areas of the studies, researchers have been attracted to apply in Structural Equation Modeling (SEM) in their modeling analysis [19]. SEM has been used in many statistical formulas. However, SEM analysis, there are different estimators announced by current modeling analysis. Jenatabadi, Moghavvemi [20] believe that maximum likelihood (ML) is the most familiar estimator among all estimators in SEM technique. Nevertheless, for SEM analysis, ML estimators often suffer from model misspecification because the models are too strict with zero residual correlations, and exact zero cross-loadings and some researchers [21] determined that by applying this estimator it will cause poor outcomes regarding model fitting. The other two studies by Asparouhov and Muthén [22] and Kolenikov [23] reveal that ML estimator has wide parameter bias in factor loadings and factor correlations. Moreover, if the researchers have to face a small sample size or presence of normal distribution among research variables, they have to find another estimator to overcome the hindrances of ML estimators in the SEM analysis. Presently, few scholars like Jenatabadi, Moghavvemi [20] and Wong, Showell [24] recommend Bayesian estimators as an alternative of the ML estimator for modeling analysis based on SEM technique to overcome those restrictions.

4. Methodology

4.1. Research Framework

Figure 2 shows the research framework of the study. In the research framework, the squares (or rectangles;) are representative of measurement variables and circles (or ellipses;) are representative of latent variables. Table 1 presents the symbols and concepts in SEM graphic modelling. In the above Fig. 2, age, glare time, and glare duration are measured variables and act as independent variables, and sensitiveness has measurement structure and is the main dependent variable. Avoidance is a latent variable and acts as a mediator between independent variables and dependent variables.

4.2. Sampling

A cross-sectional research design is used in the current study. To acquire the required data, a cross-sectional research design implements any specified research sample at a given time. Additionally, the researcher neither can provide unsystematic interpretations nor emphasis on development matters. Hair, Black [25] proposed that the smallest sample size relies on basic measurements and model complexity of model features. Hence, it required 100 surveys or more referring to model features with three basic concepts and possibly some of the constructs have less than three items after factor loading analysis (see Table 2).

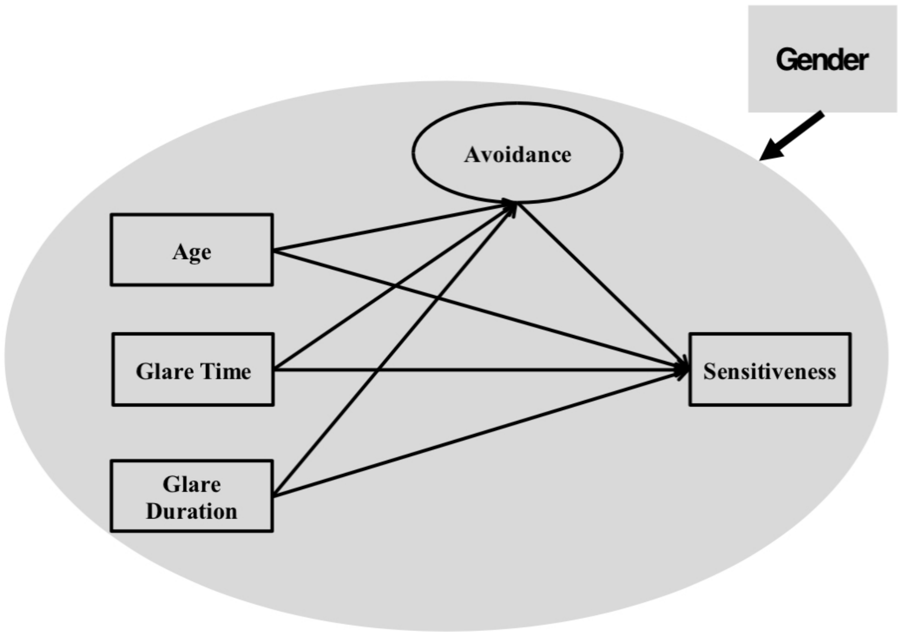


Fig. 2. Research framework.

Table 1. Symbols and concepts in SEM graphic modelling.

