PLANNING MALAYSIA:
Journal of the Malaysian Institute of Planners
VOLUME 23 ISSUE 2 (2025), Page 410 – 423

INVESTIGATING FACTORS INFLUENCING RESIDENTIAL LOCATION CHOICE USING PLS-SEM ANALYSIS: A CASE STUDY IN SEBERANG PERAI, PENANG, MALAYSIA

Syafiqah Nazurah Mukhtar[1], Ain Farhana Jamaludin[2], Muhammad Hafiz Bin Abd Razak[3], Wenny Arminda[4], Ahmad Fawwaz Saleh[5]

[1,2,5]*Faculty of Built Environment,*
UNIVERSITI MALAYA
[3]*College of Law, Government, and International Studies,*
UNIVERSITI UTARA MALAYSIA
[4]*Fakultas Teknologi Infrastruktur dan Kewilayahan,*
INSTITUT TEKNOLOGI SUMATERA

Abstract

Individuals often select their residence based on the availability of land and housing on the market and by taking into consideration of various factors involved. This is known as residential location choice. The inconsistency in earlier studies regarding modelling residential location choice persists despite numerous attempts made from a multidisciplinary background. As a result, it is difficult to understand the factors influencing residential location choice. By using PLS-SEM, this study seeks to understand the factors influencing residential location choice. Four hundred eighty-four heads of household in Seberang Perai provided primary data for the study. SMART-PLS software version 3.0 was used to assist in the PLS-SEM analysis. The results showed that social relations, neighbourhood features, and housing quality are the significant factors influencing residential location choice in Seberang Perai. These results serve as a guide for future research that considers variables from the economic, geographical, and social perspectives when examining the factors that influence residential location choice. A model of residential location choice that considers social, geographical, and economic factors can assist in creating agile cities by enabling planners to design flexible, inclusive urban environments that adapt to changing needs and conditions.

Keywords: PLS-SEM, Residential Location Choice, Accessibility, House Quality, Layout, Neighbourhood Feature, Social Relations

[1] Corresponding author. Email: syafiqahnazurah@um.edu.my

INTRODUCTION

Presenting a household's preferred spatial location and suggesting policy implications for future housing construction are two common uses of residential location choice modelling (Jin & Lee, 2017). By modelling residential location choice, researchers may get an extensive comprehension of household behaviour and the factors that influence decision-making. Morevover, modelling assists in depicting the characteristics and spatial diversity of locations.

Previous research on modelling residential location choice has been inconsistent, despite numerous attempts made from a multidisciplinary background. Economically, the development of bid rent models (Ellickson, 1981; Hurtubia et al., 2010) and utility maximization (Alonso, 1960) primarily incorporated key economic elements. On the other hand, modelling residential location choice was focused on geographical perspectives such as spatial interaction (Lowry, 1964), spatial parameters (Evans, 1973; Muth, 1969), and interaction with transportation (Pagliara et al., 2010) while from a social perspective, life cycle parameters are the focus (Lawton et al., 2013; Rossi, 1955).

Due to this issue, research on the household's choice of residential location has been negatively impacted, leading to differing interpretations of the findings depending on the methodology employed. The phenomena will remain incomprehensible, rendering it unfeasible to effectively utilise the crucial data derived from modelling the decision-making process. The data are related to the selection of residential sites by many stakeholders, including household, developers, and authorities.

Therefore, this study aims to investigate factors influencing residential location choice from various perspectives to provide a more comprehensive framework of modelling the factors from various social, geographical and economic perspectives.

Understanding the factors that influence residential location choice and developing a model that integrates the factors from various perspectives is becoming more crucial. This is particularly true when cities are more inclined towards creating agile cities. This kind of model allows for a thorough comprehension of the ways in which a variety of elements, such as links to the community, the environment, and economic prospects, influence people's decisions about where to reside. Urban planners may create more adaptable communities to changing circumstances by considering these interconnected dimensions, ensuring that housing, services, and infrastructure align with the desires of locals and the reality of the economy. This all-encompassing strategy increases the flexibility, inclusiveness, and adaptability of urban surroundings, which in turn increases the general agility and resilience of the city.

LITERATURE REVIEW

Residential Location Choice

When choosing a residential location, a decision-maker can choose from a number of possibilities (based on the evaluation of various options), even if those options do not entirely solve their problem (Aliyu et al., 2018). In reality, selecting a residential location involves making decisions about location and density depending on a number of trade-offs (Michal and Bartlomiej, 2017). Nkeki and Erimona (2018) state that households make decisions based on their needs and preferences when they are in the scenario.

