# Influence of Urban Mobility Pattern on Transport-related Carbon Dioxide Emission: A Path Analysis for Sustainable Urban Mobility

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## Abstract

*Urban mobility plays a central role in ensuring the efficient movement of people and goods while supporting economic and social activities. However, rapid urban expansion and increasing travel demand have intensified transport-related carbon dioxide ($CO_2$) emissions. This study examines how urban form and socio-economic characteristics influence transport-related $CO_2$ emissions through residents' mobility patterns using a path analysis approach within a Structural Equation Modeling (SEM). The results show that urban form and socio-economic conditions jointly shape urban mobility. Greater distance from the central business district increases travel distance ($\beta = 0.45$, $p < 0.001$) and indirectly increases $CO_2$ emissions ($\beta = 0.15$, $p < 0.05$). In contrast, higher land-use diversity indirectly reduces emissions by promoting public transport use and reducing private car dependence ($\beta = -0.13$, $p < 0.01$), while higher building density reduces emissions by increasing jeepney use ($\beta = -0.11$, $p < 0.05$). Car ownership exerts the strongest socio-economic influence, increasing private car use ($\beta = 0.45$, $p < 0.001$) and indirectly increasing $CO_2$ emissions ($\beta = 0.21$, $p < 0.001$). Higher household income also increases emissions through greater private car and taxi use ($\beta = 0.19$, $p < 0.001$), whereas older age indirectly increases emissions through reduced jeepney use ($\beta = 0.13$, $p < 0.01$). These findings demonstrate that urban structure and socio-economic characteristics influence transport-related $CO_2$ emissions primarily through travel behavior, highlighting the need for compact urban development, mixed land use, and sustainable transport policies to promote low-carbon urban mobility.*

***Keywords:*** socio-economic characteristic, travel behavior, transport-related $CO_2$ emissions, urban form, urban mobility

## 1. Introduction

Urban mobility is a crucial component of both urban theory and planning practice, as it mediates interactions among spatial structure, socioeconomic activities, and environmental outcomes. The movement of people and goods supports economic productivity (Wan *et al*., 2024), social interaction (Brzeziński, 2024), and urban functionality (El-Sherif, 2021), while shaping energy use and emissions patterns within cities. As urban areas continue to expand due to population growth, demand for mobility increases, often leading to greater reliance on motorized transport. This shift contributes significantly to transport-related carbon dioxide ($CO_2$) emissions (Intergovernmental Panel on Climate Change [IPCC], 2015).

From a theoretical standpoint, urban form is widely understood to influence travel behavior by shaping accessibility, proximity, and mode availability. Dispersed, low-density development, often conceptualized as urban sprawl (Hamidi & Ewing, 2014; Song *et al*., 2017), has been linked to longer travel distances and greater dependence on private vehicles (Fang *et al*., 2015). In addition, Ma *et al*. (2015) emphasized that job-housing spatial mismatch significantly increases commuting distances and emissions, reinforcing the need for spatial planning policies that promote decentralization of employment and land-use balance.

Conversely, compact urban development and the theory of urban fabrics emphasize the role of density, land-use diversity, and transit-oriented structures in supporting shorter trips (Newman *et al*., 2016) and enabling shifts toward active and public transport modes (Rahman *et al*., 2022). Similarly, Ma *et al*. (2015) found that in Beijing, neighborhoods with higher job and retail densities, proximity to employment centers, and better subway accessibility show shorter travel distances. Researchers therefore expect these spatial configurations to reduce transport-related $CO_2$ emissions by influencing both trip length and modal choice (Ewing *et al*., 2016; Newman, 2016). Nevertheless, Shi *et al*. (2022) found that urban complexity, sprawl, and high population densities elevate $CO_2$ emissions in cities along the Yangtze River Economic Belt, whereas urban centrality and the share of tertiary economic activity reduce emissions.

Overall, the existing evidence suggests that spatial structure alone does not fully account for observed mobility outcomes. Behavioral and socio-economic perspectives highlight that individual characteristics such as income, car ownership, age, and household composition also shape travel decisions. According to the Theory of Planned Behavior (Ajzen, 1991; Bamberg *et al.*, 2003), travel behavior reflects not only the physical environment but also travel attitudes, subjective norms, and perceived behavioral control. Empirical evidence consistently shows that higher income and vehicle ownership increase the likelihood of private car use, while lower-income groups rely more heavily on public and non-motorized transport (Dalde *et al.*, 2025; Mwale *et al.*, 2022).

For instance, wealthier households often reside in suburban areas with limited access to public transport, which contributes to longer travel distances and higher transport-related carbon dioxide emissions (Yang *et al.*, 2015). In contrast, lower-income populations typically live in high-density urban areas and rely more heavily on public transportation and non-motorized modes of travel (Allen *et al.*, 2023). However, this pattern changes when low-income households relocate to peripheral areas. In the absence of adequate public transport services, these households are increasingly compelled to adopt private vehicle use, which in turn elevates their carbon footprint (Schouten, 2022; Yousefzadeh Barri *et al.*, 2021).

Recent research increasingly conceptualizes travel behavior as a key mediator between urban form, socio-economic conditions, and transport-related $CO_2$ emissions (Dalde *et al.*, 2025). Evidence indicates that socio-economic characteristics, rather than urban form, primarily drive travel behavior, which in turn significantly affects emissions, while compact urban form has limited influence on travel behavior. Nevertheless, Hasanpour and Farooq (2025) emphasize that the effect of urban form on public transportation demand are context-specific and should be evaluated based on local mobility patterns to guide effective and location-tailored planning strategies.

Despite considerable advances in understanding the interrelationships among urban form, socio-economic characteristics, travel behavior, and transport-related $CO_2$ emissions, several research gaps persist. Previous study, particularly Dalde *et al.* (2025), is constrained by the limited scope of indicators used to measure travel behavior, which may not fully capture its multidimensional complexity. The influence of urban form on travel behavior is context-specific and requires evaluation based on local mobility patterns. In addition, reliance on grid-based spatial frameworks in prior studies may reduce alignment with barangay-level administrative and planning units. Integrating indicators at the barangay level addresses these limitations by enhancing contextual relevance while accounting for potential internal heterogeneity.

To address this gap, this study examines how urban mobility patterns—specifically travel distance and transport mode choice—mediate the relationships between urban form indicators, socio-economic characteristics, and transport-related $CO_2$ emissions. Using a path analysis approach within a structural equation modeling (SEM) framework, the study provides a context-specific and policy-relevant understanding of mobility–emissions dynamics to guide sustainable transport and urban planning strategies in Cagayan de Oro City. Furthermore, the research provides an empirical foundation to support integrated land use and transport planning in emerging urban contexts, thereby contributing to the advancement of sustainable urban mobility.

## 2. Methodology

This study employs a quantitative and cross-sectional research design to investigate the influence of urban mobility pattern on transport-related $CO_2$ emission in Cagayan de Oro City, Philippines.

### *2.1 Conceptual Framework*

Figure 1 presents the conceptual framework, illustrating the pathways through which spatial and socio-economic characteristics influence transport-related $CO_2$ emissions. Specifically, this study examines how Urban Form Indicators (UFI) such as building density, population density, land use diversity, and distance to the Central Business District (CBD), and Socio-Economic characteristics (SEC) including age, household income, family size, and car ownership, influence Travel Behavior (TB). Trip frequency, travel distance, and transport mode choice characterize travel behavior. Based on this framework, the study formulates hypotheses to examine the direct and indirect effects of UFI and SEC on $CO_2$ emissions, with TB serving as the mediating mechanism.