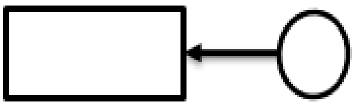
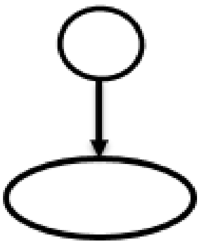
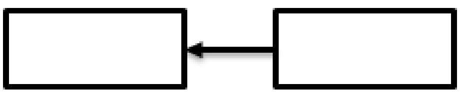
Symbol	Concept
	Displays the term of measurement error connected to an observed factor
	Shows an observed factor's regression path coefficient onto an unobserved or latent factor.
	Represents the residual error term in an unobserved or latent variable's prediction
	Represents a regression model's path coefficient of one factor or variable onto another factor or variable.

Table 2. The minimum sample size required for SEM analysis.

Model Characteristics (Number of Latent Constructs and Items)	**Minimum Sample Required**
1. Research model includes 5 or less latent variables and each latent variable has more than 3 measurement variables.	100 samples
2. Research model includes 7 or less latent variables and each latent variable has more than 3 measurement variables.	150 samples
3. Research model include 7 or less latent variables and some latent variable have less than 3 measurement variables (the identified model)	300 samples
4. Research model includes more than 7 latent variables and latent variable have less than 3 measurement variables (the identified model)	500 samples

In this study, a stratified sampling technique was used for the survey. The population survey was divided into three different sampling areas (locations). These are respectively Jalan Ampang, Jalan Binjai, Jalan Tun Razak and Persiaran KLCC located in the city of Kuala Lumpur. For each zone, about 125 questionnaires were distributed. Therefore, the sample size is equal to 500 (342 questionnaires are prepared from male and 158 questionnaires for female). Data collection was conducted from August 2018 until the end of November 2018.

5. Data Analysis

5.1. Fitting Model Analysis

In analysing the model fit using SEM, six statistical indices were used. These were GFI [goodness-of-fit index], NFI [normed fit index], IFI [incremental fit index], RFI [relative fit index], TLI [Tucker Lewis index], and CFI [comparative fit index]. Figure 3 shows the output of the model fitting indices based on the SEM approach. The values of all indices were within the acceptable range. Hence, the present framework, which is presented in Fig. 1 is a good fit for acquired data.

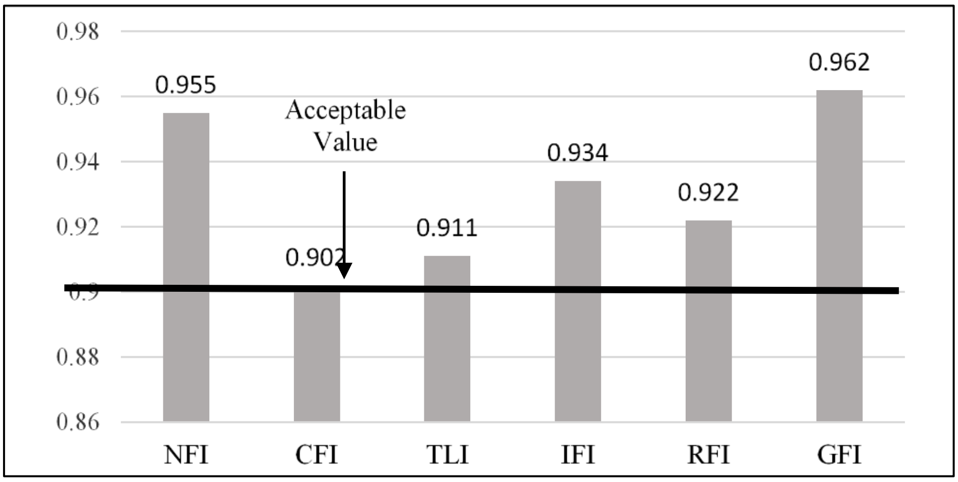


Fig. 3. Fitting Analysis.

From the study, for all the six indices, it shows that the predicted and observed data are within the acceptable range of above 0.9 hence the research framework is accepted.

5.2. Structural Model

The comparison analysis among four statistical models which are regression, partial least square, structural equation model with maximum likelihood estimator, and structural equation modeling with Bayesian estimator has been performed. Chatterjee [26] suggested four statistical modeling that has been adopted in this study namely absolute percentage error, root mean squared error, R^2 and mean absolute error which are presented by Eq. (1)-(4).

