SUSTAINABLE ENVIRONMENT
2026, VOL. 12, NO. 1, 2652166
https://doi.org/10.1080/27658511.2026.2652166

SOCIETY AND THE ENVIRONMENT | RESEARCH ARTICLE

OPEN ACCESS Check for updates

Understanding perceptions, behaviours, and population exposure risks to air pollution in a high-activity urban corridor in Nigeria

Ekpo Otu[a,b], Ajah Obia[b], Abiodun Oyetunji[c] and Theresa Eja[d]

[a]Lancaster Environment Centre, Lancaster University, Lancaster, United Kingdom; [b]Faculty of Architecture, University of Cross River State (UNICROSS), Calabar, Nigeria; [c]London Metropolitan University, School of the Built Environment, London, UK; [d]Faculty of Environmental Science, University of Cross River State (UNICROSS), Calabar, Nigeria

ABSTRACT

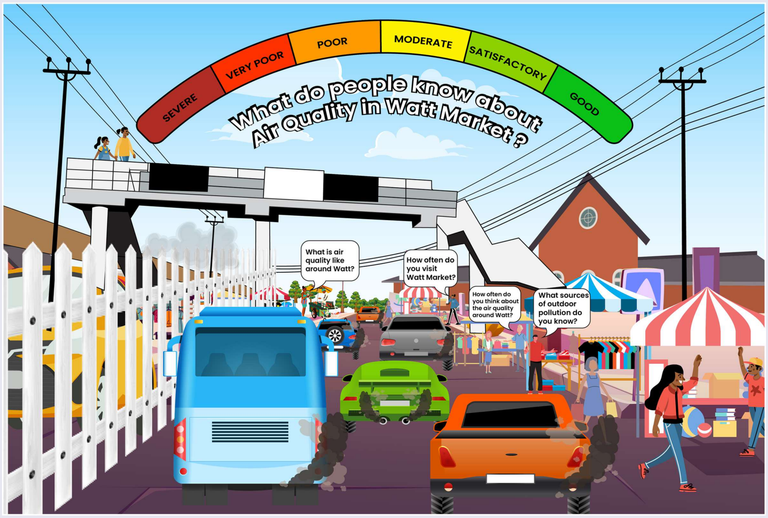
Air pollution health impacts remain a critical concern in cities worldwide, yet limited evidence exists on how informal commercial hubs, such as markets and transport corridors where large populations converge, shape exposure risks in African cities. This study examined how socio-demographics, visitation, and perceptions intersect with residential and on-site air quality to assess risks in Watt Market, Calabar, Nigeria. Data were collected through online and in-person surveys on demographics, visitation, perceptions, and behaviours, supplemented by Air Quality Index (AQI) data from a previous study. Daily market flows were estimated by combining standardised visitation frequencies and respondent counts across residential groupings, while Population Index values were derived from published thresholds and scaled to daily activity levels. AQI and Population Index data were combined using the Population Exposure Risk Index (PERI) metric developed in this study to classify exposure risk at residential and market levels. Results show Watt Market as a convergence hub, with estimated daily visitation of 14 to 400 individuals per group, all classified within Population Index 1 (low population densities). Residential AQI values ranged from 'Good' to 'Marginally Polluted,' and PERI results classified all assessed residential groups within the Very Low exposure risk category under the adopted threshold framework. Nonetheless, awareness of interventions was extremely limited (98% unaware), and behavioural adaptation was rare (12.5%). Vulnerability was concentrated among older adults (55+), 41% of whom reported underlying health conditions despite residing mainly in low-AQI zones. These findings suggest that Watt Market currently appears to be associated with relatively low cumulative exposure risk under observed conditions and within the adopted screening framework. Nonetheless, the presence of vulnerable groups and limited awareness highlights the need for continued monitoring and targeted education or interventions. Future studies using larger datasets and dynamic monitoring are also needed to track market-related exposures and strengthen evidence for air quality management in Nigeria.

ARTICLE HISTORY
Received 6 October 2025
Accepted 24 March 2026

KEYWORDS
Air quality; population exposure; Watt Market; perceptions of pollution; urban health

CONTACT Ekpo Otu papayan46@yahoo.com Lancaster Environment Centre, Lancaster University, Bailrigg, LA1 4YW, Lancaster, United Kingdom

Supplemental data for this article can be accessed online at https://doi.org/10.1080/27658511.2026.2652166.



1. Introduction

Air pollution remains one of the most significant environmental health risks worldwide, contributing to millions of premature deaths annually through its effects on respiratory, cardiovascular, and other chronic diseases (Atkinson et al., 2015; Burnett et al., 2018; Cohen et al., 2017; World health organisation (WHO), 2016). The World Health Organisation estimates that over 90% of urban centres globally exceed recommended air quality thresholds, with outdoor air pollution responsible for nearly one in every nine deaths (GBD 2019 Risk Factors Collaborators, 2020; World health organisation (WHO), 2016). The burden of these impacts disproportionately falls on populations in the densest, socio-economically deprived, and less developed urban areas, where rapid urbanisation and weak regulatory enforcement exacerbate exposure (Bell et al., 2013; Jbaily et al., 2022; Mannucci & Franchini, 2017; World health organisation (WHO), 2016).

In low- and middle-income countries (LMICs), urban environments are characterised by intense commercial activity, high traffic volumes, and inadequate waste management, resulting in elevated exposure to high concentrations of fine particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen dioxide (NO_2), and carbon monoxide (CO), with significant implications for public health (Health Effects Institute, 2022; Lelieveld et al., 2020; McDuffie et al., 2021; Owoade et al., 2021; West et al., 2021). Open-air markets and busy road corridors are particularly notable pollution hotspots, as they concentrate large numbers of people in areas with persistently high combustion-related emissions (Ajayi et al., 2024; Amegah et al., 2021; Oladejo et al., 2020; Olufemi et al., 2023; Oragba et al., 2023; Ukpebor et al., 2006). Although these conditions present clear public health risks, most environmental health research in LMICs continues to focus on pollutant measurements or emissions inventories, with far fewer studies integrating such data with human activity patterns, perceptions, or adaptive behaviours (Arku et al., 2008; Bassi et al., 2021; Ezzati et al., 2005; Jing et al., 2017).

In Nigeria, urban markets are not only economic lifelines but also central hubs of daily movement, yet many lack the infrastructure needed to manage congestion, waste disposal, and emissions effectively (Ezedike et al., 2020; Ezeudu et al., 2021**;** Ezeonyejiaku et al., 2022; Osoja, 2019; Ukpebor et al., 2006; Yaro et al., 2019). These challenges are particularly concerning in older cities, where historical layouts were not designed for modern vehicle volumes or commercial intensity. Calabar, one of Nigeria's oldest urban centres and the capital of Cross River State, provides an important case study for examining urban air pollution dynamics. Its largest and busiest market, Watt Market, is situated along the Calabar Road corridor, a major transport route that connects the city's southern districts to the Margaret Ekpo International Airport, intercity highways, and the Calabar seaport. The corridor is characterised by heavy traffic congestion, intense commercial activity, and frequent open burning of waste, further worsened by on-street parking, informal street trading, and encroachment on pedestrian walkways, leading to increased pollution and exposure risk (Abam & Unachukwu, 2009; Bassey et al., 2023; Odum & Aloba, 2014; Udo et al., 2024). The market's expansion into surrounding residential and mixed-use areas has created a complex blend of commercial and domestic land uses, heightening the potential for overlapping exposures. Such unplanned use of space prolongs vehicle idling, reduces traffic flow, and increases pollutant accumulation, creating extended exposure windows for both motorists and pedestrians. Roadside traders may face disproportionately high risks due to their proximity to emission sources and the extended hours they spend outdoors (Amegah et al., 2021; Nduka et al., 2025; Otuu et al., 2018).

Previous study has investigated pollution levels in Watt Market and environs and have reported PM_{10} concentrations far exceeding WHO Air Quality Guidelines (Abam & Unachukwu, 2009). The study attributed these high levels mainly to vehicular emissions associated with ongoing traffic congestion in the areas. However, other sources also include burning firewood, refuse burning, diesel generators, and roadside charcoal ovens. $PM_{2.5}$ pollution from these sources, although less often measured, is particularly concerning because its smaller aerodynamic diameter allows them to penetrate deep into the alveolar regions of the lungs and enter the bloodstream, where they can induce systemic inflammation, worsen chronic conditions, and elevate long-term mortality risk (Cohen et al., 2017; Hoek et al., 2013; Pope & Dockery, 2006). Similar mixed-source pollution profiles have been documented in other Nigerian cities such as Lagos, Enugu, Abuja, and Port Harcourt, where traffic emissions, biomass burning, and generator use have been linked to elevated respiratory symptoms, reduced lung function, and heightened cardiovascular risk (Obaseki et al., 2014; Ojukwu et al., 2020). Despite compelling evidence from these studies, authorities have taken limited action to reduce pollution or mitigate exposure, leaving residents and market users at continued risk.

To improve current knowledge and broaden the evidence base, the present study brings a social science perspective to the issue of air pollution by examining how exposure interacts with human activity, perceptions, and behavioural responses. Compared to more extensively studied cities, Calabar remains under-researched, particularly regarding how exposure to pollution intersects with daily routines and behaviours around Watt Market. Existing studies in the city have predominantly focused on pollutant concentrations, with little attention to how individuals experience, perceive, and adapt to air quality risks in their everyday lives. This creates a critical gap in understanding cumulative exposure, which is shaped not only by emission sources but also by mobility patterns, market activity, and coping behaviours in high-risk environments. To address this, the study integrates spatially resolved Air Quality Index (AQI) data, which provide a standardised framework for categorising pollution severity and enabling comparisons across space and time, with community survey data, thereby linking objective pollution measures to lived experiences.

Most air pollution indices base their values on ambient pollutant concentrations and associated health implications, with only limited consideration of population dynamics. A few studies have introduced population-weighted exposure indices, where air pollution data are weighted by population distribution or health outcomes at the city or regional level (Aunan et al., 2018; Chen et al., 2024; Huang & Brown, 2021; Ivy et al., 2008; Scoggins & Fisher, 2002; Shakor et al., 2020; Wu et al., 2024). While valuable, these approaches still fail to capture the fine spatial and temporal variations that shape individual exposure and hotspot dynamics. A notable methodological advance is the Air Pollution Exposure Index (APEI) developed by Otu et al., (2024) in Lancaster, UK. By integrating NO_2 and PM_{10} data with traffic and pedestrian counts as well as bus schedules, they demonstrated how rhythmanalysis can pinpoint when and where pollution coincides with population density, thereby identifying periods and locations of heightened exposure risk.

Building on these developments and drawing specifically on the empirical work of Udo et al., (2024), who mapped AQI levels in Calabar and found most locations 'marginally polluted,' the present study integrates AQI data with community survey evidence on market use, mobility, perceptions, and awareness of risks. This approach provides a context-specific understanding of exposure dynamics, enabling the identification of vulnerable groups, such as roadside traders, commuters, and residents living near the market, while also capturing behavioural adaptations and coping strategies that shape real-world exposure. Incorporating residential location data further allows exploration of how home environments interact with workplace or commercial exposures, offering a more comprehensive picture of cumulative risk. By situating reported experiences and behaviours within objectively measured pollution conditions, this study bridges the gap between technical air quality assessments and lived experience, generating evidence that is both scientifically robust and locally relevant.

Beyond its empirical contributions, this study is conceptually informed by three interrelated frameworks. First, environmental justice highlights how disadvantaged groups such as roadside traders and low-income commuters may bear a disproportionate burden of air pollution exposure, despite overall low AQI levels. Second, vulnerability theory underlines the heightened risks faced by older adults and those with pre-existing health conditions, groups that our survey shows are strongly represented among market users. Third, risk perception theory provides a lens to interpret the gap between measured conditions (often categorised as 'Good' or 'Marginally Polluted') and the widespread community perception of poor air quality and health risk. By applying these frameworks to an African informal market context, the study extends debates on how exposure, perception, and inequality intersect in under-researched LMIC urban settings. Specifically, it seeks to: (1) characterise the socio-demographic profile and residential AQI exposure of Watt Market–Calabar Road users; (2) examine patterns of market and road use in relation to potential pollution exposure periods; (3) identify perceived sources and severity of pollution in the study area; (4) explore behavioural adaptations and awareness of air quality improvement initiatives; and (5) contextualise findings using spatially resolved AQI data to assess potential compounded exposure risks.