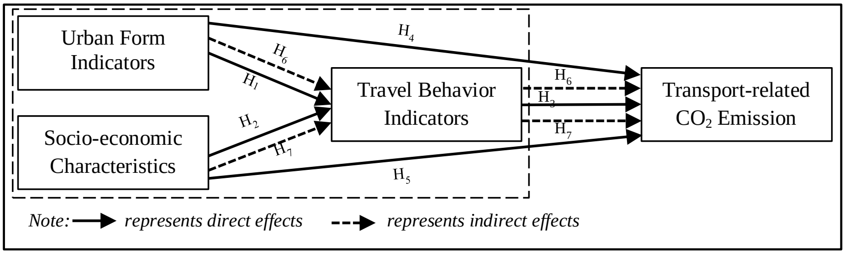



Figure 1. Conceptual framework for analyzing the influence of urban mobility patterns on transport-related $CO_2$ emissions

- $H_1$: Direct Effect of UFI on TB (UFI → TB)
- $H_2$: Direct Effect of SEC on TB (SEC → TB)
- $H_3$: Direct Effect of TB on $CO_2$ Emissions (TB → $CO_2$)
- $H_4$: Direct Effect of UFI on $CO_2$ Emissions (UFI → $CO_2$)
- $H_5$: Direct Effect of SEC on $CO_2$ Emissions (SEC → $CO_2$)
- $H_6$: Indirect Effect of UFI on $CO_2$ Emissions, with TB as mediating variable (UFI → TB → $CO_2$)
- $H_7$: Indirect Effect of SEC on $CO_2$ Emissions, with TB as mediating variable (SEC → TB → $CO_2$)

Two theories ground this framework theoretically. The Theory of Planned Behavior (TPB) explains how socio-economic characteristics and perceived behavioral control shape travel decisions (Ajzen, 1991). The Theory of Urban Fabrics conceptualizes how different urban structures (e.g., walking, transit, and automobile fabrics) influence travel distance and mode preference, which may contribute to transport-related $CO_2$ emissions (Newman *et al.*, 2016). The solid lines represent the direct effects of UFI and SEC on transport-related $CO_2$ emissions. In contrast, the dashed lines denote the indirect effects of these factors, which travel behavior mediates — specifically trip frequency, travel distance, and transport mode choice. This distinction visually conveys the hypothesized causal pathways tested in the path analysis model.

*2.2 Study Area*

Cagayan de Oro City (Figure 2), the capital of Misamis Oriental in Northern Mindanao, Philippines, is a highly urbanized center with an estimated population of approximately 700,000. Serving as the regional hub for commerce, education, and transportation, the city has experienced rapid demographic and spatial growth. Its geographic layout comprises a flat coastal plain and hinterland foothill, which support a wide range of land uses, including residential, commercial, institutional, industrial, and service-oriented developments. This spatial heterogeneity reflects the city's dynamic urban form and evolving functional structure, which regional migration and economic expansion continue to shape.

The city's transportation system is composed of arterial roads, public utility jeepneys, buses, motorcycles, and limited non-motorized transport infrastructure. This combination illustrates the coexistence of traditional and emerging mobility systems. With its expanding built environment, diverse land-use patterns, and socio-economic variability, Cagayan de Oro exemplifies a mid-sized Southeast Asian city undergoing rapid urban transformation. These conditions make it an ideal case for analyzing how urban form and socio-economic characteristics interact to shape travel behavior and contribute to transport-related $CO_2$ emissions. Understanding these interlinkages is critical for informing spatial and mobility planning in similar rapidly urbanizing contexts across the region.

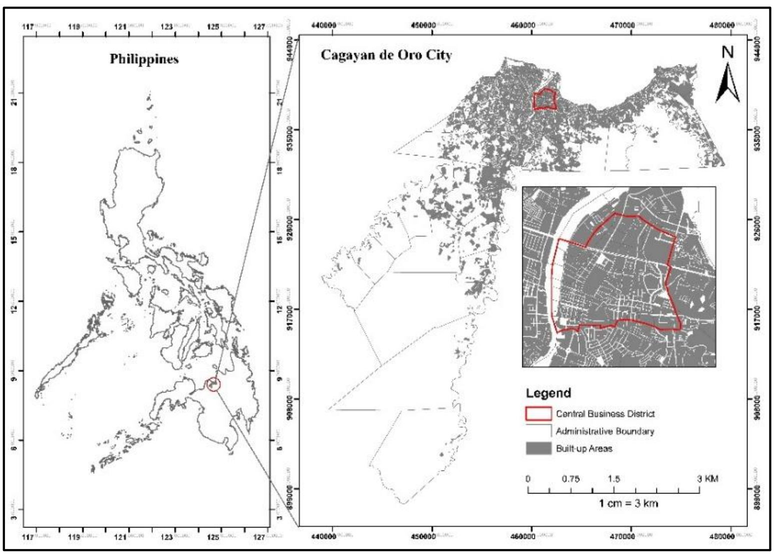



Figure 2. Location map of the study area data (source: CDO City Planning & Development Office)

*2.3 Research Workflow*

The research workflow depicted in Figure 3 outlines the systematic approach used to examine the influence of urban mobility patterns on transport-related

$CO_2$ emissions. The process begins with the collection of primary and secondary data, including socio-economic profiles, travel behavior obtained through Origin-Destination (OD) surveys. Whereas urban form indicators such as building density, land use diversity, road density, and proximity to the Central Business District (CBD), obtained from the City Planning and Development Office. Following data collection, comprehensive data preparation is conducted, involving cleaning, coding, and categorization of socio-economic and travel behavior variables.

The study used ArcGIS software (Esri, n.d.) to perform spatial analysis and further characterize urban form. The researchers then analyzed the prepared dataset using path analysis within structural equation modeling (SEM) in IBM SPSS Amos version 29 (IBM Corp., 2022) to assess the direct and indirect effects of urban form and socio-economic characteristics on travel behavior and, subsequently, on transport-related $CO_2$ emissions. This analytical workflow provides a structured framework for examining the mediating role of travel behavior in linking urban form and socio-economic characteristics to environmental outcomes, thereby supporting research on sustainable urban mobility.

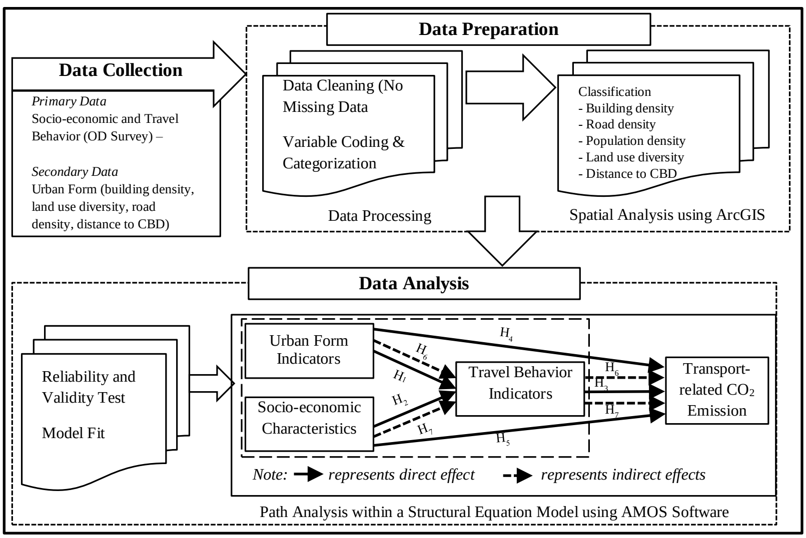



Figure 3. Research workflow

### 2.4 Data Collection

Data collection comprised both primary and secondary sources. The researchers collected primary data through a convenience-based online Origin–Destination (OD) survey administered via Google Forms. They disseminated the survey link through various digital platforms, including Facebook and email, and participation was voluntary. This approach facilitated efficient and practical data collection across different urban zones (barangays) of Cagayan de Oro City, particularly during the COVID-19 pandemic when face-to-face surveys were constrained. As the study employed a convenience sampling approach, the resulting sample is not statistically representative of the entire population of Cagayan de Oro City. Therefore, the findings should be interpreted with appropriate caution when generalizing to the broader population.