Factors Influencing Residential Location Choice

Various factors have been identified in previous literature as influencing the selection of residential locations. The compilation of factors is listed in Table 1.

Table 1: Factors Influencing Residential Location Choice from Previous Studies

Variable	Dimension	Source	
Accessibility	Work/school	(Pagliara et al., 2010) (Kim et al., 2005) (Karsten, 2007) (Lawton et al., 2013) (Beckers & Boschman, 2017) (Huri et al., 2024)	(Acheampong & Anokye, 2013) (Prashker et al., 2008) (Chiarazzo et al., 2014) (Weisbrod et al., 1980) (Rosli, Bakar, et al., 2024) (Rosli, Samat, et al., 2024)
	Shopping opportunities	(J. Guo & Bhat, 2001) (Schirmer et al., 2014) (Pagliara et al., 2010) (Ramli et al., 2024)	(Kim et al., 2005) (Beckers & Boschman, 2017) (Karsten, 2003)
	Recreation opportunities	(Karsten, 2007) (Pinjari et al., 2009)	
House quality	House price	(Mohd Thas Thaker & Chandra Sakaran, 2016) (Liu et al., 2018) (Chiarazzo et al., 2014) (Yeap & Lean, 2020) (Acheampong & Anokye, 2013) (Balbontin et al., 2015) (Choudhury & Ayaz, 2015)	(Karsten, 2007) (Usman et al., 2015) (Wang et al., 2016) (Weisbrod et al., 1980) (Zhao, 2018) (Habib & Miller, 2009) (Adedire, 2017)
	House size	(Lawton et al., 2013) (Zhou & Kockelman, 2008) (Mohd Thass Thaker & Chandra Sakaran, 2016) (Nurizan, Y., & Hashim, 2001) (Evans, 1973) (Hirt, 2007) (Pagliara et al., 2010) (J. Chen et al., 2008)	(Hurtubia et al., 2010) (Saw & Tan, 2014) (Srour et al., 2002) (Clark & Huang, 2003) (Habib & Miller, 2009) (Hu & Wang, 2017) (Kohler, 2013) (Stokenberga, 2019)

Variable	Dimension	Source	
	Design and style	(Chiarazzo et al., 2014) (Rachmawati et al., 2019)	
Layout	Single and mixed layout, population density, land use	(Hurtubia et al., 2010) (Beckers & Boschman, 2017) (J. Guo & Bhat, 2001) (Jin & Lee, 2017)	
Neighbourhood feature	Closeness to facilities and amenities	(Nurizan, Y., & Hashim, 2001) (Hurtubia et al., 2010) (Dissart, 2018) (Gbakeji & Magnus, 2007) (Habib & Miller, 2009) (de Palma et al., 2005) (Schirmer et al., 2014) (Cao, 2008) (Chiarazzo et al., 2014) (Prashker et al., 2008)	(Usman et al., 2015) (Acheampong, 2018) (Aliyu et al., 2018) (Edwin et al., 2008) (Balbontin et al., 2015) (J. Guo & Bhat, 2001) (Lo & Jim, 2010) (Luttik, 2000) (Pagliara et al., 2010) (Zhu et al., 2017)
	Ease of movement	(Guerra, 2015) (De Vos et al., 2016) (Liao et al., 2015)	(Ewing & Cervero, 2010) (Zhao, 2018)
	Cleanliness and pollution	(Chapman, D.W. and Lombard, 2006) (Chiarazzo et al., 2014) (Pagliara et al., 2010) (Teck-Hong, 2011)	(Hirt, 2007) (Acheampong & Anokye, 2013) (Acker et al., 2014) (Schirmer et al., 2014) (Habib & Miller, 2009)
	Safety and security	(Morrow-jones, 2008) (Cao, 2008) (Karsten, 2007) (Lang & LeFurgy, 2007)	(Mohd Thas Thaker & Chandra Sakaran, 2016) (Acker et al., 2014) (Schirmer et al., 2014) (Aliyu et al., 2018)
Social relation	Friends and family, same ethnicity	(Farrell et al., 2004) (Ahmad, 1992) (Gilbert & Gugler, 1982) (Kapoor et al., 2004) (Gabriel & Rosenthal, 1989) (de Palma et al., 2005) (Z. Zhang et al., 2018) (Nkeki & Erimona, 2018) (Acheampong & Anokye, 2013)	(Wang et al., 2016) (Aliyu et al., 2018) (Dökmeci et al., 1996) (Limbumba, 2010b) (Stokenberga, 2019) (Guidon et al., 2019) (Fisher et al., 2007) (Acheampong, 2018)