Accordingly, these objectives are organised around three broader research questions that guide the structure of the analysis. First, what are the spatial patterns of AQI and PERI exposure across residential areas linked to Watt Market? Second, how do residents' perceptions of air quality relate to objective exposure indicators and mobility patterns, including time of visit and duration of stay? Third, what factors predict behavioural adaptation in response to perceived air pollution? By articulating these guiding questions, the study clarifies how socio-demographic characteristics, exposure context, perception, and behavioural response are analytically linked within a unified framework.

2. Materials and methods

2.1. Study area, air quality and vulnerabilities

As shown in Figure 1, Watt Market, selected as the study site, is situated in the heart of Calabar city (Cross River State, Nigeria), within Calabar South Local Government Area. The market extends along the busy Calabar Road corridor and is bounded to the north by the African Clubhouse, to the south by the Anglican Church, to the west by the Catholic Church headquarters in the state, and to the east by an interconnected network of streets, including Queen Duke Street, King Street, Bedwell, and White House. Serving as one of

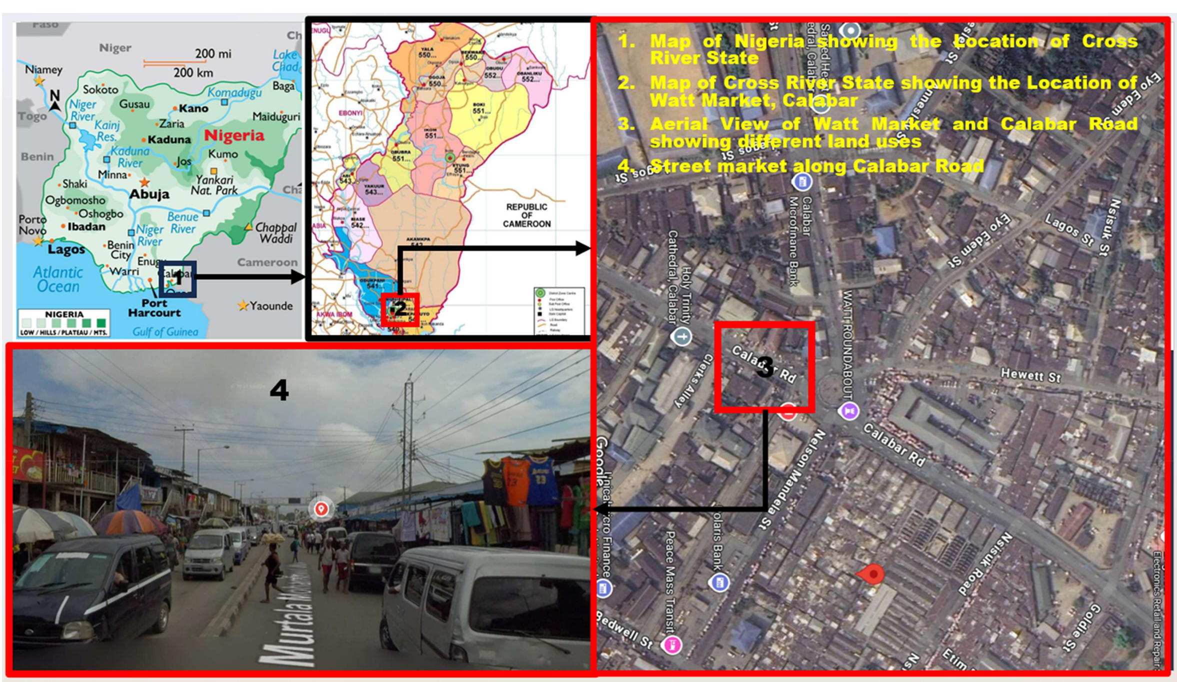


Figure 1. Location and context of Watt Market and Calabar Road, Calabar, Nigeria, showing state and city maps, aerial view, and street market scene. (Geographical Maps and Location Data retrieved from https://www.worldatlas.com/maps/nigeria, from Pinterest maps https://www.pinterest.com, https://maps.app.goo.gl/vCjxAXAUYkpM4sA67 and 3D street images from Google, https://maps.app.goo.gl/HYXdFvRepf9c6fYf9).

the largest and busiest commercial hubs in the state, Watt Market attracts a daily influx of traders, buyers, residents, commuters, and visitors from within and outside the city. The combination of heavy human activity, dense roadside commerce, and limited traffic control has created persistent congestion in the area. On-street parking and street trading along connecting roads obstruct traffic flow and reduce pedestrian space, prolonging travel times and contributing to pollutant accumulation. Roadside traders, who spend long hours near vehicular emissions and other pollution sources, are especially vulnerable to exposure-related risks. Existing studies have consistently reported pollution levels in Watt Market and its environs above WHO-recommended air quality limits for safe living (Abam & Unachukwu, 2009; Udo et al., 2024; World health organisation (WHO), 2021). As the market continues to expand into surrounding streets, residential zones, and mixed-use areas, the likelihood of overlapping exposures increases. Vulnerability is further compounded by socio-economic realities, including the high proportion of informal traders working outdoors for extended hours, dependence on polluting energy sources, and limited awareness of air quality risks.

2.2. Study design

This study employed a cross-sectional exploratory design, combining primary survey data with secondary air quality datasets from previous monitoring studies. The survey formed the core of the research, designed to capture socio-demographic characteristics, market use patterns, transport behaviours, and perceptions of air pollution exposure. By integrating these responses with existing air quality data, the study provided a more comprehensive, though exploratory, understanding of cumulative exposure risks in Watt Market and Calabar Road. Ethical approval for this study was granted by the Faculty of Science and Technology Research Ethics Committee (FSTREC) at Lancaster University, under approval reference number FST20047. The study adhered to the ethical principles outlined in the Declaration of Helsinki.

Questionnaires

A structured questionnaire was developed with four sections: (i) demographics, (ii) usage patterns, (iii) transport, and (iv) air pollution perceptions and behaviours. In total, 17 questions combined multiple-choice, ranking, and short free-text items (see Supplementary Materials for sample questionnaire).

The Demographics section gathered information on age, gender, occupation, education, and (optionally) residential area, as well as self-reported health status and pre-existing respiratory or cardiovascular conditions. The Usage Patterns section captured how participants interacted with Watt Market and the Calabar Road corridor, covering visit frequency, time of day, duration of stay, and role (trader, commuter, shopper, office worker, or resident). The Transport section identified primary and secondary travel modes (walking, public transport, motorcycle, private car) and reasons for these choices. Finally, the Perceptions and Behaviours section explored awareness of local air quality, perceived sources of pollution, health and lifestyle impacts, behavioural responses (e.g. avoidance of certain areas, use of face coverings, reduced outdoor time), and awareness of interventions.

The survey was conducted across Watt Market and Calabar Road, two of the busiest commercial nodes in Calabar, using both online and in-person modes to maximise participation. Both sites were selected because they represent high-activity corridors where large, diverse populations converge daily. Questionnaires were distributed to traders, shoppers, commuters, transport operators, and office workers to ensure broad coverage of user groups.

To maximise inclusivity, surveys were conducted in both online (in Google Forms) and in-person interviewer-administered formats. The online mode allowed low-cost, wide dissemination and secure collation of responses, while the in-person approach targeted participants with limited internet access, literacy, or language barriers. Informed consent was obtained from all participants, provided digitally before completing the online survey and in signed form for in-person interviews. During face-to-face sessions, the researcher read aloud the participant information sheet and recorded responses verbatim. Each session lasted 15–20 minutes, with ~10 interviews completed per day across four days. Only participants aged 18 years and above were eligible, and participation was voluntary and anonymous, with optional residential information stored separately.

A total of 280 questionnaires were administered, of which 200 were completed and returned, yielding an overall response rate of ~71% (as shown in supplementary material -Table S1). Sellers and buyers made up the largest participant groups, while office workers and residents recorded the highest completion rates, and transport operators the lowest. Although the total market population is far larger than this sample, the ~71% completion rate reflects strong engagement within the short fieldwork period. Importantly, the achieved sample exceeded the minimum threshold of 196 respondents (based on Cochran's formula at 95% confidence and 7% margin of error). The realised sample size was constrained by time and resource limitations and should therefore be regarded as exploratory and indicative rather than fully representative. Uneven distribution across residential groups, including a large 'Not Specified' category, partly reflects the fluid, transient mobility of informal market users, many of whom do not associate with a single fixed location.

A purposive sampling strategy was used for in-person administration, targeting individuals across different market zones (e.g. trading sections, transport stops, and adjoining office/residential clusters) to ensure spatial coverage. Convenience sampling complemented this online, disseminated through social media platforms and community networks to reach residents who commute into the market area.

Data Handling and Analysis

Survey data were exported from Google Forms into Microsoft Excel (2016), with in-person responses manually integrated using unique identifiers. Quantitative data were summarised using descriptive statistics (frequencies, percentages, means), while chi-square (χ^2) tests of independence were applied to examine bivariable associations between demographic variables (e.g. age, health status) and perceptions or behaviours. Bivariate analyses were conducted for exploratory purposes and interpreted cautiously given potential sparse cells and the relatively small number of behavioural change outcomes.

To assess independent predictors of perceptions and behavioural responses, logistic regression analyses were conducted using the SPSS statistical software package. Results are reported as adjusted odds ratios (AORs) with 95% confidence intervals. Predictor variables included age group, user category, visit frequency and duration, transport mode, health status, and frequency of thinking about air quality. Model robustness was evaluated through likelihood-based fit statistics.

Given the constraints of time, resources, and available software, these regression analyses are presented as exploratory rather than definitive. They are intended to highlight potential determinants of perception and behavioural response patterns, while pointing to the need for more sophisticated statistical modelling in future research. Free-text responses were thematically coded and triangulated with quantitative findings to provide contextual insights into patterns of exposure and adaptive behaviours.

2.3. Cumulative exposure risk assessment

To assess exposure risk, we relied on secondary Air Quality Index (AQI) data reported in Udo et al., (2024), one of the only available continuous datasets for Calabar. While this introduces possible temporal misalignment with the survey, it provided a practical and context-specific basis for this preliminary risk assessment. To link air quality with market flows, a Population Exposure Risk Index (PERI) was developed by multiplying AQI levels with estimated population indices. This method, while a simplified representation, offered a transparent and replicable screening tool for exploratory analysis. More sophisticated approaches, such as pollutant-specific weighting, time–activity diaries, or dynamic monitoring, should be considered in future research to refine exposure estimates.

2.3.1. Air quality index data

As indicated, in addition to survey data, we incorporated secondary Air Quality Index (AQI) data reported in Udo et al., (2024), in which air quality was monitored at approximately 50 locations in Calabar using mobile Aeroqual gas modules, and location-specific daily AQI values were calculated using a pollutant-specific AQI framework consistent with the methodology outlined by the U.S. Environmental Protection Agency (2024). The pollutants measured included particulate matter ($PM_{2.5}$ and PM_{10}), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), ammonia (NH_3), and total suspended particulates (TSP). The AQI standard classification ranges used in their analysis are presented in Table 1, while the

Table 1. Air Quality Index Categorisation Table from Udo et al. (2024).

Category	AQI	Description of Ambient Air
I	0-50	Good
II	51-100	Marginally polluted
III	101-200	Unhealthy
IV	201-300	Very unhealthy
V	> 300	Hazardous

distribution of results by location is shown in supplementary material, Table S2. These results indicated that 82% of monitoring stations were categorised as *marginally polluted* (AQI 51–100), 14% as *good* (AQI ≤ 50), and 4% as *unhealthy* (AQI 101–150). An air quality map (Figure 2) developed by Udo et al. illustrates these spatial patterns across the city, with Watt Market among the monitored sites. The AQI framework is used here because it provides a standardised and comparable measure of air quality severity across pollutants, time, and space. While Udo et al., (2024) concluded that Calabar is overall *marginally polluted*, the present study draws on their dataset not only to describe ambient pollution levels but also to construct a population exposure risk index, similar to the Air Pollution Exposure Risk Index (APEI) metric in Otu et al. (2024).