Prior to data collection, the researchers estimated the minimum target sample size ($n_0$) using Cochran's (1977) sample size formula, as shown in Equation 1. The calculation assumed a 95% confidence level, an assumed population proportion ($p$ = 0.50) to maximize variability, and a 5% margin of error ($e$). The estimated sample size served as a planning guide for survey implementation rather than as evidence of statistical representativeness. The researchers obtained two hundred seventy-three valid responses and included them in the subsequent analyses.

$$n_0 = \frac{Z^2 p(1-p)}{e^2} \tag{1}$$

To enhance further the robustness and representativeness of the analysis, the researchers applied a bootstrapping technique during the data analysis phase to ensure that the dataset adequately reflects the mobility patterns of the surveyed population (Chernick, 2007).

The OD survey gathered comprehensive information on respondents' socio-economic characteristics and their travel behavior. The researchers validated the survey instrument using the Content Validity Index (CVI) method, which assesses the relevance of each item through expert evaluation. A CVI value of 0.78 or higher is generally considered acceptable, with values ≥0.80 indicating good content validity (Shi *et al.*, 2012). The OD survey achieved a CVI of 0.95, exceeding the recommended threshold and confirming that the survey items are both relevant and appropriate for the study. Additionally, all respondents provided informed consent prior to participation, ensuring that they fully understood the study objectives, their rights, and the voluntary nature of their participation.

In addition, the researchers collected secondary data to complement the survey data. They obtained spatial information on urban form from the City Planning and Development Office. Geographic data layers included population distribution, building footprints, road networks, land-use classifications, and administrative boundaries. The researchers used these datasets to compute urban form indicators at the barangay level, including population density, building density, road density, land-use diversity, and proximity to the central business district, as discussed further in section 2.5.3.

### *2.5 Data Analysis*

#### 2.5.1 Descriptive Statistics

The initial step in the analysis is to summarize the data for the key variables. Descriptive statistics provide an overview of the distributions and characteristics of the variables related to urban form (e.g., urban density, land use diversity), socio-economic characteristics (e.g., income, education level), and individual travel behavior (e.g., mode of transport, frequency of travel, travel distance). This step is crucial as it lays the foundation for understanding the variation within the dataset, allowing for the identification of patterns and potential outliers that could affect subsequent analyses.

#### 2.5.2 Individual Transport-related $CO_2$ emissions

Individual transport-related $CO_2$ emissions were estimated based on the self-reported travel behavior of each respondent, modal-specific carbon emission factors and average occupancy as presented in Equation 2 (Dalde *et al*., 2025).

$$CO_2\,Emission = \sum_{m=1}^{M} \frac{TD_{i,m}\ x\ EF_m}{AO_m} \tag{2}$$

where $CO_2\,Emission$ represents the total $CO_2$ emissions for individual (g $CO_2$), $TD_{i,m}$ is the travel distance for individual $i$ using transport mode $m$ (km), $EF_m$ is the emission factor for transport mode $m$ (g $CO_2$/km), $AO_m$is the average occupancy of transport mode m (persons per vehicle), and $m$ is the transport modes includes walking, cycling, trisikad, motorela, jeepney, bus, taxi, private car, and motorcycle.

Emission factors were based on available data, and average vehicle occupancy was applied for modes with multiple passengers (Table 1). Travel distances were self-reported by respondents and represent typical daily trips, while emissions from walking and cycling were assumed to be zero. A limitation of this approach is that self-reported travel distance and mode choice may be subject to recall bias or misreporting; nevertheless, these data provide a reasonable approximation of transport-related $CO_2$ emissions at the individual level.

Table 1. Emission factor by vehicle type and average vehicle occupancy

| Transport modes | Emission factor (grams of $CO_2$/km) | Average occupancy[c] |
|---|---|---|
| Motorcycle | 60.10[a] | 1 |
| Motorela | 60.10[a] | 6 |
| Jeepney | 230.00[b] | 15 |
| Taxi | 41.92[a] | 2 |
| Car | 200.00[b] | 2 |
| Bus | 280.00[b] | 40 |

Source: [a]Rito *et al*. (2021); [b](Japan International Cooperation Agency [JICA], 2014); [c] Vergel *et al*. (2024)

### 2.5.3 Spatial Analysis of Urban Form Indicators

Spatial analysis was conducted in ArcGIS to examine the spatial distribution and patterns of urban form indicators (UFIs). Prior to analysis, all spatial datasets underwent preprocessing procedures, including data cleaning, and georeferencing. Figure 4 illustrates the spatial analysis workflow, from data preparation to the generation of output maps. UFI were calculated following the methods summarized in Table 2. Their spatial patterns were subsequently evaluated using spatial autocorrelation techniques and visualized through hotspot analysis. The resulting UFI spatial pattern served as key inputs for subsequent structural equation modeling.

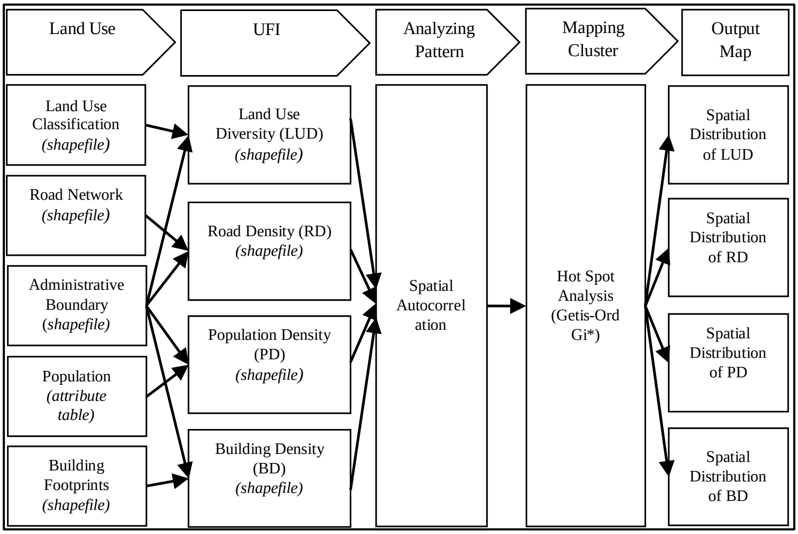



Figure 4. Spatial analysis of urban form indicators (UFI)

Urban form indicators were aggregated at the barangay level, rather than using finer grid-based approaches (Dalde *et al.*, 2025), to ensure consistency with official administrative boundaries and policy-relevant spatial units. In the Philippine context, the barangay represents the smallest formal unit for urban planning, governance, and socio-economic data reporting, making this scale appropriate for linking spatial analysis with planning practice. Although barangay-level aggregation may introduce potential bias due to variations in land area and internal heterogeneity, this scale remains suitable for the study's objectives and is accounted for in the interpretation of results. These procedures enhance the transparency, reproducibility, and robustness of the GIS analysis.