Source: Author's compilation

MATERIALS AND METHODS

This research employed a quantitative methodology. Primary data was gathered using a 5-point Likert scale in the survey that was conducted in Seberang Perai district, in which was chosen due to the areas experienced most rapid physical transformation from agricultural into built areas, with 33.8% of the area is classified as saturated built-up areas and is dominated by residential Samat & Mahamud (2017). Figure 3.2 below shows the location of the study area.

Figure 1: Study area

In Structural Equation Modelling (SEM), the measurement scale does require special consideration to guarantee that it will meet the equidistance condition, which is required for some analytic methodologies, including SEM (Hair, Jr. et al., 2017). According to Hair, Jr. et al., (2017), the most appropriate method for SEM is to use a 5-point Likert scale because the "distance" between Categories 1 and 2 is equal to that between Categories 3 and 4.

There are five (5) measuring constructs for the independent variable: Accessibility, House Quality, Layout, Neighbourhood Feature, and Social Relations. There are (9) nine indicators for the accessibility construct, (5) five for house quality, (2) two for layout, (9) nine for neighbourhood features, and (2) two for social relations. Residential location is the study's dependent variable, and it has three (3) indicators. Table 2 displays the variable, construct, and its indicators.

Table 2: Variables, constructs, and the indicators

Variable	Construct	Indicator
Independent Variable	Accessibility (9)	Access to partner's work Access to quality school Access to shopping centre/mall Access to shops and services Access to sports and recreation facilities Access to public transport services Access to eating places Access to cultural/entertainment venues Access to cultural/entertainment venues
	House Quality (5)	House price/rent Floor space Land space Number of rooms/bathrooms Design and feature
	Layout (2)	Single land use Mixed land use
	Neighbourhood Feature (9)	Closeness to highway Closeness to public transport Closeness to public facilities Closeness to sports and recreation facilities Ease of private vehicle Ease of walking Ease of cycling Cleanliness/Pollution Safety/security
	Social Relations (2)	Friends/family Same ethnicity
Dependent Variable	Residential Location (3)	House location House type House Ownership

ANALYSIS AND DISCUSSION

To analyse the 484 valid responses gathered, this study used the Partial Least-Square of Structural Equation Modelling (PLS-SEM).

PLS-SEM Analysis

This study's analysis was all carried out with SmartPLS 3.0. The variables Accessibility (ACCESS), House Quality (HQ), Layout (LAYOUT), Neighbourhood Feature (NF), and Social Relations (RELATIONS) comprise the five constructs that from the model of the study. Figure 2 shows the initial PLS path model and Table 3 shows the path coefficient for each construct.

