Lawerteh JK *et al.* (2025)
Nova Geodesia 5(2):323
Research Article

The effect of land use and residential self-selection on automobile travel in the greater Sekondi-Takoradi area of Ghana using structural equation model

Joel K. LAWERTEH*, Michael S. ADUAH, Saviour MANTEY

*University of Mines and Technology, Faculty of Geosciences, Geomatic Engineering Department, P. O. Box 237, Tarkwa, Ghana; jklawerteh@umat.edu.gh (*corresponding author); msaduah@umat.edu.gh; smantey@umat.edu.gh*

Abstract

Despite the suggestions by numerous studies over the years that spatial land use pattern influences travel behaviour, uncertainty remains about the existence, form, and the extent of any causal relationship between spatial land use and urban travel behaviour. This study seeks to provide a new dimension from the perspective of a medium-sized city in Africa by simultaneously incorporating attitudinal and socioeconomic variables in examining the relationship using structural equation model (SEM). Primary data collected using questionnaires from 534 households of adult commuters with private cars and spatial data of the built environment for households in the Greater Sekondi-Takoradi Area (GSTA) in Ghana were used in this study. Principal component analysis (PCA) was used to reduce 25 statements attributed to travel attitude to four. Similarly, 22 statements attributed to neighbourhood preferences were also reduced to three. Latent constructs of four and 20 observed variables were analysed using SEM in LISREL 10.3 software. The fitness of the final model to the data was assessed using absolute, incremental, and parsimonious fit indices. The findings from the study indicated that socio-economic factors had a stronger influence on households' automobile travel than self-selection, with land use having the least impact. The results are consistent with earlier studies that suggested self-selection has a greater impact than land use on households' automobile travel. This suggests that land use policies can effectively be used in controlling households' automobile travel when the effect of self-selection is simultaneously accounted for with the land use.

Keywords: land use; PCA; residential self-selection; structural equation modelling; travel attitude; travel behaviour

Introduction

Urban travel in the past few decades has increased astronomically in cities across the world (Coevering *et al.,* 2016; Zhao *et al.*, 2018; Faber *et al.*, 2021; Ahmad *et al.,* 2024). Decreasing the reliance on car use and advocating for other sustainable modes of travel are generally seen as positive ways of promoting sustainable mobility, improving of public health and decreasing of traffic congestion (Zhou and Kockelman, 2008; Aditjandra *et al.,* 2009, Faber *et al.*, 2021; De Abreu e Silva and Lucchesi, 2022). However, there has been a continuous debate about the existence, form, and magnitude of the causal factors that influence travel

Received: 13 Feb 2025. Received in revised form: 29 Apr 2025. Accepted: 01 May 2025. Published online: 03 May 2025.

behaviour in urban areas (Ewing and Cervero, 2010; Bhagat-Conway *et al.*, 2024). While a majority of the studies consider land use to be the influencing factor that could be used to control travel behaviour through the principles of compact development and the new urbanism (Zhou and Kockelman, 2008; Bohte *et al.*, 2009; Lin and Yang, 2009; Cao and Yang, 2017). Other studies have contended the effect of land use on travel behaviour. They argued that the observed association between land use and travel behaviour may be indirect, and that a household with a preferred mode of travel will choose a residential location that will satisfy the desired mode of travel, a hypothesis known as residential self-selection (Lin and Yang, 2009; Ewing *et al.,* 2015; Cao and Yang, 2017; Gim, 2018; De Vos *et al.*, 2021; Soinio, 2021). Most of these studies found that neglecting the issue of self-selection in land use-travel behaviour studies may lead to overestimation of the effect of land use on travel behaviour (Cao *et al.*, 2007; Pinjari *et al.*, 2007; Mokhtarian and Cao, 2008; Cao and Yang, 2017; Wolday *et al.*, 2018; Guan *et al.*, 2020; De Abreu e Silva and Lucchesi, 2022; Soinio, 2021). In contrast, other studies found that the effect of self-selection is insignificant or is of no effect (Scheiner, 2010; Chatman, 2014; Naess, 2014; Ewing *et al.*, 2015; Coevering *et al.*, 2016; Wang and Lin, 2019). The lack of clear understanding and the conflicting evidence of the effect of land use and self-selection on automobile travel pattern has made it difficult for city authorities and planners to evaluate effectively, the impact of land use policies on vehicle miles travel, and consequently on traffic congestion mitigation factors (Ewing *et al.,* 2015).

Existing literature on travel behaviour from the perspective of Global South countries is scarce, especially from Africa, due to the lack of attitudinal data on travel (Park *et al.*, 2018; Masoumi *et al.*, 2021; De Abreu e Silva and Lucchesi, 2022; Nkeki and Asikhia, 2023). Most of the studies were conducted in large cities of North America and Europe where faces of urbanization processes are different from that of Global South countries (Schwanen and Mokhtarian, 2005; Wang and Lin, 2014; De Abreu e Silva and Lucchesi, 2022). According to Wolday (2018) and Gim (2019), different urban structures exert different travel behaviour influences at different spatial scales and urban sizes. In developing countries such as Ghana, options for selecting residential locations are mostly constraint by the availability and affordability of the housing units (Wang and Lin, 2014). Additionally, travel attitude, perception, and culture of an individual in a medium-sized city in the Greater Sekondi-Takoradi Area (GSTA) of Ghana might be different from an individual in a city in North America or Europe.

Furthermore, some of the studies in which residential self-selection was considered were limited by the amount of data used to represent the built environment and travel behaviour variables, leading to aggregated-level analysis (Guan *et al.*, 2020). For instance, Parka *et al.* (2017) could not control for the issue of self-selection in their studies because the underlying household surveys did not include relevant attitudinal questions. De Abreu e Silva and Lucchesi (2022) examined the relationship between land use patterns, location choice, and travel behaviour from the perspective of a Global South country using SEM. However, their study was limited as attitudinal variables were not included. Also, Aditjandra *et al.* (2009) did not include the objective measurement of land use characteristics in their model. Their study only captured the perception of the land use characteristics and their preferences. Other studies explained the relationship by only using the physical characteristics of the land use without considering the underlying behavioural factors (Van Acker *et al.*, 2011).

Another challenge in examining this complex relationship has been the teasing out of the independent impact of land use on travel behaviour, which lies heavily on the statistical approach used in examining these relationships (Guan *et al.*, 2020). The use of traditional multivariate regression models, such as linear, multiple or logistic regressions that represent only a single relationship between the dependent and independent variables, is common in land use-travel behaviour studies (Devlin, 2010). However, single equations are limited in their ability to model complex interactions such as the relationship between land use pattern, self-selection, and travel behaviour (Bohte *et al.,* 2009; Hair *et al.*, 2014). Although a few studies have examined the influence of residential self-selection on travel behaviour, their findings have often been limited by the analytical approaches employed in examining these complex relationships (Bohte *et al.*, 2009). For instance, Soinio (2021) used multiple linear regression models to examine the influence of the built environment and residential self-selection on car use and active travel. Aditjandra *et al.* (2009) also assessed the relationship between urban form and travel behaviour using multivariate regression analysis. Wolday *et al.* (2018) also used logistic regression to examine the impact of transit preference and other residential preferences on residential location choice.

Unlike regression, Structural Equation Model (SEM) is a multivariate statistical technique that can model directly and indirectly the complex relationships among observed and unobserved variables (Maat and Timmermans, 2009; Hair *et al.,* 2014; Wala *et al.*, 2020; De Vos *et al.*, 2021; Javid *et al.,* 2021; Setiawan, 2021). SEM can be used to model measurement error for both the dependent variable and the independent variable, and it allows correlation among the error terms (Javid *et al.,* 2021; Khairi *et al.,* 2021). Since most of the traditional methods could not clarify this complex relationship, a body of studies used the SEM in examining the complex relationship between land use, travel attitude, and travel behaviour. For instance, Bagley and Mokhtarian (2002) applied SEM in examining the influence of residential type on travel behaviour, they found that attitude affects both residential neighbourhood choice and travel demand. However, in their study, they used only two variables to represent urban form, which only provides a simple representation of the effect of individual characteristics of density, design, and diversity. Research carried out by Cao and Yang (2017) used SEM to evaluate the impact of the built environment and residential self-selection on commuting trips and the related CO_2 emissions. However, the study was limited to path analysis by using only observed variables for model specification (Cao and Yang, 2017). The major limitation of models that only use observed variables is their failure to account for measurement errors, which can undermine the precision and reliability of the findings (Okyere, 2018). A complete SEM enables the simultaneous evaluation of both observed and latent variables, improving the precision and depth of insights into the relationships among constructs. Lin and Yang (2009) also examined the influence of the built environment on travel demand using SEM. Although they used a complete SEM, the data used in their studies were aggregated data; for instance, the measured indicator of diversity was measured for the whole traffic analysis zone (TAZ) rather than on a local scale, which limited their analysis at the local level. Similarly, Ewing *et al.* (2015) used SEM and aggregated data to assess the impact of compact development on traffic congestion. The results of the study were also limited in making inferences at the micro level, as the data used was aggregated. De Abreu e Silva and Lucchesi (2022) also examine the relationship between land-use patterns, location choice, and travel behaviour from the perspective of a Global South country using SEM. However, their study was limited as attitudinal variables were not included. Gim (2018) also examined the relationship between land use and weekend travel using SEM. However, the study was constrained by the absence of attitudinal variables in the model, limiting its ability to fully capture the effects of land use.