Table 2. Urban form metrics

| Metric | Equation | Description | Unit of measurement |
|---|---|---|---|
| Land use diversity (LUD) | $LUD = \frac{-\sum_{i=1}^{s}(p_i)\, ln(p_i)}{ln(s)}$ | LUD refers to the mix of different land uses within barangay | 0 = no diversity; 1 = maximum diversity |
| Population Density (PD) | $PD = \frac{P}{A}$ | PD is the number of people within barangay | # of residential units/ km$^2$ |

| | | | |
|---|---|---|---|
| Building Density (BD) | $BD = \frac{B}{A}$ | BD refers to the concentration of buildings within barangay | # of buildings / km$^2$ |
| Road Density (RD) | $RD = \frac{RN}{A}$ | RD refers to the total length of roads (km) within barangay | km/ km$^2$ |
| Distance to CBD (DisCBD) | Calculated using Google Map | DisCBD refers to the physical distance from a specific location (i.e., residential area) to the CBD | km |

Note: $p_i$ is the proportion of each land use type; s is the number of land uses; P is the number of individuals; B is the number of buildings; RN is the length of the road network; A is the land area of the barangay. Adopted in the study of (Dalde *et al*., 2025) but focus on barangay level approach not a grid-based approach.

#### 2.5.4 Path Analysis within the Structural Equation Modeling Framework

Path analysis within the Structural Equation Modeling (SEM) framework was employed to examine the direct and indirect relationships among urban form indicators (UFI), socioeconomic characteristics (SEC), travel behavior, and transport-related $CO_2$ emissions as shown in Figure 5. Unlike a full SEM, which consists of both measurement and structural models for latent constructs, the present study included only observed variables. Consequently, no measurement model or confirmatory factor analysis was required, and the analysis focused exclusively on estimating the structural relationships among the observed variables (Kline, 2016). The hypothesized path model was estimated using IBM SPSS Amos (Version 29).

Prior to path analysis, data normality and multicollinearity were assessed. Given that the dataset included both continuous variables (e.g., travel distance and household income) and binary variables (e.g., transport mode choices), Maximum Likelihood (ML) estimation with bootstrapping was adopted. Although ML assumes continuous variables, treating binary indicators as continuous is a common practice in SEM applications, and bootstrapping provides more robust parameter estimates in the presence of potential non-normality (Kline, 2016). Nevertheless, applying ML to categorical indicators remains a methodological limitation. Future studies may consider estimation methods specifically designed for categorical data, such as Weighted Least Squares Mean and Variance adjusted (WLSMV), to improve estimation accuracy.

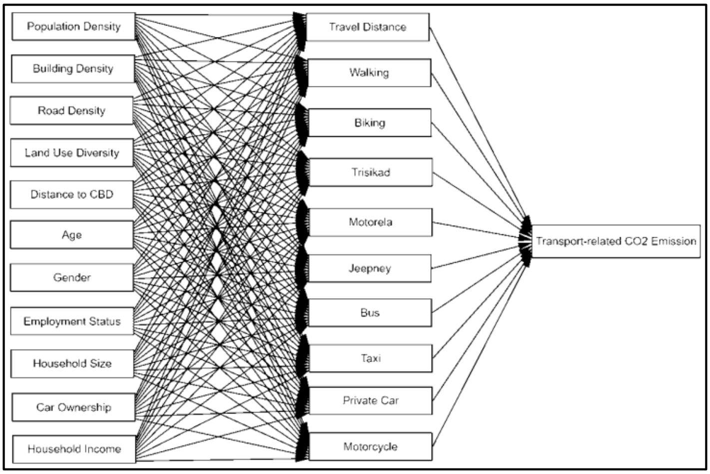



Figure 5. Path analysis framework illustrating the effects of UFI and SEC on $CO_2$ emissions, mediated by travel distance and transport mode choice

To evaluate mediation effects, the significance of the direct, indirect, and total effects was assessed using the bias-corrected (BC) bootstrap procedure implemented in IBM SPSS Amos. A total of 5,000 bootstrap resamples were generated to estimate the sampling distributions of the path coefficients. Statistical significance was determined using the bias-corrected (BC) two-tailed significance tests generated by the software. The standardized direct, indirect, and total effects were subsequently interpreted to evaluate the magnitude, direction, and mediation pathways among the study variables.

The model comprised four groups of observed variables. Urban Form Indicators (UFI) represented characteristics of the built environment aggregated at the barangay level using ArcGIS, including building density, road density, population density, land-use diversity, and distance to the central business district (CBD). Socioeconomic Characteristics (SEC) included collected demographic and household attributes associated with mobility needs and travel preferences. Travel Behavior (TB) was represented by travel distance (TD) and transport mode (TM) choice, including walking, cycling, trisikad, motorela, jeepney, bus, taxi, private car, and private motorcycle. In the hypothesized path model, travel behavior functioned as the mediating construct linking urban form and socioeconomic characteristics to transport-related $CO_2$ emissions.

Model adequacy was evaluated using multiple goodness-of-fit indices as illustrated in Table 3. These indices were interpreted according to commonly accepted SEM guidelines to assess the overall fit of the proposed path model (Kline, 2016).

Table 3. Model fit statistics

| Fit index | | | Criteria |
|---|---|---|---|
| Chi-square test | Chi-square | $x_2$ | > 0.05[a] |
| | Chi-square/df | $x_2$/df | < 3[b] |
| Absolute Fit Index | Root Mean Square Error of Approximation | RMSEA | < 0.05[a] |
| | Standard Root Mean Square | SRMR | < 0.08[a] |
| Relative / Incremental Fit Index | Normed Fit Index | NFI | > 0.90[a] |
| | Comparative Fit Index | CFI | > 0.90[a] |
| | Tucker Lewis Index | TLI | > 0.90[a] |
| | Incremental Fit Index | IFI | > 0.90[a] |
| | Relative Fit Index | RFI | > 0.90[a] |

Source: [a]Chen and Fong (2012); [b]Leung *et al*. (2011)

## 3. Results and Discussion

### *3.1 Socio-economic Profile of the Respondents*

Table 4 presents the respondents' socio-economic profile, highlighting key demographic and economic characteristics that influence travel behavior and transport-related $CO_2$ emissions. Most respondents were female, predominantly aged 25–34 years old, employed and belonged to lower- to middle-income brackets with monthly incomes ranging from Php 10,957 to Php 43,828. These findings suggest that the sample represents a relatively young, economically active population with moderate purchasing power, which are likely to influence travel distance and transportation preferences.

A substantial proportion of respondents reported owning private vehicles, particularly motorcycles and cars. This trend is consistent with mobility patterns in many emerging cities, where motorcycles serve as an affordable and flexible option and private cars for comfort and convenience for daily commuting. In contrast, bicycle ownership was comparatively low and primarily associated with leisure and social activities rather than commuting.