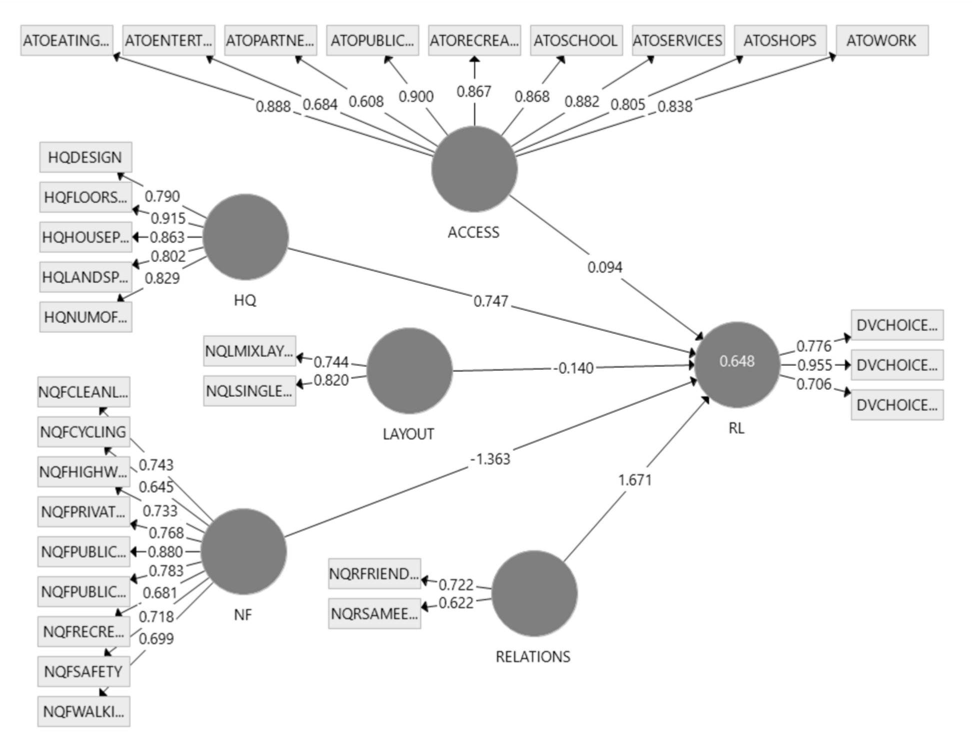

Figure 2: PLS Path Model

Table 3: Results of PLS Path Model

Construct	Path Coefficient	Number of items
Accessibility	0.094	9
House Quality	0.747	5
Layout	-0.140	2
Neighbourhood Feature	-1.363	9
Social relations	1.671	2

Source: PLS-SEM Analysis

Reflective Measurement Model Assessment

Assessing the reflective measurement model determines the internal consistency reliability, convergent validity (Indicator Reliability through Outer Loadings and Average Variance Extracted (AVE), and discriminant validity for each construct.

a) Internal consistency reliability

Internal consistency reliability is the high value resulting from high item correlations. Higher values correspond to higher correlations, which in turn indicate stronger reliability. The values fall between 0 and 1. Hair, Jr. et al., (2017) state that composite reliability values between 0.60 and 0.70 are appropriate for exploratory research, while values between 0.70 and 0.90 are deemed satisfactory in more advanced stages of the study. Values above 0.90, particularly above 0.95, are deemed undesirable as they are likely to measure the same situation and are unlikely to be valid as the construct's item.

b) Convergent validity
A high correlation between one item and other substitute items of the same construct is referred to as convergent validity (Hair, Jr. et al., 2017). Every item in a reflective construct should measure the same component of the construct. According to Hair, Jr. et al., (2017), in order to assess convergent validity, it is necessary to monitor the values of Average Variance Extracted (AVE) and outer loadings (to check for indicator reliability).

b) (i) Indicator Reliability
The constructs' outer loadings' value provides insight into the reliability of the indicators. A construct with a higher outer loading value, where all related indicators consistently reflect the same construct and measurement, is referred to as indicator reliability. Hair, Jr. et al., (2017) also argue that it is generally accepted that a substantial outer loading threshold is one that is equal to or more than 0.708.

All the constructs were reflective in this study. House Quality and Layout constructs had all their outer loadings well above the 0.708 criterion, but not those of Accessibility, Neighbourhood Feature, or Social Relations. Two indicators of accessibility—Access to Entertainment (0.684) and Access to Partner's Work (0.608)—had values below the cutoff. Three indicators of neighbourhood features—walking (0.699), cycling (0.645), and recreation (0.681)—had values below the cutoff. One social relationship indicator, Same Ethnicity (0.622), is below the threshold.

Indicators with extremely low outer loadings—below 0.40—should permanently be eliminated from the build, according to Hair et al., (2011). But before being eliminated, the loadings over 0.40 and below the cutoff value of 0.708 were thoroughly inspected in accordance with Hair et al.'s (2011) suggestions for the indicator deletion criteria based on outer loadings. Analysis of the effect of removing the indicators on the composite reliability value is required for the indication with outer loadings above 0.40 and below 0.708. Remove the indicator if doing so raises the composite reliability value. Keep the indicator inside the construct if it does not rise.

Only two indicators—Access to Entertainment and Same Ethnicity—were kept in the model after all indicators that scored lower than 0.708 and higher than 0.40 were eliminated. Table 4 summarises the analysis of the removal of the indicators.

