

Article

Transit-Oriented Development and Travel Behavior: Examining the Role of Transit Accessibility and Parking Availability in Shaping Mode Choice Preferences

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Abstract

Rapid urbanization has intensified transportation challenges in many metropolitan areas, increasing reliance on private vehicles and contributing to congestion and environmental concerns. Although transit-oriented development strategies aim to promote sustainable mobility by improving public transport accessibility, the behavioral mechanisms linking built environment characteristics to travel behavior remain insufficiently explored. This study examines the influence of transit accessibility (TA) and parking availability on mode choice preference and travel behavior. A structured questionnaire survey was conducted, and the data were analyzed using covariance-based structural equation modeling after validating the measurement constructs through exploratory and confirmatory factor analyses. The results indicate that TA positively influences mode choice preferences, whereas parking availability negatively affects them. Furthermore, mode choice preferences significantly influence travel behavior, underscoring their mediating role between built environment factors and mobility outcomes. These findings provide empirical insights for urban planners seeking to promote sustainable transportation through enhanced TA and effective parking management strategies.

Keywords: transit-oriented development; mode choice preferences; travel behavior; transit accessibility; parking availability; socioeconomic status; sustainable transportation



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1. Introduction

Rapid urbanization and increasing mobility demands have intensified transportation challenges in metropolitan areas worldwide [1]. Rising private vehicle ownership has contributed to traffic congestion, environmental degradation, and inefficient land use patterns, prompting policymakers and urban planners to seek more sustainable mobility solutions [2]. Among various planning strategies, Transit-Oriented Development (TOD) has emerged as an effective approach to promote sustainable urban transportation systems [3]. TOD emphasizes integrating high-quality public transit with compact, mixed-use, and pedestrian-friendly urban environments, encouraging residents to rely more on public transport and non-motorized modes rather than private automobiles [4]. By improving accessibility to transit services and creating supportive built environments, TOD can significantly influence individual travel decisions and promote more sustainable TB [5].

Multiple interrelated factors, including infrastructure characteristics, accessibility conditions, and individual socio-economic attributes, influence TB within TOD environments [6]. One of the most important determinants is transit accessibility, which reflects how easily individuals can access and use public transportation. Studies have widely associated higher accessibility to transit stations and networks with increased public transport usage and reduced automobile dependence [7]. Another important factor is parking availability, which can directly affect individuals' decisions to use private vehicles or alternative modes of transport. An ample parking supply often encourages private vehicle use, whereas limited or managed parking can incentivize travelers to shift toward public transportation [8]. In addition to building-environment factors, socio-economic characteristics, such as income, education level, and employment status, also play a crucial role in shaping travel decisions. These socio-economic factors influence individuals' mobility preferences, affordability of transport options, and overall travel patterns [9]. Together, these elements shape individuals' preferences for different transportation modes, referred to as mode choice preference (MCP), which subsequently influence broader travel behavior (TB) outcomes in urban areas.

Although previous studies have extensively examined the relationship between built environment characteristics and travel behavior, their focus has primarily been on the direct effects of individual factors such as TA or parking availability (PA). These studies have established that improved accessibility tends to increase public transport use, while greater PA tends to encourage private vehicle dependence [10]. However, most existing studies focus on direct relationships between built environment factors and TB, with limited attention to the underlying behavioral processes through which these effects occur. In particular, the role of MCP as a mediating mechanism linking TA and PA to TB remains insufficiently examined within a unified empirical framework [11,12]. Moreover, existing studies often rely on traditional regression-based approaches that are limited in their ability to incorporate latent behavioral constructs derived from survey data. As a result, the underlying behavioral mechanisms through which built environment factors influence travel decisions remain insufficiently explored. In particular, limited empirical research has explicitly examined the mediating role of MCP in linking transit accessibility and parking conditions to travel behavior, especially within transit-oriented development contexts.

To address this gap, this study develops an integrated structural framework that explicitly models MCP as a mediating mechanism between built environment factors and travel behavior within a TOD context. By doing so, the study moves beyond direct effect analysis and captures both behavioral pathways and indirect influences that are typically overlooked in existing research. This study develops an integrated analytical framework to examine the relationships between TA, PA, MCP, and TB within a TOD context. Unlike previous studies that focus primarily on direct relationships, this research explicitly models MCP as a mediating mechanism through which built environment factors influence travel behavior. In addition, Perceived Socio-economic Influence (PSI) is incorporated as a control variable to account for variations in individual characteristics that may shape transportation decisions. The socio-economic construct was incorporated as a covariate to account for individual heterogeneity among respondents. It is included to control for background socio-economic differences that may influence travel behavior, rather than as a primary explanatory construct within the conceptual framework.

The findings of this research provide empirical insights into the mechanisms through which accessibility, parking conditions, and socio-economic characteristics shape TB within TOD environments. Such insights are important for urban planners and policymakers aiming to design effective transportation policies that encourage sustainable mobility

and reduce dependence on private vehicles. The results may also contribute to the growing literature on TOD by offering an integrated behavioral perspective informed by advanced statistical modeling techniques.

While previous studies have examined the effects of transit accessibility and parking availability on travel behavior, most of them focused on direct relationships and treat travel outcomes as immediate responses to built environment conditions. As a result, the underlying behavioral mechanisms that connect these factors to travel decisions remain insufficiently explored. This study extends the existing literature by introducing mode choice preference (MCP) as an intermediate mechanism that links built environment attributes to travel behavior. By doing so, the study captures both direct and indirect effects within a unified analytical framework. This approach provides a more detailed understanding of how and why transit accessibility and parking availability influence travel behavior, rather than only whether they do.

In summary, this study contributes to the existing literature in three ways. First, it integrates built-environment factors, such as TA and parking availability, within a structural equation modeling framework to examine their influence on MCP and TB. Second, it incorporates PSI as a control variable to capture demographic influences on mobility decisions. Third, the study provides empirical evidence from a large sample dataset, offering insights for transportation planning and TOD policies.

The remainder of this paper is organized as follows. The next section reviews relevant literature on TA, PA, socio-economic influences, and TB in TOD environments, and develops the research hypotheses. The methodology section then describes the survey design, data collection procedures, measurement variables, and analytical methods used in the study. The results section presents the outcomes of the factor analysis and structural equation modeling. Finally, the discussion and conclusion sections interpret the findings, highlight policy implications, and suggest directions for future research.