2.3.2. Population density data

To estimate the population associated with Watt Market, we derived the average number of person-visits per day generated by each residential area reported in the questionnaire survey. These estimates represent population per residential area rather than a pooled or citywide count of total market attendance.

Because respondents reported visitation frequency in different time units (per day, per week, per month, or per year), all responses were first standardised to a common daily metric to ensure comparability. For each respondent i residing in area a, the reported visitation frequency was converted into an equivalent number of visits per day (f_i). Weekly responses were divided by 7, monthly responses by 30.4 (average days per month), and yearly responses by 365. Daily responses required no adjustment. This procedure ensured that all visitation patterns were expressed as average daily visit rates per respondent.

After standardisation, the estimated average daily population for each residential area was obtained by aggregating the daily visit rates of all respondents from that area. Each respondent contributes their individual daily visit rate to the total population estimate. The total estimated daily person-visits for residential area a were therefore calculated as shown in Equation (1).

$$P_a = \sum_{i=1}^{n_a} f_i \tag{1}$$

where P_a = Estimated average daily person-visits from residential area a,

where n_a = Number of respondents residing in residential area a,

f_i = Standardised daily visit rate for respondent i.

Mathematically, this summation is equivalent to multiplying the number of respondents by the mean daily visit rate for that residential area, as shown in Equation (2).

$$P_a = n_a \times \bar{f} \tag{2}$$

where $\bar{f}$ denotes the mean daily visit rate for respondents in that residential area.

For example, if 12 respondents from a residential area each reported visiting the market six times per week, the daily visit rate per respondent would be 6/7, resulting in:

$$P_a = 12 \times \frac{6}{7} \approx 10.3 \text{ person} - \text{visits per day}$$

The same standardisation and aggregation approach was applied to all residential areas, including respondents classified as ‘Not specified.’ Using this approach, estimated daily flows ranged from 14 to 400

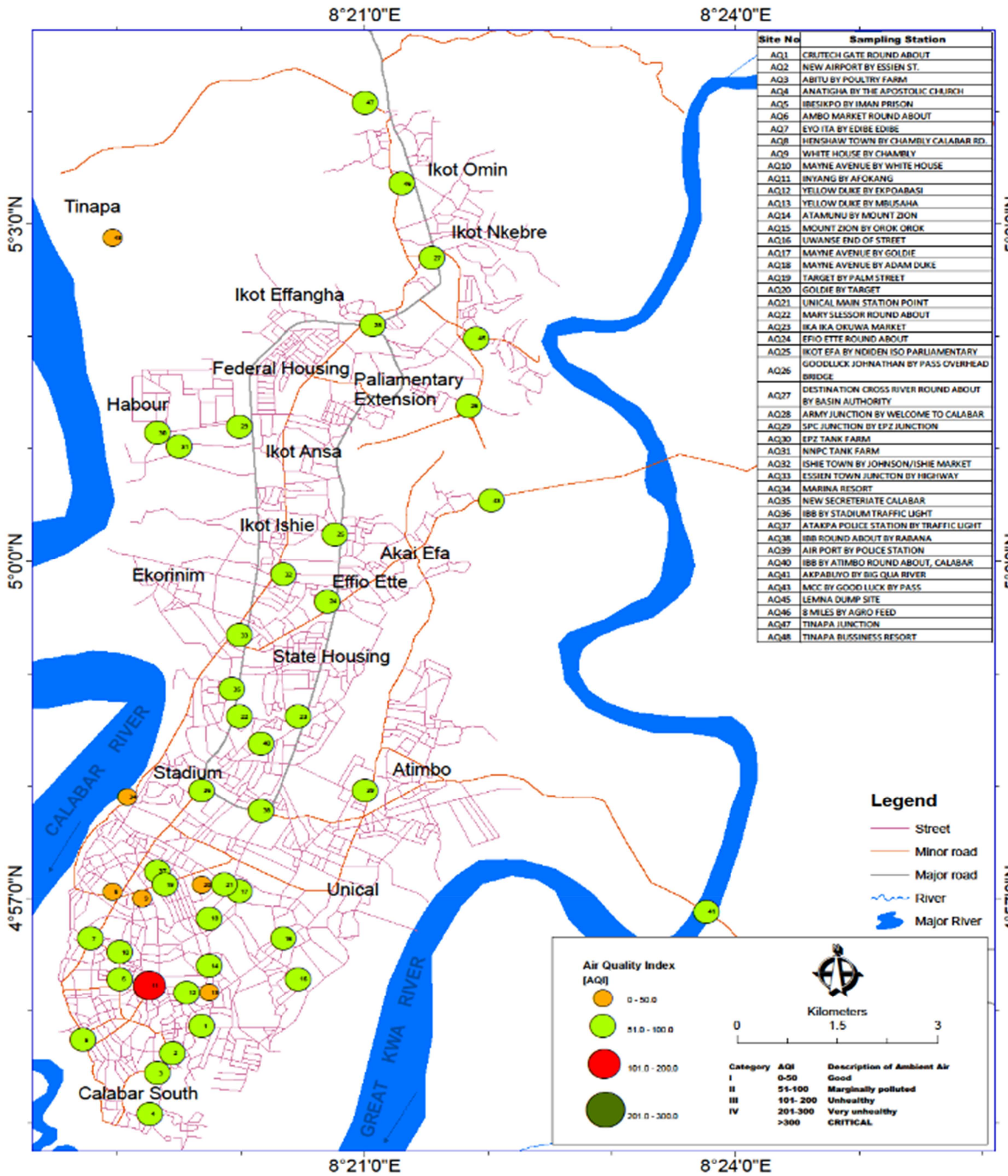


Figure 2. Air quality map of Calabar from Udo et al. (2024).

person-visits per residential area, as presented in Table 2. These values reflect group-level daily visitation intensity rather than aggregated market-wide traffic volumes.

Population Index classification was subsequently applied at the residential-area level using daily thresholds adapted from Otu et al. (2024). In the original framework, population density thresholds were defined on an hourly basis. To align these with the daily visitation estimates used in this study, hourly thresholds were converted to daily equivalents (×24 hours). Accordingly, Population Index 1 ('Very Low'), originally defined in the previous study as fewer than 180 pedestrians per hour, was redefined as fewer than 4,320 people per day. Index 2 ('Low'), previously defined as 181–360 pedestrians per hour, was redefined as 4,321–8,640 people per day. Index 3 ('Moderate'), originally 361–540 pedestrians per hour, was redefined as 8,641–12,960 people per

Table 2. Population Index and hourly threshold values defined by Otu et al., (2024) and daily threshold values defined in this study.

Population Index Category	1 Very Low	2 Low	3 Moderate	4 High	5 Very High
Pedestrians per hour	0–180	181–360	361–540	541–720	721 or more
People per day	0–4,320	4,321–8,640	8,641–12,960	12,961–17,280	17,281 or more

Table 3. Air Quality Index levels and scores adapted from Otu et al., (2024) AQI.

AQI Levels	AQI by Index Score	Category
1	0-50	Very Low
2	51-100	Low
3	101-200	Moderate
4	201-300	High
5	> 300	Very High

day. Index 4 ('High'), 541–720 pedestrians per hour, was redefined as 12,961–17,280 people per day. Finally, Population Index 5 ('Very High'), defined as more than 720 pedestrians per hour, was redefined as more than 17,280 people per day. These redefined thresholds, presented in Table 2, allowed consistent classification of average daily population density across the different locations.

Following this classification, all estimated group-level daily flows (14–400 people per day) fall within Population Index 1 (Very Low). Importantly, Population Index classification was applied at the individual residential-area level, not to a pooled total across all areas.

These estimates represent a proxy measure of population activity derived from self-reported survey data rather than direct pedestrian counts or time-resolved mobility tracking. The resulting values are therefore subject to recall bias, sampling variability, and uneven spatial representation. Accordingly, they should be interpreted as indicative and exploratory, providing a transparent screening-level basis for exposure assessment rather than precise measurements of total market attendance.

2.3.3. Population exposure risk assessment

To estimate the daily population exposure risk, we combined Air Quality Index (AQI) data presented in Udo et al., (2024) with population data extrapolated from location information in the questionnaire survey. The spatially based AQI data served as indicators of pollution, while population estimates reflected the population density in each location.

Initially, both datasets were sorted using a pivot table according to location. Following this, pollution indicators were assigned values ranging from 1 to 5, corresponding to air quality categories and threshold levels consistent with those of Udo et al. (2024). In Udo et al., (2024), AQI categories were reported using the standard framework: Category I described as 'Good' (0–50), Category II described as 'Marginally Polluted' (51–100), Category III described as 'Unhealthy' (101–200), Category IV described as 'Very Unhealthy' (201–300), and Category V described as 'Critical' (201–300). For this study, these were redefined numerically with values for AQI levels ranging from 1 to 5 in order to allow integration with population index data. Specifically, Category I ('Good') was assigned number 1, representing very low pollution concentration; Category II ('Marginally Polluted') was given number 2, representing low pollution concentration; Category III ('Unhealthy') was given number 3, representing moderate pollution concentration; Category IV ('Very Unhealthy') was given number 4, representing high pollution concentration; and Category V ('Hazardous') was given number 5, representing very high pollution concentration levels, as shown in Table 3.

Subsequently, population exposure risk index (PERI) for each location was calculated by multiplying the AQI levels index (Ci) by the corresponding population density index (Pie) defined in Table 2:

$$\mathrm{PERI} = \mathrm{C_i} \times \mathrm{P_i} \tag{3}$$

where $i = 1, 2, 3, \ldots.., n$

where $\mathrm{C_i}$ = AQI concentration index at location i (values 1–5, corresponding to pollution severity categories).

$\mathrm{P_i}$ = Population density index at location i (values 1–5, corresponding to levels of human activity).

This produced composite values ranging from 1 to 25. Population exposure risk was classified according to Otu et al., (2024), with scores between 1–5 representing very low exposure risk, 6, 8, 9, and 10 indicating low exposure risk, 12 and 15 moderate risk, 16 and 20 high risk, and 25 indicating very high population exposure risk (Table 4). For example, if a location recorded an AQI level of 3 (moderate pollution) and a population density score of 4 (high), the resulting PERI value would be 12, placing that site in the Moderate population exposure risk category. By contrast, a location with an AQI level of 2 (low pollution) and a population density of 2 (low) would produce a PERI of 4, indicating Very Low population exposure risk. This illustrates that exposure risk depends jointly on pollution severity and the intensity of human activity.

In the present study, observed input ranges were predominantly AQI Category 1–2 and Population Index 1, producing PERI values between 1 and 2. Even if either AQI category or Population Index increased by one level independently, PERI values would remain within the Very Low classification range under the adopted threshold framework. Only simultaneous increases in both parameters (e.g. AQI = 3 and Population Index = 2) would shift classification to the Low exposure category. This indicates that, within the defined index structure, PERI classification remains stable under moderate variation in either parameter.

It should be noted that, unlike the weighted APEI approach recommended by Otu et al. (2024), this study did not apply pollutant-specific weighting prior to combining indices. The AQI dataset obtained from Udo et al. (2024) represents an aggregated multi-pollutant indicator, and pollutant-specific concentration data required for weighting were unavailable despite efforts to obtain them. Consequently, PERI was constructed as a screening-level composite index integrating overall air quality status with population density, rather than as a pollutant-specific exposure model. When disaggregated pollutant concentration data are available, weighting can be applied following established AQI calculation methodologies, such as those outlined in Udo et al. (2024), before deriving the pollution index and integrating it with population indices to determine PERI values.

Finally, PERI values were applied to characterise population exposure risks across residential locations and to examine the spatial distribution of cumulative exposure risks associated with daily usage of Watt Market. These classifications informed subsequent analyses of prolonged exposure patterns among market users at home and within the market environment.

3. Results

3.1. Respondent characteristics and exposure context

Visitor flows to watt market and residential exposure risks

Respondents were asked about their residential area, which revealed a mix of visitors from central clusters and more peripheral settlements. For this study, residential areas were grouped into neighbourhood

Table 4. Interpretation of the Population Exposure Risk Index adopted from Otu (2025).