$$Mean\ Absolute\ Error = \frac{\sum_{i=1}^{n} |y_i^{\prime} - y_i|}{n} \quad (1)$$

$$R^2 = \frac{[\sum_{i=1}^{n} \left(y_i^{\prime} - \underline{y_i^{\prime}}\right) . (y_i - \underline{y_i})]^2}{\sum_{i=1}^{n} \left(y_i^{\prime} - \underline{y_i^{\prime}}\right) . \sum_{i=1}^{n} (y_i - \underline{y_i})} \quad (2)$$

$$Mean\ Absolute\ Percentage\ Error = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{y_i^{\prime} - y_i}{y_i}\right| \quad (3)$$

$$Root\ Mean\ Squared\ Error = \sqrt[2]{\frac{\sum_{i=1}^{n} (y_i^{\prime} - y_i)^2}{n}}, \quad (4)$$

In the above equations, y_i denotes the *i*th real value of the dependent indicator and $y_i^{\prime}$ is the *i*th predicted value. Table 3 illustrates the performance of the four indices above for the regression, partial least square, structural equation model with maximum likelihood estimator, and structural equation modeling with Bayesian estimator approaches.

Table 3. Comparison analysis of four statistical model

	Performance Indices			
	R^2	Mean Absolute Error	Mean Absolute Percentage Error	Root Mean Squared Error
Regression	0.672	0.342	0.143	0.098
Partial Least Square	0.763	0.299	0.122	0.076
SEM with Maximum Likelihood	0.811	0.251	0.056	0.049
SEM with Bayesian	0.841	0.211	0.021	0.033

The R^2 of SEM with Bayesian estimator is higher than SEM with Maximum likelihood estimator, partial least square, and regression which means that the strength of the relationship between independent variables and the dependent variable in SEM with Bayesian estimator is bigger than the other three statistical models. Moreover, the other three indices (root mean squared error, mean absolute percentage error and mean absolute error) values for the SEM with Bayesian estimator (0.211; 0.021; 0.033) are less than for SEM with maximum likelihood estimator (0.251; 0.056; 0.049), partial least square (0.299, 0.122, 0.076), and regression (0.342, 0.143, 0.098) . Consequently, it is more accurate to apply the SEM with Bayesian estimator to predict dependent variable index rather than regression, partial least square, structural equation model with maximum likelihood estimator.

The next part of data analysis to do a comparison analysis between male and female based on SEM with Bayesian predictor. Figure 4 shows the two models of male and female.

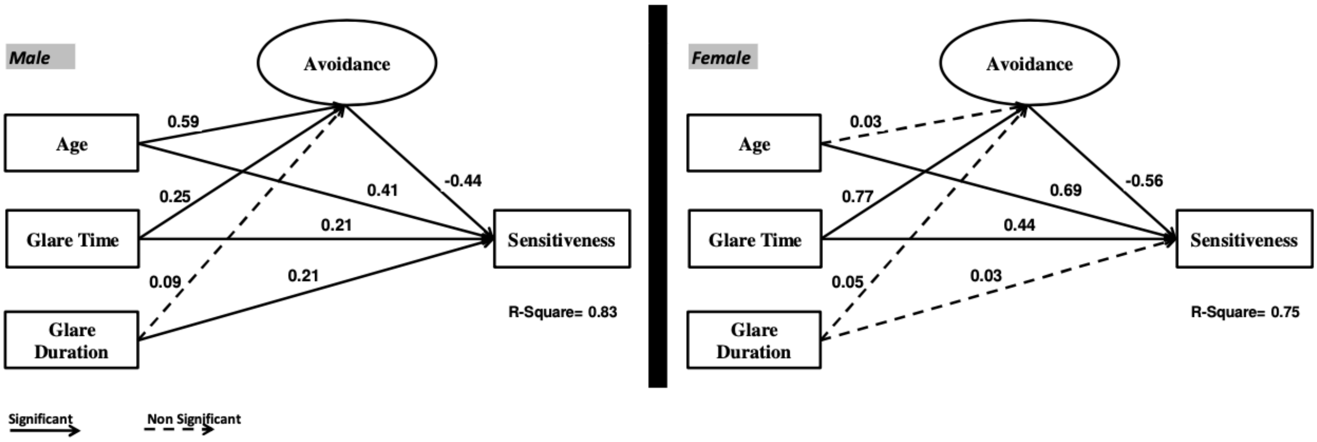


Fig. 4. Research model among male and female.

6. Discussion

This study aims to examine a multi-factorial model for the relationship between pedestrians and outdoor glare issues based on four statistical models which are regression, partial least square, structural equation model with maximum likelihood estimator, and structural equation modeling with Bayesian estimator between male and female. The research framework contains four measurable variables (age, glare time, glare duration, and sensitiveness) and one latent variable (avoidance). The sensitiveness is the main dependent variable; the age of the road users, glare time, and glare duration status are the main independent variables, whereas avoidance is considered the mediator between the dependent and independent variables. Gender is acting as a moderator, which means two different models will be presented in this paper. Moreover, the introduced framework is also designed with improvements from previous modelling studies, using a combination of different relations among research variables.