2. Literature Review

TOD has emerged as a widely recognized urban planning strategy to promote sustainable mobility and reduce dependence on private automobiles [13]. TOD focuses on developing compact, mixed-use, and pedestrian-friendly communities around high-capacity public transportation systems, thereby improving accessibility and encouraging the use of sustainable transport modes such as public transit, walking, and cycling. By integrating land-use planning with transportation infrastructure, TOD facilitates efficient mobility patterns while supporting environmental sustainability and urban livability [14]. Previous studies have shown that well-designed TOD environments can significantly influence individuals' travel decisions by improving accessibility to transit services and reducing reliance on private vehicles [13]. Among the various factors influencing TB within TOD environments, TA plays a particularly important role [15]. TA refers to the ease with which individuals can reach and utilize public transportation systems, including factors such as proximity to transit stations, service frequency, network connectivity, and pedestrian accessibility [16]. Higher levels of TA have been consistently associated with increased use of public transportation and reduced automobile dependence [17]. Studies have demonstrated that individuals living in areas with convenient access to transit infrastructure are more likely to adopt sustainable travel modes and reduce private vehicle usage [18]. Improved TA also enhances the attractiveness of public transportation by reducing travel time and increasing connectivity to employment centers, commercial areas, and other key urban destinations [19]. In addition to accessibility, PA represents another critical determinant of transportation choices in urban environments. Parking supply and management policies can significantly influence individuals' MCP by affecting the convenience

and cost associated with private vehicle use [20]. When parking spaces are abundant and easily accessible, individuals are more likely to rely on private cars for their daily travel needs [21]. Conversely, limited parking supply or higher parking costs can discourage private vehicle use and encourage travelers to shift toward public transit or active transportation modes [22]. Empirical research has shown that parking availability and search time are important factors influencing travel behavior, particularly in dense urban areas and transit-oriented developments, where land-use constraints and transportation policies shape mobility patterns [5].

Beyond built-environment characteristics, PSI also plays a significant role in shaping individuals' transportation preferences and travel behavior. Socio-economic factors such as income, education level, and occupation influence individuals' access to transportation resources, including vehicle ownership and the affordability of different transport modes [23]. Previous studies have found that higher-income individuals often have greater access to private vehicles and therefore exhibit stronger preferences for automobile travel [24]. In contrast, individuals with lower PSI may rely more heavily on public transportation and non-motorized modes due to financial constraints [25]. These variations highlight the importance of considering socio-economic differences when examining TB in TOD environments. While previous research has provided valuable insights into the individual effects of accessibility, parking conditions, and socio-economic characteristics on travel behavior, many studies have examined these factors in isolation. However, travel decisions are inherently complex and influenced by multiple interrelated variables. To capture these complex relationships, advanced analytical approaches are required. Structural Equation Modeling (SEM) has become increasingly popular in transportation research because it allows researchers to simultaneously analyze relationships between latent behavioral constructs and observed variables [26]. In particular, Covariance-Based Structural Equation Modeling (CB-SEM) enables the evaluation of both measurement models and structural relationships among theoretical constructs [27]. In this study, an integrated analytical framework is developed to examine how TA and Parking Availability (PA) influence MCP and TB within TOD environments, with PSI as a control variable. Using survey data, the latent constructs are first identified through EFA, and the relationships among constructs are subsequently tested using Covariance-Based Structural Equation Modeling (CB-SEM). This integrated approach provides a more comprehensive understanding of the mechanisms by which TOD-related factors shape transportation decisions.

2.1. Conceptual Framework and Hypothesis Development

The conceptual model of this study (Figure 1) examines how key attributes of TOD influence individuals' transportation decisions. Specifically, TA and PA are treated as primary explanatory variables that influence MCP and TB. TA reflects the ease with which individuals can access and use public transportation services [26]. At the same time, PA represents the level of parking supply and the convenience associated with private vehicle use [21].

MCP refers to individuals' tendency to prefer certain transportation modes based on their attitudes and perceptions. These modes represent individuals' inclinations toward specific modes of transportation, such as public transit, private vehicles, walking, or cycling [28]. It is different from actual travel behavior, which reflects the modes people actually use. Instead, MCP captures the underlying preferences that influence decision-making. This allows the study to examine MCP as a mediating factor between built environment characteristics and TB. In this study, the socio-economic construct reflects respondents' perceived influence of income and occupational position on transportation decisions rather than objective socio-economic classification. The construct was included to capture

how individuals perceive socio-economic conditions as shaping their travel preferences and mobility behavior. Although PSI characteristics may influence travel behavior, they are included in this study as covariates to control for demographic heterogeneity. The primary analytical focus remains on the relationships among TA, PA, MCP, and TB.

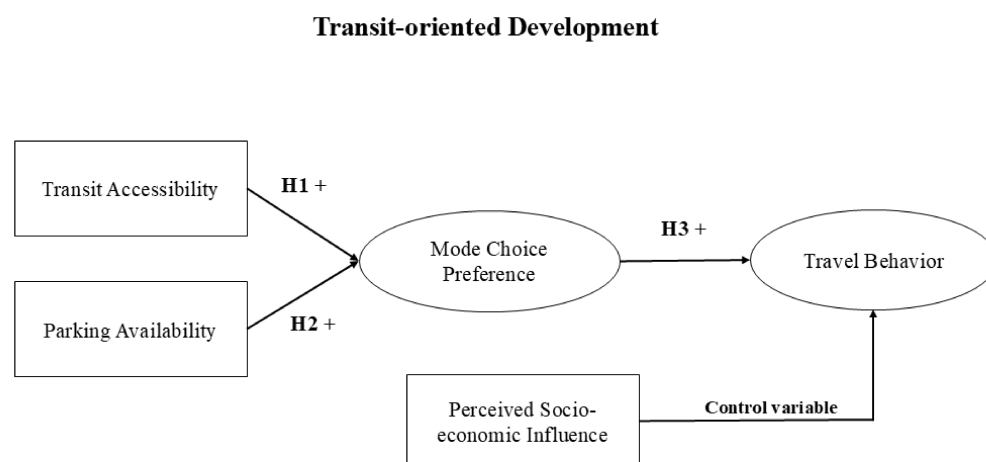


Figure 1. Conceptual framework of the study.

The relationships among these constructs are empirically examined using Covariance-Based Structural Equation Modeling (CB-SEM), which allows simultaneous estimation of measurement and structural relationships between latent variables.

2.2. Hypothesis Development

2.2.1. Transit Accessibility (TA), Mode Choice Preference (MCP), and Travel Behavior

TA is widely recognized as a key determinant of transportation choices in urban environments. Areas with shorter walking distances to transit stations, higher service frequency, and better network connectivity tend to exhibit higher public transport usage and lower dependence on private automobiles [10]. Empirical research has demonstrated that improved TA increases the likelihood that individuals will choose public transportation, walking, or cycling as their primary travel modes [29]. In TOD environments, enhanced accessibility to transit services creates favorable conditions for sustainable mobility by reducing travel time and improving connectivity between residential areas and major activity centers [30]. Residents located near transit stations are therefore more likely to shift their transportation preferences toward public transit and other alternative modes [31]. These accessibility advantages can ultimately influence broader TB patterns by encouraging the use of environmentally sustainable transportation options.

