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Statistical Road Traffic Noise in Residential Area: Case Study of Shah Alam City

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Abstract: Traffic noise has become an increasingly important environmental concern due to rapid urbanisation and growing vehicular activity in residential areas. This study aims to identify the factors influencing traffic noise and develop a predictive framework using partial least squares structural equation modelling (PLS-SEM). Traffic noise measurements were conducted across four residential sections of Shah Alam (Seksyen 7, 9, 20, and 27) using a sound level meter (SLM) at three observation periods: morning (08:00–11:00), afternoon (12:00–15:00), and evening (16:00–19:00). Data collection included traffic volume observations, road geometry measurements, and climatic variables obtained from secondary environmental sources. A total of 504 observations were analysed using SmartPLS 4.0. The measurement model assessment demonstrated that the reflective constructs—traffic volume, road geometry, and the equivalent traffic noise level (i.e., the A-weighted equivalent continuous sound level, L_{Aeq})—achieved acceptable reliability and validity. In contrast, climate conditions were evaluated as a formative construct to better represent the multidimensional contribution of temperature, humidity, and wind speed across observation periods. Structural model results indicated that Climate Condition exhibited the strongest influence within the model and contributed significantly to both traffic volume and L_{Aeq}, while road geometry showed a positive relationship with traffic volume. Traffic volume did not demonstrate a statistically significant direct relationship with L_{Aeq}, suggesting that residential traffic noise may be influenced by interactions among environmental and roadway conditions rather than vehicle quantity alone. The model demonstrated acceptable explanatory capability, with coefficient of determination (R^2) values of 0.727 for L_{Aeq} and 0.552 for traffic volume. These findings highlight the importance of integrating climatic and roadway variables into residential traffic noise assessment and support more context-sensitive approaches for urban transport planning and environmental noise management. Future studies are recommended to incorporate additional operational traffic variables and advanced predictive techniques to improve model generalisability and prediction performance.

Keywords: Road traffic noise; Residential area; Urban transportation; Statistical modelling; Partial least squares structural equation modeling; Traffic volume; Road geometry; Climate condition

1 Introduction

Shah Alam's economy and urban development have expanded significantly over the past four decades, turning the city into an industrial hub. Industrial activity led to a massive increase in population and the expansion of new housing developments [1]. According to the Department of Statistics Malaysia (DOSM), the total population of Shah Alam reached 438,745 residents [2]. The built environment is an important component of public health-oriented urban planning because it influences physical activity patterns and supports health benefits associated with transportation and recreational activities [3]. The ecology and the standard of living of city people are unavoidably impacted by dissatisfaction with living conditions, which has been associated with lower subjective well-being, while poor environmental quality, including degraded air conditions, may contribute to adverse mental health outcomes [4].

To estimate traffic noise emissions for unmonitored roads, previous studies have developed predictive relationships based on noise monitoring data and daily traffic flow characteristics [5–7]. Recent studies have also employed IoT-assisted monitoring systems and deep learning techniques to support real-time traffic observation and improve mobility efficiency [8]. This type of approach partially addresses the issue of noise map computational efficiency. On the one hand, the computational accuracy of noise maps is impacted by these approaches' failure to adequately account for the combined effects of traffic flow and speed on road noise emissions [9]. However, these techniques are unable to avoid relying on monitoring sensors, and even their forecast accuracy is highly dependent on the quantity and placement of deployed sensors [10]. Furthermore, it is challenging to track the strength of undisturbed traffic noise sources in the real world. Another issue to take into account is the high cost of acoustic monitoring devices [11].

The scientific contribution of this study has also been clarified by explicitly positioning the research within the current limitations of traffic noise modelling literature. Previous studies have extensively applied regression analysis [12], GIS-based simulations [13], artificial neural networks [13], land-use regression [14], and machine learning techniques for traffic noise prediction and mapping [15]. However, these approaches primarily emphasize prediction accuracy and spatial estimation while providing a limited explanation of the complex causal relationships among traffic, environmental, and urban variables influencing noise exposure [16]. Recent reviews by researchers in environmental acoustics have highlighted that many traffic noise models remain site-dependent and often lack integrated analytical frameworks capable of explaining multidimensional interactions among variables [17]. Therefore, the present study addresses an important research gap by introducing partial least squares structural equation modelling (PLS-SEM) as an integrated framework to simultaneously evaluate both direct and indirect relationships among latent constructs associated with urban traffic noise generation [18, 19].

Existing modelling techniques also present several methodological limitations. Conventional regression models generally assume linear and independent relationships among variables and require strict statistical assumptions such as multicollinearity, independence, and data normality, which may not adequately represent real urban traffic systems [17]. Meanwhile, machine learning and neural network approaches are highly effective for prediction purposes but are frequently criticised as "black-box" models due to their limited interpretability regarding causal mechanisms and inter-variable relationships [20, 21]. In contrast, PLS-SEM provides both predictive and explanatory capabilities by enabling simultaneous assessment of measurement reliability, latent variable interactions, and structural path relationships within a single analytical model [22]. This capability makes PLS-SEM particularly suitable for traffic noise assessment, where traffic flow, vehicle composition, road geometry, climatic conditions, and built environment characteristics interact simultaneously and influence environmental noise exposure in a highly interconnected manner [23].

The theoretical and practical advantage of applying PLS-SEM in this study lies in its ability to analyse complex causal structures involving multiple latent variables while accommodating relatively small sample sizes and non-normal environmental datasets commonly encountered in field-based noise monitoring studies [24]. Previous studies applying SEM approaches in transportation and environmental acoustics have demonstrated that the method is effective in identifying both direct and indirect effects among variables, thereby improving understanding of environmental noise mechanisms beyond conventional prediction-oriented approaches [23, 25]. Furthermore, unlike purely predictive models, PLS-SEM enables the development of a theoretically grounded structural framework capable of explaining how urban traffic characteristics collectively contribute to residential traffic noise conditions [26]. Such information is valuable for urban planners, environmental regulators, and transport authorities because it supports evidence-based mitigation strategies focusing on influential causal pathways rather than solely on predicted noise levels.

The findings of the present study, therefore, differ from earlier transport noise studies by emphasizing the structural relationships and mediating effects among contributing variables rather than focusing exclusively on prediction performance or spatial mapping accuracy. While earlier traffic noise studies mainly concentrated on estimating equivalent noise levels using regression-based or artificial intelligence approaches, the present research demonstrates how PLS-SEM can function as both a predictive and theory-building framework for environmental noise assessment. Specifically, the study identifies the interrelationship between built environment factors, climatic conditions, and traffic flow characteristics within a unified structural model, thereby contributing new methodological insight to the field of transportation noise research. This expands the application of PLS-SEM within environmental acoustics and provides a more holistic understanding of urban traffic noise generation mechanisms compared to earlier modelling approaches.

2 Methodology

2.1 Study Location

This study was conducted in various parts of Shah Alam, Selangor, Malaysia, which is Seksyen 7, 9, 20, and 27, which can be seen at Figure 1. Shah Alam is a city and the state capital of Selangor, situated within the Petaling District and a small portion of the neighbouring Klang District, with a total population of 438745 [2]. Table 1 shows the sampling point location, latitude, and longitude in four Seksyen of Shah Alam that were assessed, with each Seksyen having three sampling point locations. The measurements were conducted during morning, afternoon, and evening periods for two weeks. The data encompassed equivalent sound pressure levels (i.e., the A-weighted equivalent continuous sound level, L_{Aeq}), minimum sound pressure levels ($L_{\min}$), and maximum sound pressure levels ($L_{\max}$).