Table 4. Socio-economic profile of the respondents

| Variables | Symbol | Category Description | Categorical # | Categorical % | Continuous Mean | Continuous SD |
|---|---|---|---|---|---|---|
| Age group (years) | Age | 1 - 15 to 24 | 41 | 15 | | |
| | | 2 - 25 to 34 | 102 | 38 | | |
| | | 3 - 35 to 44 | 77 | 28 | | |
| | | 4 - 45 to 54 | 39 | 14 | | |
| | | 5 - 55 to 64 | 14 | 5 | | |
| Gender | Gen | 1 - Male | 105 | 39 | | |
| | | 0 - Female | 168 | 61 | | |
| Employment Status | ES | 1 - employed | 256 | 94 | | |
| | | 2 - unemployed | 17 | 6 | | |
| Family Size | HHS | # of persons | | | 4.85 | 2.04 |
| Household Income (Php/month) | HHI | 1 - below 10,957 | 24 | 9 | | |
| | | 2 - 10,957 to 21,194 | 67 | 24 | | |
| | | 3 - 21,194 to 43,828 | 68 | 25 | | |
| | | 4 - 43,828 to 76,669 | 59 | 22 | | |
| | | 5 - 76,669 to 131,484 | 34 | 13 | | |
| | | 6 - 131,484 to 219,140 | 12 | 4 | | |
| | | 7 - Above 219,140 | 9 | 3 | | |
| Car ownership | Car | 1 - No | 129 | 47 | | |
| | | 2 - Yes | 144 | 53 | | |
| Bike Ownership | Bike | 1 - No | 153 | 56 | | |
| | | 2 - Yes | 120 | 44 | | |

Note: Sample size (n)=273; The bootstrap method was applied using 5,000 resamples. Abbreviations: SD = Standard Deviation; Php = Philippine Peso.

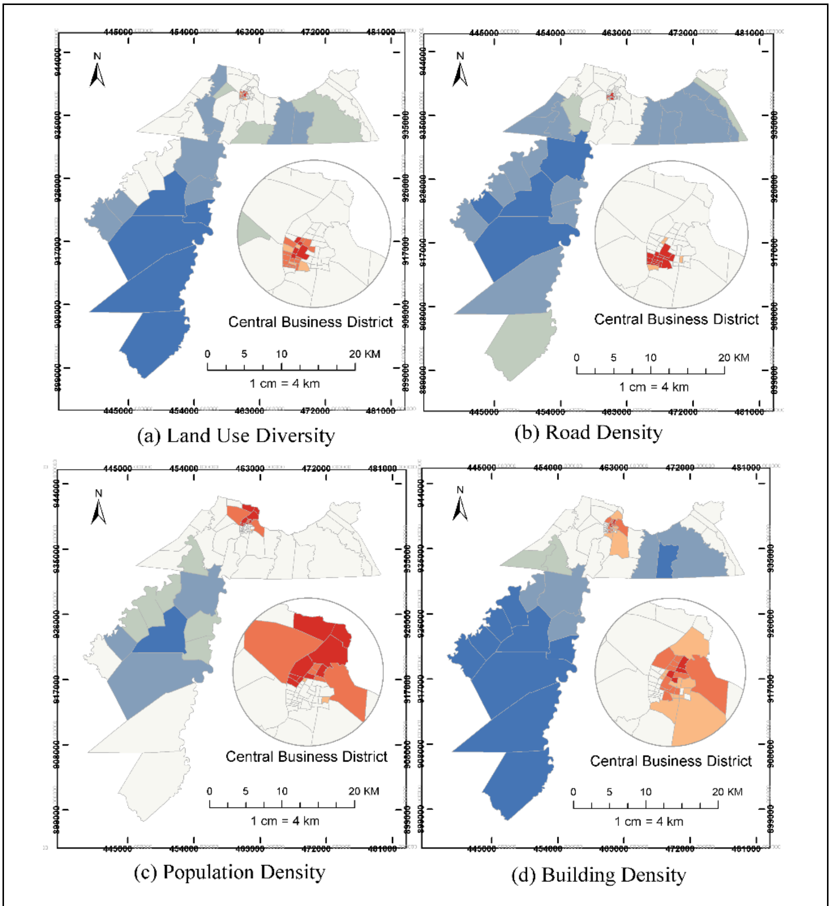
### *3.2 Urban Form Characteristics of Barangay in Cagayan de Oro City*

Figure 6 demonstrates the spatial patterns of urban form indicators in Cagayan de Oro City using Global Moran's I and Getis–Ord Gi* hot spot analysis. The results reveal statistically significant spatial clustering for land use diversity, road density, population density, and building density, as supported by the spatial autocorrelation report. High-value clusters (hot spots) indicate areas where intensive urban development and infrastructure concentration are spatially reinforced, while low-value clusters (cold spots) reflect less developed or more dispersed urban areas.

Land-use diversity (Figure 6a) reveals pronounced hot spot clustering within Central Business District (CBD). Barangays located in the urban core exhibit high levels of mixed land use, reflecting the historical concentration of commercial, institutional, and residential functions in central areas. This pattern is consistent with monocentric urban development, where functional diversity intensifies near the CBD due to agglomeration economies and accessibility advantages. Conversely, cold spots dominate peripheral barangays, suggesting more homogeneous land-use patterns, often characterized by predominantly residential, agricultural or forest uses. This spatial differentiation highlights the limited extent of mixed-use development beyond the urban core, which may contribute to longer travel distances and greater transport dependency for peripheral residents.

Road density (Figure 6b) also displays strong clustering, with statistically significant hot spots concentrated within the CBD. These areas benefit from dense and well-connected road networks developed through successive phases of urban expansion. The presence of road density cold spots in outer barangays reflects comparatively sparse transport infrastructure, likely shaped by topographic constraints or lower development intensity. The strong spatial correspondence between road density hot spots and the CBD underscores the role of transport infrastructure in structuring urban accessibility and guiding development intensity.

Population density (Figure 6c) exhibits a distinct clustering pattern, with hot spots extending beyond the CBD into adjacent barangays. This suggests that high residential concentrations are not confined solely to the urban core but have expanded into surrounding areas, potentially due to housing demand, land scarcity in the CBD, and the emergence of high-density residential developments. However, the coexistence of population density hot spots and land-use diversity cold spots in some areas indicates a spatial mismatch between residential concentration and functional mix, which may contribute to increased travel demand and commuting pressures.




**Legend**

**Gi_Bin**

- Cold Spot - 99% Confidence
- Cold Spot - 95% Confidence
- Cold Spot - 90% Confidence
- Not Significant
- Hot Spot - 90% Confidence
- Hot Spot - 95% Confidence
- Hot Spot - 99% Confidence

**Spatial Autocorrelation Report**

| UFI | Moran's Index | z-score | p-value | Pattern |
|---|---|---|---|---|
| LUD | 0.420 | 6.567 | 0.000 | Clustered |
| RD | 0.675 | 10.436 | 0.000 | Clustered |
| PD | 0.357 | 5.791 | 0.000 | Clustered |
| BD | 0.602 | 9.330 | 0.000 | Clustered |

*Note: Conceptualization of spatial relationship is based on contiguity (edges-corners), and the distance method applied is Euclidian Distance*

Figure 6. Spatial distribution of urban form indicators in Cagayan de Oro City using Hot Spot Analysis (Getis-Ord Gi*) at the barangay level

Building density (Figure 6d) shows significant hot spot clustering both within the CBD and in selected inner-city barangays. This pattern reflects vertical and horizontal intensification of the built environment in areas with high accessibility and economic activity. The partial overlap between building density and population density hot spots suggests that some dense built-up areas may be dominated by commercial or institutional structures rather than residential uses. In contrast, cold spots in building density are prevalent in peripheral barangays, consistent with lower development intensity and more dispersed settlement patterns.