Population Exposure Index and Risk		Description
1	Very Low Population Exposure	Combination of either: very low pollution & very low population;
2	Very Low Population Exposure	low pollution & very low population; very low pollution & low population;
3	Very Low Population Exposure	moderate pollution & very low population; very low pollution & moderate population.
4	Very Low Population Exposure	low pollution & low population; very low pollution & high population; high pollution & very low population;
5	Very Low Population Exposure	very high pollution & very low population; very high population & very low pollution.
6	Low Population Exposure	Combination of either: low pollution & moderate population; moderate pollution & low population;
8	Low Population Exposure	high pollution & low population; low pollution & high population;
9	Low Population Exposure	moderate pollution & moderate population;
10	Low Population Exposure	very high pollution & low population; low pollution & very high population.
12	Moderate Population Exposure	Combination of either: moderate pollution & high population; high pollution & moderate population;
15	Moderate	moderate pollution & very high population; very high pollution & moderate population.
16	High Population Exposure Risk	Combination of either: high pollution & high population;
20	High Population Exposure Risk	high pollution & very high population; very high pollution & high population.
25	Very High Population Exposure Risk	Combination of very high pollution & very high population.

categories within Calabar and cross-referenced with available air quality data. Specifically, daily Air Quality Index (AQI) values reported by Udo et al. (2024), which ranged from 'Good' to 'Marginally Polluted' across Calabar, were used alongside the Population Exposure Risk Index (PERI) derived here to link residential patterns with exposure risk. Survey responses ($n = 200$) showed that Watt Market functions as a major convergence point, attracting residents from both the Central Business District (e.g. Watt Market/ Calabar Road/Goldie and environs) and shuburbs (e.g. Akpabuyo, Atimbo). This highlights the market's dual role as a commercial hub and a focal node of daily mobility, making it a critical site for assessing cumulative population exposure in Calabar.

The estimated daily population per location group reflects the number of individuals travelling from each residential area to Watt Market on a typical day (Table 5). Visitor flows varied substantially, with peripheral settlements such as Diamond/Ekorinim and Atuambom/Target contributing only about 14 daily visitors each, while the Not Specified group accounted for as many as 400, indicating that a significant share of market users could not be linked to a specific residential cluster. Watt Market and its adjoining neighbourhoods themselves contributed 267 daily visitors, making this the largest identifiable flow. This underscores the significance of the market not only to its immediate environs but also to the wider city. The large share of 'Not Specified' responses also introduces uncertainty into flow distribution estimates, underlining the need for more detailed sampling.

Despite these marked differences in visitor flows, all groups were categorised under Population Index 1, reflecting relatively low population densities when assessed against the study's classification framework. At their places of residence, average AQI scores ranged from 44.67 to 70.47, corresponding to Levels 1–2 (Very Low to Low Pollution). These conditions fall within the 'Good' to 'Marginally Polluted' categories of the adopted AQI framework, which are typically associated with a lower probability of acute health impacts for the general

Table 5. Daily visitor flows to Watt Market and residential exposure risk categories based on survey responses.

Group	Residential Area(s)	Frequency of Responses	Standardised Visitation Frequency per Location (in days)	Average Population per Day per Location Group	Population Index	Avg. AQI Score	AQI Level	PERI Level	% of Watt Population Exposed at Home	Exposure Risk Category
1	Afokang, Ambo, Anantigha, etc.	12	6	72	1	70.47	2	2	6.8	Very Low Population Exposure
2	Akia Efa, Ediba, Efio-ette, Atekong, etc.	9	5	45	1	63.22	2	2	4.3	Very Low Population Exposure
3	8 Miles, Federal Housing, Highway, etc.	9	3	27	1	67.12	2	2	2.6	Very Low
4	Etta Agbor, IBB-Way, Akim, UNICAL, etc.	18	4	72	1	62.78	2	2	6.8	Very Low
5	Watt Market, Calabar Road, Edgerly, etc.	41	6.5	267	1	61.61	2	2	25.2	Very Low
6	Atakpa Street, Atamunu, CRUTECH, etc.	20	6	120	1	70.32	2	2	11.3	Very Low
7	Akpabuyo, Atimbo, Edim Otop	7	4	28	1	59.60	2	2	2.6	Very Low
8	Diamond, Ekorinim	2	7	14	1	55.09	2	2	1.3	Very Low
9	Atuambom, Target	2	7	14	1	48.80	1	1	1.3	Very Low
10	Not Specified	80	5	400	1	44.67	1	1	37.8	Very Low

A full list of residential areas included in each location group can be found in Supplementary Materials.

population. Importantly, World health organisation (WHO), 2021 Global Air Quality Guidelines highlight that even exposures within ranges commonly classified as 'moderate' by AQI frameworks can exceed health-based concentration thresholds, underscoring the need for continued monitoring and precaution (World health organisation (WHO), 2021). Consistent with this, PERI values were also low (Levels 1–2), placing all groups in the Very Low Population Exposure Risk category. The proportion of Watt Market's total visitor population exposed while at home ranged from 1.3% in smaller settlements (Diamond/Ekorinim; Atuambom/Target) to 37.8% among respondents who did not specify a residence.

Consistent with previous findings suggesting that Watt Market generally falls within 'Good' to 'Marginally Polluted' AQI categories, these results indicate that surveyed residential groups were classified within the Very Low PERI category under the adopted threshold framework. In other words, cumulative exposure appears relatively low under the observed AQI and population-index conditions. However, this should be interpreted as screening-level evidence rather than definitive confirmation of the absence of risk. Nonetheless, markets are dynamic environments where pollution can change due to traffic, waste management, and seasonal variations, which highlights the importance of sustained monitoring. These patterns underscore the importance of viewing Watt Market not simply as a physical location of potential exposure, but as a mobility-based hub where the daily convergence of people from multiple residential areas may shape cumulative exposure risks across the city.

While the results indicate that both residential and market exposures were classified within lower risk categories under the adopted screening framework, these findings should be viewed as indicative rather than definitive. The survey sample was modest ($n = 200$) and unevenly distributed across location groups, with some residential areas represented by only a handful of respondents. In addition, the exposure classification relied on simplified threshold conversions rather than continuous monitoring. A larger, more representative dataset would enable more robust estimates of visitor flows and exposure risks and may reveal spatial variations that were not fully captured in this preliminary survey.

Visitor demographics and residential exposure risk profiles

The survey sample ($n = 200$) reflected a broad demographic distribution of Watt Market users. When asked about the population group they fall into, almost half of the respondents said they were young adults aged 18–35 years (49.5%), followed by middle-aged adults aged 36–55 years (39.5%), and a smaller share of older adults aged 55 years and above (11%), as shown in Table S3. In terms of underlying health conditions, 85.5% of respondents reported none, while 14.5% reported at least one, with the most common conditions being ulcer, asthma, and diabetes (Table S4). The burden of health vulnerability was not evenly distributed across age groups, with older adults being significantly more likely to report underlying conditions (41%) compared to 13% of middle-aged adults and 10% of young adults (shown in Table S5).

When mapped against residential air quality classifications from the previous AQI study (Udo et al., 2024), both younger and older adults were disproportionately located in areas rated as 'Good' or 'Marginally Polluted.' Notably, no older adult was reported as residing in areas classified as 'Unhealthy' (Table 5). This indicates that, although health vulnerabilities were greater in this group, their residential exposure environments remained relatively favourable. Middle-aged adults were more widely distributed across the city, but the majority were also concentrated in 'Good' and 'Marginally Polluted' zones.

Across all groups, PERI data indicated uniformly Very Low Population Exposure Risk (Table 4). This suggests that, despite differences in age and health status, the actual exposure conditions in residential environments are not currently severe enough to elevate cumulative health risks. However, although overall exposure risk was low, the presence of underlying health conditions such as asthma and diabetes means that even low-level exposures could disproportionately affect these individuals. This highlights that population-level findings of low risk do not necessarily translate into equal protection for sensitive sub-groups. It is also important to note that the single largest category of respondents across all age groups was those who did not specify their residential location. Because this 'Not Specified' group could not be linked to AQI or PERI categories defined in this study, their cumulative exposure risk could not be fully assessed, introducing uncertainty into the analysis.

Overall, the demographic profile of Watt Market visitors and their associated residential exposure conditions indicates that, under current conditions, both home and market environments do not pose significant air quality-related health risks for most individuals. Nonetheless, the presence of vulnerable groups, particularly older adults with underlying health conditions, could have health implications for some individuals. Since air quality is dynamic and influenced by seasonal and urban factors, these results should not be interpreted as an assurance of safety, but rather as an indication of generally low risk within the period assessed.

Importantly, the modest dataset and the large proportion of respondents with unspecified residential locations limit the robustness of these findings. They should therefore be regarded as preliminary, with a larger and more representative dataset needed to confirm these patterns and to determine whether sub-groups of the market-going population face disproportionate risks not captured in this study.

3.2. Visitation, mobility, and exposure pathways at watt market and Calabar road

Market use patterns, transport choices, and exposure context

The survey data suggest participants represented a diverse mix of Watt Market users. When asked about their role, about 24% identified as buyers, 56.5% as sellers, 7.0% as residents, 3.5% as commuters or motorists, 4.0% as office workers, and 3.5% as visitors or in other categories (Figure 3). In terms of frequency, the majority (67.5%) reported visiting daily, followed by 10% who visited weekly, 15.5% monthly, and 5% yearly or less often, while 2% did not respond. The most common destinations were the main market (60.5%) and the street market (21%), with smaller proportions reporting visits to offices, residences, or other locations (Table S6).

When asked about the time of day they most often visited, peak visiting times were concentrated in the early morning (44.5%), with smaller proportions reporting mid-afternoon (5.5%) and evening visits (6.0%). In addition to visit timing, the length of stay in the market also varied, with 21.5% of respondents remaining 1–3 hours, 5% staying between 3–6 hours, 20% staying for half a day, and 2% spending a full day at the market. These temporal patterns suggest distinct ‘rhythms of exposure,’ where individuals experience varying exposure levels depending on arrival time, duration of stay, and mobility between zones. Early morning peaks may coincide with traffic build-up, waste handling, and generator start-up activities, potentially elevating short-term concentrations even where average daily AQI remains low. Overlaying these usage patterns with AQI and PERI data revealed that daily and long-duration visitors were more likely to reside in zones with higher AQI values, suggesting a potential ‘compounded exposure’ effect where both home and market environments contribute to cumulative risk. However, Watt Market itself recorded relatively low AQI values and was classified under Very Low Population Exposure Risk (PERI Level 1) in this study, indicating that the market environment is unlikely to elevate risk even for frequent visitors substantially.

In terms of travel choices, the majority of respondents reported travelling to Watt Market by public bus (42%), followed by walking (26.5%). Smaller proportions used private cars (11.5%), motorcycles or bicycles (7.5%), or other modes such as tricycles (12%) (Figure 4). When asked to explain their transport decisions, respondents most often cited convenience (43.0%), followed by cost (19.0%) and distance from work (19.0%) (Figure 5). A smaller share reported environmental concerns (7.5%), while the remainder gave individualised responses such as proximity to specific streets or workplaces

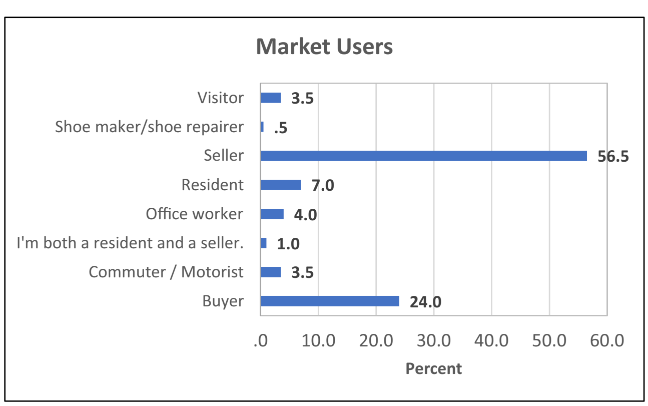


Figure 3. Category of space users at Watt Market and Calabar Road.