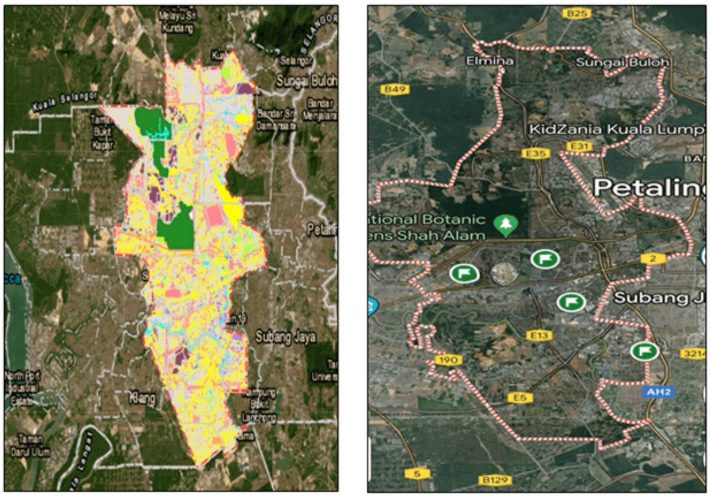

Figure 1. Study point location

Table 1. Sampling point location

Location	Sampling Location	Latitude and Longitude
	S1	3°04′02.4″N101°29′29.3″E
Seksyen 7	S2	3°04′25.7″N101°29′31.6″E
	S3	3°04′12.2″N101°28′50.5″E
	S1	3°05′01.4″N101°31′23.4″E
Seksyen 9	S2	3°04′36.0″N101°31′48.8″E
	S3	3°05′12.8″N101°31′21.8″E
	S1	3°03′11.1″N101°32′34.7″E
Seksyen 20	S2	3°02′55.5″N101°31′54.6″E
	S3	3°02′52.4″N101°31′34.8″E
	S1	3°01′20.5″N101°34′36.3″E
Seksyen 27	S2	3°01′32.7″N101°33′51.0″E
	S3	3°02′08.8″N101°33′20.0″E

2.2 Data Collection

To collect traffic noise data and evaluate noise indices, on-site field measurements were conducted using a sound level meter (SLM) in accordance with the guidelines issued by the Malaysian Department of Environment (DOE). Traffic noise monitoring was performed at three-hour intervals during three observation periods: morning (08:00–11:00), afternoon (12:00–15:00), and evening (16:00–19:00). The measurement procedure consisted of the following steps:

(a) Monitoring locations were selected according to the DOE guidelines prior to field data collection. The SLM was positioned at designated monitoring points located at least 3.5 m away from walls, buildings, and other reflective surfaces to minimise sound reflection effects.

(b) The microphone was mounted on a tripod and positioned at a height between 1.2 and 1.5 m above ground level. The microphone orientation was adjusted to face the dominant traffic noise source to ensure consistent acoustic measurement.

(c) It has been ensured that the portable SLMs are never kept inside an enclosure.

(d) The SLM's scale was set to "A-weighting," and the time response was set to "Fast," in order to measure the traffic noise.

(e) The field data sheet, which included information like road distance measurements and a site diagram of the measurement area, was fully documented.

Simultaneously, additional traffic noise attribute variables were collected during each observation period. Traffic volume data were obtained through manual vehicle counting, covering five vehicle categories: bus, lorry, van, motorcycle, and passenger car. In addition, road geometry data were collected through direct field measurements, where road width was measured using a tape measure at each sampling location.

2.3 Data Analysis

Descriptive and correlational analyses were performed to examine the characteristics and relationships among the study variables. Descriptive analysis was used to summarise the collected data and provide an overview of traffic noise conditions across the study locations and observation periods. The findings were subsequently presented using tables and graphical representations to support interpretation and discussion.

The acoustic measurements obtained from field monitoring were processed into three standard environmental noise indicators: maximum sound pressure level ($L_{\max}$), minimum sound pressure level ($L_{\min}$), and equivalent continuous sound pressure level over time ($L_{A\text{eq},T}$). These indicators represent the highest, lowest, and time-averaged sound pressure levels recorded by the SLM during each observation period.

In addition to acoustic measurements, supplementary variables including Climate Condition, traffic volume, and road geometry were analysed to identify the factors contributing to traffic noise variation. Climate conditions included measurements of humidity, temperature, and wind speed, while traffic volume consisted of vehicle counts across five categories (bus, car, van, motorcycle, and lorry). Road geometry was represented by roadway width measurements collected at each monitoring location. All datasets were subsequently processed and analysed using SmartPLS version 4.0 to develop and evaluate the traffic noise prediction model.

The sample size for PLS-SEM was determined based on the total number of field observations collected throughout the monitoring campaign. Traffic noise assessment was conducted across 12 monitoring locations over a two-week observation period, with measurements performed during three daily intervals representing temporal traffic variation: morning (08:00–11:00), afternoon (12:00–15:00), and evening (16:00–19:00). At each observation interval, simultaneous observations were collected for all study variables. Consequently, each location–time measurement represented one independent observation. The final dataset consisted of 504 observations, which were used for the PLS-SEM estimation.

2.4 Data Modelling

In this study, the PLS-SEM approach was employed to evaluate the conceptual model. The rationale for choosing the PLS-SEM method in this study has been thoroughly examined. The choice of PLS-SEM for data analysis is rooted in the study's emphasis on predictive factors of traffic noise attributes such as climate conditions, road geometry, and traffic volume. Consequently, the latent variable scores play a pivotal role in investigating the underlying relationships between these constructs. Moreover, given the study's complexity, characterised by numerous latent variables, PLS-SEM was considered a suitable choice. It is well-suited for complex models featuring multiple latent variables [27].

The adequacy of the sample size for PLS-SEM was evaluated based on established methodological recommendations in the structural equation modelling literature. Unlike covariance-based SEM, PLS-SEM is considered appropriate for exploratory and predictive modelling studies involving relatively smaller datasets and complex models with multiple constructs and indicators [28]. In this study, the minimum sample size requirement was assessed using the commonly adopted "10-times rule," which recommends that the minimum sample size should be at least ten times the maximum number of structural paths directed at any endogenous construct or ten times the largest number of indicators used to measure a single construct [29].

Sample adequacy was further evaluated using the 10-times rule, which recommends a minimum sample size equal to ten times the maximum number of structural paths directed at any endogenous construct. In the present model, the highest complexity occurred in the Climate Condition construct, which included 9 indicators, resulting in a minimum required sample size of 90. Since the final sample (N = 504) substantially exceeded the recommended threshold, the dataset was considered sufficient for reliable parameter estimation and structural model evaluation using PLS-SEM in SmartPLS 4.0. Bootstrapping with 5,000 resamples, and a significance level of $p <$ 0.05 (two-tailed) was applied to evaluate statistical significance.

2.4.1 Path relation

The path coefficient's value aids researchers in gauging the strength of the relationship between two latent variables. The path coefficients and formative indicator weights can be interpreted similarly. In other words, researchers must use bootstrapping to determine the importance of the route coefficients and their values, which are usually between +1 and -1. Additionally, they can decipher how one or more intervening constructs indirectly affect a particular target construct. When evaluating mediating effects, this effect type is especially relevant. For a path coefficient to be considered significant within the model, it should exceed 0.1 and carry a significance level of at least 0.05 [30].

2.4.2 Reflective model measurement

Reflective constructs were evaluated using indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability was assessed through outer loading values, where loading values greater than 0.70 indicate satisfactory indicator contribution, although values above 0.40 may be retained when supported by theoretical considerations. Internal consistency reliability was examined using Cronbach's alpha (CA) and Composite Reliability (CR). Values exceeding 0.70 were considered acceptable for establishing construct reliability. Convergent validity was assessed using average variance extracted (AVE), with values greater than 0.50 indicating that the construct explained more than half of the indicator variance. Discriminant validity was evaluated using the heterotrait–monotrait ratio of correlations (HTMT). HTMT values below 0.90 indicate adequate construct distinctiveness and support the absence of discriminant validity issues [31].

Reflective assessment was applied only to the constructs L_{Aeq}, traffic volume, and road geometry, as these indicators were conceptually expected to represent manifestations of common latent variables.