GSTA in recent years have witnessed a rapid rate of urbanization due to oil discovery in commercial quantities in 2007, off the coast of the Western Region in Ghana. The city has been characterised by a disorganised urban growth, which has led to urban sprawl boosted by car-oriented development with no clear policy to control these externalities (Biney *et al.,* 2024).

From the discussion of earlier works in literature and the identified limitations in the above paragraphs, an understanding of the impact of land use, self-selection on travel behaviour, is critical in aiding sustainable mobility, especially in a medium-sized city of a developing country such as Ghana. Hence, this study seeks to use rare, disaggregated household travel data to examine the geospatial impact of land use and self-selection on travel behaviour of adult workers who commutes by automobile mode of travel within the GSTA, using a structural equation model.

Materials and Methods

The study area

The study was undertaken in the Greater Sekondi Takoradi Area (GSTA) in the Western Region of Ghana. The GSTA is made up of Sekondi Sub-metropolitan area, Takoradi Sub metropolitan area, Essikado/Ketan Sub-metropolitan area and Effia-Kwesimimtsim Municipality. The study area falls between latitudes 4° 52′ 30″ N and 5° 04′ 00″ N and longitudes 1° 37′ 00″ W and 1° 52′ 30″ W with an area of approximately 191.7 km^2 (GSS, 2010). It is the administrative capital of the Western Region with a population of about 419,357 (GSS, 2021). The climate of the area is equatorial with an average annual temperature of 22 °C. Rainfall is bimodal, the major season is experienced between March and July, and the minor season between August and November. There are two major rivers that flow through the city: the Whin River and the Kansaworado River. The city hosts about 60% of the industries in the Western Region. The economic activities in the area have been boosted in the past few years by the discovery of oil in commercial quantities in 2007 at Cape Three Points, off the coast of Ghana. This has led to a rapid growth in urbanisation, population and car ownership over the past few years. Thus, posing challenges to sustainable mobility within GSTA (STMA, 2021). Figure 1 is a map showing the study area.

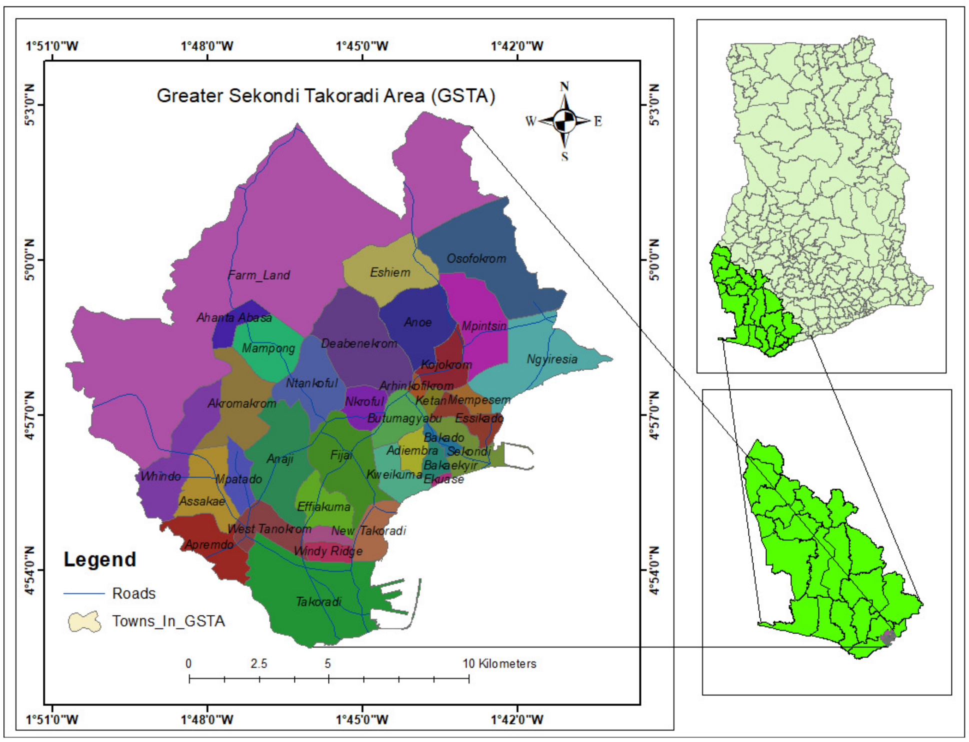

Figure 1. Map of study area

Data collection

A cross-sectional survey was conducted using a well-structured paper-based questionnaire from December 2023 to February 2024. Information such as socio-demographic characteristics, work trips, non-work trips, residential preferences, travel-related attitudes, work and household locations of respondents, etc., was gathered from respondents. A multistage sampling procedure was used, starting from cluster sampling to systematic sampling to ensure the sample characteristics were representative of the population, as well as urban form and socio-economic characteristics. The study focused on the active working group with a minimum age of 18 years and a maximum of 60 years. The survey was conducted as part of a PhD research being conducted by the principal author. A total of 1,344 household respondents from 36 communities in the GSTA were interviewed. This was reduced to 1,298 after data cleaning and removal of incomplete forms. This paper focuses on 534 household respondents who commute using the automobile mode of travel in a typical working week in the 36 communities in GSTA. Although the sample cannot be said to have represented the sample population perfectly after data cleaning, it remains suitable for this research, which is to examine the relationship among the variables involved (Bagley and Mokhtarian, 2002; Cao *et al.,* 2006; Cao and Ettema, 2014; Gim, 2016; Sinniah *et al.,* 2016). Table 1 presents the sample characteristics of respondents.

Table 1. Sample characteristics of respondents

Socio-demographic features	Description	N = 534	Percentage (%)
Gender	Male	315	58.99
	Female	219	41.01
Age (in years)	18-24	69	12.92
	25-39	230	43.07
	40-59	235	44.01
Educational level	Primary school	8	1.5
	Junior Secondary/Middle school	26	4.87
	Senior Secondary school/A' Level	59	11.05
	Bachelors	211	39.51
	Masters	188	35.21
	PhD	42	7.87
Household monthly income (Ghana cedis)	Less than 2,000	105	19.66
	2,000-4,999	158	29.59
	5,000-7,999	150	28.09
	8,000-9,999	56	10.49
	10,000 or more	65	12.17
Household size	1	58	10.86
	2	48	8.99
	3	85	15.92
	4	169	31.65
	5	75	14.04
	6 and above	99	18.54
Households with cars	Households with one car	295	55.24
	Households with two cars	162	30.34
	Households with three cars	49	9.18
	Households with four cars	18	3.37
	Households with five cars	8	1.5
	Households with six cars	1	10.19
	Households with seven cars	1	10.19

Source: Field survey, December 2023–February 2024

Variables

The variables of interest used in this study were categorized into four: socioeconomic variables, travel behaviour variables, attitude variables, and built environment variables. Socioeconomic variables were obtained using the data provided in the first section of the questionnaire. These include age, gender, household size, household income, educational level and car ownership. The travel behaviour variables were also determined using reported personal vehicle miles travelled on weekdays. The third section of the questionnaire presented respondents with 25 statements reflecting their attitudes towards travel, from which they were asked to assess their travel-related attributes using a five-point Likert scale, ranging from 'strongly disagree' to 'strongly agree'. Similarly, respondents identified in the fourth section, the factors that influenced their choice of residence when they were selecting their current neighbourhood from 22 statements that reflected their neighbourhood characteristics on a five-point Likert scale, ranging from 'very unimportant' to 'very important'.

Geospatial data, which forms the nucleus around which the built environment variables were determined, was collected using handheld GPS and smartphone GPS. With the assistance of the smartphone GPS, respondents voluntarily mapped the approximate spatial locations of their jobs and households. Other built environment data collected for the study were bus stop locations within the GSTA and the Central Business District (CBD) location. Land use data were obtained from the Sekondi-Takoradi Metropolitan Assembly (STMA) and subsequently reclassified for this study. Data on street and road networks, as well as structures, were obtained from Open Street Map (OSM). All the secondary data obtained were confirmed in the field through ground truthing and cleaned before being used. Some of the built environment and continuous variables were normalised using square root or log transformation before their application in SEM. This reduces the impact of outliers and allows for the generation of elasticities (Ewing *et al.*, 2015; Sardari, 2018). The spatial distribution of respondents' households in the GSTA is illustrated in Figure 2.