Table 4: The analysis of the deletion of the indicators

Variable	Items below 0.70	Composite reliability value if delete	Items status
Accessibility (composite reliability = 0.948)	A to partner's work (0.608)	0.945 (not increase)	retain
House quality (composite reliability = 0.923)	-	-	No items deleted
Layout (composite reliability = 0.760)	-	-	No items deleted
Neighbourhood feature (composite reliability = 0.916)	Nqf cycling (0.645)	0.911 (not increase)	Retain
Social relations (composite reliability = 0.623)	Same ethnic (0.622)	1.000 (increase)	delete

b) (ii) Average Variance Extracted (AVE)
As the total of the squared loadings divided by the number of indicators, Average Variance Extracted (AVE) is a frequently used metric to demonstrate convergent validity at the measurement model level (Hair, Jr. et al., 2017). AVE stands for a construct's similarities. As a result, the variance explained by the indicators inside a construct increases with a larger AVE value. Hair, Jr. et al., (2017) state that an ideal AVE value is 0.50 or above.

All constructs in this study had AVE values above the minimal value necessary (0.50) with accessibility (0.706), house quality (0.708), layout (0.613), neighbourhood feature (0.550), and social relations (1.000). This suggests strong convergent validity among all the reflective constructs in this study.

c) Discriminant validity
When determining if a construct is more distinctive than others in terms of accurately representing a phenomenon in a model, discriminant validity should be employed. To what extent a construct is genuinely different from other constructs in the model can be determined by looking at the value of discriminant validity (Hair, Jr. et al., 2017) One can assess discriminant validity using the Heterotrait-Monotrait ratio of correlations (HTMT), which is a more dependable method than the Fornell-Larcker criterion.

According to Hair, Jr. et al., (2017), HTMT is the ratio of the between-trait correlations, which belong to a different construct called heterotrait-heteromethod correlations, to the within-trait correlations, which belong to the same construct called the monotrait-heteromethod correlations. According to (Henseler et al., 2015), discriminant validity is absent the closer the value gets to approaching 1. Although 0.90 is the recommended threshold value, 0.85 would be a more prudent choice. Except for Layout (0.852), which is somewhat above the cautious threshold value of 0.85 but still below 0.90 and acceptable, all the HTMT values in the results are lower than 0.90. The HTMT ratios for accessibility, house quality, neighbourhood features, and social relations are 0.334, 0.573, 0.613, and 0.562, respectively.

Structural Model Assessment

The most crucial aspect of the structural model assessment is analysing the connections between the constructs as well as the model's predictive ability (Hair, Jr. et al., 2017). Collinearity assessment, significance and relevance, R^2 (explanatory power), and f^2 (effect size for exogenous latent variable) make up the assessment.

a) Collinearity assessment

Variance Inflation Factor (VIF) value is observed to see if there are any collinearity problems. The collinearity increases with the VIF value. VIF values greater than five suggest the possibility of a collinearity issue (Hair et al., 2011).

Apart from neighbourhood characteristics, which have a VIF value of 5.542, all constructs have values below the threshold of 5. This suggests that the neighbourhood feature construct—also referred to as the method bias—has a collinearity problem or issue. It is necessary to address the collinearity issue before moving on to the subsequent analysis. To address the collinearity problem, the researcher must either create higher-order constructs or eliminate the constructs by combining predictors into a single construct (Hair, Jr. et al., 2017). Since the higher-order constructs approach effectively addresses the collinearity problems for the neighbourhood feature construct, it was selected for this investigation. Prioritization of one approach over another has not been stated in the prior study. The procedure can be utilized to address the issue and move on to the other analysis if it addresses the collinearity issues.

To address the collinearity problem in the neighbourhood feature construct, the Higher Order Construct, also known as the Higher Order Component (HOC), was developed. The HOC for the neighbourhood feature construct is shown in Figure 2 below, and Table 4 displays the VIF value result following the creation of the HOC. The neighbourhood characteristics' VIF value decreased from 5.542 to 3.172 in Table 5 below, and it is currently below the five-point threshold. This suggested that the collinearity problem had been resolved.