H1. *TA positively influences MCP by increasing the perceived convenience and attractiveness of public transport options as a TB on an individual.*

2.2.2. Parking Availability, Mode Choice Preference, and Travel Behavior

Parking availability (PA) has long been identified as a critical factor influencing TB and transportation mode choice [32]. When parking spaces are abundant, convenient, and inexpensive, individuals are more likely to rely on private vehicles for daily travel [33]. Conversely, limited parking supply or higher parking costs can discourage private vehicle use and promote the adoption of alternative transportation modes [34]. In TOD environments, parking management policies play a crucial role in shaping travel behavior. Restricting PA or implementing pricing strategies can reduce automobile dependence and encourage individuals to choose public transportation, walking, or cycling instead [35].

Previous studies have shown that areas with greater PA often experience increased car use, even when efficient public transport is available.

H2. *Higher Parking Availability (PA) increases the likelihood of choosing private vehicle modes and significantly influences MCP and TB within TOD environments.*

2.2.3. Mode Choice Preference (MCP) and Travel Behavior (TB)

TB is strongly shaped by individuals' preferences toward available transportation modes. Previous studies have shown that when travelers develop favorable preferences for particular modes, such as public transit, walking, or private vehicles, these preferences significantly influence their actual travel decisions and patterns [30]. MCP reflects individuals' attitudes, perceptions of convenience, cost considerations, and the accessibility of transport options, which ultimately determine how frequently a specific mode is used for daily activities [36]. Research on TB and urban transportation has consistently demonstrated that behavioral preferences serve as an important psychological mechanism linking the built environment to actual mobility outcomes [37]. In the context of TOD, improved accessibility and supportive urban design can shape individuals' preferences for sustainable transport modes, which, in turn, influence their TB [38]. Therefore, understanding the role of MCP is essential for explaining how transportation environments translate into observable mobility patterns. Based on this reasoning, it is hypothesized that MCP has a significant influence on TB.

H3. *Mode choice preference has a significant influence on TB.*

3. Methodology

3.1. Research Design

This study adopts a quantitative research design to examine the factors influencing MCP and TB within TOD environments. The research examines how TA and PA influence individuals' transportation preferences and travel patterns, with PSI as a control variable. Control variables are included to account for other factors that may influence travel behavior but are not the main focus of this study. In this research, PSI characteristics such as income and social status are treated as control variables because they can affect individuals' access to transport options and their travel decisions [39,40]. By including these variables in the model, the analysis reduces the risk that the observed relationships are driven by individual differences rather than by TA or PA. This approach allows the study to more accurately isolate and estimate the effects of built environment factors on MCP and TB. Household income is included as an indicator of individuals' economic capacity, which influences their access to different transportation options and their ability to afford private or public transport services. Social status refers to an individual's perceived position within the social and economic hierarchy, which is commonly associated with factors such as education, occupation, and income. This variable is included to capture broader socio-economic differences that may influence travel-related preferences and decisions. For example, higher-income individuals may have greater access to private vehicles, while lower-income groups may rely more on public transport [41]. A structured questionnaire was used to collect data from respondents regarding their perceptions of accessibility, parking conditions, and travel behavior. The collected data were analyzed using EFA and Covariance-Based Structural Equation Modeling (CB-SEM) to examine relationships among the latent constructs.

3.2. Methodological Framework of the Study

To improve the clarity of the analytical process, Figure 2 presents a graphical overview of the methodological framework adopted in this study. The figure illustrates the sequential steps of the analysis, starting from Hypothesis development, data collection and pre-processing, followed by exploratory factor analysis (EFA), reliability and validity assessment, confirmatory factor analysis (CFA), and finally structural equation modeling (SEM) for hypothesis testing. This structured approach ensures that the measurement model is validated before estimating the structural relationships among the constructs.

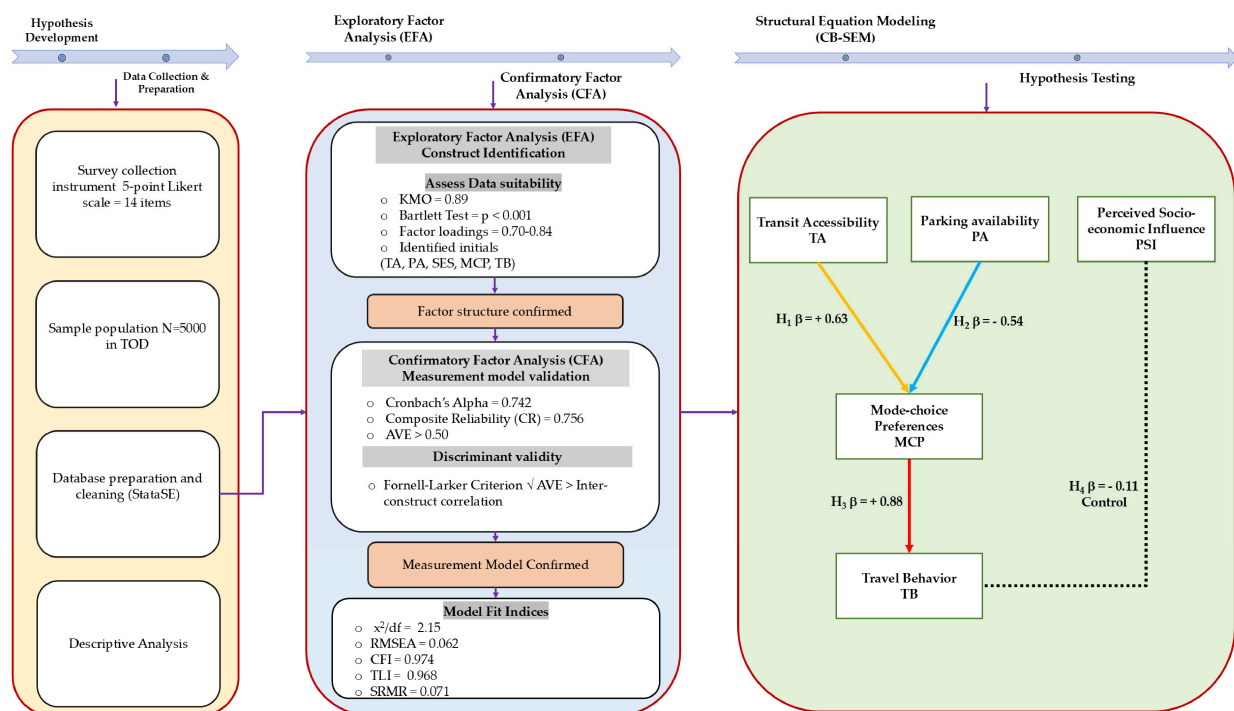


Figure 2. Methodological Framework of the Study.