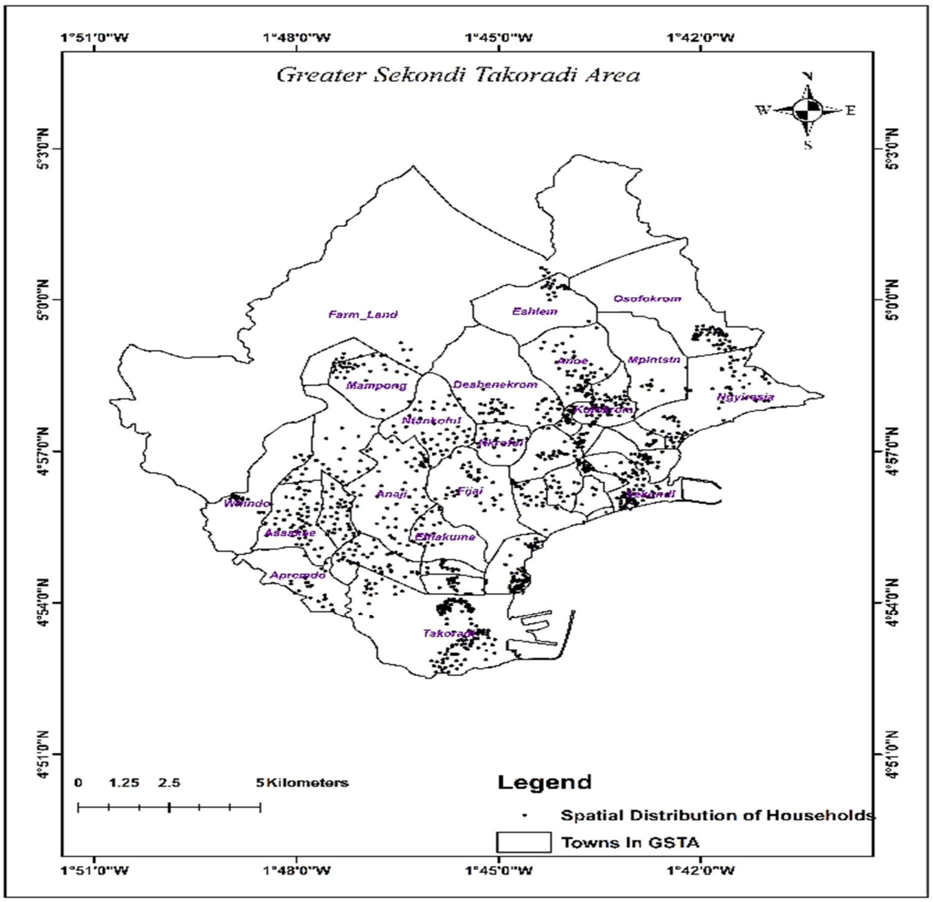

Figure 2. Spatial distribution of respondents' households in the GSTA

Data processing and descriptive statistics

Processing of data was carried out in four stages. Firstly, a buffer of 600 m was created around each respondent's household within the study area. This was used as the spatial unit to measure the built environment characteristics around each household. Secondly, exploratory factor analysis was conducted on the statements measuring attitudes and preferences to segment the diverse travel-related attitudes and preferences within the population. Thirdly, travel behaviour parameters were determined, using the reported travel frequency, travel duration, and the "crow flies" distance measured between the household locations and the work locations of each respondent using ArcGIS 10.7.1. Lastly, the variables measured in the preceding stages were used in the structural equation model to examine any relationship among the variables. The flow chart of the methods used is illustrated in Figure 3.

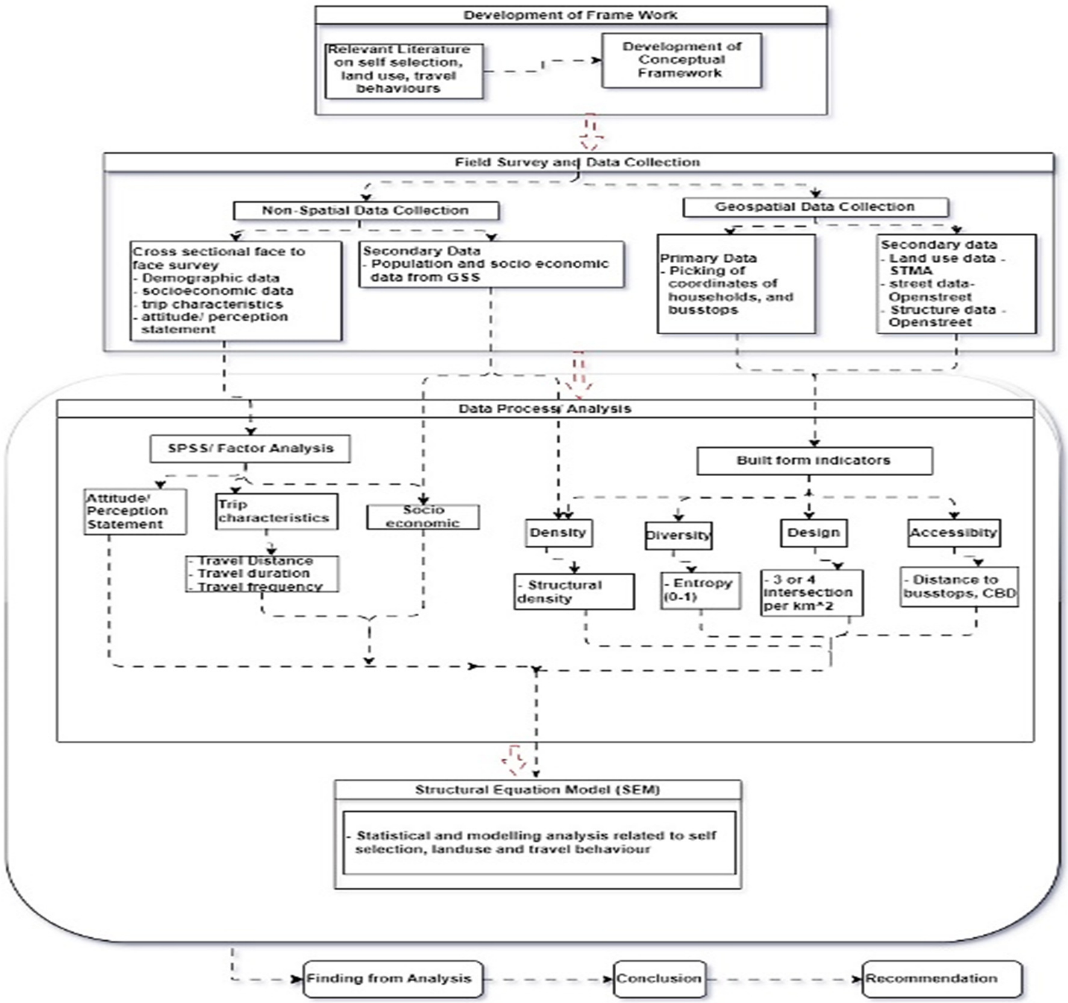

Figure 3. Flow chart of the methods used

Measurement of land use factors

Following the survey, the objective spatial characteristics of the built environment variables were computed using various metrics, including diversity, density, design, distance to the CBD, and accessibility. These computations were conducted within a 600 m buffer around each respondent's household, using ArcGIS 10.7.1 software. The use of a 600 m buffer was based on the average walking distance that residents typically cover within ten minutes to reach a bus stop or shared taxi rank from a household in the GSTA, as reported by GSS (2013). In GSTA, informal transport services dominate the public transit landscape, with minibuses commonly referred to as "trotro" and shared taxis serving as essential modes of daily commuting for much of the population. Most studies used 400 m to 800 m as the common distance measurement that transit users are willing to walk to reach the nearest bus stop or transport facility (Frank *et al.*, 2005; García-Palomares *et al.*, 2013; La Paix *et al.*, 2013; Ivan *et al.*, 2019; Masoumi, 2021; Rahman and Nilufar, 2024; Yang *et al.*, 2025). Additionally, analysing the built environment characteristics in a more detailed administrative unit or at a parcel level presents an individual's sensitivity to the built environment (La Paix *et al.*, 2013; Biba *et al.*, 2014; Ivan *et al.*, 2019). This approach offers a more effective way of evaluating the explanatory power of land use variables, as opposed to assessing the built environment characteristics across large traffic analysis zones (La

Paix *et al.*, 2013; Biba *et al.*, 2014; Ivan *et al.*, 2019). Below are the specific land use factors considered in this study:

Diversity: the mix of land use around each household was measured using the entropy index. The entropy index describes the heterogeneity or diversity balance between the land use classes around each household. The land use classes used in this study were five: Commercial, industrial, institutional, recreation/open space, and residential. The entropy index was computed using equation (1) (Ewing and Cervero, 2010).

$$\text{Entropy index} = -\sum j\ Pj * \ln Pj / \ln (J) \qquad (1)$$

Where: Pj is the portion of the buffer covered by land use, j is the sum area for land-use categories of interest, and J is the number of land-use categories within the buffer (commercial, industrial, institutional, residential, recreation/open space). The entropy ranges from 0 to 1, with zero indicating homogeneous land use and 1 indicating a highly diversified land use.