Overall, the spatial autocorrelation statistics confirm that all four urban form indicators exhibit high z-scores and statistically significant p-values ($p < 0.001$), indicating strong positive spatial clustering. These results underscore the presence of spatially structured urban development patterns in Cagayan de Oro City, shaped by historical growth trajectories, infrastructure provision, and planning decisions. The concentration of multiple urban form hot spots around the CBD highlights the continued dominance of a centralized urban structure, while the peripheral cold spots point to uneven development and potential accessibility gaps.

### *3.3 Travel Behavior of the Respondents*

Travel behavior is measured using three indicators: trip frequency, travel distance and transport modes (Figure 7). Transport modes are classified into active transport (walking and cycling), public transport (jeepneys, motorelas, and buses), private transport (cars and motorcycles), and car-sharing options (taxis and company vehicles). The results indicate that most residents travel an average of 8 km from their residences to their workplaces and commute approximately 5 days per week.

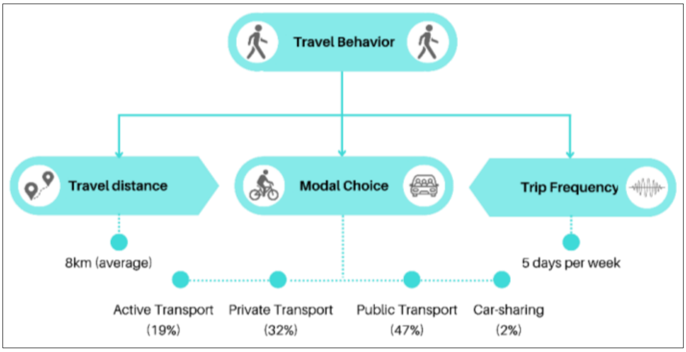
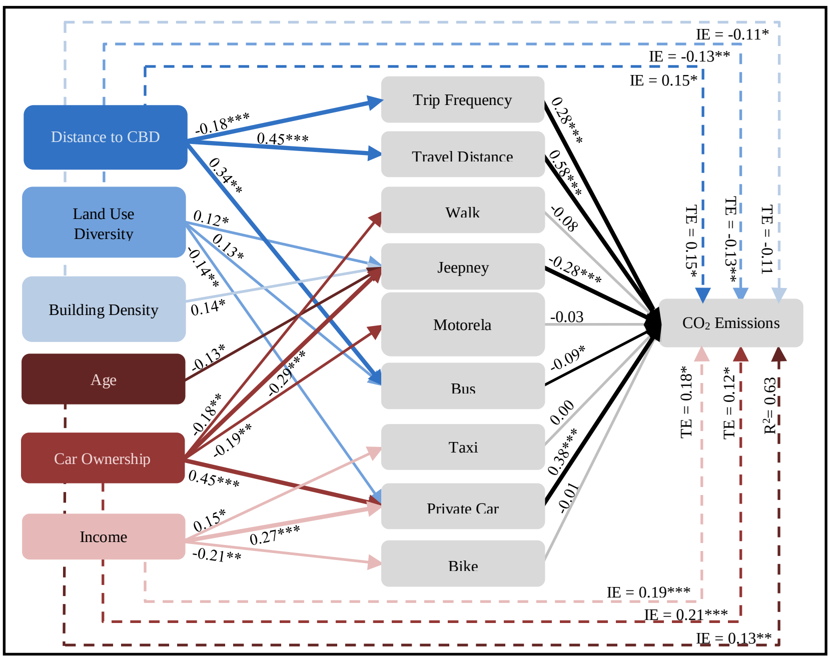



Figure 7. Respondent's Travel behavior (Data source: OD Survey)

Public transport (particularly jeepneys) emerges as the most frequently used mode, highlighting its continued relevance and accessibility in the local mobility system, although a substantial proportion of residents also rely on private transport, mainly personal cars, reflecting preferences for convenience and comfort.

### *3.4 Path Model Analysis*

Figure 8 illustrates the complex relationships among urban form indicators (UFI), socio-economic characteristics (SEC), travel behavior, and transport-related $CO_2$ emissions. Solid arrows indicate direct effects, while dashed arrows represent indirect effects mediated by travel behavior (i.e., trip frequency, travel distance, and transport modes). Asterisks (*) denote statistical significance, with more asterisks indicating higher significance levels. The model highlights the mediating role of travel behavior in linking UFI and SEC on transport-related $CO_2$ emissions.




Model fit indices: $x^2$ = 34.43, $x^2$/df = 1.13, RMSEA = 0.03; SRMR = 0.03, NFI = 0.98, CFI = 1.00, TLI = 0.97; IFI = 1.00, $R^2$ = 0.63. Abbreviations: IE = Indirect Effect; TE = Total Effect. Data sources: OD Survey & CDO CPDO

Figure 8. Path analysis illustrating the effects of UFI and SEC on transport-related $CO_2$ emissions, mediated by travel behavior

### 3.4.1 Effects of Urban Form Indicators on Transport-related $CO_2$ Emissions

Among the Urban Form Indicators (UFI), only distance to the Central Business District (CBD), Land-Use Diversity (LUD), and Building Density (BD) exhibited significant indirect effects on transport-related $CO_2$ emissions (Table 5). In contrast, population density and road density showed no direct and indirect effects on emissions. The observed indirect effects were mediated through travel behavior, including trip frequency, travel distance, and selected transport modes, highlighting the central role of behavioral pathways in translating spatial characteristics into environmental impacts.

Table 5. Effects of urban form indicators on transport-related $CO_2$ emissions

| Exogenous Variable | Endogenous Variables | Mediation Pathway | Direct Effect | Indirect Effect | Total Effects |
|---|---|---|---|---|---|
| DisCBD | TF | DisCBD → TF, TD, & Bus → $CO_2$ | -0.18*** | 0.15* | 0.15* |
| DisCBD | TD | | 0.45*** | | |
| DisCBD | Bus | | 0.34*** | | |
| DisCBD | $CO_2$ | | --- | | |
| LUM | JP | LUM → JP, Bus, & PriCar → $CO_2$ | 0.12* | -0.13** | -0.13** |
| LUM | Bus | | 0.13* | | |
| LUM | PriCar | | -0.14** | | |
| LUM | $CO_2$ | | --- | | |
| BD | Jeepney | BD → JP → $CO_2$ | 0.14* | -0.11* | -0.11 |
| BD | $CO_2$ | | --- | | |

Note: Standardized direct, indirect, and total effects were estimated using path analysis in IBM SPSS Amos (Version 29). Statistical significance was evaluated using the bias-corrected (BC) bootstrap procedure with 5,000 bootstrap resamples, and the reported significance levels correspond to the BC two-tailed significance tests generated by the software ($p < 0.05$*, $p < 0.01$**, $p < 0.001$***). Model fit indices: $\chi^2 = 34.43$, $\chi^2/df = 1.13$, RMSEA = 0.03, SRMR = 0.03, NFI = 0.98, CFI = 1.00, TLI = 0.97, IFI = 1.00, and $R^2 = 0.63$. Abbreviations: TF = Trip Frequency; TD = Travel Distance; JP = Jeepney; PriCar = Private Car.

Distance to the CBD exerts a significant influence on travel behavior, which subsequently impacts transport-related $CO_2$ emissions. Residents located farther from the CBD tend to make fewer trips ($\beta = -0.18$, $p < 0.001$) but travel longer distances ($\beta = 0.45$, $p < 0.001$) and rely more on buses ($\beta = 0.34$, $p < 0.001$), reflecting the spatial structure of the city. The increased use of buses for longer commutes mitigates per-capita $CO_2$ emissions relative to private vehicles, as indicated by both indirect and total effect of distance to the CBD on emissions ($\beta = 0.15$, $p < 0.05$), which is smaller than the direct effect of travel distance. These findings underscore the importance of efficient public transport in peripheral areas to reduce transport-related $CO_2$ emissions despite longer trip distances.