3.3. Survey Instrument and Measurement Variables

We designed the survey questionnaire to capture respondents' perceptions of TA, PA, PSI, MCP, and TB within TOD environments. The questionnaire consisted of multiple items measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). We grouped the measurement variables into five latent constructs, based on previous studies on transportation behavior and TOD planning, as presented in Table 1.

The questionnaire items were adapted from prior studies in transportation and TB research, particularly those addressing TA, PA, PSI, MCP, and TB [4,14,20,42–44], see Supplementary Materials. Table 2 presents the demographic characteristics of the respondents, including gender, education level, and survey mode. The results indicate a relatively balanced gender distribution, with female respondents accounting for 52.2% and male respondents for 47.8% of the sample. In terms of educational attainment, the largest proportion of respondents have an undergraduate-level education (43.3%), followed by those with master's-level and higher qualifications (38.1%), while respondents with a bachelor's degree represent 18.5% of the sample. This distribution reflects a diverse educational background among participants. Regarding the data collection approach, we obtained 64.0% of responses through online surveys, while we collected 36.0% through face-to-face interactions. The use of both methods improves the coverage of the sample and reduces potential bias associated with a single survey mode.

Table 1. Measurement items.

Construct	Code	Measurement Item (Questionnaire Indicator)	Source
Transit Accessibility (TA)	TA1	Public transport stations are easily accessible from my residence.	Adapted from [4]
	TA2	The distance to the nearest public transport stop is convenient.	Adapted from [14]
	TA3	Public transport services are easily available in my area.	Adapted from [42]
Parking Availability (PA)	PA1	Parking spaces are easily available at my destination.	Adapted from [20]
	PA2	Parking spaces are available within a reasonable walking distance from my destination.	Adapted from [20]
	PA3	Adequate parking facilities encourage the use of private vehicles.	Adapted from [42]
Mode Choice Preference (MCP)	MCP1	I prefer using public transportation for daily travel.	Adapted from [43]
	MCP2	I prefer transportation modes that reduce travel time.	Adapted from [43]
	MCP3	I prefer transportation modes that are convenient and reliable.	Adapted from [44]
Travel Behavior (TB)	TB1	I frequently use public transport for my daily trips.	Adapted from [44]
	TB2	I rely on sustainable transportation modes for most trips.	Adapted from [44]
	TB3	The availability of transportation options influences my travel decisions.	Adapted from [42]
Perceived Socio-economic Influence (PSI)	PSI1	My household income influences my transportation choices.	Adapted from [14]
	PSI2	My occupation and social status affect my travel decisions.	Adapted from [42]

Table 2. Demographic Characteristics of Respondents.

Variable	Category	Frequency	Percentage (%)
Gender	Female	2611	52.20%
	Male	2389	47.80%
	Total	5000	100%
Education	Undergraduate	2167	43.30%
	Bachelor's	927	18.50%
	Master's and above	1906	38.10%
	Total	5000	100%
Survey Mode	Online	3200	64.00%
	Face-to-face	1800	36.00%
	Total	5000	100%

Figure 3 provides a visual representation of the distribution of respondents across gender, education level, and survey mode, supporting the patterns observed in Table 2.

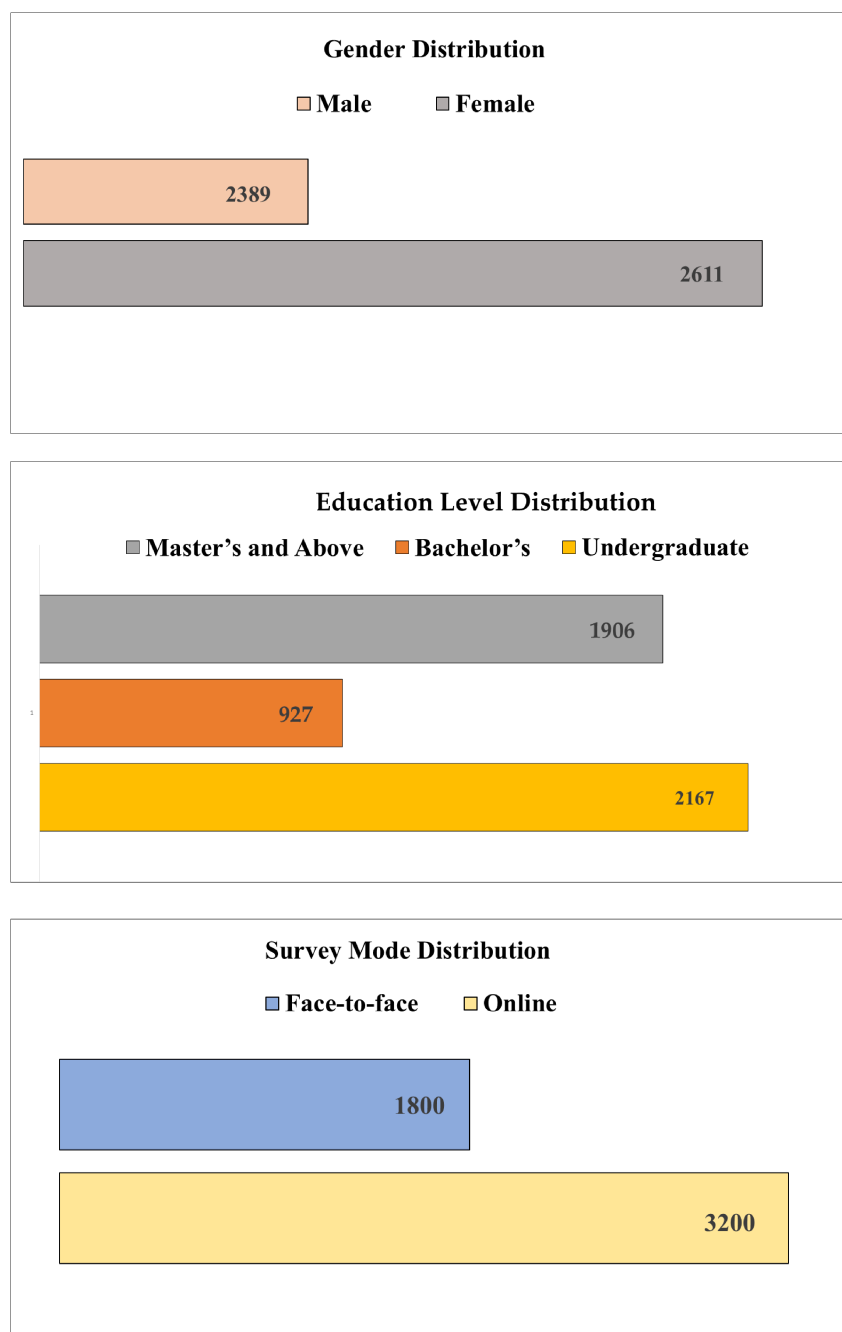


Figure 3. Demographic Profile of Respondents.