2.4.3 Formative model measurement

The Climate Condition construct was evaluated separately using formative measurement procedures because humidity, temperature, and wind speed represent complementary environmental dimensions that collectively define climatic exposure rather than interchangeable indicators of a single latent characteristic. Formative assessment focused on evaluating indicator contribution and indicator relevance rather than internal consistency reliability. Indicator contribution was assessed using outer weights, while indicator relevance was evaluated using outer loadings obtained through bootstrapping procedures [30].

Outer weights were examined to determine the relative contribution of each climatic indicator to construct formation. Indicators with non-significant outer weights were not automatically removed, provided that their outer loading values and theoretical relevance remained acceptable. Outer loadings were additionally evaluated to determine the absolute contribution of indicators to the construct. Retention decisions considered both statistical evidence and conceptual importance in representing temporal environmental variability. Unlike reflective constructs, CA, Composite Reliability, and AVE were not interpreted for Climate Condition, because high internal consistency is not theoretically expected among environmental indicators measured across different climatic periods.

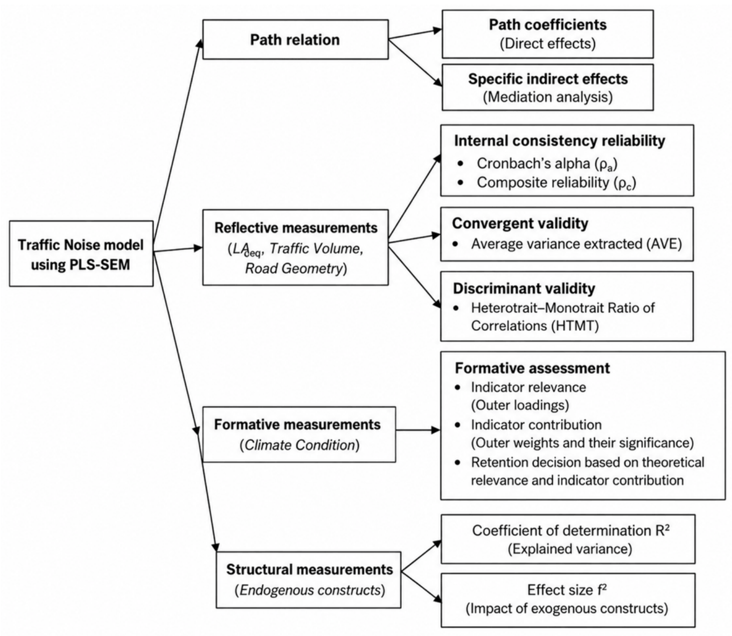

Figure 2. Traffic noise model assessment using partial least squares structural equation modelling (PLS-SEM)

2.4.4 Structural model measurement

The evaluation of the structural model typically relies on two key statistical methods: the coefficient of determination (R^2) and path coefficients. R^2 values, which fall within the range of 0 to 1, indicate the predictive accuracy of the model. A score close to 1 signifies a high level of predictability. For each endogenous latent variable, R^2 values are considered significant when they approach approximately 0.67, with an average value of

0.333 indicating a moderate level of significance, and values as low as 0.19. Alternatively, a more lenient scale defines values above 0.75 as good, values around 0.5 as average, and values below 0.25 as weak or unreliable [32].

Furthermore, alongside assessing R^2 values for endogenous constructs, the effect size (f^2) can be computed using Smart PLS 4.0 to measure the impact or f^2 of each exogenous construct on the endogenous construct. The interpretation of the t value assigns a value of 0.02 to a small effect, 0.15 to a medium effect, and 0.35 to a large effect [32].

Figure 2 explains the summary of the traffic noise model using PLS-SEM, whereby there are four assessments, including path relation, reflective measurement, formative measurement, and structural measurement. All assessments have been conducted in order to know the effects of each factor on another, as well as the validity and reliability of the model.

3 Results and Discussion

Low Carbon City development has become an important strategic objective in Shah Alam as part of the city's commitment to improving environmental quality and promoting sustainable urban growth. Particular attention has been directed toward the city centre through the increasing implementation of low-carbon buildings and initiatives aimed at enhancing sustainable and environmentally friendly urban transportation systems. To support planned urban expansion, Shah Alam is geographically organised into 56 sections grouped into five development blocks, as illustrated in Figure 3. Each development block comprises both development and conservation areas to balance urban growth and environmental sustainability.

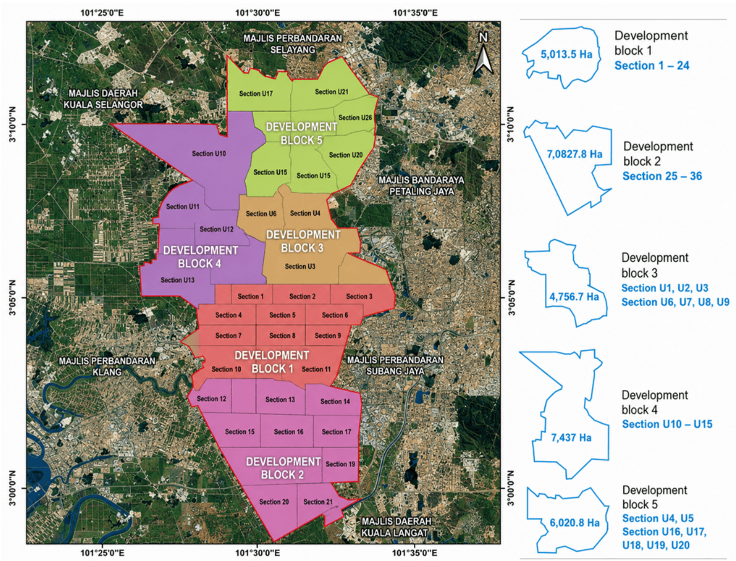

Figure 3. Shah Alam's development block

Current land use distribution shows that transportation occupies the largest proportion of developed land (20%), followed by residential (16.8%) and industrial areas (10.3%). According to future development projections, residential areas are expected to become the dominant land use category by 2035, accounting for 22.1% of total land use, while commercial and business areas are projected to experience the greatest expansion, increasing from 2.5% to 4.4%. Simultaneously, non-development zones are expected to decrease from approximately 40% to below 30%, accompanied by expansion of open and recreational spaces and a reduction in agricultural land. These projected changes indicate an ongoing transition from an industry-oriented urban structure toward stronger secondary and tertiary economic activities. Such urban transformation may contribute to increased transportation demand, changes in traffic movement patterns, and greater environmental pressure, highlighting the importance of understanding traffic-related environmental impacts, including urban noise exposure [1].

One of the main causes of noise pollution in the modern world is the unrelenting advancement of infrastructure and urbanization [33, 34]. The development of buildings, roads, bridges, and other vital infrastructure has become a distinguishing feature of modern life as cities enlarge to accommodate growing populations [35]. However, because of the substantial and frequently intrusive noise pollution it produces, this urban transformation has a sonic cost. Increased traffic from vehicles brought on by urbanisation can create a constant stream of noise [36]. The rumble of motors, the screech of brakes, and the honking of horns all add to the metropolitan soundscape, particularly during rush hour [37]. Significant noise emissions are frequently a result of the development of transportation networks like highways and railroads. Noise pollution is a problem that affects not just metropolitan areas but also neighbouring suburban and rural areas [38]. It is caused by the development of new transport routes as well as the upkeep and operation of existing ones [39].

In Malaysia, the Department of Environment introduced guidelines for Environmental Noise Limits and Control specifies the recommended allowable sound level (L_{Aeq}) for receptor locations inside an existing developed area. Table 2 shows noise level standards from the World Health Organization (WHO) and other countries. Each country has its own guidelines and recommendations for noise limits. It depends on the sensitivity of the area and the type of location.

Table 2. Noise level standards set by World Health Organization (WHO) and other countries

Sound Level Limit	Level Noise (L_{Aeq}) dBA Day Time	Night Time	References
Malaysia (suburban and urban residential (medium and high density))	65	60	[40]
WHO	53	45	[41]
Indonesia (noise level limit for residential)	55	45	[42]
Australia (road noise mitigation guideline)	65	60	[43]
Japan (noise regulation law)	60	50	[44]
UK (noise action plan)	55	50	[45]
Philippines (guidelines for environmental quality)	55	50	[46]

Note: L_{Aeq}—the A-weighted equivalent continuous sound level.