Land-use diversity exhibits behaviorally favorable effects on transport choices, which consequently influence transport-related $CO_2$ emissions. Higher land-use diversity significantly increases jeepney use ($\beta = 0.12$, $p < 0.05$) and bus use ($\beta = 0.13$, $p < 0.05$), while significantly reduces private car use ($\beta = -0.14$, $p < 0.01$), indicating that mixed-use environments enhance public transport accessibility and discourage private vehicle dependence. Building density shows a similar pattern, positively associating with jeepney use ($\beta = 0.14$, $p < 0.05$) and supporting the efficiency of high-occupancy public transport in denser urban areas. Consistent with Theory of Urban Fabrics (Newman *et al*., 2016), neither land-use diversity nor building density directly affects $CO_2$ emissions; rather, both indirectly contribute to emission reductions by promoting shifts toward lower carbon transport modes. Therefore, these findings suggest that urban form indicators primarily affect $CO_2$ emissions indirectly through travel behavior, rather than through direct effects.

These findings suggest that compact, mixed-use, and higher density development can indirectly reduce emissions by shortening travel distances and promoting public transport use. This aligns with previous research showing that higher building density (Dalde *et al*., 2025) and mixed-use urban environments (Cao & Yang, 2017) promote lower-carbon travel by improving access to public transport and reducing dependence on private vehicles (Rahman *et al*., 2022). For instance, areas closer to the CBD or with higher building density and land-use diversity tend to encourage shorter trips and increased use of active or public transport (Hasanpour & Farooq, 2025), thereby indirectly mitigating $CO_2$ emissions. These results emphasize the importance of integrating urban form considerations into sustainable mobility planning, as targeted spatial interventions can effectively shape travel behavior and support low-carbon urban transport systems.

### 3.4.2 Effects of Socio-economic Characteristics on Transport-related $CO_2$ Emissions

Socio-economic characteristics play a fundamental role in shaping travel behavior and, consequently, transport-related $CO_2$ emissions. In this study, only age, car ownership, and household income exhibited significant indirect effects on emissions, mediated through transport mode choices (Table 6). Other socio-economic characteristics, including gender, employment status, family size, and the presence of workers, showed no significant effects. These findings differ from previous studies, which have correlated gender (Yang *et* *al.*, 2018) , households with children or elderly members (Pan *et al.*, 2016), and larger family sizes (Mwale *et al.*, 2022) to higher private car ownership and increased emissions. This variation may reflect regional or cultural differences in travel behavior and mobility preferences.

Table 6. Effects of socio-economic characteristics on transport-related $CO_2$ emissions

| Exogenous Variable | Endogenous Variables | Mediation Pathway | Direct Effect | Indirect Effect | Total Effects |
|---|---|---|---|---|---|
| Age | JP | Age → JP → $CO_2$ | -0.13* | 0.13** | 0.16** |
| Age | $CO_2$ | | --- | | |
| CarOwn | Walk | CarOwn → Walk, Motorela, JP & PriCar → $CO_2$ | -0.18** | 0.21*** | 0.12* |
| CarOwn | Motorela | | -0.19** | | |
| CarOwn | JP | | -0.29*** | | |
| CarOwn | PriCar | | 0.45*** | | |
| CarOwn | $CO_2$ | | --- | | |
| HHI | PriCar | I → PriCar, Taxi & Bike → $CO_2$ | 0.27*** | 0.19*** | 0.18* |
| HHI | Taxi | | 0.15* | | |
| HHI | Bike | | -0.21** | | |
| HHI | $CO_2$ | | --- | | |

Note: Standardized direct, indirect, and total effects were estimated using path analysis in IBM SPSS Amos (Version 29). Statistical significance was evaluated using the bias-corrected (BC) bootstrap procedure with 5,000 bootstrap resamples, and the reported significance levels correspond to the BC two-tailed significance tests generated by the software ($p < 0.05$*, $p < 0.01$**, $p < 0.001$***). Model fit indices: $\chi^2 = 34.43$, $\chi^2/df = 1.13$, RMSEA = 0.03, SRMR = 0.03, NFI = 0.98, CFI = 1.00, TLI = 0.97, IFI = 1.00, and $R^2 = 0.63$. Abbreviations: TF = Trip Frequency; TD = Travel Distance; JP = Jeepney; PriCar = Private Car.

Age significantly reduces jeepney use ($\beta = -0.13$, $p < 0.05$), suggesting that older individuals are less inclined to rely on public transport. This behavioral shift indirectly contributes to higher $CO_2$ emissions ($\beta = 0.13$, $p < 0.01$), as older travelers may increasingly rely on private or motorized modes that are more carbon-intensive. Such patterns underscore the importance of considering socio-demographic characteristics in urban transport planning, as aging populations could exacerbate reliance on private vehicles and increase environmental impacts.

Car ownership emerges as one of the strongest determinants of travel behavior in the model. It significantly reduces walking ($\beta = -0.18$, $p < 0.01$), motorela ($\beta = -0.19$, $p < 0.01$), and jeepney use ($\beta = -0.29$, $p < 0.001$), while exerting a strong positive effect on private car use ($\beta = 0.45$, $p < 0.001$). These results reflect a structural lock-in effect, whereby private vehicle access reinforces reliance on motorized travel and limits shifts to sustainable modes. Even with available public transport, car-oriented patterns entrench higher transport-related $CO_2$ emissions, highlighting the long-term environmental consequences of rising private vehicle use.

Income also significantly influences modal choice and indirectly affects $CO_2$ emissions. Higher-income individuals are more likely to use private cars ($\beta = 0.27$, $p < 0.001$) and taxis ($\beta = 0.15$, $p < 0.05$), while being less likely to cycle ($\beta = -0.21$, $p < 0.01$). This reflects a lifestyle preference for private vehicles that provide convenience, comfort, and greater flexibility, reducing travel effort compared with active or public transport modes. Through these behavioral pathways, higher income indirectly contributes to increased $CO_2$ emissions ($\beta = 0.19$, $p < 0.001$), highlighting the link between socio-economic status and carbon-intensive travel patterns.

Overall, these findings emphasize the need for targeted interventions to reduce transport-related $CO_2$ emissions among high-income individuals, private car owners, and older populations, who are more likely to rely on motorized travel. Effective strategies include improving the accessibility and convenience of public transport, promoting high-occupancy and low-carbon travel modes, providing incentives to reduce private vehicle use, and integrating land-use planning with transport provision to shorten travel distances. By addressing structural car dependence and the specific travel patterns of these groups, urban mobility policies can encourage sustainable travel behavior and achieve meaningful reductions in transport-related emissions.

### 3.4.3 Effects of Travel Behavior on Transport-related $CO_2$ Emissions

While the Urban Form Indicators (UFI) and Socio-Economic Characteristics (SEC) do not exhibit significant direct effects on transport-related $CO_2$ emissions, travel behavior indicators exert the strongest direct influence, as presented in Table 7. Specifically, travel distance ($\beta = 0.58$, $p < 0.001$), private car usage ($\beta = 0.38$, $p < 0.001$), and trip frequency ($\beta = 0.28$, $p < 0.001$) are positively associated with transport-related $CO_2$ emissions, indicating that longer travel distances, increased reliance on private vehicles, and more frequent trips substantially contribute to higher emissions.