3.4. Data Collection

We conducted the survey using a convenience sampling approach, collecting responses via online platforms (e.g., Google Forms and social media) and face-to-face interviews in transit-oriented development (TOD) areas over a period of approximately 3 months. In this study, we operationalize TOD areas based on their spatial proximity to public transport stations, following established definitions in the literature that conceptualize TOD as a high-density, mixed-use development pattern centered on transit nodes. Prior studies indicate that the effective catchment area of transit stations varies depending on mode and urban context, typically ranging from 300 m to 1000 m, and in some cases extending further. For example, walking-based access distances are typically 300–1000 m,

while extended service areas may extend to 1500–2000 m in high-capacity systems [45]. Similarly, researchers have used buffer distances of approximately 300 m for bus rapid transit (BRT) TOD contexts [46].

In contrast, studies have also applied multi-level buffer frameworks (e.g., 300 m, 1000 m, and 1 km) to capture varying levels of accessibility [47]. Because the study focuses on district-level survey implementation, Figure 4 illustrates the selected administrative districts where we collected TOD-related data. The actual TOD analytical scope was defined using station-centered buffer distances derived from prior literature (300–1000 m walking catchment), rather than displayed as a separate map layer. We used these buffers as the operational criterion for identifying survey locations within transit-oriented environments.

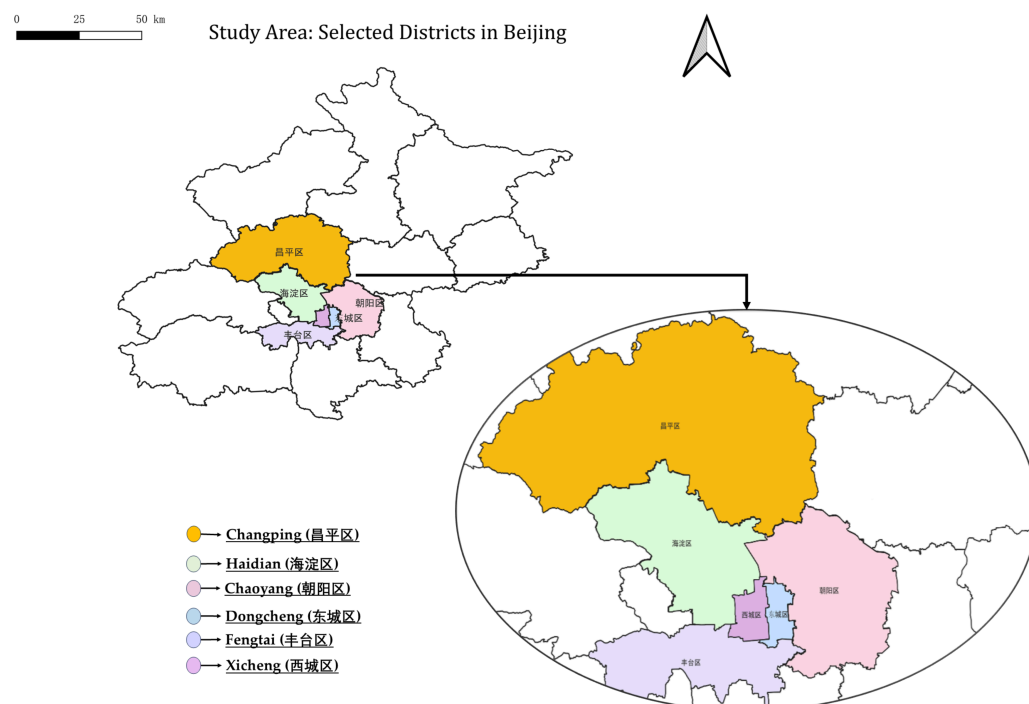


Figure 4. Spatial distribution of selected study districts in Beijing. TOD analytical boundaries were defined based on transit station catchment buffers (300–1000 m), as described in Section 3.4.

Building on this theoretical and empirical foundation, the present study focuses on TOD areas within the central urban districts of Beijing, specifically Dongcheng (东城区), Xicheng (西城区), Chaoyang (朝阳区), Fengtai (丰台区), Changping (昌平区), and Haidian (海淀区). These districts were selected because they represent the primary urban core of Beijing, where transit infrastructure is most developed, population density is highest, and land-use patterns strongly reflect TOD characteristics such as mixed-use development and high accessibility. Compared to peripheral districts, these areas integrate land use and public transport systems more closely, making them suitable for examining the relationships among transit accessibility, parking conditions, and travel behavior.

Figure 4 illustrates the spatial distribution of the selected districts and their corresponding TOD areas. A total of 5000 valid responses were obtained after excluding incomplete and inconsistent questionnaires, providing sufficient statistical power for conducting exploratory factor analysis (EFA) and structural equation modeling (SEM).

3.5. Data Analysis Procedure

To examine the relationships among the study variables, a multistage statistical analysis was conducted. SEM is widely used in transportation and behavioral research because it allows the simultaneous examination of relationships among latent constructs measured

by multiple indicators [26]. SEM provides a comprehensive framework for testing both the measurement properties of constructs and the causal relationships between them [48]. In this study, the analysis was conducted in three main stages: EFA, CFA, and SEM. This sequential approach ensures that the measurement instruments are reliable and valid before estimating the structural relationships among the variables.

The measurement model describes the relationship between latent constructs and their observed indicators. The measurement model in Structural Equation Modeling can be expressed as:

$$x = \Lambda_x \xi + \delta$$

$$y = \Lambda_y \eta + \epsilon$$

where x and y represent observed indicators of exogenous and endogenous latent variables, Λ_x and Λ_y denote the factor loading matrices, ξ represents exogenous latent constructs, η represents endogenous latent constructs, and δ and ϵ represent measurement errors.

The structural model specifies the relationships among latent constructs and can be expressed as:

$$\eta = B\eta + \Gamma\xi + \zeta$$

where B represents the relationships among endogenous constructs, Γ represents the effects of exogenous constructs on endogenous constructs, and ζ denotes the structural error term.

Based on the conceptual framework of this study, the structural relationships among the variables can be represented as:

$$MCP = \beta_1 TA + \beta_2 PA + \epsilon_1$$

$$TB = \beta_3 MCP + \beta_4 PSI + \epsilon_2$$

where TA represents Transit Accessibility, PA represents Parking Availability, MCP represents Mode Choice Preference, PSI represents Perceived Socio-economic Influence, and TB represents Travel Behavior.

4. Results

4.1. Descriptive Statistics

Descriptive statistics are presented in Table 3 to summarize the basic characteristics of the collected survey data. They provide an overview of the central tendency and variability for each measurement item, allowing researchers to understand participants' general response patterns [49]. Reporting the mean and standard deviation helps assess whether respondents' perceptions are concentrated around particular values or widely distributed across the measurement scale [50]. This preliminary analysis is important before conducting advanced analyses such as measurement model validation and structural model estimation in SEM [51].