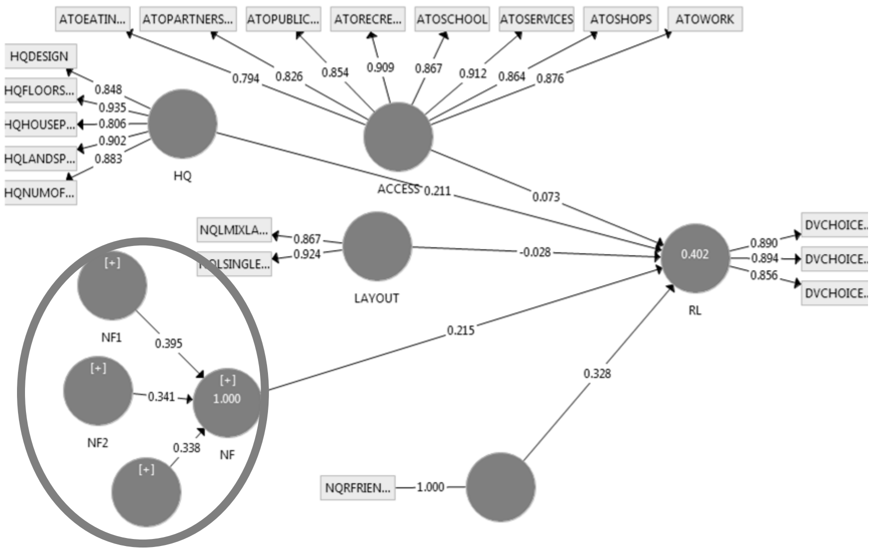

Figure 2: HOC for neighbourhood feature

Table 5: VIF value after HOC created

Construct	VIF (<5)
Accessibility	1.223
House Quality	1.736
Layout	2.048
Neighbourhood Feature	3.172
Social relations	1.579
Construct	**VIF (<5)**

Source: PLS-SEM Analysis

b) Significance and relevance

The path coefficients were used to estimate the structural model relationship. According to Hair, Jr. et al., (2017), the path coefficients have a value between -1 and +1. The stronger the link, the farther the value is from zero. Stronger effects on the endogenous variable are indicated by a larger coefficient value deviating from zero (Hair, Jr. et al., 2017). P values were examined for every construct.

Neighbourhood feature (0.344), followed by social relations (0.339) and house quality (0.215), is the strongest influencer, according to the values of the path coefficients. At 0.060, accessibility is the least significant factor. Apart from layout, all factors are positively correlated with residential location. The only determinant with an inverse relationship with the endogenous variable, residential location, is layout (-0.131).

A relationship's significance is determined by its standard error, which is determined by bootstrapping and provides the t and p values (Hair, Jr. et al., 2017). The p-values show that there is a substantial association between House Quality → RL, Neighbourhood Feature → RL, and Social Relations → RL, but not between Layout → RL and Accessibility → RL.

c) R^2 (explanatory power)
According to Hair, Jr. et al., (2017), explanatory power (R^2) is a measure of how well the model predicts the future. It is also the total of the effects of exogenous factors on the endogenous variable. The study's R^2 value is 0.470. This shows that the study's constructs accounted for 47% of the endogenous variables (residential location).

d) f^2 (effect size for exogenous latent variable)
According to Hair, Jr. et al., (2017), the effect size f^2 is the result of eliminating a particular exogenous construct from the model and its effect on the endogenous construct. Here is how the f^2 value is calculated:

$$f^2 = \frac{R^{2^{included}} - R^{2^{excluded}}}{1 - R^{2^{included}}}$$

The formula can be used to determine the values of f^2 for each exogenous variable. It may be computed automatically in SmartPLS 3.0. (Cohen, 1988) classed 0.02, 0.15, and 0.35 as minor, medium, and large effects in their guidelines for determining the value of f^2. According to this study, accessibility (0.005) and layout (0.009) have no significant effects on the residential location of households' residential location in Seberang Perai, which is consistent with all the results discussed in the previous sections. House quality (0.043), neighbourhood feature (0.041), and social relations (0.130) have only minor effects. Thus, these findings showed that while accessibility and layout had little bearing on where households in Seberang Perai resided, housing quality, neighbourhood characteristics, and social relationships did, albeit to a minor extent.

CONCLUSION

The primary goal of this study is to model the factors influencing residential location choice from economic, geography, and social aspects to gain a more thorough understanding of the issues. Moreover, the created model offers more thorough frameworks that offer comprehension from a holistic viewpoint by considering all elements from potentially disparate perspectives.

This model shows that only three factors—house quality, neighbourhood features, and social relationships—significantly influence residents' choice of residential location in Seberang Perai. The developed model will serve as a good foundation for future research, either by reproducing it in other contexts (urban and peri-urban areas may yield different results in terms of significance) or by identifying additional variables that may have an impact on the choice of residential location and incorporating them into the model to make it more comprehensive and holistic.