3.1 Statistical Model Results

3.1.1 Path relations

According to Hair et al. [32], a path coefficient that is more than 0.2 at a 95% confidence interval is typically used to illustrate the extent of influence of the examined path relation among the components. At a significance threshold of 0.001, the table reveals that every path link obtained significant path coefficients. Table 3 provides the traffic noise model with important path relations. The only one that has a positive path relation is road geometry, which is the direct antecedent of both traffic volume and equivalent traffic noise; the other three have a negative impact on both.

Table 3. Path coefficients of traffic noise model

Attribute Factors	Path Coefficients
Climate condition $\rightarrow L_{Aeq}$	-0.760
Climate condition $\rightarrow$ traffic volume	-0.687
Road geometry $\rightarrow L_{Aeq}$	0.279
Road geometry $\rightarrow$ traffic volume	0.182
Traffic volume $\rightarrow L_{Aeq}$	-0.006

Note: L_{Aeq}—the A-weighted equivalent continuous sound level.

Furthermore, based on the results shown in Table 4, there are 2 specific indirect effects: climate condition $\rightarrow$ traffic volume $\rightarrow L_{Aeq}$, with a positive value of 0.004, and road geometry $\rightarrow$ traffic volume $\rightarrow L_{Aeq}$, which has a negative value of -0.001. Meaning that climate conditions influence traffic volume and traffic noise level. In fact, road geometry has a negative direct influence (-0.001) on Equivalent traffic noise. Nonetheless, their influence on traffic noise is visible indirectly through other factors. The specific indirect effect is attained for some path relations. It implies that most path relations have a significant, specific indirect effect at a 0.001 significance level, and eventually all of them at a 0.01 significance level [28].

Table 4. Specific indirect effect of traffic noise model

Attribute Factors	Specific Indirect Effects
Climate condition $\rightarrow$ traffic volume $\rightarrow L_{Aeq}$	0.004
Road geometry $\rightarrow$ traffic volume $\rightarrow L_{Aeq}$	-0.001

Note: L_{Aeq}—the A-weighted equivalent continuous sound level.

However, the total effects of the traffic noise model in Table 5 showed that Climate Condition has the strongest influence on L_{Aeq} with a negative coefficient (β = -0.755), indicating that meteorological factors such as temperature, humidity, and wind conditions may affect sound propagation and reduce measured noise levels under certain environmental conditions. Road Geometry shows a positive relationship with L_{Aeq} (β = 0.278), suggesting that road design characteristics such as road width, alignment, and traffic flow conditions contribute to higher traffic noise exposure in residential areas. In addition, Road Geometry also positively influences traffic volume (β = 0.182), indicating that better road infrastructure may accommodate greater vehicle movement.

Table 5. Total effect of the traffic noise model

Attribute Factors	Climate Condition	L_{Aeq}	Road Geometry	Traffic Volume
Climate condition	—	-0.755	—	-0.687
L_{Aeq}	—	—	—	—
Road geometry	—	0.278	—	0.182
Traffic volume	—	-0.006	—	—

Note: L_{Aeq}—the A-weighted equivalent continuous sound level; em dash (—) indicates not applicable or data not available.

Traffic volume shows a very small negative effect on L_{Aeq} (β = -0.006). Although this finding differs from conventional traffic noise theory, the coefficient magnitude is extremely weak and may be influenced by multicollinearity, suppression effects, or interactions with road geometry and traffic operating conditions. In urban residential areas, higher traffic volume does not always produce higher noise levels because congested or slow-moving traffic may generate lower noise emissions compared to free-flow traffic at higher speeds [37].

The structural model identified a negative relationship between traffic volume and L_{Aeq}. However, this finding should be interpreted with caution due to several limitations of the present study. Although traffic volume is generally recognised as an important contributor to environmental noise, the current model did not incorporate operational traffic variables such as vehicle speed, traffic density, acceleration-deceleration patterns, queue length, or congestion level, which may influence acoustic conditions in urban road environments. Recent studies have demonstrated that environmental noise variability is influenced by interactions between traffic characteristics and surrounding environmental conditions, suggesting that vehicle volume alone may not sufficiently explain observed acoustic conditions [10].

A possible interpretation is that residential traffic environments may exhibit more complex traffic behaviour than conventional linear assumptions imply. Under certain traffic conditions, larger traffic volumes may coincide with reduced speed variation, smoother flow conditions, or different vehicle composition, producing lower fluctuation in measured equivalent noise levels [12]. Previous studies have shown that traffic noise does not depend exclusively on vehicle counts and that speed-related characteristics and traffic operation can substantially influence environmental sound exposure. In particular, roadway noise has been reported to vary according to traffic speed, meteorological conditions, and traffic heterogeneity rather than traffic volume alone [12, 23]. Therefore, the present findings should not be interpreted as contradicting established traffic noise theory but rather as indicating that additional explanatory variables may be necessary to fully explain the relationship between traffic activity and environmental noise in residential urban settings. Future studies should integrate traffic speed, density, road surface conditions, and temporal traffic behaviour to improve the interpretability and predictive capability of urban traffic noise models.

In conclusion, the results from Tables 3, 4, and 5 indicate that climate conditions and road geometry are the primary factors influencing traffic noise levels (L_{Aeq}) in the studied residential areas, whereas traffic volume contributes only marginally. The strong direct effect of climate conditions on L_{Aeq} demonstrates that meteorological variables significantly affect sound propagation and attenuation within urban residential environments. Road geometry also positively contributes to traffic noise generation, suggesting that road alignment, street configuration, and surrounding built environments play important roles in determining environmental noise exposure. Meanwhile, the negligible indirect effects through traffic volume indicate that traffic volume does not substantially mediate the relationship between the studied variables and traffic noise. This suggests that traffic noise in residential areas is not solely dependent on vehicle quantity, but is also strongly affected by environmental and physical urban characteristics.

The findings are consistent with several recent studies. A study by González et al. [47] reported that parameters such as humidity, wind speed, and temperature significantly influence urban traffic noise distribution and sound attenuation patterns. Similarly, research by Montenegro et al. [48] found that urban road geometry, building density, and street canyon characteristics strongly contribute to noise amplification in residential areas. Studies conducted in rapidly urbanizing cities also highlighted that road design and surrounding land use patterns may exert greater influence on traffic noise exposure than traffic flow alone [6]. However, the weak relationship between traffic volume and L_{Aeq} observed in this study differs from findings by Ruškić et al. [49], who identified traffic volume as a dominant predictor of urban environmental noise. The discrepancy may be associated with differences in local traffic composition, vehicle speed characteristics, urban morphology, and residential layouts within the Shah Alam study area. Therefore, the present study emphasizes the importance of integrating climate-responsive planning and improved road geometry into urban noise mitigation strategies rather than relying solely on traffic reduction measures.

3.1.2 Reflective measurement models

Table 6 presents the reliability and convergent validity results of the traffic noise model, while Table 7 summarizes the discriminant validity assessment using the HTMT. These analyses were conducted to evaluate the adequacy of the reflective measurement model prior to structural model interpretation in the PLS-SEM framework.

Table 6. Reliability and validity result of traffic noise model

Attribute Factors	Cronbach's Alpha (CA)	Composite Reliability (ρ_a)	Composite Reliability (ρ_c)	Average Variance Extracted (AVE)
L_{Aeq}	0.937	0.943	0.960	0.888
Road geometry	0.924	0.964	0.963	0.928
Traffic volume	0.898	0.972	0.928	0.730

Note: L_{Aeq}—the A-weighted equivalent continuous sound level.