Density: The structure density was determined for each household by dividing the number of structures in a buffer by its corresponding area around each household in square kilometres.

Design: This indicates the interconnectivity of the road network around each household. This was determined by measuring the number of three or four intersections within a buffer in square kilometres, also known as intersection density. A higher intersection density indicates a higher connectivity.

Distance to CBD: Distance to CBD was measured using the Euclidean distance from a respondent's household to the CBD. The CBD serves as a centre of attraction for activities within GSTA.

Accessibility: This was determined by measuring the shortest distance from a respondent's household to the nearest bus stop using the network analysis tool in ArcGIS 10.7.1.

Measurement of travel-related attitudes and neighbourhood preferences

Most of the variables used in the questionnaire to aid in gathering data from respondents, measure similar dimensions of residential preferences and travel-related attitudes, hence the was a need to conduct factor analysis (Ramezani *et al.,* 2021). Exploratory factor analysis was conducted separately for statements attributed to attitude towards travel and neighbourhood preferences. Principal component analysis was conducted in SPSS to reduce the 25 statements related to travel attitudes to 4 factors after varimax rotation, namely, pro-car, pro-independent, pro-bike, pro-transit, time sensitive, cost sensitive, and pro-safety. All factor loadings below 0.4 were suppressed. The reliability of the scales used in the measurement was evaluated using Cronbach's alpha coefficient (α). A Cronbach's alpha of 0.66 was achieved on 18 statements considered to have sufficient reliability after the removal of 7 statements. The four selected factors have eigenvalues greater than 1, and the total variance explained by the factors was 51.71% after rotation and five iterations with similar explained values by Etminani-Ghasrodashti and Ardeshiri (2015). Bartlett's test of sphericity was significant with P<0.001 and with a Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) of 0.69. Hair *et al.* (2019) recommended 0.5 as the minimum threshold for KMO, with higher values considered to be desirable. Three statements which loaded on two factors were deleted. Similarly, the underlying construct and indicators were extracted from the list of 22 statements related to residential choice preferences into three underlying dimensions, namely cost sensitive, proximity, and comfortability. PCA with an orthogonal rotated correlation matrix (Varimax) was also used. The KMO for the second set of statements was 0.69, and a Bartlett's test of sphericity of P<0.001. A Cronbach's alpha of 0.81 was obtained on the 22 statements attributed to neighbourhood preferences, which is greater than the threshold of 0.6 (Sangkapichai and Saphores, 2009). The identified factors or constructs were able to explain 54.69% of the total variance. Similarly, factors with a loading less than 0.4 were suppressed. The results of these exploratory factor analyses were, in turn, subjected to structural equation modelling. The factors and their associated statements with factor loadings are presented in Tables 2 and 3.

Table 2. Land-use factors and their factor loadings (KMO = 0.685)

Factors	Statements	Loadings 1	Loadings 2	Loadings 3
Cost sensitive (PR1)	Accommodate travel costs (money, time, stress)	0.779		
	Low housing cost (rent, mortgage)	0.746		
	Stores are within easy walking distance from my home	0.630		
Proximity (PR2)	Proximity to the city centre		0.793	
	Proximity to a bus stop		0.759	
	Closeness to family/friends		0.585	
Comfortability (PR3)	Safety of the neighbourhood			0.723
	Parking spaces for Household use			0.628
	Proximity to the workplace			0.625

Extraction method: Principal component analysis; Rotation method: Varimax with Kaiser normalization; Rotation converged in 5 iterations

Table 3. Attitudinal factors and their defining factor loadings (KMO=0.687)

Factors	Statements	Loadings 1	Loadings 2	Loadings 3	Loadings 4
Pro-car (AT1)	The car provides the flexibility needed for my schedule	0.738			
	The car is reliable in getting me to my destination on time	0.729			
	The car provides me with the privacy I need	0.691			
	Prefer parks and open spaces nearby	0.568			
	Prefer a quiet neighbourhood	0.505			
Pro-independent (AT2)	Taking public transit is less stressful		0.826		
	Having a car indicates my status in society		0.590		
	Having space and separation from others		0.450		
Pro-bike (AT3)	I perceive it as safe to bike in my city of residence			0.804	
	Car usage is bad for the environment			0.663	
Pro-transit (AT4)	Public transport is located close to most of my destinations				0.742
	I prefer to walk/bike instead of driving whenever possible				0.740

Extraction method: Principal component analysis; Rotation method: Varimax with Kaiser normalization; Rotation converged in 5 iterations

Modelling approach

Structural equation modelling (SEM) approach was employed in estimating the relationship among the variables used in this study. SEM is made up of a measured model and a structural model (Setiawan *et al.*, 2021). The structural model defines the relationships between latent variables through path analysis while the measurement model examines the relationships between latent variables and a manifest variable through a confirmatory factor analysis (Gim, 2011; Joe-Asare *et al.*, 2023). A latent variable is a construct that cannot be measured directly but is inferred from its association with other observable variables (Westland, 2015). SEM was used because it explicitly makes it possible to model and examine various dimensions of relationships among sets of variables that can act as endogenous as well as exogenous in a specified model at the same time (De Abreu e Silva, 2014; Gim, 2018).

The structural model can be expressed as (Cao and Yang, 2017):

$$Y = BY + \Gamma X + \zeta \qquad (2)$$

With Y as the vector of l endogenous variables, X is a vector for k exogenous variables, and B refers to the matrix $(l \times l)$ of coefficient relating to pairs of endogenous variables, Γ refers to the matrix $(k \times k)$ with regression coefficient between exogenous and endogenous variables, ζ is a column vector of residuals relating to the endogenous variables.

Model specification

To examine the effects of land use, self-selection on travel behaviour, an initial SEM was constructed based on theory. Three exogenous constructs (socioeconomic, land use, and attitude variables), one endogenous variable (travel behaviour), and 20 indicators were used in the initial model. Maximum likelihood (ML) estimation in LISREL 10.3 was used in this study. ML operates in SEM based on multivariate normality (Coevering *et al.*, 2021; Ramezani *et al.*, 2021). Hence, it is important that variables used in SEM meet this requirement otherwise, estimates from the model may be rendered inaccurate. The variables of each respondent were evaluated for the potential problem of non-normality. The non-normal data and potential outliers were transformed using square root or log transformation (Coogan *et al.,* 2012, Cheng *et al.*, 2017; Coevering *et al.*, 2021). The following measured indicators for travel behaviour were transformed using square root before being used in SEM; travel frequency (TF) in a week, travel distance covered in a week (TDWK), and total travel duration in a week (TPW). Land use indicators that were also transformed using square root were net residential structural density (NRD) and the distance from the household to the CBD, while the distance from a household to a bus stop (DB) was log transformed. According to Cao *et al.* (2007) and De Vos *et al.* (2021), the issue of multivariate normality assumption could also be reduced if the ratio between the sample size and the number of observed variables is at least 15. In this study, the sample size was 534, and the ratio was 26.7, which indicates a good sample size.

Path diagrams were used to visually depict the relationship between variables in the equations (Mcintosh *et al.* 2014; Ahmad, 2024). Rectangles were used to represent indicators, while ovals were used in the path diagram to represent latent variables. An arrow in the path diagram indicates the direction of relationship. An arrow emanating from a variable indicates the variable to be a regressor in the equation and an arrow entering a variable indicates that variable to be a dependent variable (Mcintosh *et al.*, 2014). The issue of model identification was not a problem as the number of exogenous variables used in the SEM were more than that of the endogenous variables (Cao *et al.*, 2007).

The initial model was estimated, and paths that showed consistently insignificant values were deleted to ensure that the model is parsimonious (Coevering *et al.*, 2016; Hair *et al.*, 2019). Two indicators of socioeconomic construct (the available number of cars in a household (CR), educational level (EL)); one indicator of land use construct (diversity (D)); three indicators of attitude construct (pro-bike (AT3), pro-transit (AT4) and cost sensitive (PR1)) were excluded from the model. Indicators that had low standard solution figures but were statistically and theoretically significant were kept in the model (Ewing *et al.,* 2015; Coevering *et al.*, 2021). A number of iterations were conducted and the model with the best fit to the data was selected as the final model.