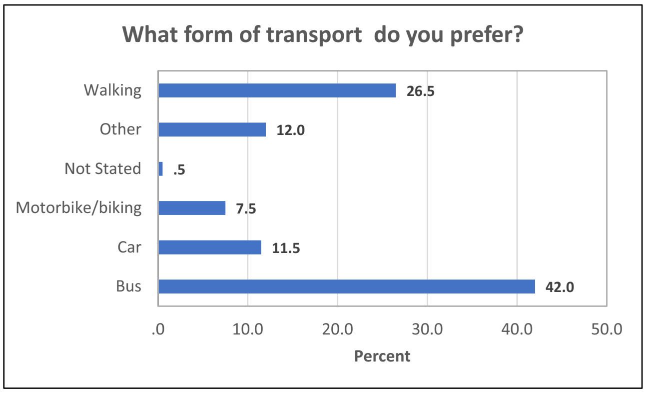


Figure 4. Perception of transport choices.

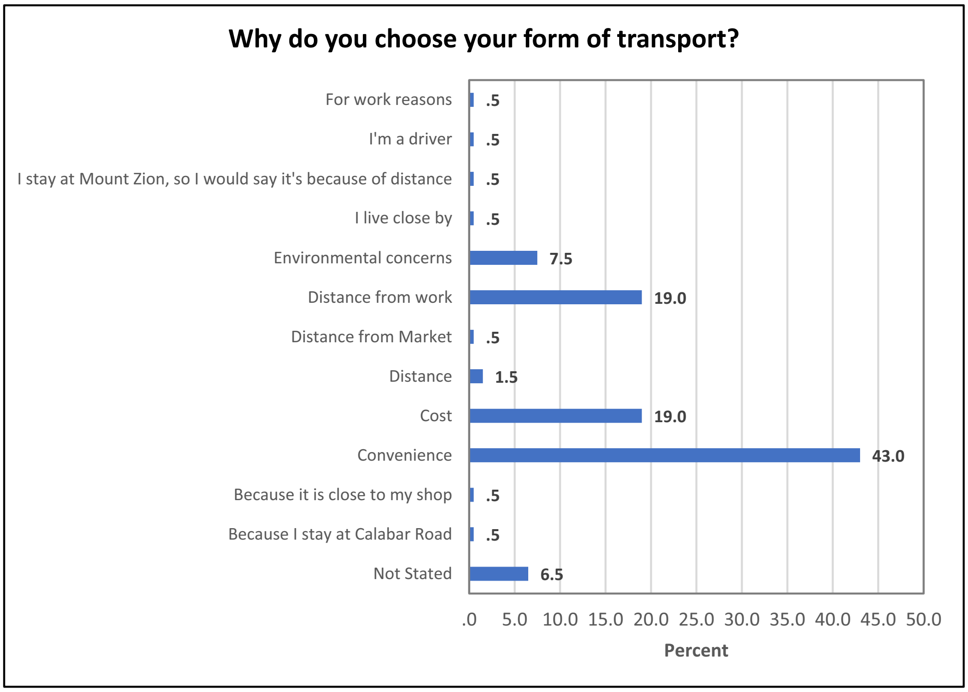


Figure 5. Perception of transport reasons.

(Table S7). This ranking indicates that practical and economic factors dominate mobility choices, with environmental concerns playing only a minor role in shaping behaviour, a pattern consistent with findings from other urban settings where economic constraints typically outweigh environmental considerations.

These patterns highlight the importance of mobility in shaping exposure risk. Sellers and long-stay visitors may accumulate longer daily exposures due to time spent in and around the market, but their risks remain limited by Watt Market's relatively low AQI. Travel to and from the market, however, introduces an additional exposure pathway, particularly for respondents who walk or use motorcycles in higher-AQI neighbourhoods. The predominance of convenience and cost as transport priorities suggests that exposure considerations currently play little role in decision-making, a pattern consistent with urban settings where economic constraints outweigh environmental concerns. Importantly, older adults and those with asthma or diabetes may be disproportionately affected if their travel routes pass through more polluted corridors. At the same time, the preference among residents of high-AQI zones for enclosed or motorised transport suggests some adaptive behaviour, potentially limiting exposure during travel.

Overall, these results show that market users' exposure is shaped less by conditions at Watt Market itself and more by the combined influence of residential origin, transport mode, and visit frequency. While Watt Market serves as a major convergence hub for the city, the intersection of daily travel patterns, practical transport decisions, and residential environments underscores the need to assess home-to-market exposure pathways alongside on-site conditions when evaluating cumulative risk.

3.3. Perceptions of air pollution and exposure risk at Watt Market and Calabar Road

Perceptions of air pollution, behavioural responses, and awareness of interventions.
When asked about sources of air pollution around Watt Market and Calabar Road, respondents most frequently cited traffic emissions (36.5%), followed by refuse burning and poor waste management (28%), and petrol/diesel generators (17.5%) (Figure 6). Firewood or charcoal burning was rarely mentioned (2%), while a small minority reported 'none' (3%) or stated they did not know (2.5%), and about 10.5% did not respond. These findings indicate that traffic is widely perceived as the dominant contributor to local air pollution, with waste burning and generator use also recognised as significant sources. Since these are highly visible and directly encountered during travel or trading, residents likely associate them with immediate exposure risks in their daily routines. These perceptions are consistent with studies in African cities where traffic emissions are most often identified as the primary source of urban air pollution (e.g. Ajayi et al., 2023; Amegah et al., 2021; Isangadighi & Ukudo, 2025; Obinna et al., 2025).

Perceptions of overall air quality were more varied (Figure 7). More than half of respondents (55%) rated air quality as 'okay,' while 32.5% described it as 'poor' and 6.5% as 'very poor'. Only a small minority considered local air quality to be 'good' (5.5%). These results suggest that although many respondents

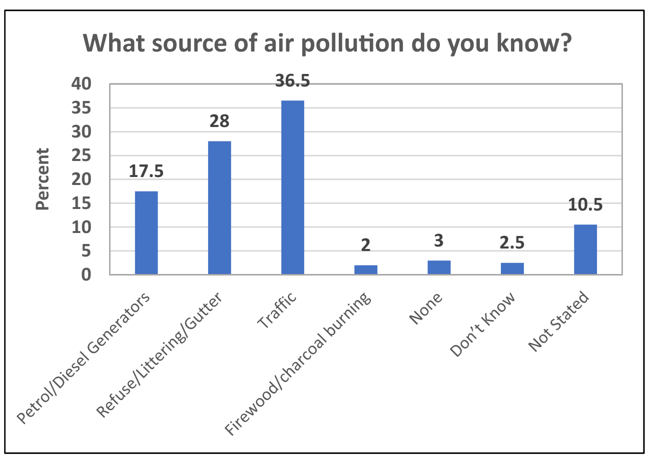


Figure 6. Perception of pollution source.

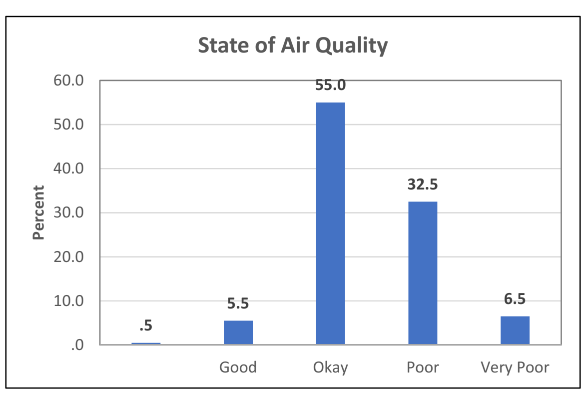


Figure 7. Perception of state of local air quality.

perceived air quality as tolerable, a significant proportion still considered themselves to be living and working in conditions of elevated exposure risk, even if not at critical levels.

Behavioural responses to air pollution were limited (Table S8). Only 12.5% of respondents reported changing when, how, or for what they visit Watt Market and Calabar Road because of air pollution, while the majority (87.5%) did not alter their behaviour. Among those who did report changes, common adjustments included avoiding specific areas perceived as polluted, shifting visit times to reduce exposure to traffic emissions, using alternative routes, or reducing visit frequency. This suggests that while many recognise traffic and waste as pollutants, only a small minority actively adjust their behaviour to reduce exposure pathways between home and market. Similar behavioural trends have been reported elsewhere, where awareness of pollution does not always translate into consistent protective action (Jiang et al., 2019; Levasseur et al., 2022; McKercher et al., 2010; Muindi et al., 2014).

Awareness of formal air quality interventions in Calabar was extremely limited (Table S9). Of the 200 respondents, 196 (98%) reported no knowledge of any initiatives, regardless of whether they were young adults (18–35 years), middle-aged adults (36–55 years), or older adults (55+). Only four individuals provided specific responses. One young adult suggested that government or market agencies should take action to manage waste in drains, one middle-aged adult called for more education on pollution at Watt Market, one older adult mentioned concern about noise pollution, and one middle-aged adult believed that there 'should be' interventions even if they were not directly aware of them. This gap highlights a lack of institutional protection from cumulative exposure risk, as most residents were unaware of systemic measures to address pollution. This is consistent with evidence from global studies, where weak communication of environmental policy and low public awareness of interventions remain common (De Vries, 2019; Ramírez et al., 2019).

In general, these findings highlight a contrast between perception and measurement. While residents widely attributed pollution to traffic, waste burning, and generators, and in some cases adjusted their behaviours accordingly, AQI and PERI data indicated that actual exposure risk levels at Watt Market remained relatively low. This suggests that concern about pollution is strongly shaped by visible and familiar sources, even when measured risks are low.

3.4. Determinants of perceptions, exposure risk and behavioural responses at Watt Market and Calabar Road

Socio-demographic, air quality perceptions and behavioural responses

Out of 200 respondents, 39.0% ($n = 78$) rated air quality as Poor/Very Poor, while 61.0% ($n = 122$) rated it Okay/Good (Table S10 and Figure 7). This split suggests that a substantial minority perceive air conditions as unhealthy, consistent with exposure to AQI levels in the moderate to unhealthy range at least intermittently in the Watt Market and Calabar Road area.

Perceptions of air quality varied significantly across socio-demographic, behavioural, and cognitive factors. Young adults were more likely than middle-aged and older adults to report poor or very poor conditions (Table S11). This may reflect greater mobility, increased sensitivity to traffic-related exposures, or heightened environmental awareness. Sellers, who typically spent longer hours in the market, also reported more negative perceptions relative to buyers, residents, and visitors (Table S12). This aligns with the likelihood of higher cumulative exposures to traffic emissions, refuse burning, and generator fumes in trading spaces.

Market use and duration of stay showed a strong gradient, with 44% of respondents staying 6–12 hours and 52% of those staying ≥12 hours rated air quality as Poor or Very Poor, compared with only 18% of those staying <1 hour (Table S13). This indicates that extended market presence translates into higher perceived exposure risk, corresponding to prolonged contact with pollutants likely above the WHO air quality guideline thresholds.

Transport mode was another important factor. Nearly half of bus users (49%) and motorbike users (46%) reported Poor/Very Poor air quality, compared with 28% of those who walked (Table S14). Motorised transport exposes individuals to direct emissions from congested traffic along Calabar Road, suggesting that commuters and commercial drivers face consistently higher AQI-related risks.

Cognitive attention was also a significant determinant, with frequency of thinking about air quality being the strongest cognitive predictor. About 47% of daily users rated air as Poor/Very Poor, compared with 28% of weekly thinkers and 18% of those thinking monthly or less (Table S15 and Figure 7). Multivariable analysis confirmed this association, with daily thinkers having 2.6 times higher odds (95% CI: 1.4–5.0) of poor or very poor perceptions (Table 6). Longer durations of stay and motorised transport use were also significant predictors. By contrast, underlying health status was not independently associated with perception after adjustment. Logistic regression analysis indicated that having an underlying health condition was not a significant predictor of air quality perception (AOR = 1.21, 95% CI: 0.63–2.35, $p = 0.56$). This suggests that respondents' health conditions do not meaningfully influence how they perceive air quality in Calabar.