Table 3. Descriptive statistics of survey variables.

Construct	Item	Mean	Std. Deviation
Transit Accessibility (TA)	TA1	3	0.92
	TA2	3.2	0.88
	TA3	3	0.95
Parking Availability (PA)	PA1	3	0.87
	PA2	2.9	0.91
	PA3	3	0.89

Table 3. *Cont.*

Construct	Item	Mean	Std. Deviation
Perceived Socio-economic Influence (PSI)	PSI1	3.1	0.84
	PSI2	2.8	0.9
Mode Choice Preference (MCP)	MCP1	3	0.85
	MCP2	3.2	0.88
	MCP3	3.1	0.86
Travel Behavior (TB)	TB1	3.1	0.89
	TB2	3	0.92
	TB3	3	0.9

The descriptive statistics indicate that respondents reported moderate perceptions regarding transit accessibility, parking availability, and travel behavior. The mean values for most variables range between 2.8 and 3.2, suggesting relatively balanced responses across the five-point Likert scale.

4.2. Exploratory Factor Analysis (EFA)

EFA was conducted as an initial step to identify the underlying structure of the survey variables and to verify whether the observed indicators represent the intended latent constructs. EFA is commonly used in survey-based research to explore the dimensionality of measurement items and to ensure that variables associated with a particular construct load onto the same factor [52]. By examining factor loadings, EFA helps determine whether the measurement items are appropriate indicators of their respective latent variables [53]. Before performing factor extraction, the suitability of the dataset for factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett’s Test of Sphericity, as shown in Table 4. The KMO statistic assesses whether the correlations among variables are sufficiently strong to justify factor analysis, while Bartlett’s Test examines whether the correlation matrix differs significantly from an identity matrix [54,55].

Table 4. KMO and Bartlett’s Test.

Test	Value
Kaiser–Meyer–Olkin (KMO)	0.89
Bartlett’s Test (χ^2)	3567.42
Significance	$p < 0.001$

In the context of this study, EFA ensures that the questionnaire items designed to measure TA, PA, MCP, PSI, and TB are statistically grouped into their respective constructs. This step is important because it confirms that the survey indicators accurately represent the theoretical variables before proceeding to structural modeling. The KMO value of 0.89 indicates a high level of sampling adequacy, suggesting that the correlations among variables are sufficiently strong for factor analysis. According to commonly accepted guidelines, KMO values above 0.80 are considered excellent. In addition, Bartlett’s Test of Sphericity is statistically significant ($p < 0.001$), indicating that the correlation matrix differs significantly from an identity matrix [54,55]. This result confirms that meaningful relationships exist among the variables, indicating that the dataset is suitable for factor extraction.

The factor loading results Table 5. demonstrate that all observed variables load strongly on their respective constructs, with values ranging from 0.70 to 0.84. Factor loadings above 0.50 are generally considered acceptable, while values above 0.70 indicate strong relationships between observed indicators and their corresponding latent vari-

ables [56]. These results confirm that the questionnaire items provide reliable measurements of the study constructs.

Table 5. Factor Loadings from EFA.

Construct	Item	Factor Loading
Transit Accessibility	TA1	0.78
	TA2	0.82
	TA3	0.75
Parking Availability	PA1	0.72
	PA2	0.79
	PA3	0.76
Perceived Socio-economic Influence (PSI)	PSI1	0.7
	PSI2	0.73
Mode Choice Preference	MCP1	0.81
	MCP2	0.84
	MCP3	0.8
Travel Behavior	TB1	0.83
	TB2	0.79
	TB3	0.82

4.3. Measurement Model (CFA)

After identifying the factor structure through EFA, CFA was performed to evaluate the measurement model, as illustrated in Table 6. CFA is used to confirm whether the observed indicators adequately represent the hypothesized latent constructs. Unlike EFA, which explores the factor structure, CFA tests whether the proposed measurement relationships are supported by the data [56]. The measurement model assessment involves evaluating several reliability and validity indicators, including factor loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Cronbach's alpha and composite reliability assess the internal consistency of the measurement items, while AVE measures the degree to which a construct explains the variance of its indicators [57–59]. In this study, CFA ensures that the constructs representing Transit Accessibility, Parking Availability, Mode Choice Preference, Perceived Socio-economic Influence (PSI), and TB are measured reliably and validly. Establishing measurement reliability and validity is necessary before examining the structural relationships among the constructs.

Table 6. Reliability and validity.

Construct	Cronbach's Alpha	CR	AVE	TA	PA	PSI	MCP	TB
Transit Accessibility	0.821	0.835	0.628	0.79				
Parking Availability	0.803	0.814	0.594	0.41	0.77			
Perceived Socio-economic Influence	0.742	0.756	0.612	0.29	0.35	0.78		
Mode Choice Preference	0.846	0.858	0.669	0.55	0.48	0.31	0.82	
Travel Behavior	0.832	0.845	0.646	0.49	0.46	0.37	0.71	0.8

The results reported in Table 6 demonstrate that the measurement model achieves satisfactory levels of reliability and validity across all constructs, thereby supporting its suitability for structural analysis.

Internal consistency is confirmed by Cronbach's alpha values ranging from 0.742 to 0.846 and composite reliability (CR) values between 0.756 and 0.858. Notably, MCP ($\alpha = 0.846$; CR = 0.858) and TB ($\alpha = 0.832$; CR = 0.845) exhibit particularly strong reliability, indicating a high degree of consistency among their measurement items. Although PSI shows comparatively lower values ($\alpha = 0.742$; CR = 0.756), these still exceed the acceptable threshold, suggesting adequate reliability despite the inherent heterogeneity of socio-economic indicators. Cronbach's alpha values exceed the minimum acceptable level of 0.70, indicating strong internal consistency among the measurement items. Similarly, composite reliability values are above the recommended threshold of 0.70, demonstrating that the constructs are measured reliably [57]. Convergent validity is established through average variance extracted (AVE) values, which range from 0.594 to 0.669, all exceeding the recommended minimum of 0.50. Among the constructs, MCP demonstrates the highest AVE (0.669), indicating that its indicators provide a strong representation of the underlying latent concept. Similarly, TA (AVE = 0.628) and Travel Behavior (AVE = 0.646) also show substantial explanatory power, reinforcing the robustness of the measurement model. Discriminant validity is further supported using the Fornell–Larcker criterion. The square root of AVE for each construct (e.g., 0.79 for TA, 0.77 for PA, and 0.82 for MCP) exceeds the corresponding inter-construct correlations. For instance, the correlation between TA and MCP (0.55) is notably lower than the square root of AVE for both constructs (0.79 and 0.82, respectively), confirming that these variables capture distinct conceptual dimensions. Even in cases of relatively higher correlations, such as between MCP and TB (0.71), discriminant validity remains intact as the square root of AVE for both constructs (0.82 and 0.80) remains higher. The square root of AVE for each construct is greater than the inter-construct correlations, confirming discriminant validity according to the Fornell–Larcker criterion. The average variance extracted values exceed 0.50, confirming adequate convergent validity [59].