The final model was evaluated using goodness of fit indices commonly used in SEM. These include the comparative fit index (CFI), goodness of fit index (GFI), root mean square error of approximation (RMSEA), the ratio of chi-square (χ^2) over the degrees of freedom, the incremental fit index (IFI), adjusted goodness of fit Index (AGFI) and parsimonious normed fit index (PGFI) (Westland, 2015; Khairi *et al.*, 2021). According to Hair *et al.* (2010), the use of four to five goodness of fit indices to assess a model is considered sufficient provided the three groups of goodness of fit measures are represented, that is, absolute fit indices, incremental fit indices, and parsimonious fit indices. The final output of the model is presented in the result section and the conceptual framework for the initial model is presented in Figure 4 with a path diagram

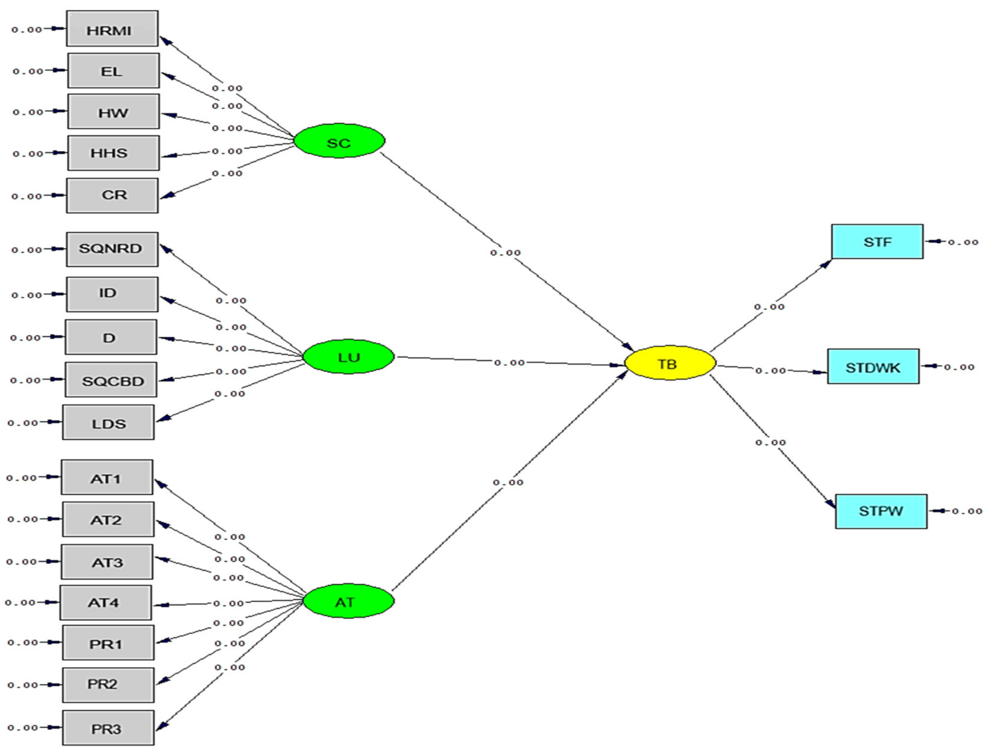

Figure 4. The initial concept of the structural equation model

Results and Discussion

Descriptive results

The descriptive statistics of the sampled respondents (n=534) are shown in Table 1. Among the respondents considered for this study, an average of 55.24% of households have one car available for commuting. The sample population also had more men commuting with private cars (58%) than women. Considering the educational background, respondents with bachelor's degrees were the highest group (39.55%) of commuters with a private car. The average household size of the sample population with private cars available for commuting is 4, representing 31.65%. Among the household composition, couples with children were the highest (43.45%) group of commuters with private cars.

Model modification

The model was assessed after the initial estimation based on the model fit indices (Hair *et al.*, 2014; Javid *et al.*, 2021). However, the initial model did not meet the fit indices and hence had to be modified based on theory and the modification indices (Akinyode, 2016). The modification indices reported by the LISREL software indicated the amount by which the chi-square value is expected to reduce if the corresponding parameters are freed. As a result, an error covariance was added between AT1 and PR2, necessitating the model's re-estimation. While this adjustment led to an improvement in the model fit indices over the initial results, the chi-square value was still high. The modification process was repeated by adding the following covariates: HW↔HHS, HHS↔SQCBD, ID↔SQCBD, and ID↔LDB, sequentially, until the fit indices were met. Each time an error covariance was added, the model was re-estimated, and the standard solution, as well as the T-values, were examined to meet the critical values. The T-value is determined by dividing the estimated parameter by its standard error, which is considered the critical ratio (Joe-Asare *et al.*, 2023). A T-value >1.96 implies the p-value of the estimate is significant at the 0.05 level, and a T-value >2.58 implies the p-value is significant at the 0.01.

From the results obtained in Figures 5 and 6, the causal path between socioeconomic (SC) factors and travel behaviour (TB) had a standardised solution value of 2.66 with a T-value of 41.35, indicating a significant relationship between socioeconomic factors and travel behaviour. The causal path between the land use (LU) factors and TB also had a standard solution of 1.37 and a T-value of 18.93, which also indicates a significant relationship between land use and travel behaviour. The relationship between the third exogenous variable (attitudinal factors (AT)) and TB also had a standard solution of 2.11 and a T-value of 17.97, which also indicated a significant relationship between attitudinal factors and travel behaviour. Considering the impact of the three exogenous factors on travel behaviour, SC factors had the highest impact, followed by AT factors and finally LU factors. The influence of the various indicators on each construct is shown in Table 4. Among the indicators for travel behaviour, trip frequency (STF) emerged as the highest (0.66) contributor in defining the travel behaviour construct. With respect to attitudinal factors, proximity (PR2) was the highest (1.03) contributor in defining the attitudinal construct. The land use construct has intersection density (ID) as the highest (1.03) contributor in defining the construct. Under the socioeconomic construct, the monthly income of the household was the highest (-0.14) contributor in defining the construct. Although some indicators had low absolute values of the standardised solution, as shown in Table 4, they all met the minimum critical ratio of T > 1.96.

Goodness of fit indices for SEMs

Over the years, various goodness of fit indices have been recognised as reliable tools for evaluating the effectiveness of a model (Setiawan *et al.,* 2021). These indicators measure how the researcher's model reproduces the actual phenomenon presented in the data (Akinyode, 2016; Kang and Ahn, 2021). The goodness of fit measures used in this study were based on the recommendations of Schumacker and Lomax (2010), Westland (2015), Hair *et al.* (2019), and Khairi *et al.* (2021). These indices include chi-square (χ^2), which is used to test how close the sample covariance matrix is to the implied covariance matrix of the model. Chi-square is sensitive to sample size; hence, the ratio of χ^2 to the degrees of freedom is recommended, with values less than 5 considered to be good. Other goodness of fit test indices are root mean square error of approximation (RMSEA), comparative fit index (CFI), the incremental fit index (IFI), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), standardised root mean square residual (SRMR) and parsimonious normed fit index (PGFI). The goodness of fit indices utilised in this study are presented in Table 5, with the recommended threshold. From the results in Table 5, the RMSEA, χ^2/df, GFI, SRMR, AGFI, and PGFI all had a good fit. CFI, NFI, and IFI had a marginally good fit. As stated by Hair *et al.* (2010), the use of 4 to 5 indices to evaluate a model is good, provided the three main groups of goodness of fit indices (absolute fit indices, incremental fit indices, and parsimonious fit indices) are represented. In general, the model's goodness of fit could be considered good, and that the model fits the data well. Figure 5 indicates the standardised solution of the final model, whereas Figure 6 illustrates the T-values of the final model.

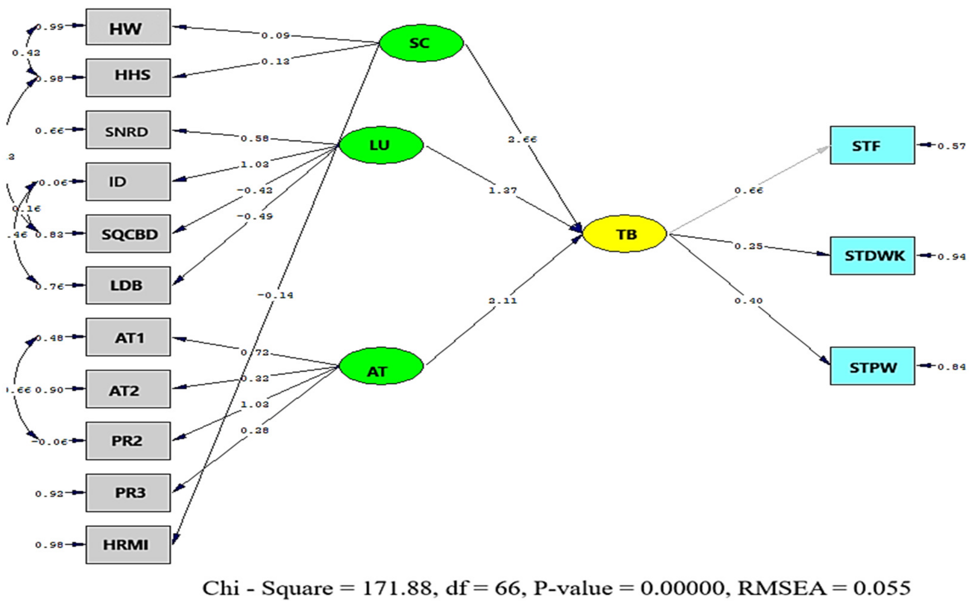

Figure 5. The standardised solution of the final model
Note: HW = Number of household workers; HHS = Household size; HRMI = Household monthly income; SQNRD = Square root of net residential structural density; ID = Intersection density; SQCBD = Square root of distance to Central Business District; LDB = Log transformation of distance to the nearest bus stop; AT1 = Pro-car; AT2 = Pro-independent; PR2 = Proximity; PR3 = Comfortability; STF = Square root of travel frequency; STDWK = Square root of travel distance; STPW = Square root of travel duration