Table 6 presents the results of the reliability and validity assessment for the reflective constructs. Overall, the reflective measurement model demonstrated satisfactory measurement quality. All constructs exceeded the recommended thresholds for internal consistency reliability and convergent validity. The L_{Aeq} construct showed excellent reliability, with CA of 0.937, composite reliability values of 0.943 (ρ_a) and 0.960 (ρ_c), and an AVE of 0.888. These results indicate strong consistency among the indicators used to represent equivalent traffic noise. Similarly, road geometry achieved high reliability performance, with CA of 0.924, composite reliability of 0.964 (ρ_a) and 0.963 (ρ_c), and AVE of 0.928. These values suggest that the road width indicators consistently represented the geometric characteristics of the study locations. The traffic volume construct also demonstrated acceptable measurement quality. CA reached 0.898, while composite reliability values were 0.972 (ρ_a) and 0.928 (ρ_c). The AVE value of 0.730 exceeded the recommended threshold, confirming adequate convergent validity. All AVE values ranged between 0.730 and 0.928, indicating that each reflective construct explained more than 50% of the variance of its observed indicators. Therefore, the reflective measurement model achieved acceptable reliability and convergent validity for subsequent structural model analysis.

The reflective measurement assessment demonstrated that the latent constructs used in the traffic noise model were measured consistently and accurately. The high reliability values observed for L_{Aeq} indicate that the selected noise indicators captured equivalent traffic noise exposure effectively across the monitoring locations. The strong reliability and convergent validity achieved for road geometry suggest that road width measurements provided a stable representation of geometric conditions affecting traffic movement and subsequent noise generation. Likewise, traffic volume demonstrated satisfactory construct reliability, indicating that vehicle categories collectively represented overall traffic intensity. Among the reflective constructs, road geometry recorded the highest convergent validity (AVE = 0.928), suggesting strong explanatory capability of its indicators. Traffic volume exhibited slightly lower indicator consistency compared with L_{Aeq} and road geometry, which may reflect variability among different vehicle classes and their contributions to traffic flow.

Discriminant validity was assessed using the HTMT to determine whether reflective constructs measured conceptually distinct phenomena within the traffic noise model. The recommended HTMT threshold is below 0.85 for stricter assessment and below 0.90 for acceptable discriminant validity. As presented in Table 7, all HTMT values were below the recommended threshold, ranging from 0.342 to 0.648, indicating adequate discriminant validity among the reflective constructs. The highest HTMT value was observed between traffic volume and L_{Aeq} (0.648), suggesting a moderate association while remaining sufficiently distinct. This result indicates that although traffic intensity contributes to traffic noise generation, both constructs represent different conceptual domains. The HTMT value between L_{Aeq} and road geometry (0.437) demonstrated satisfactory construct separation, indicating that road characteristics and noise exposure are measured independently. Similarly, the HTMT value between traffic volume and road geometry (0.342) was the lowest among the reflective constructs, suggesting strong discriminant validity and confirming that geometric road attributes and traffic intensity capture different aspects of the transport environment. Since all values remained below the recommended threshold, discriminant validity was considered established.

The HTMT results indicate that the reflective constructs retained conceptual distinctiveness despite being incorporated within the same structural framework. The moderate relationship observed between traffic volume and L_{Aeq} supports the theoretical expectation that increasing traffic activity contributes to higher environmental noise levels; however, the HTMT value below the threshold confirms that both constructs are not measuring the same phenomenon. The lower HTMT values involving Road Geometry indicate that geometric road characteristics influence traffic behaviour and noise generation indirectly rather than representing overlapping dimensions. Overall, the discriminant validity assessment supports the appropriateness of the measurement model and strengthens confidence in subsequent structural relationship analysis.

Table 7. Heterotrait–monotrait ratio of correlations (HTMT) of the traffic noise model

Attribute Factors	$L_{A\mathrm{eq}}$	Road Geometry	Traffic Volume
$L_{A\mathrm{eq}}$	—	—	—
Road geometry	0.437	—	—
Traffic volume	0.648	0.342	—

Note: $L_{A\mathrm{eq}}$—the A-weighted equivalent continuous sound level; em dash (—) indicates not applicable or data not available.

The strong reliability and convergent validity demonstrated by the reflective constructs indicate that the model captured important dimensions of urban traffic noise generation with a high degree of consistency. In particular, the high reliability of $L_{A\mathrm{eq}}$ confirms that the selected acoustic indicators consistently represented environmental noise exposure across monitoring periods, while traffic volume and Road Geometry provided stable representations of traffic intensity and physical road characteristics. In an urban residential context, this finding has important practical implications because residents are continuously exposed to cumulative noise originating from vehicle movement and road configuration rather than from isolated traffic events. The strong measurement performance suggests that traffic management strategies targeting vehicle composition and road design may produce measurable improvements in environmental noise conditions. The relatively high loading values observed for heavy vehicles and motorcycles further imply that urban noise mitigation policies should extend beyond reducing total traffic counts and include vehicle-type regulation, traffic calming, speed control, and road hierarchy planning in residential corridors. These findings support the need for integrated urban transport and environmental planning approaches to improve residential liveability and reduce long-term exposure to environmental noise.

The results are generally consistent with previous studies reporting that traffic-related variables and road characteristics remain dominant determinants of environmental noise in urban areas [50]. Studies conducted in recent years have shown that reliable representation of traffic flow and road infrastructure significantly improves the predictive capability of traffic noise models and supports evidence-based transport interventions [51]. For example, research using SEM-based approaches demonstrated that traffic composition and roadway characteristics contribute substantially to explaining urban noise variability and should be treated as separate but complementary constructs in environmental modelling [23]. Similarly, studies examining residential traffic exposure reported that higher measurement reliability improves confidence in estimating environmental impacts and identifying mitigation priorities for urban communities. Compared with previous findings, the present reflective measurement model produced relatively high reliability and validity values, indicating strong consistency of the selected indicators in representing urban traffic conditions and supporting their application for planning decisions related to residential zoning, sustainable mobility, and noise-sensitive land use management.

The climate condition construct was not included in the reflective measurement assessment and was evaluated separately using formative measurement procedures. This revision was made after reassessing both the statistical results and the conceptual structure of the construct. Unlike $L_{A\mathrm{eq}}$, Road Geometry, and traffic volume, which were represented by indicators expected to reflect the same underlying concept, climate conditions were formed by multiple environmental parameters consisting of humidity, temperature, and wind speed measured during morning, afternoon, and evening periods. These indicators represent different aspects of environmental exposure and are not expected to exhibit high internal consistency or strong intercorrelation. Therefore, conventional reflective reliability and validity criteria such as CA, composite reliability, and AVE were considered inappropriate for evaluating this construct. In accordance with PLS-SEM guidelines, climate condition was reassessed as a formative construct and evaluated based on indicator contribution, outer weights, outer loadings, and collinearity diagnostics. This approach provides a more theoretically and statistically appropriate representation of climatic variability and strengthens the overall validity of the traffic noise model.

3.1.3 Assessing formative measurement models

The climate condition construct was evaluated using formative measurement procedures because the construct was formed by multiple environmental dimensions rather than reflected by interchangeable indicators. The construct consisted of relative humidity, temperature, and wind speed measured across morning, afternoon, and evening observation periods. The assessment began with the evaluation of outer weights to determine the relative contribution of each indicator to construct formation. The bootstrapping results shown in Table 8 indicated that none of the indicators achieved statistical significance at $p < 0.05$. This suggests that no individual climatic variable independently dominated the overall climate construct. However, formative construct assessment does not rely exclusively on indicator significance.

Outer loadings were further examined to determine the absolute contribution of each indicator. Several indicators demonstrated moderate-to-high loading values, particularly morning temperature (0.789), evening temperature (-0.790), afternoon temperature (0.682), and evening relative humidity (0.681). These results indicate that temperature and humidity contributed more strongly to defining climatic variability than wind-related indicators. Indicators such as afternoon relative humidity and afternoon wind speed showed comparatively lower contribution values. Nevertheless, these indicators were retained because formative indicators are intended to represent complementary dimensions of environmental exposure rather than redundant measures of a single phenomenon. The presence of both positive and negative loadings indicates heterogeneous environmental interactions. Positive values suggest direct contribution to climatic intensity, whereas negative values indicate inverse environmental influence associated with atmospheric variation throughout the observation periods.