Based on the SEM with Bayesian predictor output which is presented in Fig. 4, the R-square of the male model (0.83) is higher than the female model (0.75) which indicates the sensitiveness variation is depending on age, glare time, glare duration, and avoidance. Three independent variables have been defined in the research model which are age, glare time, and glare duration. Age in the male model has a significant impact on avoidance (0.59) and sensitiveness (0.41). However, in the female model, age has significant effects on sensitiveness (0.69). Glare time for both models has significant implications on avoidance and sensitiveness. Those impacts, glare time on both avoidance and sensitiveness, for the female model is higher than the male model. In the male model, the impact of glare duration on avoidance is not significant (0.09) but significant towards sensitiveness (0.21). Hence, in the female model glare duration is not a significant effect on both avoidance (0.03) and sensitiveness (0.05). The last relation is about the impact of avoidance on sensitiveness. For both models, this impact is negative and significant, and the value of correlation for a male model (-0.44) is bigger than the female model (-0.56). Another result from SEM with Bayesian estimator analysis is that avoidance, for both models, is a mediator between glare time and sensitiveness. However, mediating of avoidance between age and sensitiveness, glare duration and sensitiveness for both models are rejected.

7. Conclusion

An awareness of the impact of the material's selection between project stakeholders should not be done in isolation. Being in a tropical country, where a large amount of solar insolation occurs, reflected glare from the building façade will have a significant impact on the surrounding environment. Furthermore, heat will also be reflected and cause the ambient temperature to rise and indirectly promotes the issue of urban heat islands. This study presents the application of SEM in modelling the impact of the reflected outdoor glare from reflective building facades by pedestrians in the city of Kuala Lumpur. It is detrimental to understand the behavior and properties of building materials before they can be deployed.

The current paper introduced that the structural equation modeling with Bayesian predictor is deemed to be suitable statistical modeling among other statistical modeling such as regression, partial least square, and structural equation modeling with maximum likelihood predictor. SEM with Bayesian Predictor has been applying in many kinds of areas [27-31]. Lee [32] book, "Structural Equation Modeling: A Bayesian Approach" lists several assistances of considering the SEM with Bayesian predictor as follows:

- *First,* statistical techniques are superior in terms of the first moment attributes of individual raw observations that are simpler than the second moment attributes of the covariance matrix sample. Therefore, this Bayesian predictor is easier to apply in more composite situations.
- *Second*, Bayesian predictor directly estimates latent variables and is considered superior to an old-style of regression approaches.
- *Third*, the Bayesian Predictor is not only for modeling latent variables (unobserved variables) directly through familiar regression functions but it also provides more direct interpretations to conduct statistical analysis. Hence, it can be employed along with the most common regression modeling methods, such as residual and outlier analyses.

In terms of Bayesian approach estimation, Scheines, Hoijtink [33], Dunson [34], and Lee and Song [35] approved that this procedure is able to assist research scholars to operate effective prior information and information available in the observed data. Therefore, it is possible to produce boosted outputs and deliver suitable statistics and indices, e.g. the mean and percentiles of the posterior distribution of unidentified parameters. The Bayesian approach also yields more dependable outcomes for smaller sample sizes.

References

[1] T. Sharmin, et al., "Outdoor thermal comfort and summer PET range: A field study in tropical city Dhaka," *Energy and Buildings*, vol. 198, pp. 149-159, 2019.

[2] M. M. Baruti, E. Johansson, and J. Åstrand, "Review of studies on outdoor thermal comfort in warm humid climates: challenges of informal urban fabric," *International Journal of Biometeorology*, vol. 63, no. 10, pp. 1449-1462, 2019.

[3] J. A. Acero, et al., "Clustering weather types for urban outdoor thermal comfort evaluation in a tropical area," *Theoretical and Applied Climatology*, vol. 139, no. 1-2, pp. 659-675, 2020.

[4] P. K. Cheung and C. Y. Jim, "Subjective outdoor thermal comfort and urban green space usage in humid-subtropical Hong Kong," *Energy and Buildings*, vol. 173, pp. 150-162, 2018.