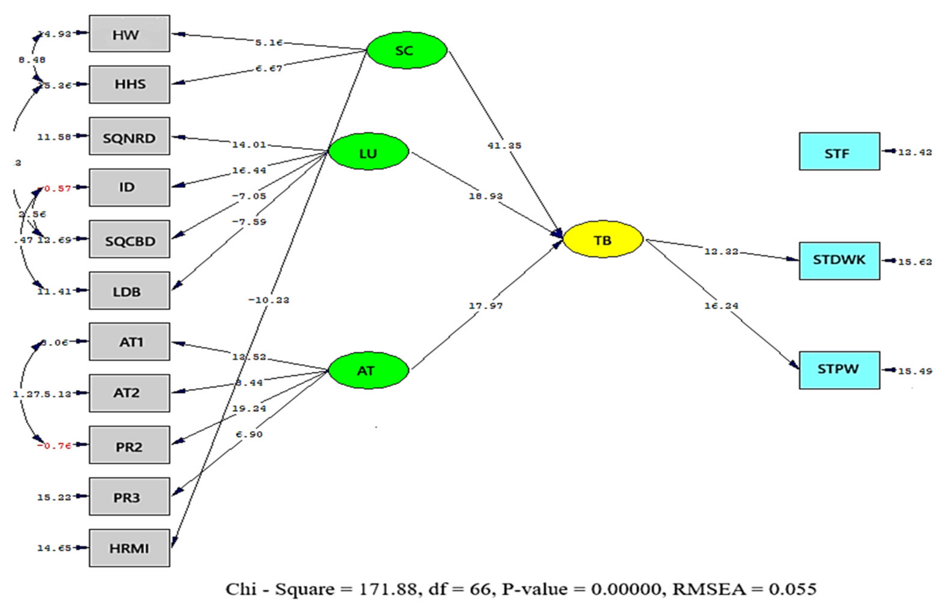

Figure 6. The T-values of the final model
Note: HW = Number of household workers; HHS = Household size; HRMI = Household monthly income; SQNRD = Square root of net residential structural density; ID = Intersection density; SQCBD = Square root of distance to Central Business District; LDB = Log transformation of distance to the nearest bus stop; AT1 = Pro-car; AT2 = Pro-independent; PR2 = Proximity; PR3 = Comfortability; STF = Square root of travel frequency; STDWK = Square root of travel distance; STPW = Square root of travel duration

Table 4. Factor loadings of indicators in SEM

Latent variable	Indicator	Standardised factor loading	T-value
Socioeconomic status (SC)	Number of Household workers (HW)	0.09	5.16
	Household size (HHS)	0.13	6.67
	Household monthly income (HRMI)	-0.14	-10.22
Land Use (LU)	Square root of net residential structural density (SNRD)	0.58	14.01
	Intersection density (ID)	1.03	16.44
	Square root of Distance to Central Business District (SQCBD)	-0.42	-7.05
	Log transformation of Distance to the nearest bus stop (LDB)	0.49	7.59
Attitudinal factors (AT)	Pro-car (AT1)	0.72	13.52
	Pro-independent (AT2)	0.32	8.44
	Proximity (PR2)	1.03	19.24
	Comfortability (PR3)	0.28	6.90
Travel Behaviour (TB)	Square root of Travel Frequency (STF)	0.66	
	Square root of Travel Distance (STDWK)	0.25	12.32
	Square root of Travel duration (STPW)	0.40	16.24

Table 5. Model fit indices assessment

Model fit indices	Reference value	Final model
Chi-square (χ^2)		171.888
Degrees of freedom (df)		66
Chi-square/df	<5	2.6
Goodness of Fit Index (GFI)	>0.9	0.964
Adjusted Goodness of Fit Index (AGFI)	>0.9	0.942
Comparative Fit Index (CFI)	>0.9	0.863
Normed Fit Index (NFI)	>0.9	0.801
Incremental Fit Index (IFI)	>0.9	0.867
Root Mean Square Error of Approximation (RMSEA)	<0.08	0.055
Standardised Root Mean Square Residual (SRMR)	<0.08	0.057
Parsimony Goodness of Fit Index (PGFI)	Closer to 1, the better	0.606

Table 6. Summary of results among constructs in the final structural model

Path of Relationship Among Constructs	Standardised Coefficient	T-value	Level of Relationship
SC→TB	2.66	41.35	Significant
LU→TB	1.37	18.93	Significant
TA→TB	2.11	17.97	Significant

Discussion

The standardised solution derived from the final model in Figure 5 reveals that socioeconomic factors exerted the strongest influence on travel behaviour, with a coefficient of 2.66. This was followed by attitudinal factors, with a coefficient of 2.034, while land use demonstrated the least impact with a coefficient of 1.319. The positive coefficient of 2.66 for socioeconomic factors indicates that an increase in socioeconomic factors among adult workers in the GSTA is associated with a 2.66 increase in travel, indicating a complementary effect. Similarly, an increase in attitude corresponds to an associated effect of 2.034 in travel. Likewise, a rise in land use activities corresponds to an effect of 1.319 on travel patterns among adult workers commuting by automobile.

The relationship between latent constructs and their indicators are shown in Table 4. Some of these indicators have negative relationships with their defining latent variables. For instance, the distance between a household and the central business district (SQCBD) had a negative relationship (-0.42) with the land use (LU) construct. This implies that an increase in distance between a household and CBD tends to result in fewer land use activities on the city's outskirts and encourages commuters residing in peripheral areas to rely on car usage. This reflects the spatial land use activities observed in the field as the distance from CBD to households widens. Also, the relationship between land use construct and the distance between a household and a bus stop was negative (-0.49). This also implies that an increase in distance from a household to a bus stop may lead to a decrease in accessibility for other modes of travel and a motivation for automobile use. The Household's monthly income (HRMI) indicator for socioeconomic construct had a negative factor loading of -0.14. This also indicates that an increase in household monthly income tends to increase the desire for automobile usage compared to other modes. The results also revealed that, among the indicators of the attitude construct, proximity emerged as the most influential indicator. This indicates that the residential location choices of most private car owners in GSTA were driven more by preferences for urban location characteristics than by travel-related considerations. With land use latent construct, intersection density, which represents road connectivity, was identified as the most influential indicator. This implies that among the physical and objective land use factors, road connectivity substantially influenced the travel behaviour of automobile commuters within the GSTA. Diversity, an indicator of the land use construct, exhibited insignificant effect on the land use construct. As a result, it was excluded from the model during the modification process. The limited influence of diversity on land use might be attributed to the low level of mixed land use in the locality of most respondents, coupled with the influence of self-selection, which often promotes the reliance on automobile travel. Thus, addressing the influence of the interplay between self-selection and mixed land use on travel behaviour could contribute significantly to sustainable mobility within the GSTA. The findings aligned with previous research on the significant roles of residential self-selection and land use in shaping travel behaviour (De Abreu e Silva *et al.*, 2008; De Abreu e Silva, 2014; Parady *et al.*, 2014; Gim, 2016).

Conclusion

This study applies SEM to examine the spatial effect of the relationship among land use, self-selection and socioeconomic factors on travel behaviour of adult commuters with automobile mode of travel in GSTA, a medium-sized city of Ghana, using disaggregated data. The results indicated primarily the presence of self-selection in GSTA and secondly, the magnitude of influence by self-selection is slightly higher than the land use effect on travel behaviour. The result also confirms the complementary influence of the relationship among the three exogenous variables on travel behaviour.

To this end, the study makes four key contributions to the understanding of this complex relationship from the perspective of a medium-sized city in Africa. First, it employs structural equation modelling to analyse the intricate relationships within this context. Second, it integrates attitudinal, socioeconomic, and land use factors to assess how the built environment influences travel behaviour from the perspective of a medium-sized city in Ghana. Third, it utilises disaggregated data to capture the objective aspects of the built environment. Finally, it provides the first empirical evidence of the impact of self-selection, land use, and socioeconomic factors on the travel behaviour of adult commuters using automobile mode of travel in the GSTA. This study offers valuable insights for urban planners aiming to optimise land use and transportation systems, thereby enhancing sustainable mobility and environmental health. Future research should explore longitudinal data to further investigate the effects of land use and self-selection on travel behaviour in similar settings.

Authors' Contributions

Conceptualization: JKL; Data curation: JKL; Formal analysis: JKL; Investigation: JKL; Methodology: JKL; Project administration; Resources; Software: JKL; Supervision: MSA and SM; Validation: MSA and SM; Visualization: JKL, MSA and SM; Writing - original draft: JKL; Writing - review and editing: JKL, MSA and SM. All authors read and approved the final manuscript.

Ethical approval

This research received an ethical approval with reference UREC/ETH/24/006 from the ethical committee of the University of Mines and Technology, Tarkwa, Ghana.