Table 8. Outer weight and outer loading for formative measurement model

Indicators	Outer Weight	t-Value	p-Value	Outer Loading	t-Value	p-Value	Decision
Morning relative humidity	-0.104	0.891	0.373	-0.427	0.907	0.364	Retained
Morning temperature	0.317	1.192	0.233	0.789	1.044	0.296	Retained
Morning wind speed	-0.155	1.002	0.317	-0.470	0.872	0.383	Retained
Afternoon relative humidity	0.001	0.010	0.992	-0.317	0.846	0.397	Retained
Afternoon temperature	0.188	1.191	0.234	0.682	1.038	0.299	Retained
Afternoon wind speed	-0.038	0.416	0.677	-0.183	0.472	0.637	Retained
Evening relative humidity	0.260	1.189	0.234	0.681	1.030	0.303	Retained
Evening temperature	-0.310	1.168	0.243	-0.790	1.054	0.292	Retained
Evening wind speed	-0.171	1.038	0.300	-0.438	0.781	0.435	Retained

The formative assessment demonstrates that climate conditions behave as a multidimensional environmental construct rather than a homogeneous latent variable. Unlike reflective constructs that require high internal consistency, climatic variables naturally fluctuate independently depending on atmospheric processes and local environmental conditions. The stronger contribution observed for temperature indicators suggests that thermal conditions may play a greater role in shaping environmental conditions associated with traffic noise propagation. Temperature influences atmospheric density and sound transmission characteristics, potentially affecting perceived traffic noise levels across urban corridors. Relative humidity also demonstrated a meaningful contribution, particularly during evening periods, indicating that moisture conditions may influence environmental exposure during lower-temperature periods. Wind speed showed comparatively weaker contributions across observation periods. This finding suggests that under the monitored urban conditions, local airflow variation contributed less consistently than thermal conditions. Nevertheless, wind conditions remain theoretically important because air movement affects sound dispersion and noise propagation patterns [52]. The absence of statistically dominant indicators indicates that climatic influence on traffic noise should not be interpreted through a single environmental parameter. Instead, climatic exposure emerges from interaction among multiple environmental variables operating simultaneously.

The formative measurement results have important implications for residential urban environments. The findings suggest that environmental conditions influencing traffic noise are dynamic and vary throughout the day rather than remaining constant across observation periods [53]. Consequently, residents living near urban roads may experience different levels of perceived noise exposure even under similar traffic conditions due to variation in temperature, humidity, and atmospheric movement [53]. From an urban planning perspective, this finding supports the need for context-sensitive noise mitigation strategies. Conventional approaches that focus primarily on reducing traffic volume may overlook environmental mechanisms that influence actual community exposure. Urban design interventions such as roadside vegetation, microclimate-sensitive street layouts, residential setback distances, and time-based traffic management may contribute to reducing environmental noise burden in residential areas [54]. These findings also indicate that traffic noise assessment should incorporate environmental variability to improve prediction accuracy and support sustainable urban mobility planning.

The present findings align with previous studies reporting that climatic conditions influence environmental noise through complex and non-uniform mechanisms. Recent traffic noise studies have demonstrated that meteorological variables rarely operate as highly correlated indicators because environmental parameters interact differently depending on temporal and spatial conditions [12]. Lin et al. [12] reported that temperature and humidity frequently exert stronger influence on environmental noise propagation than wind speed due to their effect on atmospheric absorption and acoustic transmission. Studies conducted in urban transport environments similarly reported that climatic variables should be interpreted as complementary environmental factors rather than interchangeable measurements. Compared with previous studies that evaluated environmental variables independently, the present study extends current understanding by integrating multiple climatic indicators into a formative PLS-SEM framework. This approach provides a more comprehensive representation of environmental exposure and allows temporal climatic variability to be incorporated into traffic noise modelling for residential urban settings.

3.1.4 Assessing structural models

Table 9 and Table 10 present the structural model assessment of the traffic noise model developed using the PLS-SEM approach. The evaluation includes the R^2 and f^2, which collectively assess the explanatory capability and relative contribution of each predictor construct within the model.

Table 9. R^2 of traffic noise model

Attribute Factors	R^2	R^2 Adjusted
L_{Aeq}	0.727	0.625
Traffic volume	0.552	0.453

Note: R^2—R-square; L_{Aeq}—the A-weighted equivalent continuous sound level.

Table 10. f^2 of traffic noise model

Attribute Factors	f^2
Climate condition $\rightarrow L_{Aeq}$	1.012
Climate condition $\rightarrow$ traffic volume	1.017
Road geometry $\rightarrow L_{Aeq}$	0.257
Road geometry $\rightarrow$ traffic volume	0.071
Traffic volume $\rightarrow L_{Aeq}$	0.000

Note: f^2–effect size; L_{Aeq}—the A-weighted equivalent continuous sound level.

The R^2 analysis demonstrates that the model achieved substantial explanatory power for the endogenous construct L_{Aeq}, with an R^2 value of 0.727. This indicates that approximately 72.7% of the variance in equivalent traffic noise levels was explained by the predictor constructs included in the model, namely climate condition, road geometry, and traffic volume. The adjusted R^2 value of 0.625 further confirms the robustness of the model after accounting for sample size and the number of predictors. According to PLS-SEM guidelines, this value can be interpreted as substantial predictive accuracy, suggesting that the proposed framework effectively explains residential traffic noise behaviour.

For the traffic volume construct, the model produced an R^2 value of 0.552 and an adjusted R^2 value of 0.453, indicating moderate explanatory capability. Approximately 55.2% of the variation in traffic volume was explained by climate conditions and road geometry. Although lower than the explanatory strength observed for L_{Aeq}, the result still indicates that the selected predictor variables contributed meaningfully to traffic flow characteristics within the residential study area.

The f^2 analysis shown in Table 10 further clarifies the relative importance of each structural relationship in the model. Climate conditions exhibited the largest effect sizes on both L_{Aeq} (f^2 = 1.012) and traffic volume (f^2 = 1.017), indicating extremely strong contributions to both endogenous constructs. Based on established interpretation criteria, f^2 values above 0.35 are considered large effects. Therefore, the results demonstrate that climatic parameters such as temperature, humidity, and wind speed play dominant roles in influencing environmental traffic noise and traffic movement patterns. This finding highlights the importance of incorporating meteorological variables into traffic noise prediction frameworks rather than relying solely on traffic flow parameters.

Road geometry showed a moderate effect on L_{Aeq} (f^2 = 0.257), suggesting that roadway characteristics such as road width contributed meaningfully to environmental noise propagation within residential areas. Wider road sections may alter traffic movement behaviour and influence sound dispersion patterns, thereby affecting measured noise exposure levels. However, the effect of road geometry on traffic volume was relatively weak (f^2 = 0.071), indicating that roadway width alone may not strongly determine traffic intensity within the observed residential roads.

In contrast, traffic volume demonstrated no meaningful effect on L_{Aeq}, with an f^2 value of 0.000. This finding is consistent with the structural path analysis, where the relationship between traffic volume and equivalent traffic noise was statistically insignificant. The result suggests that environmental noise levels within the study area were more strongly influenced by climatic and roadway conditions than by vehicle quantity alone. This may be attributed to the influence of atmospheric absorption, environmental sound reflection, traffic operating patterns, and localized acoustic conditions that were not fully captured through traffic counts alone.

The combined interpretation of R^2 and f^2 values indicates that climate condition was the most influential predictor in the structural model. The strong explanatory power obtained for L_{Aeq} demonstrates that residential traffic noise is a multidimensional environmental issue influenced by both transportation and environmental parameters. The findings support previous studies reporting that meteorological conditions significantly affect outdoor sound propagation and urban environmental noise variability.