[5] K. Mihara, et al., "Thermal comfort and energy performance of a dedicated outdoor air system with ceiling fans in hot and humid climate," *Energy and Buildings*, vol. 203, p.109448, 2019.

[6] C. W. Kwon, K. J. Lee, and S. J. S. Cho, "Numerical study of balancing between indoor building energy and outdoor thermal comfort with a flexible building element," *Sustainability*, vol. 11, no. 23, p. 6654, 2019.

[7] A. Scognamiglio and F. Garde, "Photovoltaics' architectural and landscape design options for net zero energy buildings, towards net zero energy communities: Spatial features and outdoor thermal comfort related considerations, *Progress in Photovoltaics: Research and Applications*, vol. 24, no. 4, pp. 477-495, 2016.

[8] T. Koch, M. Korner, and F. Fraundorfer. "Automatic alignment of indoor and outdoor building models using 3D line segments," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 2016.

[9] J. Y. Suk, et al., "Absolute glare factor and relative glare factor based metric: Predicting and quantifying levels of daylight glare in office space," *Energy and Buildings*, vol. 130, pp. 8-19, 2016.

[10] J.Y. Suk, et al., "Investigation of existing discomfort glare indices using human subject study data," *Building and Environment*, vol. 113, pp. 121-130, 2017.

[11] R. Danks and J. Good. "Urban scale simulations of solar reflections in the built environment: Methodology and validation, in *2016 Proceedings of the Symposium on Simulation for Architecture and Urban Design. London*, 2016.

[12] T. Theodosiou, et al., "Thermal bridging problems on advanced cladding systems and smart building

facades," *Journal of Cleaner Production*, vol. 214, pp. 62-69, 2019.

[13] M. Hirning, et al., "Post occupancy evaluations relating to discomfort glare: A study of green buildings in Brisbane," *Building and Environment*, vol. 59, pp. 349-357, 2013.

[14] V. L. R. Gil, "Evaluation of solar glare from reflective facades: A general method," *Lighting Research & Technology*, vol. 48, no. 5, pp. 521-538, 2016.

[15] M. Hirning, et al., "Discomfort glare in open plan green buildings," *Energy and Buildings*, vol. 70, pp. 427-440, 2014.

[16] M. Schiler and E. Valmont, "Microclimatic impact: Glare around the Walt Disney Concert Hall," in *Proceedings of the Solar World Congress 2005 Joint American Solar Energy Society/International Solar Energy Society Conference*, 2005.

[17] M. Hirning, G. Lim, and G. Reimann, "Discomfort glare in energy efficient buildings: A case study in the malaysian context," in *Proceedings of CIE*, 2016.

[18] M. Schiler, "Examples of glare remediation techniques: four buildings," in *26th Conference on Passive and Low Energy Architecture*, 2009, Quebec City, Canada.

[19] T. Wossen and T. Berger, "Climate variability, food security and poverty: Agent-based assessment of policy options for farm households in Northern Ghana," *Environmental Science & Policy*, vol. 47, pp. 95-107, 2015.

[20] H. S. Jenatabadi, et al., "Testing students' e-learning via Facebook through Bayesian structural equation modeling," *PloS One*, vol. 12, no. 9, p. e0182311, 2017.

[21] D. A. Cole, J. A. Ciesla, and J. H. Steiger, "The insidious effects of failing to include design-driven correlated residuals in latent-variable covariance structure analysis," *Psychological Methods*, vol. 12, no. 4, 2007.

[22] T. Asparouhov and B. Muthén, "Exploratory structural equation modelling," *Structural Equation Modeling: A Multidisciplinary Journal*, vol. 16, no. 3, pp. 397-438, 2009.

[23] S. Kolenikov, "Biases of parameter estimates in misspecified structural equation models," *Sociological Methodology*, vol. 41, no. 1, pp. 119-157, 2011.

[24] M. S. Wong, et al., "The association between parent-reported provider communication quality and child obesity status: Variation by parent obesity and child race/ethnicity," *Patient Education and Counseling*, vol. 100, no. 8, pp. 1588-1597, 2017.

[25] J. Hair, et al., *Multivariate Data Analysis: Pearson New International Edition*. New Jersey: Pearson/Prentice Hall, 2014.

[26] S. Chatterjee, "Development of uncertainty-based work injury model using Bayesian structural equation modelling," *International Journal of Injury Control and Safety Promotion*, vol. 21, no. 4, pp. 318-327, 2014.