Acknowledgements

This work was partially supported by the University of Mines and Technology, Tarkwa, Ghana, grant number S.31.

Conflict of Interests

The authors declare that there are no conflicts of interest related to this article.

References

Aditjandra PT, Mulley C, Nelson JD (2009). Extent to which sustainable travel to work can be explained by neighborhood design characteristics. Journal of the Transportation Research Board 2134:114-122. *https://doi.org/10.3141/2134-14*

Ahmad M, Anwer I, Yousuf MI, Javid MA, Ali N, Tesoriere G, Campisi T (2024). Investigating the key factors affecting public transport ridership in developing countries through Structural Equation Modeling. Sustainability 16(11):4426. *https://doi.org/10.3390/su16114426*

Akinyode BF (2016). The use of Structural Equation Modeling (SEM) in built environment disciplines. Research on Humanities and Social Sciences 6(6):2224-5766. *https://core.ac.uk/download/pdf/234674991.pdf*

Bagley MN, Mokhtarian PL (2002). The impact of residential neighborhood type on travel behaviour: A structural equations modeling approach. The Annals of Regional Science 36:279-297. *https://doi.org/10.1007/s001680200083*

Bhagat-Conway MW, Mirtich L, Salon D (2024). Subjective variables in travel behavior models: a critical review and standardized transport attitude measurement protocol (STAMP). Transportation 51:155-191. *https://doi.org/10.1007/s11116-022-10323-7*

Biba S, Curtin KM, Manca G (2014). Who can access transit? Reviewing methods for determining population access to bus transit. A Journal of Policy Development and Research 16(2):193-204. *https://www.jstor.org/stable/26326896*

Biney E, Forkuo EK, Poku-Boansi M, Asare YM, Hackman KO, Yankey DB, Agbenorhevi AE, Annan E (2024). A comprehensive analysis and future projection of land use and land cover dynamics in a fast-growing city: A case study of Sekondi-Takoradi metropolis, Ghana. Scientific African 24:e02207. *https://doi.org/10.1016/j.sciaf.2024.e02366*

Bohte W, Maat K, Wee BV (2009). Measuring attitudes in research on residential self-selection and travel behaviour: A review of theories and empirical research. Transport Reviews 29(3):325-357. *https://10.1080/01441640902808441*

Cao X, Ettema DF (2014). Satisfaction with travel and residential self-selection: How do preferences moderate the impact of the Hiawatha Light Rail Transit line? Journal of Transport and Land Use 7(3):93-108. *https://doi.org/10.5198/jtlu.v7i3.485*

Cao X, Handy SL, Mokhtarian P (2006). The influences of the built environment and residential self-selection on pedestrian behavior: Evidence from Austin, TX. Transportation 33:1-20. *https://doi.org/10.1007/s11116-005-7027-2*

Cao X, Mokhtarian PL, Handy SL (2007). Do changes in neighborhood characteristics lead to changes in travel behaviour? A Structural Equations Modeling Approach 34:535-556. *https://doi.org/10.1007/s11116-007-9132-x*

Cao X, Yang W (2017). Examining the effects of the built environment and residential self-selection on commuting trips and the related CO_2 emissions: An empirical study in Guangzhou, China Transport. Transportation Research Part D: Transport and Environment 52:480-494. *https://doi.org/10.1016/j.trd.2017.02.003*

Chatman D (2014). Estimating the effect of land use and transportation planning on travel patterns: Three problems in controlling for residential self-selection. The Journal of Transport and Land Use 7(3):47-56. *http://dx.doi.org/10.5198/jtlu.v7i3.729*

Cheng L, Chen X, Yang S, Wu J, Yang M (2017). Structural equation models to analyze activity participation, trip generation, and mode choice of low-income commuters. Transportation Letters 11(6):341-349. *https://doi.org/10.1080/19427867.2017.1364460*

Coevering van de P, Maat K, Kroesen M, Wee van B (2016). Causal effects of built environment characteristics on travel behaviour: a longitudinal approach. European Journal of Transport and Infrastructure Research 16(4):674-697. *https://doi.org/10.18757/ejtir.2016.16.4.3165*

Coogan MA, Adler T, Karash H (2012). The paths from walk preference to walk behavior: applying latent factors in Structural Equation Modeling. Journal of Transport and Land Use 5(3):68-82. *https://doi.org/10.5198/jtlu.v5i3.269*

De Abreu e Silva J (2014). Spatial self-selection in land-use-travel behaviour interactions: Accounting simultaneously for attitudes and socioeconomic characteristics. Journal of Transport and Land Use 7(2):63-84. *https://doi.org/10.5198/jtlu.v7i2.696*

De Abreu e Silva J, Konstadinos G, Goulias (2008). Using structural equations modeling to unravel the influence of land use patterns on travel behaviour of urban adult workers of Puget sound region. In: 88th Transportation Research Board Annual Meeting. Transportation Research Record, Washington DC pp 1-17. *https://escholarship.org/uc/item/0j18r6fk*

De Abreu e Silva J, Lucchesi S (2022). Land-use patterns, location choice, and travel behavior: Evidence from São Paulo. Journal of Transport and Land Use 15(1):315-332. *https://doi.org/10.5198/jtlu.2022.2125*

De Vos J, Cheng L, Witlox F (2021). Do changes in the residential location lead to changes in travel attitudes? A structural equation modeling approach. Transportation 48:2011-2034. *https://doi.org/10.1007/s11116-020-10119-7*

Devlin JA (2010). Structural effects of the built environment on vehicle greenhouse gas emissions: evidence from Vancouver, Canada. MSc Dissertation, The University of British Columbia. *https://dx.doi.org/10.14288/1.0068848*

Etminani-Ghasrodashti R, Ardeshiri M (2015). Modeling travel behaviour by the structural relationships between lifestyle, built environment and non-working trips. Transportation Research Part A 78:506-518. *https://doi.org/10.1016/j.tra.2015.06.016*

Ewing R, Cervero R (2010). The role of built environment characteristics and residential self- selection on car use and active travel. Journal of the American Planning Association 76(3):265-294. *https://doi.org/10.1080/01944361003766766*

Ewing R, Hamidi S, Grace JB (2015). Compact development and VMT – Environmental determinism, self-selection, or some of both? Environment and Planning B: Planning and Design 1-19. *https://doi.org/10.1177/0265813515594811*

Faber R, Merkies R, Damen W, Oirbans L, Massa D, Kroesen M, Molin E (2021). The role of travel-related reasons for location choice in residential self-selection. Travel Behaviour and Society 25:120-132. *https://doi.org/10.1016/j.tbs.2021.07.003*

Frank LD, Schmid TL, Sallis J, Chapman FJ, Saelens BE (2005). Linking objectively measured physical activity with objectively measured urban form findings from SMARTRAQ. American Journal of Preventive Medicine 28(2):117-25. *https://10.1016/j.amepre.2004.11.001*

García-Palomares JC, Gutiérrez J, Cardozo OD (2013). Walking accessibility to public transport: An analysis based on microdata and GIS. Environment and Planning B: Planning and Design 40(6):1087-1102. *https://doi.org/10.1068/b39008*

Gim TT (2011). Influences on trip frequency according to travel purposes: A structural equation modeling approach in Seoul, South Korea. Environment and Planning B: Planning and Design 38(3):429-446. *https://doi.org/10.1068/b36061*

Gim TT (2016). Testing the reciprocal relationship between attitudes and land use in relation to trip frequencies: A nonrecursive model. International Regional Science Review 39(2):203-227. *https://doi.org/10.1177/0160017613512651*

Gim TT (2018). An analysis of the relationship between land use and weekend travel: focusing on the internal capture of trips. Sustainability 10:425. *https://doi.org/10.3390/su10020425*

Gim TT (2019). Examining the effects of residential self-selection on internal and external validity: an interaction moderation analysis using structural equation modeling. Transportation Letters 11(5):275-286 *https://doi.org/10.1080/19427867.2017.1338544*

GSS (2010). Population and housing census 2010: Summary of final report. Ghana Statistical Services, Accra. Retrieved 2024 August 20 from *https://www.statsghana.gov.gh/gssmain/storage/img/marqueeupdater/Census2010_Summary_report_of_final_results.pdf*

GSS (2013). Second national household transport survey report 2012. Ministry of Roads and Highways, Ministry of Transport, and Ghana Statistical Service, Accra. Retrieved 2023 November 23 from *https://www2.statsghana.gov.gh/docfiles/publications/Second%20National%20Household%20Transport%20Survey%20Report%202012.pdf*

GSS (2021). Population and housing census, 2021. Ghana Statistical Services, Accra. Retrieved 2024 September 10 from *https://census2021.statsghana.gov.gh/*

Guan X, Wang D Jason Cao X (2020). The role of residential self-selection in land use-travel research: a review of recent findings. Transport Reviews 40(3):267-287. *https://doi.org/10.1080/01441647.2019.1692965*

Hair JF, Anderson RF, Black WC, Babin BJ, Anderson RE (2014) Multivariate Data Analysis: Pearson New International Edition. Seventh Edition. Edinburgh Gate, Pearson Education Limited.