Overall, these patterns suggest that poor perceptions are not randomly distributed but cluster among groups with greater exposure duration (sellers, long-stayers), transport-related risk (bus/motorbike users), and stronger cognitive engagement with environmental risks. These findings are consistent with AQI variability driven by traffic congestion, refuse burning, and generator emissions in Calabar's urban core.

Despite 39% perceiving poor/very poor air quality, only 10.5% ($n = 21$) reported adapting their behaviour (Table S16 and Figure 8). These adaptations included avoiding certain areas, changing routes, reducing visit frequency, or altering visit times. The low overall prevalence of behavioural change suggests that even when residents recognise pollution, practical or economic constraints limit protective responses. Given the small

Table 6. Multivariable logistic regression predicting perception of air quality as 'Poor/Very Poor' ($n = 200$).

Predictor	Adjusted Odds Ratio (AOR)	95% CI	*p*-value
Age group (ref: Middle-aged)			
Young adults	1.32	0.70–2.49	0.39
Older adults	0.88	0.41–1.91	0.74
User type (ref: Buyers/Visitors)			
Sellers	1.54	0.82–2.88	0.17
Residents/Office workers	1.12	0.53–2.37	0.76
Duration of stay (ref: <1 h)			
1–5 h	1.47	0.65–3.33	0.35
6–12 h	2.32	1.05–5.12	*0.037*
≥12 h	3.10	1.21–7.94	*0.018*
Transport mode (ref: Walking)			
Bus	2.08	1.05–4.11	*0.035*
Motorbike	1.96	0.92–4.18	0.08
Car	1.64	0.73–3.69	0.23
Thinking about air quality (ref: Rarely/Yearly)			
Monthly	1.34	0.59–3.05	0.48
Weekly	2.04	1.01–4.10	*0.046*
Daily	2.60	1.40–5.00	*0.003*
Underlying health condition (ref: No)	1.21	0.63–2.35	*0.56*

Notes: Multivariable logistic regression; dependent variable = perceived air quality (Poor/Very Poor vs. Okay/Good). Bold *p*-values indicate significance at $p < 0.05$.

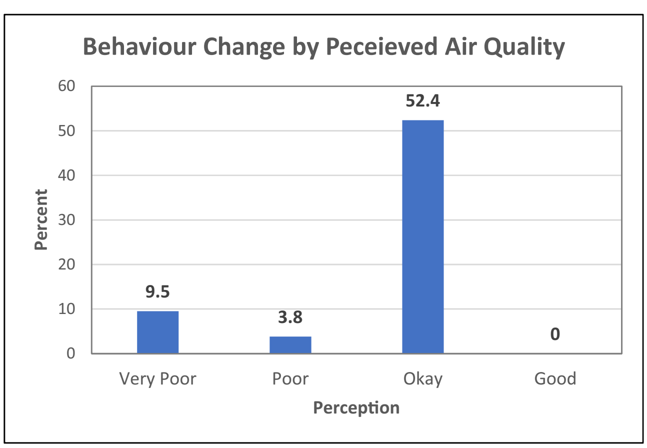


Figure 8. Percentage reporting behavioural change by perceived air quality level.

Table 7. Multivariable logistic regression predicting behavioural change due to air pollution (n = 200).

Predictor	Adjusted Odds Ratio (AOR)	95% CI	*p*-value
Age group (ref: Middle-aged)			
Young adults	1.22	0.51–2.90	0.65
Older adults	1.36	0.54–3.43	0.52
User type (ref: Buyers/Visitors)			
Sellers	1.74	0.77–3.92	0.18
Residents/Office workers	1.11	0.44–2.78	0.82
Duration of stay (ref: <1 h)			
1–5 h	1.21	0.39–3.75	0.74
6–12 h	1.58	0.53–4.74	0.41
≥12 h	1.92	0.62–5.92	0.26
Transport mode (ref: Walking)			
Bus	1.41	0.64–3.11	0.39
Motorbike	1.55	0.59–4.08	0.37
Car	1.28	0.46–3.53	0.63
Thinking about air quality (ref: Rarely/Yearly)			
Monthly	1.44	0.49–4.22	0.51
Weekly	1.72	0.67–4.41	0.26
Daily	2.05	0.87–4.85	0.10
Perceived air quality (Poor/Very Poor vs. Okay/Good)	3.10	1.60–6.00	*0.001*
Underlying health condition (ref: No)	1.17	0.54–2.53	0.69

Notes: Multivariable logistic regression; dependent variable = reported behavioural change (Yes vs. No). Perception of Poor/Very Poor air quality was the strongest independent predictor.

number of respondents reporting behavioural change (n = 21), bivariate comparisons are interpreted as exploratory.

Behavioural adaptations were closely linked to perception. About 13% of respondents rating air as Poor/Very Poor reported adaptations, compared with only 9% of those rating it Okay/Good (Table S17 and Figure 8). Logistic regression confirmed this, with poor/very poor perception associated with 3.1 times higher odds (95% CI: 1.6–6.0) of behaviour change, independent of socio-demographic, market-use, or health variables (Table 7). Again, health status was not a statistically significant predictor of behavioural change in these models. However, this null finding should be interpreted cautiously given limited power for subgroup comparisons and potential exposure misclassification.

This indicates a clear perception–behaviour pathway, from higher perceived pollution to greater likelihood of adaptation. However, given that fewer than one in ten respondents changed behaviour overall, this suggests that awareness of exposure risk does not consistently translate into protective practices. Barriers may include economic dependence on the market, limited transport alternatives, or normalisation of pollution exposure.

The results suggest that subjective perceptions are influenced by exposure duration and transport-related contexts, both of which may correspond to micro-environmental conditions characterised by traffic density, visible emissions, and prolonged time spent in high-activity zones within Watt Market and Calabar Road. Perceptions, in turn, appear to be associated with behavioural responses. However, only a small proportion of respondents translated concern into protective adaptation.

This mismatch reflects a perception–behaviour gap, whereby many respondents recognised pollution hazards (39% reporting Poor/Very Poor air quality), yet relatively few reported changing behaviour (10.5%). Rather than indicating that average AQI values necessarily fall within higher-risk categories, this pattern may reflect short-term exposure episodes, sensory cues, and structural or economic constraints that limit adaptive capacity. In particular, sellers and frequent commuters may experience longer exposure within traffic-influenced micro-environments, even where aggregated AQI and PERI classifications remain within lower-risk categories.

4. Discussion and conclusion

4.1. Interpretation of findings

This study examined patterns of Watt Market and Calabar Road use, perceptions of air pollution, and population exposure risks in Calabar, Nigeria. Survey data (n = 200) suggest that the market functions as a convergence point for respondents drawn from multiple residential areas across the city, drawing visitors from both central neighbourhoods and peripheral settlements. Despite these flows, all residential groups fell under Population Index 1, and AQI and PERI data indicated very low cumulative exposure risk levels. These findings suggest that Watt Market, while central to daily mobility and commerce, currently appears to pose relatively low cumulative exposure risk under observed conditions and within the adopted screening framework.

A key finding is the clear gap between measured air quality and public perception. Although AQI and PERI results placed most locations in 'Good' or 'Marginally Polluted' categories, 39% of respondents rated conditions as poor/very poor. Multivariable analysis revealed perception clustered in identifiable groups such as respondents who thought about air quality daily (AOR 2.6, 95% CI: 1.4–5.0), long-stayers spending ≥12 hours in the market (AOR 3.1, 95% CI: 1.2–7.9), and bus users (AOR 2.1, 95% CI: 1.1–4.1). These predictors align with contexts where exposure to traffic emissions, refuse burning, and generator fumes is most visible and odorous, even if average AQI levels remain low. This supports risk perception theory (Slovic, 1987) by showing how sensory cues, rather than measured concentrations alone, shape public assessments of environmental hazards. Similar mismatches have been documented in Lagos and Nairobi (Ajayi et al., 2023; Muindi et al., 2014). Calabar contributes to this literature by illustrating that even under comparatively low measured risks, perception of pollution remains heightened when exposure is prolonged or traffic-related.

Despite widespread recognition of pollution sources, behavioural responses were low. Only 10.5% of respondents reported changes such as altering routes, visit times, or reducing frequency. Logistic regression confirmed that perception of poor/very poor air quality was the only significant independent predictor of behaviour change (AOR 3.1, 95% CI: 1.6–6.0). At the same time, socio-demographic and health variables showed no effect. However, these null associations should be interpreted cautiously, given limited statistical power for some subgroup comparisons and potential non-differential exposure misclassification. This indicates a clear perception–behaviour pathway, where frequent cognitive attention is associated with poorer perception and a greater likelihood of behavioural adjustment. However, the low overall prevalence of adaptation suggests that structural constraints, including economic dependence on daily trading, limited transport alternatives, and normalisation of exposure, restrict protective responses.

Although AQI and PERI indicated generally low cumulative risk at the population level, vulnerability theory helps explain why specific groups may remain disproportionately affected. Older adults reported higher rates of chronic health conditions (41%) compared with younger respondents, making them more susceptible to even modest exposure levels. WHO and Global Burden of Disease literature indicate that low to moderate air pollution exposure can exacerbate cardiovascular and respiratory conditions among older adults and individuals with pre-existing illnesses (GBD 2019 Risk Factors Collaborators, 2020; World health organisation (WHO), 2021). Sellers and transport operators, who spend prolonged periods in traffic-congested or generator-dense environments, also reported poorer perceived air quality and may experience greater cumulative exposure duration. From an environmental justice perspective, these findings highlight inequalities in exposure and adaptive capacity: those least able to avoid pollution are also those most vulnerable to its health consequences.

Exposure at Watt Market is not static but rhythmically structured by daily mobility patterns. Vendors typically remain in fixed stalls for extended periods (6–12 hours), transport operators cycle between roadside loading zones and arterial routes, and customers move intermittently between stalls and transport corridors. While this study relied on static AQI averages, exposure intensity likely varies across time and micro-locations, particularly during peak traffic hours. Future research integrating time-resolved AQI monitoring with time–activity tracking would allow more precise assessment of these rhythms of exposure.

4.2. Policy and practice implications

Findings from this study carry several practical implications. In the short term, community-based monitoring using low-cost air quality sensors at key market entrances and transport hubs could provide locally relevant data and enhance transparency. Public AQI display boards and targeted communication strategies may help translate technical air quality information into context-specific messages linked to visible sources such as refuse burning or generator emissions. Improved waste management practices and enforcement of generator emission controls represent feasible immediate interventions.

Longer-term structural measures may include traffic flow reorganisation around Calabar Road, designated loading and unloading zones to reduce curbside congestion, and phased redesign of market layouts to improve ventilation and pedestrian flow. Integrating air quality considerations into urban transport and land-use planning will be essential as Calabar continues to urbanise.

4.3. Limitations and threats to validity

This study has several limitations that should be considered when interpreting the findings. The sample size ($n = 200$), while adequate for exploratory analysis, represents a small proportion of total market users and was unevenly distributed across residential areas. A substantial proportion of respondents did not specify residence, limiting spatial precision in exposure differentiation.

Reliance on secondary AQI data introduced potential temporal misalignment between environmental measurements and survey responses. Although the AQI dataset provides a structured baseline of air quality conditions, it may not fully capture short-term changes during peak activity periods.

The PERI framework, while transparent and replicable, simplifies exposure dynamics by combining aggregated AQI values with population density indices. Pollutant-specific weighting was not applied because disaggregated concentration data were unavailable for the study area despite attempts to obtain them. In addition, the absence of location weighting and dynamic time–activity tracking limits micro-scale exposure differentiation within specific market zones.

Accordingly, findings should be interpreted as initial guidance based on currently available data rather than definitive risk quantification. Future research incorporating pollutant-specific weighting, time–activity diaries, and dynamic flow monitoring would enable more refined exposure assessment and strengthen internal validity.

4.4. Conclusion

Watt Market and Calabar Road appear central to urban mobility patterns among surveyed participants, yet under currently observed conditions and within the adopted screening framework, appear to be associated with relatively low cumulative exposure risk according to AQI and PERI indicators. Nevertheless, perceptions of poor air quality remain widespread and are concentrated among individuals with prolonged exposure durations and higher contextual vulnerability.