The present study is consistent with recent traffic noise modelling research conducted between 2020 and 2024, which reported that integrating climatic and roadway variables substantially improves prediction accuracy compared with conventional traffic-flow-based models [23, 26]. Several urban environmental studies have reported R^2 values ranging from approximately 0.60 to 0.75 when meteorological parameters were incorporated into traffic noise assessment models. Similarly, previous researchers concluded that humidity, wind speed, and temperature significantly influence sound attenuation and environmental noise dispersion in urban residential environments [55].

Compared with earlier regression-based traffic noise prediction approaches, the present study demonstrates the advantage of the PLS-SEM method in evaluating both direct and indirect relationships among latent variables simultaneously. The approach provides a more comprehensive understanding of the interaction between environmental conditions, roadway characteristics, traffic flow, and equivalent traffic noise exposure. Consequently, the findings offer important implications for sustainable urban transport planning, residential road design, and urban environmental noise mitigation strategies.

3.1.5 Final model of traffic noise assessment

Figure 4 illustrates the structural model developed using the PLS-SEM approach to evaluate the relationships among climate conditions, road geometry, traffic volume, and equivalent traffic noise level (L_{Aeq}). The model demonstrates acceptable explanatory capability, with the R^2 values indicating that climate conditions and road geometry collectively explained 72.7% of the variance in L_{Aeq} and 55.2% of the variance in traffic volume. These findings suggest that the proposed model possesses substantial predictive relevance for residential traffic noise assessment.

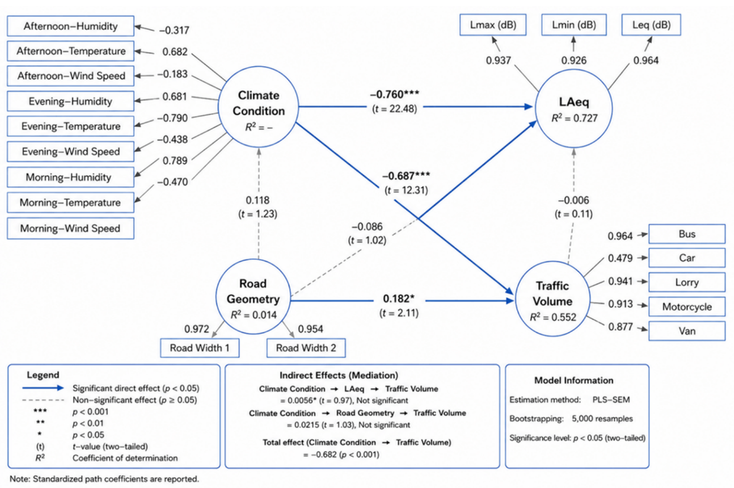

Figure 4. Final traffic noise model

The reflective measurement model showed strong indicator reliability for most observed variables. For the traffic noise construct (L_{Aeq}), the indicator loadings for $L_{\max}$ (0.937), $L_{\min}$ (0.926), and equivalent noise level readings (0.964) exceeded the recommended threshold of 0.70, indicating strong convergent validity. Similarly, the road geometry construct demonstrated high loadings for both road width indicators, with values of 0.972 and 0.954, respectively. Traffic volume indicators also exhibited satisfactory loadings for most vehicle categories, particularly buses (0.964), lorries (0.941), motorcycles (0.913), and vans (0.877), although the loading for cars (0.479) was comparatively lower, suggesting a weaker contribution of passenger cars to the latent traffic volume construct.

The structural model assessment revealed that climate conditions exerted a strong and statistically significant negative effect on $L_{A\mathrm{eq}}$ (β = -0.760, $p < 0.001$). This result indicates that variations in climatic parameters such as humidity, temperature, and wind speed significantly influenced environmental noise propagation within residential areas. The negative coefficient suggests that increases in certain climatic conditions may contribute to reductions in measured equivalent traffic noise levels, potentially due to atmospheric absorption and sound dispersion effects. This finding is consistent with environmental acoustics studies reporting that meteorological factors can substantially alter outdoor sound propagation characteristics.

Climate conditions also showed a significant negative relationship with traffic volume (β = -0.687, $p < 0.001$), indicating that adverse climatic conditions may influence traffic movement patterns and reduce vehicle activity along residential roads. In contrast, road geometry demonstrated a positive and statistically significant relationship with traffic volume (β = 0.182, $p < 0.05$), suggesting that wider road sections tend to accommodate greater vehicle movement and traffic intensity. This finding aligns with transportation engineering principles whereby larger roadway capacity encourages higher traffic flow.

However, the direct relationship between traffic volume and $L_{A\mathrm{eq}}$ was found to be statistically insignificant (β = -0.006, $p > 0.05$). Similarly, the path between road geometry and $L_{A\mathrm{eq}}$ was also not significant. These findings imply that, within the present study area, traffic noise levels may be more strongly influenced by environmental and meteorological conditions than by traffic quantity alone. The insignificant direct effect may also indicate the presence of moderating or mediating environmental factors affecting acoustic propagation in residential environments.

The graphical presentation further distinguishes significant and insignificant relationships through solid and dashed arrows, respectively. Significant direct effects were represented by solid blue arrows, while dashed grey arrows indicated statistically insignificant relationships. This improved visualization enhances the interpretation of the structural model by clearly differentiating meaningful causal paths from unsupported relationships.

The structural model reveals important spatial differences between the studied residential sections. Areas located closer to primary roads, intersections, and mixed land-use activities generally recorded higher equivalent noise levels compared to internally located residential streets with lower traffic accessibility. These findings indicate that traffic noise exposure in urban residential areas is spatially uneven and strongly associated with road hierarchy, land-use intensity, and urban morphology. Similar spatial relationships have been reported in studies conducted in Khorramabad city, where compact urban form, dense road networks, and high-rise developments significantly increased residential traffic noise exposure [56]. In particular, research by Huang et al. [57] demonstrated that urban geometry and traffic distribution are strongly interconnected and directly influence pedestrian and residential noise exposure patterns in dense urban environments.

The model also highlights the importance of traffic patterns in residential areas. Although traffic volume is traditionally expected to show a strong positive relationship with $L_{A\mathrm{eq}}$, the present study recorded a very small negative coefficient (β = -0.006). This result suggests that traffic noise generation is not solely dependent on vehicle quantity but is also influenced by vehicle speed, traffic congestion, braking frequency, and traffic flow conditions. In residential areas, congested traffic movement and lower vehicle speeds may sometimes reduce tyre-road interaction noise compared to free-flow traffic operating at higher speeds [6]. Similar observations have been discussed in urban traffic noise studies where traffic operating behaviour was found to influence environmental noise levels beyond simple traffic count measurements. Therefore, the findings indicate that urban traffic noise should be interpreted as a multidimensional transport phenomenon involving interactions between operational, geometric, and environmental factors.

From an urban planning and transportation engineering perspective, the findings provide important implications for urban road design and residential planning strategies. The positive influence of road geometry on traffic volume suggests that road infrastructure design directly affects vehicle movement efficiency and environmental noise exposure. Wider roads, open intersections, and high-accessibility corridors may encourage higher traffic intensity and increase residential noise propagation. Previous studies conducted in European and Asian cities similarly concluded that urban morphology, road layout, and building arrangement significantly influence environmental noise distribution. Forssén et al. [51] reported that urban morphology, building enclosure, and road organization strongly affect both direct and indirect traffic noise exposure in residential environments. Consequently, the present study suggests that urban planners should incorporate traffic noise mitigation considerations during the early stages of residential development planning through traffic calming measures, landscape buffers, road setback distances, optimized junction layouts, and noise-sensitive urban design approaches.

Compared with findings reported in other countries, the present study demonstrates similar patterns regarding the influence of traffic infrastructure and urban form on residential noise exposure, particularly in rapidly urbanising cities. However, the current research contributes additional methodological insight by applying PLS-SEM to simultaneously evaluate the structural relationships among climate conditions, traffic flow, and road geometry within a single integrated framework. Unlike many previous studies that focused primarily on GIS-based mapping, regression analysis, or machine learning prediction, the present model provides an explanatory understanding of how multiple urban transport variables interact collectively to influence $L_{A\mathrm{eq}}$. This contributes to the growing body of transportation acoustics research by extending the application of PLS-SEM in environmental noise assessment within developing urban residential contexts.