Overall, these findings indicate that the constructs are both internally consistent and empirically distinct. This reduces the risk of multicollinearity and measurement overlap, ensuring that the estimated structural relationships reflect true behavioral mechanisms rather than artifacts of poorly specified measurement. Consequently, the measurement model provides a robust foundation for subsequent SEM analysis.

4.4. Model Fit Assessment

The goodness-of-fit indices indicate that the model adequately fits the observed data, as presented in Table 7.

Table 7. Model fit indices.

Fit Index	Value	Recommended
χ^2/df	2.15	<3
RMSEA	0.062	<0.08
CFI	0.974	>0.90
TLI	0.968	>0.90
SRMR	0.071	<0.08

The goodness-of-fit indices suggest that the proposed model provides an adequate representation of the observed data. The chi-square to degrees-of-freedom ratio (χ^2/df) is below the recommended threshold of 3, indicating acceptable model fit. The comparative fit index (CFI) and Tucker–Lewis index (TLI) both exceed the recommended value of 0.90, demonstrating good model fit. Furthermore, the RMSEA and SRMR values fall below the threshold of 0.08, indicating that the model fits the data well [60,61].

4.5. Structural Model Results

The structural model was then estimated to test the hypothesized relationships between constructs. The structural path results are presented in Table 8.

Table 8. Structural path results.

Hypothesis	Relationship	Standardized β	z-Value	p-Value
H1	TA $\rightarrow$ MCP	0.63	66.19	<0.001
H2	PA $\rightarrow$ MCP	−0.54	−47.91	<0.001
H3	MCP $\rightarrow$ TB	0.88	165.35	<0.001
Control Variable	PSI $\rightarrow$ TB	−0.11	−10.18	<0.001

The structural model results provide empirical support for the hypothesized relationships. TA demonstrates a strong positive influence on MCP, indicating that improved access to public transportation encourages individuals to adopt alternative transport modes. In contrast, PA shows a negative relationship with MCP, suggesting that greater availability of parking facilities may reinforce reliance on private vehicles. Furthermore, MCP exhibits a strong positive influence on TB, confirming that individuals' transportation preferences significantly shape their travel patterns. PSI also shows a statistically significant influence on TB, indicating that demographic and economic conditions remain important determinants of mobility behavior.

4.6. Structural Equation Model

SEM was employed to test the hypothesized relationships among the study constructs, see Figure 5. SEM is a multivariate statistical technique that enables researchers to analyze complex relationships between latent variables simultaneously. Compared with traditional regression methods, SEM allows the estimation of multiple relationships within a single integrated model while accounting for measurement error [26]. In the present study, SEM was used to examine how TA and PA influence MCP and TB, while PSI was included as a control variable. This approach provides a comprehensive understanding of how built environment factors and socio-economic characteristics interact to influence TB within TOD contexts.

The results reveal that TA exerts a significant positive influence on MCP, indicating that improved access to transit systems encourages individuals to shift toward more sustainable transportation options, including public transport and non-motorized modes. In contrast, PA shows a negative relationship with MCP, suggesting that greater parking availability reinforces private vehicle dependence and reduces the attractiveness of alternative modes. Among all relationships, MCP shows the strongest positive effect on travel behavior, highlighting its central role as a mediating mechanism through which built environment factors influence actual travel decisions. This finding underscores that changes in accessibility and parking conditions do not directly translate into behavioral outcomes unless they first shape individual preferences. Furthermore, PSI shows a modest negative association with TB, suggesting that higher socio-economic groups may have greater access to private transport, thereby reducing reliance on transit-oriented mobility. Overall, the structural results emphasize that while built environment attributes such as accessibility and parking are critical, their effects on travel behavior are largely indirect, operating through behavioral preferences, reinforcing the importance of MCP as a key explanatory construct in TOD contexts.

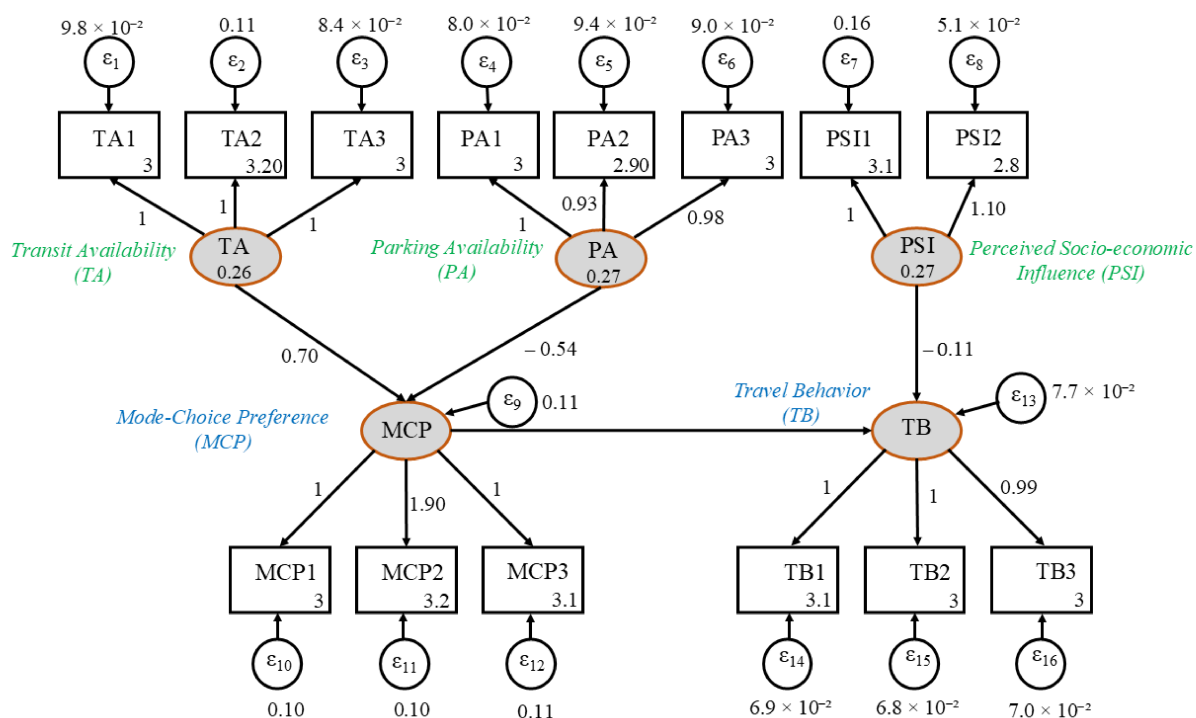


Figure 5. Final structural equation model illustrating the relationships among TA, PA, MCP, PSI, and TB.