Even where measured risks are low, inequalities in exposure duration, health status, and adaptive capacity mean that vulnerability cannot be dismissed. As Calabar continues to urbanise, proactive monitoring, targeted education, and participatory interventions will be essential to sustain low-risk conditions while addressing inequities in exposure and resilience.

Public interest statement

Informal markets and transport corridors are vital economic and social hubs in urban centres, especially in rapidly growing low- and middle-income countries (LMICs). Yet these high-activity spaces can expose users to environmental health risks, notably air pollution, during everyday mobility and trading activities. Limited evidence exists on how such environments shape population exposure, risk perception, and behavioural responses. This study examines Watt Market and its adjoining transport corridor in Calabar, Nigeria, integrating survey data with air quality indicators to assess exposure patterns and vulnerability. While objective classifications placed the market and surrounding residential areas within lower exposure categories under the adopted screening framework, many respondents perceived air quality as poor and reported limited awareness of protective measures. The findings reveal a gap between measured conditions and lived experience, underscoring the need for community-based monitoring, targeted risk communication, and more inclusive urban environmental planning to support sustainable public health protection.

Acknowledgements

The authors thank the University of Cross River students, market authorities, and community members for their support in data collection for this study.

CRediT: All authors made substantial contributions to this study. **Ekpo Otu and Ajah Obia** contributed to the conceptualisation and study design. **Ekpo Otu** conducted the formal analysis, data visualisation, and draughted the original manuscript. **Abiodun Oyetunji and Ajah Obia** provided overall supervision and critical review of the manuscript. **Theresa Eja** coordinated and supervised field data collection (questionnaires) and data management. All authors read and approved the final version of the manuscript.

Author contributions

CRediT: **Ekpo Otu:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft; **Ajah Obia:** Conceptualization, Supervision, Writing – review & editing; **Abiodun Oyetunji:** Supervision, Writing – review & editing; **Theresa Eja:** Investigation, Writing – review & editing.

Notes on contributors

Dr. Ekpo Ekpenyong Otu is an interdisciplinary environmental scientist, architectural researcher, and academic whose work focuses on air quality, public health, and design for the built environment. Trained as an architect and in environmental sciences, he completed his PhD in Environmental Sciences at Lancaster University, United Kingdom, where his research explored design-based interventions to mitigate the public health impacts of urban air pollution. His research interests include air pollution exposure assessment, environmental health, urban resilience, sustainable architecture and urban design, and participatory community interventions. Dr. Otu's recent work integrates social and urban design perspectives into air pollution research, traditionally driven by epidemiological and natural science methods, to develop evidence-based solutions for reducing pollution exposure risks in cities, drawing on research conducted in both the United Kingdom and Nigeria.

Professor Ajah Ekpeni Obia is a Professor of Sustainable Architecture and Dean of the Faculty of Architecture at the University of Cross River State, Calabar, Nigeria. A chartered architect and academic, his work focuses on sustainable architecture, environmental management, and the built environment. He holds degrees in Architecture and Environmental Management from the University of Nigeria, University of Calabar, and Imo State University, including dual doctoral qualifications in Environmental Management and Architecture. Professor Obia's research interests include sustainable design, environmental planning, and resilient built environments, with extensive contributions to architectural education and professional practice in Nigeria.

Dr. Oyetunji is an academic and researcher in the built and environmental sciences whose work focuses on sustainability, flood risk management, housing, and climate-resilient urban development. He holds a PhD in Built and Environmental Sciences, with research centred on the impact of flood risk on residential property investment decisions. His expertise spans the wider built environment, including real estate, urban studies, and resilient development practices. He has held academic appointments at London Metropolitan University, the University of Benin, and the Federal University of Technology, Akure. Dr. Oyetunji has published extensively in peer-reviewed journals and contributes actively to research, teaching, and professional practice in the built environment sector.

Theresa Theodore Eja is an estate management professional and sustainability advocate with interests in sustainable land use, resource management, and the built environment. A graduate of Estate Management from the Faculty of Environmental Sciences at the University of Cross River State, her work focuses on the intersection of environmental sustainability, urban development, and human livelihoods, particularly in emerging African contexts. She is the Founder and Executive Director of Girls in Power Foundation and contributes to community development initiatives that advance women's leadership, youth empowerment, and long-term social and environmental resilience.

Disclosure statement

The authors declare no known conflict of interest.

Funding

Open-access funding was provided by Lancaster University under the OA agreement. This research received no external funding.

ORCID

Ekpo Otu 0009-0007-5625-7023
Abiodun Oyetunji 0000-0002-5396-4722

Data availability statement

The authors will share the research data upon request.

Ethical approval

This study was reviewed and approved by the Faculty of Science and Technology Research Ethics Committee (FSTREC), Lancaster University, under approval reference number FST20047. All procedures were conducted in accordance with the ethical standards of the institutional research committee and the 1964 Declaration of Helsinki and its later amendments.

Consent to publish

All authors have read and approved the final version of the manuscript and agree to its publication.

Consent to participate

Informed consent was obtained from all participants involved in the study. As all participants were aged 18 years and above, consent was sought from each participant before participating in both the online and face-to-face surveys. Online participants provided digital consent before accessing the first survey question, while written (signed) consent was obtained for in-person interviews, including consent to record responses (where literacy and language barriers were encountered).

Declaration of generative AI and AI-assisted technology in scientific writing

No scientific or pedagogic insights, scientific conclusions, or recommendations in this manuscript or the initial draft were drawn using AI-related technologies.

References

Abam, F. I., & Unachukwu, G. O. (2009). Vehicular emissions and air quality standards in Nigeria. *European Journal of Scientific Research*, *34*(4), 550–560.

Ajayi, S. A., Adams, C. A., Dumedah, G., Adebanji, O. A., & Ackaah, W. (2024). Modelling of risk of health burden based on residents' exposure near trafficked intersection. *Journal of Transport & Health*, *37*. 101833. https://doi.org/10.1016/j.jth.2024.101833

Ajayi, S. A., Adams, C. A., Dumedah, G., Adebanji, O. A., Ababio-Donkor, A., Ackaah, W., & Kehinde, A. (2023). Public perceptions of vehicular traffic emissions on health risk in lagos metropolis Nigeria: A critical survey. *Heliyon*, *9*(5), e15712. https://doi.org/10.1016/j.heliyon.2023.e15712

Amegah, A. K., Dakuu, G., Mudu, P., & Jaakkola, J. J. K. (2021). Particulate matter pollution at traffic hotspots of Accra, Ghana: levels, exposure experiences of street traders, and associated respiratory and cardiovascular symptoms. *Journal of Exposure Science & Environmental Epidemiology*, *32*(2), 333–342. https://doi.org/10.1038/s41370-021-00357-x

Arku, R. E., Vallarino, J., Dionisio, K. L., Willis, R., Choi, H., Wilson, J. G., Hemphill, C., Agyei-Mensah, S., Spengler, J. D., & Ezzati, M. (2008). Characterizing air pollution in two low-income neighborhoods in Accra, Ghana. *The Science of the Total Environment*, *402*(2–3), 217–231. https://doi.org/10.1016/j.scitotenv.2008.04.042

Atkinson, R. W., Mills, I. C., Walton, H. A., & Anderson, H. R. (2015). Fine particle components and health—A systematic review and meta-analysis of epidemiological time series studies of daily mortality and hospital admissions. *Journal of exposure science & environmental epidemiology*, *25*, 208–214. https://doi.org/10.1038/jes.2014.63

Aunan, K., Ma, Q., Lund, M. T., & Wang, S. (2018). Population-weighted exposure to $PM_{2.5}$ pollution in China: an integrated approach. *Environment International*, *120*, 111–120. https://doi.org/10.1016/j.envint.2018.07.041

Bassey, B., Eni, D., & Bassey, A. (2023). Implications of urban traffic congestion calabar, Nigeria. *Saudi Journal of Humanities and Social Sciences*, *12*, 26–40. https://www.researchgate.net/publication/374004872_Implications_of_Urban_Traffic_Congestion_Calabar_Nigeria

Bassi, V., Kahn, M. E., Gracia, N. L., Porzio, T., & Sorin, J. (2021). Pollution in Ugandan cities: do managers avoid it or adapt in place? *UC Berkeley: Center for Effective Global Action*, http://dx.doi.org/10.26085/C3W01Q

Bell, M. L., Zanobetti, A., & Dominici, F. (2013). Evidence on vulnerability and susceptibility to health risks associated with short-term exposure to particulate matter: A systematic review and meta-analysis. *American Journal of Epidemiology*, *178*(6), 865–876. https://doi.org/10.1093/aje/kwt090

Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C. A., 3rd, Apte, J. S., Brauer, M., Cohen, A., Weichenthal, S., Coggins, J., Di, Q., Brunekreef, B., Frostad, J., Lim, S. S., Kan, H., Walker, K. D., Thurston, G. D., Hayes, R. B., … Spadaro, J. V. (2018). Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proceedings of the National Academy of Sciences of the USA*, *115*, 9592–9597. https://doi.org/10.1073/pnas.1803222115

Chen, Z., Petetin, H., Turrubiates, R. F. M., Achebak, H., García-Pando, C. P., & Ballester, J. (2094). Population exposure to multiple air pollutants and its compound episodes in Europe. *Nature Communications*, *15*, 2024. https://doi.org/10.1038/s41467-024-39701-7

Cohen, A. J., Brauer, M., Burnett, R., Anderson, H. R., Frostad, J., Estep, K., Balakrishnan, K., Brunekreef, B., Dandona, L., Dandona, R., Feigin, V., Freedman, G., Hubbell, B., Jobling, A., Kan, H., Knibbs, L., Liu, Y., Martin, R., Morawska, L., … Murray, C. J. L. (2017). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the global burden of diseases study 2015. *The Lancet*, *389*(10082), 1907–1918. https://doi.org/10.1016/s0140-6736(17)30505-6

De Vries, G. (2019). Public communication as a tool to implement environmental policies. *Social Issues and Policy Review*, *14*(1), 244–272. https://doi.org/10.1111/sipr.12061

Ezedike, C., Ohazurike, E., Emetumah, F. C., & Ajaegbu, O. O. (2020). Health-seeking behavior and waste management practices among women in major urban markets in owerri, Nigeria. *AIMS public health*, *7*(1), 169–187. https://doi.org/10.3934/publichealth.2020015

Ezeonyejiaku, C. D., Okoye, C. O., Ezeonyejiaku, N. J., & Obiakor, M. O. (2022). Air quality in Nigerian urban environments: A comprehensive assessment of gaseous pollutants and particle concentrations. *Current Applied Science and Technology*, *22*(5), 1–15. https://doi.org/10.55003/cast.2022.05.22.011

Ezeudu, O. B., Ezeudu, T. S., Ugochukwu, U. C., Agunwamba, J. C., & Oraelosi, T. C. (2021). Enablers and barriers to implementation of circular economy in solid waste valorization: the case of urban markets in anambra, southeast Nigeria. *Environmental and Sustainability Indicators*, *12*. 100150. https://doi.org/10.1016/j.indic.2021.100150

Ezzati, M., Utzinger, J., Cairncross, S., Cohen, A. J., & Singer, B. H. (2005). Environmental risks in the developing world: exposure indicators for evaluating interventions, programmes, and policies. *Journal of epidemiology and community health*, 59(1), 15–22. https://doi.org/10.1136/jech.2003.019471

GBD 2019 Risk Factors Collaborators. (2020). Global burden of 87 risk factors in 204 countries and territories, 1990–2019: A systematic analysis for the global burden of disease study 2019. *Lancet*, *396*, 1223–1249. https://doi.org/10.1016/S0140-6736(20)30752-2

Health Effects Institute (2022). *Air Quality and Health In Cities: A State of Global Air Report 2022*. Boston, MA: Health Effects Institute. https://www.stateofglobalair.org/sites/default/files/documents/2022-08/2022-soga-cities-report.pdf

Hoek, G., Krishnan, R., Beelen, R., Peters, A., Ostro, B., Brunekreef, B., & Kaufman, J. D. (2013). Long-term air pollution exposure and cardio-respiratory mortality: A review. *Environmental Health*, *12*(1), 43. https://doi.org/10.1186/1476-069x-12-43