Beyond statistical interpretation, the findings indicate that traffic noise conditions varied across the monitored sections due to differences in local traffic characteristics and surrounding environmental conditions. Although the study sections were located within the same residential urban setting, variations in roadway configuration, vehicle movement patterns, and temporal traffic intensity contributed to differences in observed noise exposure. Sections with greater traffic concentration and more continuous vehicle movement generally demonstrated different acoustic responses compared with sections characterised by lower traffic activity or more dispersed traffic flow. These findings suggest that residential traffic noise should be interpreted as a spatially dependent environmental issue rather than as a uniform response to increasing vehicle numbers [58].

From a transport planning perspective, the observed differences among study sections highlight the importance of context-specific mitigation strategies. Road geometry, surrounding land use, and temporal traffic distribution may influence environmental noise exposure differently across residential corridors. Therefore, urban traffic management policies should move beyond aggregate traffic reduction approaches and consider local operational conditions, roadway characteristics, and neighbourhood context when designing mitigation measures. Such approaches may include traffic calming, time-based vehicle management, roadside buffering, and residential road design improvements to support sustainable urban mobility and improved environmental quality [54, 59].

3.2 Limitation of the Study

This study has several limitations that should be considered when interpreting the findings. First, the environmental noise monitoring was conducted over relatively short measurement periods, which may not adequately represent long-term traffic noise exposure in residential areas. Traffic flow and noise conditions are inherently dynamic and may vary according to peak-hour conditions, daily traffic fluctuations, and special events. Therefore, the recorded equivalent noise levels should be interpreted as representative of the observed monitoring periods rather than continuous long-term exposure.

Second, the investigation was confined to selected residential road sections within a limited geographical coverage. Although the selected locations reflect common urban residential traffic conditions, the spatial scope of the study may restrict the generalizability of the findings to other cities or regions with different urban forms, transportation systems, roadway hierarchies, and land-use characteristics. Future investigations involving broader spatial sampling across multiple urban environments would improve the external validity of the developed model.

Another limitation is the absence of traffic speed data during the field measurements. Vehicle speed is an important parameter influencing traffic noise emission, particularly in relation to engine operation, acceleration behaviour, and tire–pavement interaction. The omission of speed-related variables may therefore reduce the comprehensiveness of the traffic noise prediction framework and partially explain unexplained variance within the structural model.

In addition, the present study did not incorporate seasonal variability and meteorological influences into the analysis. Data collection was conducted within a specific monitoring period and did not account for potential seasonal changes in traffic demand, weather conditions, atmospheric absorption, wind direction, or rainfall intensity, all of which may affect environmental noise propagation and exposure levels. Longitudinal monitoring across different seasons would provide a more robust assessment of residential traffic noise behaviour.

The study also did not consider building reflection effects and urban canyon characteristics that may influence acoustic propagation within residential environments. Reflections from surrounding buildings, walls, and other physical structures can alter sound dispersion patterns and increase localized noise amplification, particularly in densely developed urban areas. Integrating urban morphology and acoustic reflection parameters into future modelling efforts would improve the accuracy and practical applicability of traffic noise assessment.

Despite these limitations, the study contributes meaningful empirical evidence regarding the relationships between traffic characteristics, road geometry, and equivalent traffic noise using the PLS-SEM approach. The findings provide a useful basis for future research and support the development of more comprehensive urban traffic noise management strategies for sustainable residential and transportation planning.

4 Conclusion

This study successfully developed a traffic noise prediction model using the PLS-SEM approach to evaluate the relationship between climate conditions, road geometry, traffic volume, and equivalent traffic noise level ($L_{A\mathrm{eq}}$) in residential areas. The overall findings demonstrated that the developed model possesses satisfactory reliability, validity, and predictive capability for assessing urban traffic noise conditions. The path relationship analysis revealed that road geometry was the only construct with a positive direct relationship toward both traffic volume and traffic noise level, indicating that roadway characteristics significantly influence vehicular movement and environmental noise generation. In contrast, climate conditions showed negative direct effects on both traffic volume and noise level, although their indirect influence through traffic volume remained slightly positive. The total effects analysis further confirmed that road geometry contributed positively to traffic noise and traffic volume, while climate conditions maintained an overall negative contribution.

The measurement model assessment demonstrated that construct performance varied according to measurement specification. Reflective measurement evaluation indicated that $L_{A\mathrm{eq}}$, traffic volume, and road geometry achieved acceptable reliability and validity performance, supporting their suitability for structural analysis. The reflective indicators showed satisfactory internal consistency, convergent validity, and discriminant validity, indicating that the selected variables consistently represented their corresponding latent constructs. In contrast, the climate condition construct exhibited heterogeneous indicator behaviour and was therefore reassessed using formative measurement procedures. This revision provided a more appropriate representation of environmental variability because climatic exposure was formed by multiple dimensions of humidity, temperature, and wind speed measured across different observation periods rather than reflected by a single latent characteristic.

The structural model findings showed that Climate Condition emerged as the strongest predictor in the model, demonstrating significant direct effects on both traffic volume and equivalent traffic noise level ($L_{A\mathrm{eq}}$). Road Geometry showed a positive relationship with traffic volume but did not directly influence $L_{A\mathrm{eq}}$. Furthermore, traffic volume did not demonstrate a significant direct contribution to equivalent traffic noise within the estimated structural relationships. These findings indicate that environmental and spatial characteristics jointly influence residential traffic noise conditions and suggest that noise exposure cannot be explained solely by traffic intensity. The results further demonstrate that atmospheric conditions contribute meaningfully to environmental noise dynamics and should be incorporated into urban traffic noise assessment.

From a practical perspective, the findings provide useful implications for urban transport planning and residential environmental management. Traffic noise mitigation strategies should move beyond conventional approaches focused exclusively on reducing vehicle numbers and instead consider environmental conditions and roadway characteristics that influence actual community exposure. Urban planning interventions such as context-sensitive road design, roadside vegetation, residential setback policies, and time-based traffic management may contribute to improving environmental quality and reducing long-term noise exposure in residential areas. Integrating climatic variability into traffic noise assessment may also improve decision-making for sustainable urban mobility and healthier residential development.

Several limitations should be acknowledged. First, the study was conducted within a limited spatial coverage consisting of 12 observation locations and a two-week monitoring period, which may not fully represent long-term environmental variability. Second, the Climate Condition construct showed heterogeneous indicator contribution, suggesting that environmental conditions may involve more complex interactions than represented in the present model. Third, additional explanatory variables such as traffic speed, land-use characteristics, road surface conditions, building configuration, and seasonal variation were not included and may influence environmental noise behaviour.

Future studies are recommended to expand observation duration and spatial coverage to improve model generalisability across different urban contexts. Further refinement of environmental measurement specification may also strengthen the representation of climatic variability through alternative temporal aggregation approaches or additional atmospheric indicators. Future research may integrate spatial modelling, GIS-based analysis, machine learning approaches, and longitudinal monitoring to improve prediction accuracy and support evidence-based urban transport and environmental planning. Such developments would contribute to more comprehensive and sustainable traffic noise management in rapidly urbanising residential environments.

Author Contributions

Conceptualization, Z.S.I.; methodology, A.A.; software, R.A.M.; validation, Z.S.I., F.M.D., and M.M.; formal analysis, A.A. and R.A.M.; investigation, A.A.; resources, A.A.; data curation, M.H.J.; writing—original draft preparation, R.A.M.; writing—review and editing, R.A.M.; visualization, M.M. and M.H.J.; supervision, Z.S.I.; project administration, Z.S.I. and F.M.D.; funding acquisition, Z.S.I. and A.A. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflicts of interest.

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