In contrast, the use of public transport demonstrates significant mitigating effects, with jeepney use ($\beta = -0.28$, $p < 0.001$) and bus use ($\beta = -0.09$, $p < 0.05$) associated with reductions in $CO_2$ emissions. Interpreted in standardized terms, a one–standard deviation increase in travel distance, private car use, and trip frequency leads to corresponding increases of 0.58, 0.38, and 0.28 standard deviations in emissions, whereas a one–standard deviation increase in jeepney and bus usage reduces emissions by 0.28 and 0.09 standard deviations, respectively.

Table 7. Direct effects of travel behavior on transport-related $CO_2$ emissions

| Exogenous Variable | Endogenous Variables | Direct Effect |
|---|---|---|
| TF | $CO_2$ | 0.28*** |
| TD | $CO_2$ | 0.58*** |
| Bus | $CO_2$ | -0.09* |
| JP | $CO_2$ | -0.28*** |
| PriCar | $CO_2$ | 0.38*** |

Note: ***p < 0.001; **p < 0.01; *p < 0.05. Only significant standardized coefficients are presented. Model fit indices: $\chi^2 = 34.43$, $\chi^2/df = 1.13$, RMSEA = 0.03, SRMR = 0.03, NFI = 0.98, CFI = 1.00, TLI = 0.97, IFI = 1.00; $R^2 = 0.63$. Abbreviations: TF = Trip Frequency; TD = Travel Distance; JP = Jeepney, PriCar = Private Car.

These results underscore the central role of individual travel behavior in determining transport-related $CO_2$ emissions, exceeding the direct influence of structural urban form and socio-economic characteristics. Consistent with previous studies (Rahman *et al.*, 2017; Shi *et al.*, 2022), the findings indicate that while urban form and socio-economic conditions may indirectly influence emissions by shaping travel behavior, it is the actual mobility patterns (i.e., specifically, the travel distance, trip frequency, and mode choice) that primarily drive emission outcomes.

The findings also point to a dual strategy for mitigating transport emissions in Cagayan de Oro City. First, promoting modal shifts from private vehicles to efficient and accessible public transport systems, such as jeepneys and buses, can directly reduce emissions. Second, urban planning strategies should aim to reduce the necessity for long-distance trips and frequent travel. This may include encouraging mixed-use and compact developments, improving accessibility to essential services, and enhancing active mobility infrastructure (e.g., cycling and pedestrian pathways). Collectively, these strategies can effectively reduce transport-related $CO_2$ emissions, aligning urban mobility planning with sustainable development goals and climate change mitigation objectives.

### 3.4.4 Policy and Planning Implications of Path Analysis

The path analysis provides empirical evidence that urban form and socio-economic characteristics influence transport-related $CO_2$ emissions indirectly through travel behavior. Specifically, urban form indicators and socioeconomic characteristics were found to affect travel distance and transport mode choice, which subsequently influenced transport-related $CO_2$ emissions. These observed relationships provide insights into the mechanisms through which urban development, socio-economic characteristics and travel behavior contribute to emissions and offer an empirical basis for the integration of transport and land-use planning (Cao & Yang, 2017; Yang *et al.*, 2015).

Based on these observed relationships, several policy implications can be inferred. The findings suggest that urban form characteristics, such as distance to the CBD, land-use diversity, and building density, are associated with travel behavior that influences transport-related $CO_2$ emissions. Consequently, planning approaches that promote compact, mixed-use, and transit-oriented development (TOD) may contribute to reducing travel distances and encouraging greater use of walking, cycling, and public transport. These implications are consistent with previous studies demonstrating that compact urban development and integrated land-use and transport planning can support more sustainable travel patterns and lower transport-related emissions (Ewing *et al.*, 2016; Newman *et al.*, 2016; Fang *et al.*, 2015). However, the effectiveness of TOD or other land-use interventions was not directly evaluated in the present study.

Similarly, the observed associations between higher household income, car ownership, and greater reliance on private vehicles suggest that transport demand management strategies may represent potential approaches for encouraging more sustainable travel behavior. Measures such as improving the quality and accessibility of public transport, expanding active transport infrastructure, and enhancing multimodal connectivity could reduce dependence on private vehicles. Likewise, congestion pricing, parking management (e.g., pay parking), and incentives for shared mobility represent policy options supported by the broader transport literature (IPCC, 2015; Hasanpour & Farooq, 2025; Newman *et al.*, 2016), rather than interventions directly examined in this study.

The results also emphasize the importance of integrating land-use and transport planning. The indirect pathways identified in the path analysis indicate that changes in urban form alone may not necessarily reduce transport-related $CO_2$ emissions unless accompanied by accessible, reliable, and affordable transport alternatives. This finding reinforces previous research highlighting that coordinated land-use and transport policies are more likely to encourage sustainable mobility and reduce reliance on private motorized travel (Cao & Yang, 2017; Ewing *et al.*, 2016).

These policy implications are particularly relevant for rapidly urbanizing cities in Southeast Asia, including Cagayan de Oro, where increasing urbanization and motorization present significant challenges for sustainable mobility. While the present study did not directly assess the effectiveness of specific policy interventions, the observed relationships identified through the path analysis suggest that integrated land-use and transport strategies may provide promising directions for reducing transport-related $CO_2$ emissions. Future studies employing policy simulation, scenario analysis, or quasi-experimental approaches are needed to evaluate the effectiveness and context-specific impacts of interventions such as transit-oriented development, congestion pricing, and parking management.

## 4. Conclusions and Recommendations

This study demonstrates that transport-related $CO_2$ emissions are influenced not only by urban form and socioeconomic characteristics but also by the behavioral pathways through which these factors shape travel decisions. The findings highlight travel behavior as the principal mechanism linking the built environment and socioeconomic conditions to transport-related emissions, underscoring the need to consider these interrelationships in urban and transport planning. By applying path analysis within the SEM framework, the study provides a more comprehensive understanding of the mechanisms underlying transport-related $CO_2$ emissions and contributes empirical evidence from a rapidly urbanizing city in a developing-country context.

The findings suggest that integrated land-use and transport planning may provide a more effective approach to promoting low-carbon urban mobility than isolated interventions. The policy recommendations presented in this study should be interpreted as evidence-informed implications derived from the observed relationships rather than as interventions directly evaluated. Consequently, strategies such as transit-oriented development, enhanced public transport, and transport demand management represent potential planning approaches that warrant further investigation.

Several limitations should be acknowledged. First, the study employed a convenience-based online survey, which limits the statistical representativeness and generalizability of the findings. Second, the cross-sectional design precludes causal inference, as the observed relationships represent associations at a single point in time. Third, although bootstrapping was used to improve the robustness of parameter estimation, the model was estimated using Maximum Likelihood with observed variables, including categorical transport mode indicators, which may introduce estimation bias. Finally, the analysis focused on behavioral pathways and did not explicitly incorporate other factors such as traffic congestion, fuel consumption, vehicle technology, or temporal variations in travel behavior that may also influence transport-related emissions.

Future research should employ probability-based and longitudinal study designs to improve the generalizability of the findings and strengthen causal inference. In addition, studies should evaluate the effectiveness of specific land-use and transport interventions, such as transit-oriented development, public transport improvements, parking management, and congestion pricing, using policy simulation, scenario analysis, or quasi-experimental approaches. Incorporating additional factors, including traffic conditions, vehicle technology, fuel consumption, and temporal variations in travel behavior, together with estimation methods that better accommodate categorical variables, would provide a more comprehensive understanding of the determinants of transport-related $CO_2$ emissions and support the development of more effective low-carbon urban transport policies.

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