[27] J. Guo, et al., "A systematic evaluation and comparison between exploratory structural equation modeling and Bayesian structural equation modelling," *Structural Equation Modeling: A Multidisciplinary Journal*, vol. 26, no. 4, pp. 529-556, 2019.

[28] L. T. De Beer and R. Bianchi, "Confirmatory factor analysis of the Maslach Burnout Inventory: A Bayesian structural equation modeling approach, *European Journal of Psychological Assessment*, vol. 35, no. 2, p. 217, 2019.

[29] H. Salarzadeh Jenatabadi, et al., "Airline sustainability modeling: A new framework with application of Bayesian structural equation modeling," *Sustainability*, vol. 8, no. 11, p. 1204, 2016.

[30] M. Garnier-Villarreal and T. D. Jorgensen, "Adapting fit indices for Bayesian structural equation modeling: Comparison to maximum likelihood, *Psychological Methods*, vol. 25, no. 1, pp. 46-70, 2020.

[31] A. Jesus, et al., "Bayesian structural identification of a long suspension bridge considering temperature and traffic load effects," *Structural Health Monitoring*, vol. 18, no. 4, pp. 1310-1323, 2019.

[32] S.-Y. Lee, *Structural Equation Modeling: A Bayesian Approach*. John Wiley & Sons, 2007, vol. 711.

[33] R. Scheines, H. Hoijtink, and A. Boomsma, "Bayesian estimation and testing of structural equation models," *Psychometrika*, vol. 64, no. 1, pp. 37-52, 1999.

[34] D. B. Dunson, "Bayesian latent variable models for clustered mixed outcomes," *Journal of the Royal Statistical Society. Series B, Statistical Methodology*, vol. 62, no. 2, pp. 355-366, 2000.

[35] S.-Y. Lee and X.-Y. Song, "Evaluation of the Bayesian and maximum likelihood approaches in analyzing structural equation models with small sample sizes," *Multivariate Behavioral Research*, vol. 39, no. 4, pp. 653-686, 2004.

Norishahaini Mohamed Ishak was born in Kuala Lumpur in 1979. She received the BSc degree in Construction management from the Universiti Teknologi MARA, (UiTM) Shah Alam. Malaysia and M.Sc degree in Building Science from National University of Singapore (NUS) in 2008.

She is currently a senior lecturer in Centre of Studies for Construction, Faculty of Architecture, Planning & Surveying, UiTM Shah Alam, Malaysia. Her research interests include urban microclimate, outdoor thermal comfort and building performance

Ts. Norishahaini Mohamed Ishak is a Professional Technologist member of Malaysia Board of Technologies.

Hashem Salarzadeh Jenatabadi is a Senior Lecturer at the Department of Science and Technology Studies, Faculty of Science, University of Malaya. He holds Postdoc, PhD degrees in Applied Statistics, from University of Malaya, and Master, Bachelor degrees in Mathematical Statistics areas from Ferdowsi University of Mashhad, Iran. His expertise involves application of Statistical and Mathematical modeling in Engineering, Management, Public health, Chemistry, and Economics.

Siti, N. A. was born in Kuala Terengganu, Terengganu, Malaysia in 1991. She received the B.Sc. in Construction Management from Universiti Teknologi MARA, Shah Alam, Malaysia in 2014 and M.Sc. in Building Performance & Sustainability from National University of Singapore (NUS), Singapore in 2017.

Currently, she is a full-time lecturer at Universiti Teknologi MARA, Sarawak Branch, Malaysia. Her research interest includes Building Performance Evaluation, Post Occupancy Evaluation, and Construction Green Procurement.

Jamalunlaili Abdullah was born in Bota, Perak in 1965. He received his B.Sc. in Urban and Regional Planning from East Carolina University, North Carolina, USA in 1987, Master of Urban and Regional Planning from Virginia Commonwealth University, Virginia, USA in 1989 and PhD in City and Regional Planning from Cornell University, New York, USA in 1997.

He is currently Professor of Town and Regional Planning as well as Dean of Faculty of Architecture, Planning and Surveying, Universiti Teknologi MARA, Shah Alam, Malaysia which he joined in 1997. Previously he worked at Chesterfield County Planning Department, Virginia and Institute of Stategic and International Studies, Malaysia. He has published over 70 articles and involved in over 30 research and consultancy projects.

Jamalunlaili is a Registered Town Planner of Board of Town Planners Malaysia. He is also an appointed member of Board of Town Planners and previously an elected Council Member of Malaysian Institute of Planners.