Hair JF, Black W, Babin B, Anderson R (2019). Multivariate Data Analysis. Eighth edition, Cengage, Andover, United Kingdom. *https://eli.johogo.com/Class/CCU/SEM/_Multivariate%20Data%20Analysis_Hair.pdf*

Hair JF, Black WC, Babin BJ, Anderson RE (2010). Multivariate data analysis. Seventh edition, Pearson, New York.

Ivan I, Horak J, Zajickova L, Burian J, Fojtik D (2019). Factors influencing walking distance to the preferred public transport stop in selected urban centres of Czechia. GeoScape 13:16-30. *https://doi.org/10.2478/geosc-2019-0002*

Javid MA, Abdullah M, Ali N, Dias C (2021). Structural equation modeling of public transport use with COVID-19 precautions: An extension of the norm activation model. Transportation Research Interdisciplinary Perspectives 12:100474. *https://doi.org/10.1016/j.trip.2021.100474*

Joe-Asare T, Stemn E, Amegbey N (2023). Relationships among causal factors influencing mine accidents using structural equation modelling. International Journal of Injury Control and Safety Promotion 30(4):643-651, *https://doi.org/10.1080/17457300.2023.2248491*

Kang H, Ahn J (2021). Model setting and interpretation of results in research using structural equation modeling: a checklist with guiding questions for reporting. Asian Nursing Research 15:157-162. *https://10.1016/j.anr.2021.06.001*

Khairi MI, Susanti D, Firman S (2021). Study on structural equation modeling for analyzing data. International Journal of Ethno-Sciences and Education Research 1(3):52-60. *https://10.46336/ijeer.v1i3.295*

La Paix Puello L, Monzón A, Cherchi E, Loro M (2013). Residential self-selection and geographical scales in trip frequency. In: Proceedings of the 13th World Conference of Transport Research, WCTR, Río, Brazil pp 1-24. *https://ris.utwente.nl/ws/portalfiles/portal/5520654/2876.pdf*

Lin J, Yang A (2009). Structural analysis of how urban form impacts travel demand: evidence from Taipei. Urban Studies 46(9):1951-1967. *https://doi.org/10.1177/0042098009106017*

Maat K, Timmermans HJP (2009). A causal model relating urban form with daily travel distance through activity/travel decisions. Transportation Planning and Technology 32(2):115-134. *https://doi.org/10.1080/03081060902861285*

Masoumi H (2021). Residential location choice in Istanbul, Tehran, and Cairo: The Importance of Commuting to Work. Sustainability 13(10):5757. *https://doi.org/10.3390/su13105757*

McIntosh J, Trubka R, Kenworthy J, Newman P (2014). The role of urban form and transit in city car dependence: Analysis of 26 global cities from 1960 to 2000. Transportation Research Part D 33:95-110. *https://doi.org/10.1016/j.trd.2014.08.013*

Mokhtarian PL, Cao X (2008). Examining the impacts of residential self-selection on travel behavior: a focus on methodologies. Transportation Research Part B: Methodological 43(3):204-228. *https://doi.org/10.1016/j.trb.2007.07.006*

Naess P (2014). Tempest in a teapot: The exaggerated problem of transport-related residential self-selection as a source of error in empirical studies. Journal of Transport and Land Use 7:57-79. *https://doi.org/10.5198/jtlu.v7i3.491*

Nkeki FN, Asikhia OM (2023). Does built environment matter in a medium-sized African city? Empirical evidence from the interaction between land use and travel behavior. Transportation Research Interdisciplinary Perspectives 21:100881. *https://doi.org/10.1016/j.trip.2023.100881*

Okyere DK (2018). Effects of mobile phone use on household travel behavior in Kumasi, Ghana. PhD Thesis, University of Texas, Dallas.

Parady GT, Chikaraishi M, Takami K, Harata N (2014). A panel data approach to understanding the effect of the built environment on travel behavior - A case study of the Kashiwanoha Area, Chiba, Japan. Urban and Regional Planning Review 1:18-38. *https://doi.org/10.14398/urpr.1.18*

Park K, Ewing R, Scheer BC, Tian G (2018). The impacts of built environment characteristics of rail station areas on household travel behavior. Cities 74:277-283. *https://doi.org/10.1016/j.cities.2017.12.015*.

Pinjari AR, Pendyala RM, Bhat C, Waddell P (2007). Modeling residential sorting effects to understand the impact of the built environment on commute mode choice. Transportation 34(5):557-573. *https://doi.org/10.1007/s11116-007-9127-7*

Rahman MM, Nilufar F (2024). An investigation into the land use pattern of Dhaka: Identifying activity nodes for a compact city. Spatium 52:1-13. *http://dx.doi.org/10.2298/SPAT240630014R*

Ramezani S, Hasanzadeh K, Rinne T, Kajosaari A, Kyttä M (2021). Residential relocation and travel behavior change: Investigating the effects of changes in the built environment, activity space dispersion, car and bike ownership, and travel attitudes. Transportation Research Part A: Policy and Practice 147:28-48. *https://doi.org/10.1016/j.tra.2021.02.016*

Sardari R, Hamidi S, Pouladi R (2018). Effects of traffic congestion on vehicle miles traveled. Transportation Research Record 2672(47):92-102. *https://doi.org/10.1177/0361198118791865*

Scheiner J (2010). Social inequalities in travel behaviour: trip distances in the context of residential self-selection and lifestyles. Journal of Transport Geography 18(6):679-690. *https://doi.org/10.1016/j.jtrangeo.2009.09.002*

Schumacker RE, Lomax RG (2010). A beginner's guide to structural equation. Third edition, Rutledge. New York.

Schwanen T, Mokhtarian PL (2005). What affects commute mode choice: neighborhood physical structure or preferences toward neighborhoods. Journal of Transport Geography 13:83-99. *https://doi.org/10.1016/j.jtrangeo.2004.11.001*

Setiawan E, Pratiwi A, Herawati N, Nisa K, Faisol A (2021). A structural equation modeling of factors affecting student motivation in thesis preparation. Journal of Physics 1751:012030. *https://doi:10.1088/1742-6596/1751/1/012030*

Sinniah GK, Shah MZ, Vigar G, Aditjandra PT (2016). Residential Location Preferences: New Perspective. Transportation Research Procedia 17:369-383. *https://doi.org/10.1016/j.trpro.2016.11.128*

Soinio L (2021). The role of built environment characteristics and residential self-selection on car use and active travel. MSc Thesis, Aalto University. *https://urn.fi/URN:NBN:fi:aalto-202105236909*

STMA (2021). Medium-term development plan 2022-2025. Sekondi Takoradi Metropolitan Assembly, Ghana. Retrieved 2024 September 6 from *https://stma.gov.gh/documents/STMA%20MEDIUMTERM%20DEVELOPMENT%20PLAN%20%202022%202025%20final.pdf*

Van Acker V, Boussauw K, Witlox F (2011). Understanding modal choices for leisure activities. Is it just objectively determined? Belgian Journal of Geography 1-2:105-120. *https://doi.org/10.4000/belgeo.6395*

Wala AA, Alim S, Setyatama F (2020). Use of structural equation modeling method for analysis of factors affecting the quality of library services of Bhayangkara University. Journal of Electrical Engineering and Computer Sciences 5(2):835-844. *https://doi.org/10.54732/jeecs.v5i2.89*.

Wang D, Lin T (2019). Built environment, travel behavior, and residential self-selection: a study based on panel data from Beijing, China. Transportation 46(1):51-74. *https://doi.org/10.1007/s11116-017-9783-1*

Wang D, Lin T (2014). Residential self-selection, built environment, and travel behaviour in the Chinese context. Journal of Transport and Land Use 7(3):5-14. *https://doi.org/10.5198/jtlu.v7i3.486*

Westland JC (2015). Structural equation models, from paths to networks. Springer International Publishing Vol 22. Springer, Cham (2015). *https://doi.org/10.1007/978-3-319-16507-3*

Wolday F (2018). Land use and travel behavior in small cities. PhD Thesis, Norwegian University of Life Sciences. *http://dx.doi.org/10.13140/RG.2.2.16227.50724*

Yang Q, Zhang Z, Cai J, Ding M, Li L, Zhang S, Song Z, Chen F, Ling Y (2025). Quality of pedestrian networks around metro stations: An assessment based on approach routes. Systems 13:63. *http://dx.doi.org/10.3390/systems13010063*

Zhao C, Nielsen TA, Olafsson AS, Carstensen TA, Meng X (2018). Urban form, demographic and socio-economic correlates of walking, cycling, and e-biking: Evidence from eight neighborhoods in Beijing. Transport Policy 64:102-112. *https://doi.org/10.1016/j.tranpol.2018.01.018*

Zhou B, Kockelman KM (2008). Self-selection in home choice: Use of treatment effects in evaluating relationship between built environment and travel behaviour. Transportation Research Record 2077(1):54-61. *https://doi.org/10.3141/2077-08*