Huang, G., & Brown, P. E. (2021). Population-weighted exposure to air pollution and COVID-19 incidence in Germany. *Spatial Statistics*, *41*. 100480. https://doi.org/10.1016/j.spasta.2020.100480

Isangadighi, G., & Ukudo, B. (2025). Perceptions and Awareness of Air Quality and Its Health Impacts in Agbarho Community, Ughelli North, Delta State. *Journal of African Innovation and Advanced Studies*, 7(2), https://doi.org/10.70382/ajaias.v7i2.030

Ivy, D., Mulholland, J. A., & Russell, A. G. (2008). Development of ambient air quality population-weighted metrics for use in time-series health studies. *Journal of the Air & Waste Management Association*, *58*(5), 711–720. https://doi.org/10.3155/1047-3289.58.5.711

Jbaily, A., Zhou, X., Liu, J., Lee, T., Kamareddine, L., Verguet, S., & Dominici, F. (2022). Air pollution exposure disparities across US population and income groups. *Nature (London, United Kingdom)*, *601*(7892), 228–233. https://doi.org/10.1038/s41586-021-04190-y

Jiang, Y., Huang, G., & Fisher, B. (2019). Air quality, human behavior and urban park visit: A case study in Beijing. *Journal of Cleaner Production*, *240*. 118000. https://doi.org/10.1016/j.jclepro.2019.118000

Jing, M. A., Yanwei, C., & Tingting, F. U. (2017). Progress of research on the health impact of people' space-time behavior and environmental pollution exposure. *Progress in Geography*, *36*, 1260–1269. https://doi.org/10.18306/dlkxjz.2017.10.008

Lelieveld, J., Pozzer, A., Pöschl, U., Fnais, M., Haines, A., & Münzel, T. (2020). Loss of life expectancy from air pollution compared to other risk factors: A worldwide perspective. *Cardiovascular Research*, *116*(11), 1910–1917. https://doi.org/10.1093/cvr/cvaa025

Levasseur, P., Erdlenbruch, K., Gramaglia, C., Bento, S., Fernandes, L., & Páez, P. B. (2022). Does pollution perception lead to risk avoidance behaviour? A mixed methods analysis. *Review of Social Economy*, *82*(4), 581–607. https://doi.org/10.1080/00346764.2022.2030542

Mannucci, P. M., & Franchini, M. (2017). Health effects of ambient air pollution in developing countries. *International journal of environmental research and public health*, *14*(9), 1048. https://doi.org/10.3390/ijerph14091048

McDuffie, E. E., Martin, R. V., Spadaro, J. V., Burnett, R., Smith, S. J., O'Rourke, P., Hammer, M. S., Van Donkelaar, A., Bindle, L., Shah, V., Jaeglé, L., Luo, G., Yu, F., Adeniran, J. A., Lin, J., & Brauer, M. (2021). Source sector and fuel contributions to ambient PM2.5 and attributable mortality across multiple spatial scales. *Nature Communications*, *12*(1), 3594. https://doi.org/10.1038/s41467-021-23853-y

McKercher, B., Prideaux, B., Cheung, C., & Law, R. (2010). Achieving voluntary reductions in the carbon footprint of tourism and climate change. *Journal of Sustainable Tourism*, *18*(3), 297–317. https://doi.org/10.1080/09669580903395022

Muindi, K., Egondi, T., Kimani-Murage, E., Rocklov, J., & Ng, N. (2014). "We are used to this": A qualitative assessment of the perceptions of and attitudes towards air pollution amongst slum residents in Nairobi. *BMC public health*, *14*(1), 226. https://doi.org/10.1186/1471-2458-14-226

Nduka, J. K., Offor, C. C., & Mgboh, V. O. (2025). Health risk status of roadside dwellers by heavy metal(loid) contamination of dusts of major and remote roads from selected areas of eastern Nigeria. *Discover Environment*, *3*(1), 130. https://doi.org/10.1007/s44274-025-00313-8

Obaseki, D. O., Adeniyi, B., Jumbo, J., Oyewo, A., Irabor, I., & Erhabor, G. E. (2014). Respiratory symptom, lung function and exhaled carbon monoxide among a sample of traffic workers in lagos, Nigeria: A pilot survey. *Nigerian medical journal: journal of the Nigeria Medical Association*, *55*(4), 306–309. https://doi.org/10.4103/0300-1652.137190

Obinna, R. O., Oparaocha, E. T., Okaba, A. E., Igiri, V. C., Paul, J. N., O, O. R., T, O. E., E, O. A., C, I. V., N, P. J., F, C. I., W, K., I, A., & U, I. A. (2025). Awareness and perceptions of reisdents of port harcourt on the health effects of pollutants from vehicular emissions in port harourt metropolis. *Scholars Journal of Applied Medical Sciences*, *13*(04), 887–892. https://doi.org/10.36347/sjams.2025.v13i04.010

Odum, O., & Aloba, O. (2014). Urban transportation challenges in calabar: causes, implications and solutions. *International Journal of Scientific and Technology Research*, *3*(11), 266–269. https://www.ijstr.org/final-print/nov2014/Urban-Transportation-Challenges-In-Calabar-Causes-Implications-And-Solutions.pdf

Ojukwu, C. P., Okemuo, A. J., Madu, C. V., Ativie, R. N., Caesar, C. S., & Moris, A. E. (2020). Pulmonary functions of commercial tricyclists (Keke Napep riders) in enugu state, Nigeria. *African health sciences*, *20*(2), 798–805. https://doi.org/10.4314/ahs.v20i2.33

Oladejo, O. J., Odeyale, T. O., & Adiamo, B. R. (2020). Effect of air pollution from pedestrian traffic in an open market: A case study of bodija market, Nigeria. *International Journal of Sustainable Development and Planning*, *15*(7), 1137–11444. https://doi.org/10.18280/ijsdp.150718

Olufemi, A. P., Fawole, O. G., Owoade, O. K., Popoola, O. A. M., Jones, R. L., Toyeje, A. B., Abiodun, P. O., Omokungbe, O. R., Abiye, O. E., & Sunmonu, L. A. (2023). Spatiotemporal distribution of pollutants and impact of local meteorology on source influence on pollutants' level in a traffic air-shed in lagos megacity, Nigeria. *Environmental Monitoring And Assessment*, *195*, 1126. https://doi.org/10.1007/s10661-023-11757-x

Oragba, CH, Okeke, PN, & Ejiogu, CC (2023). Determination of air quality levels in selected markets in owerri metropolis and its environs imo state, Nigeria. *International Journal of Innovative Science and Research Technology (IJISRT)*, *8*(1), 2288–2299. https://doi.org/10.5281/zenodo.7643096

Osoja, A. O. (2019). The effects of market location on traffic flow in lagos state. *International Journal of Research and Innovation in Social Scienc*, *3*(2), 79–89 https://www.researchgate.net/publication/357032138_The_Effects_of_Market_Location_on_Traffic_Flow_in_Lagos_State#fullTextFileContent.

Otu, E. (2025). *Exploring design-based interventions for mitigating public health impacts of urban air pollution. PhD dissertation, Lancaster University.* [Doctoral Thesis, Lancaster University]. Lancaster, UK. https://doi.org/10.17635/lancaster/thesis/2737

Otu, E., Ashworth, K., & Tsekleves, E. (2024). Rhythm of exposure in town centres: A case study of lancaster city centre. *Environments*, *11*, 132. https://doi.org/10.3390/environments11070132

Otuu, F. C., Shu, E. N., Maduka, I. C., Ilouno, L., & Orjiocha, S. I., et al. (2018). Vehicular activities and tailpipe carbon (II) oxide emission at osisioma-aba, abia state, Nigeria: A potential public health hazard to roadside traders and artisans. *Journal of Medical Toxicology Research*, *1*, 2. https://www.scitechnol.com/peer-review/vehicular-activities-and-tailpipe-carbon-ii-oxide-emission-at-osisiomaaba-abia-state-nigeria-a-potential-public-health-hazard-to-r-ySrh.php?article_id=7760

Owoade, O. K., Abiodun, P. O., Omokungbe, O. R., Fawole, O. G., Olise, F. S., Popoola, O. O. M., Jones, R. L., & Hopke, P. K. (2021). Spatial-temporal variation and local source identification of air pollutants in a semi-urban settlement in Nigeria using low-cost sensors. *Aerosol and Air Quality Research*, *21*, 200598. https://doi.org/10.4209/aaqr.200598

Pope, C. A., & Dockery, D. W. (2006). Health effects of fine particulate air pollution: lines that connect. *Journal of the Air & Waste Management Association*, *56*(6), 709–742. https://doi.org/10.1080/10473289.2006.10464485

Ramírez, A. S., Ramondt, S., Van Bogart, K., & Perez-Zuniga, R. (2019). Public awareness of air pollution and health threats: challenges and opportunities for communication strategies to improve environmental health literacy. *Journal of Health Communication*, *24*(1), 75–83. https://doi.org/10.1080/10810730.2019.1574320

Scoggins, A., & Fisher, G. (2002). Air pollution exposure index for New Zealand. *New Zealand Geographer*, *58*(2), 56–64. https://doi.org/10.1111/j.1745-7939.2002.tb00459.x

Shakor, A. S. A., Pahrol, M. A., & Mazeli, M. I. (2020). Effects of population weighting on PM_{10} concentration estimation. *Journal of Environmental and Public Health*, *2020*. 1561823. https://doi.org/10.1155/2020/1561823

Slovic, P. (1987). Perception of risk. *Science (New York, N.Y.)*, *236*(4799), 280–285. https://doi.org/10.1126/science.3563507. http://www.jstor.org/stable/1698637

U.S. Environmental Protection Agency (2024). *Technical assistance document for the reporting of daily air quality – the Air Quality Index (AQI)*. U.S. Environmental Protection Agency. https://nepis.epa.gov/Exe/ZyPDF.cgi/P101AP0Q.PDF?Dockey=P101AP0Q.PDF

Udo, S., Umoh, M., & Ewona, I. (2024). Evaluating the impact of renewable energy integration on air quality: A study of pollutant reduction in an urban city of calabar. *Trends in Renewable Energy*, *11*(1), 24–51. https://doi.org/10.17737/tre.2025.11.1.00184

Ukpebor, E. E., Ukpebor, J. E., Oviasogie, P. O., Odiase, J. I., & Egbeme, M. A. (2006). Field comparison of two total suspended particulates (TSP) samplers to assess spatial variation. *International Journal of Environmental Studies*, *63*(5), 567–577. https://doi.org/10.1080/00207230600963866

West, S., Loh, M., Malley, C., & Bowyer, C. (2021). Urban air pollution and children in low- and middle-income countries." In Research Series: Cities for Children and Youth, edited by Sarah Sabry. Zurich: Global Alliance - Cities 4 Children.

World health organization (WHO) (2016). *Ambient air pollution: A global assessment of exposure and burden of disease*. Geneva, Switzerland: WHO. Available online: (accessed on 17 July 2023). https://www.WHO.int/publications/i/item/9789241511353

World health organization (WHO) (2021). *WHO global air quality guidelines: Particulate matter ($PM_{2.5}$ and PM_{10}), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide.* Geneva, Switzerland: WHO. Available online: (accessed on 27 December 2022) https://www.WHO.int/publications/i/item/9789240034228

Wu, Y., Xu, J., Liu, Z., Han, B., Yang, W., & Bai, Z. (2024). Comparison of population-weighted exposure estimates of air pollutants based on multiple geostatistical models in Beijing, China. Toxics, *12*(3), 197. https://doi.org/10.3390/toxics12030197

Yaro, M., Obongha, U., & Okon, A. (2019). WASTE DISPOSAL SCENARIO IN COMMERCIAL MARKET OF CALABAR, Southern Nigeria. *Journal of Global Biosciences*, 8, 6301–6312. https://www.researchgate.net/publication/353701552_WASTE_DISPOSAL_SCENARIO_IN_COMMERCIAL_MARKET_OF_CALABAR_SOUTHERN_NIGERIA