5. Discussion

This study examined the influence of TA, PA, and PSI on MCP and TB within a TOD context. The structural relationships were analyzed using Structural Equation Modeling after validating the constructs through EFA and CFA. The structural model results indicate that TA has a positive and significant effect on mode choice preference ($\beta = 0.63$, $p < 0.001$). This suggests that individuals who perceive better accessibility to public transport are more likely to prefer sustainable travel modes such as public transit, walking, and cycling. The result highlights the importance of accessibility in shaping transportation preferences in TOD environments. In contrast, parking availability shows a negative relationship with mode choice preference ($\beta = -0.54$, $p < 0.01$), indicating that greater parking availability may discourage the adoption of alternative transportation modes. This finding suggests that the availability of convenient parking may reinforce reliance on private vehicles, even in areas with relatively good public transport accessibility.

Furthermore, mode choice preference has a strong positive effect on TB ($\beta = 0.88$, $p < 0.001$), demonstrating that individuals' travel patterns are strongly influenced by their preferences toward different transport modes. This relationship confirms that behavioral preferences act as an important mechanism linking built environment characteristics with actual mobility decisions. The results also indicate that PSI has a negative but significant effect on TB ($\beta = -0.11$, $p < 0.05$). This suggests that demographic and economic characteristics continue to play a role in shaping mobility patterns, reflecting differences in travel needs, access to private vehicles, and transportation affordability. The covariate effect suggests that individual socio-economic differences may influence travel behavior; however, these effects were included primarily to control for respondent heterogeneity rather than to test an independent explanatory relationship.

The primary objective of this research was to examine how TOD-related factors influence TB through mode choice preferences. The structural relationships identified in this study provide empirical support for this conceptual pathway. Specifically, the findings show that built environment characteristics such as TA and parking availability influence

individuals' transportation preferences, which in turn shape their travel behavior. This mediating role of mode choice preference highlights the importance of considering behavioral factors when evaluating the effectiveness of TOD policies. Infrastructure improvements alone may not fully influence travel outcomes unless they also affect individuals' perceptions and preferences regarding transportation options.

The positive effect of TA identified in this study is consistent with previous research examining the relationship between accessibility and travel behavior. For example, studies by [14,16] demonstrated that accessibility to public transport significantly influences travel demand and encourages the use of non-automobile modes. Similarly, the meta-analysis conducted by [4,14] found that built environment characteristics, such as accessibility and urban design, play a key role in shaping mobility patterns. The negative association between parking availability and mode choice preference observed in this study also aligns with earlier research on parking policies. Reference [20] emphasized that excessive parking supply encourages automobile dependency and undermines sustainable transportation strategies. The results of the present study provide further empirical support for this argument by demonstrating that parking availability can indirectly influence TB by affecting MCP. In addition, the strong relationship between MCP and TB supports the behavioral framework proposed by [32,37], who argued that travel attitudes and preferences mediate the relationship between the built environment and observed travel outcomes. The relatively high standardized coefficient identified in this study indicates that behavioral preferences play a central role in shaping travel decisions in TOD environments.

From a methodological perspective, this study contributes to the literature by employing a two-step measurement validation process using EFA and CFA before estimating the structural relationships through SEM. This approach strengthens the reliability and validity of the latent constructs and provides a more robust framework for examining the relationships between built environment factors and travel behavior. Despite the contributions of this study, several limitations should be acknowledged. First, the analysis is based on cross-sectional survey data, which limits the ability to capture temporal changes in travel behavior. Second, the data rely on self-reported responses, which may introduce reporting bias or inaccuracies due to perception-based factors. Third, the structural model focuses primarily on accessibility, PA, and socio-economic variables, while other potentially relevant factors, such as service quality, safety perceptions, and urban design characteristics, were not explicitly included in the analysis.

Future research could extend this study by incorporating additional variables related to service quality, land-use characteristics, and psychological attitudes toward transportation. Longitudinal studies would also provide valuable insights into how TB evolves as transportation infrastructure and urban development patterns change over time. Furthermore, comparative analyses across different cities or metropolitan regions could help determine whether the relationships identified in this study are consistent across diverse urban contexts.

6. Conclusions

This study examined the relationships between TA, PA, PSI characteristics, MCP, and TB within the context of TOD. Using a survey-based dataset and a structural SEM framework, the study investigated how built environment characteristics influence TB through individuals' transportation preferences. The findings indicate that TA plays an important role in shaping individuals' preferences for transportation modes, thereby influencing their travel behavior. Improved accessibility to public transport services increases the likelihood that individuals will prefer sustainable travel options. In contrast, we found that greater PA negatively influenced MCP, suggesting that excessive parking supply may

encourage private vehicle use and reduce the attractiveness of alternative modes. In addition, the results confirm that MCP is a key determinant of travel behavior, highlighting the importance of behavioral factors in understanding mobility decisions.

Beyond confirming existing relationships, this study contributes by developing an integrated analytical framework that examines TA and PA as interacting built environment factors, providing a more comprehensive understanding of their combined influence on TB. The study also identifies the mediating role of MCP, demonstrating that the effects of built environment characteristics on TB operate primarily through behavioral mechanisms rather than direct relationships, thereby strengthening the application of SEM in this context. From a policy perspective, the findings highlight the critical balance between improving TA and managing parking supply. While enhanced accessibility promotes sustainable travel choices, excessive PA counteracts these benefits by reinforcing private vehicle dependence. This trade-off underscores that infrastructure improvements alone are insufficient unless accompanied by coordinated parking management strategies.

To translate these findings into actionable strategies, targeted policy measures should be implemented within TOD contexts. Improving transit accessibility requires strengthening first- and last-mile connectivity through pedestrian-friendly infrastructure within 300–600 m of transit stations, better integration of feeder services, and increased service frequency in high-demand corridors. At the same time, effective parking management should rely on demand-responsive approaches, including the reduction of parking minimums, the use of dynamic pricing, and the prioritization of short-term and shared parking over long-term private vehicle storage. In addition, the strong mediating role of mode choice preference suggests that behavioral interventions such as travel demand management programs, public transport incentives, and awareness campaigns are necessary to influence individual travel decisions. These measures collectively support a coordinated approach that aligns infrastructure provision with behavioral change to promote sustainable travel outcomes in TOD environments. Overall, the study suggests that improving public transport accessibility while managing parking supply can help promote more sustainable TB in urban areas. Future research may extend this work by incorporating additional built environment and service-related variables and by examining these relationships across different urban contexts.

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