ACKNOWLEDGEMENT

My greatest gratitude to Allah SWT that enable me to complete this research. I would like to express my infinite gratitude to Associate Professor Dr. Kausar Hj. Ali (former lecturer in School of Housing, Building and Planning, Universiti Sains Malaysia) for her endless guide, advice, and patience in guiding me throughout the research. I wish to thanks to all individuals and organisations (Kementerian Perumahan dan Kerajaan Tempatan, Jabatan Perpaduan Negara dan Integrasi Nasional, and Jabatan Perangkaan Malaysia Negeri Pulau Pinang) for your cooperation. Also, many thanks to co-authors for collaborating in writing this research paper.

REFERENCES

Aliyu, S. J., Shaibu, S. I., Medayese, S. O., Bala, M. K., & Ajayi, M. T. A. (2018). Analysis Of Factors Influencing Choice of Residential Location in Minna, Nigeria. *International Journal of Innovative Research and Advanced Studies*, *5*(6), 162–166.

Alonso, W. (1960). A Theory of the Urban Land Market. *Papers and Proceedings of the Regional Science Association*, *6*(1), 149-157.

Cohen, J. (1988). *Statistical power analysis for the behavioural sciences* (2nd ed.). Lawrence Erlbaum Associates.

Ellickson, B. (1981). An alternatice test of the hedonic theory of housing markets. *Journal of Urban Economics*, *9*(1), 56–79.

Evans, A. W. (1973). *The economics of residential location*. The Macmillan Press Ltd.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications, Inc.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–151. https://doi.org/10.2753/MTP1069-6679190202

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Huri, N., Baharum, Z. A., Hwa, T. K., Adnan, Y. M., & Ishak, N. F. A. (2024). a Conceptual Paper on Stigmatised Dimension Towards Residential Overhang. *Planning Malaysia*, *22*(3), 379–393. https://doi.org/10.21837/pm.v22i32.1514

Hurtubia, R., Gallay, O., & Bierlaire, M. (2010). Attributes of households, locations and real-estate markets for land use modeling. In *SustainCity*.

Jin, J., & Lee, H.-Y. (2017). Understanding residential location choices: an application of the UrbanSim residential location model on Suwon, Korea. *International Journal of Urban Sciences*, *22*(2), 1–20. https://doi.org/10.1080/12265934.2017.1336469

Lawton, P., Murphy, E., & Redmond, D. (2013). Residential preferences of the 'creative class'? *Cities*, *31*, 47–56. https://doi.org/10.1016/j.cities.2012.04.002

Lowry, I. S. (1964). *A model of metropolis*.

Michal, G., & Bartlomiej, M. (2017). Discrete choice model of residential location in Krakow. *Journal of European Real Estate Research*, *10*(1), 4–16.

Muth, R. F. (1969). *Cities and housing*. University of Chicago Press.

Nkeki, N. F., & Erimona, E. O. (2018). Sector-Wise Exploratory Analysis of Household Residential Location Choice in the African Context: Empirical Evidence from Benin City, Nigeria. *Current Urban Studies*, *6*, 37–69. https://doi.org/10.4236/cus.2018.61003

Pagliara, F., Preston, J., & Simmonds, D. (Eds.). (2010). *Residential Location Choice: Models and Applications*. Springer. https://doi.org/10.1007/978-3-642-17940-2

Ramli, N. A., Zainol, N. N., Sukereman, A. S., & Ishak, N. A. (2024). Exploring Issues and Enhancing Sustainability: Affordable Housing Dynamics in Malaysia. *Planning Malaysia*, *22*(5), 376–390. https://doi.org/10.21837/pm.v22i34.1596

Rosli, H., Bakar, M. A. A., Yusoh, M. P., Latip, N. A., & Mansor, K. (2024). Assessing job-housing balance among low-income households in penang island, malaysia. *Planning Malaysia*, *22*(6), 157–170.

Rosli, H., Samat, N., & Bakar, M. A. A. (2024). Accessibility To Workplace and Housing Location Choice Among the Low-Income Group: a Case Study of Pulau Pinang, Malaysia. *Planning Malaysia*, *22*(1), 96–109. https://doi.org/10.21837/pm.v22i30.1426

Rossi, P. H. (1955). *Why families move?* The Free Press.

Samat, N., & Mahamud, M. A. (2017). Simulating Urban Growth in the George Town Conurbation. *Journal of Fundamental and Applied Sciences*, *9*(7S), 144–156. https://doi.org/10.1016/j.jco.2005.11.005

Received: 7th December 2024. Accepted: 5th March 2025