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Research article

Personal air pollution exposure assessment with schoolchildren in rural Wales

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ABSTRACT

Children are particularly vulnerable to air pollution. However, most UK exposure studies focus on urban areas, mainly school environments and commutes. Rural settings, where distinct pollution sources and personal exposure patterns can differ, are often overlooked. This study assessed schoolchildren's personal $PM_{2.5}$ exposure across home, school, and commute settings on the Isle of Anglesey, a rural area in North Wales. Using low-cost sensors and a citizen science approach, it generated first-hand data while engaging children in monitoring. The pilot study involved 53 children from two primary schools, with 94 % providing valid data. Results showed that the average daily mean $PM_{2.5}$ exposure across all participants was 6.5 μg/m^3, though individual daily means reached as high as 43.5 μg/m^3. Home environments exhibited the highest and most variable $PM_{2.5}$ levels, linked to indoor sources such as wood burners and adult smoking reported by the participating students. The placement of sensors within households also significantly influenced exposure measurements. In contrast, levels during school hours and commutes were lower and more stable, with occasional spikes, for instance, during walks (depending on the route) or when exposed to second-hand smoke from adult smoking in cars. Children attending the rural school had slightly higher $PM_{2.5}$ exposure across all microenvironments when compared to the urban school, potentially tied to higher wood burner use, suggesting links between heating practices, fuel poverty, and socioeconomic factors. Crucially, the findings highlight that parents' behaviours play a more significant role in determining children's exposure levels than the children's own choices.

1. Introduction

Air pollution poses significant health risks, particularly to children, who are more vulnerable due to their immature respiratory systems and higher inhalation rates relative to body weight (Carroquino et al., 2013). The World Health Organization (WHO) estimates that over 90 % of children worldwide live in environments where air pollution exceeds the annual mean $PM_{2.5}$ limit of 10 μg/m^3 (WHO, 2018). Short-term exposure to particulate matter (PM) can aggravate asthma, reduce lung function, and increase respiratory infections (Liu et al., 2018), while long-term exposure is linked to impaired lung growth, asthma onset, and other atopic conditions (Aithal et al., 2023). Evidence also links air pollution to adverse neurocognitive outcomes, including autism and ADHD (Ha, 2020). Reflecting these risks, the WHO revised its air quality guidelines in 2021, halving the annual mean PM2.5 limit to 5 μg/m^3 and the 24-h mean to 15 μg/m^3, indicating that the health risks of PM2.5 are greater than previously recognized and warrant heightened attention (WHO, 2021).

The UK has made significant progress in reducing ambient air pollution since 1990, with PM emissions decreasing by 73 % (DEFRA, 2025). However, many children remain exposed to levels above WHO guidelines, with over a third of English schools located in areas where annual mean $PM_{2.5}$ exceeds 10 μg/m^3 (Osborne et al., 2021a). Air pollution exposure among UK children has traditionally been assessed using fixed-site monitoring stations and school-based sensor networks (Osborne et al., 2021b). However, these methods often overlook the spatial and temporal variability of exposure and fail to account for individual behaviours and mobility patterns (Steinle et al., 2013).

To improve the accuracy of personal exposure estimates, researchers have increasingly used portable air pollution sensors combined with GPS

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tracking to monitor children's exposure across different microenvironments. Numerous urban studies have adopted this approach. For example, in Barcelona, the highest personal black carbon (BC) exposures occurred during commutes, with the lowest levels at home (Alvarez-Pedrerol et al., 2017). Similarly, research in Cincinnati showed that ultrafine particle (UFP) exposure was highest at home, followed by transit, and lowest at school (Ryan et al., 2015). These studies clearly demonstrate that children's exposure varies significantly by activity and location.

In the UK, personal exposure monitoring has focused almost exclusively on urban children. Projects such as BREATHE London project involved 258 children across five primary schools and found peak $PM_{2.5}$ and NO_2 exposure during commutes (Varaden et al., 2021). Similarly, the study in Bradford (Dirks et al., 2016) and the UNICEF's Toxic School Run study (Edwards and Whitehouse, 2018) reported significant exposure during school journeys and break times. However, these studies overlook home environments and focus on children in high-traffic urban areas like London (Osborne et al., 2021b), leaving rural children's exposure understudied.

Rural areas present different air pollution profiles, with key sources including agricultural emissions and residential biomass burning. In 2016, agriculture accounted for 88 % of the UK's ammonia emissions, which contribute to secondary $PM_{2.5}$ formation (DEFRA, 2018; Wyer et al., 2022). In Wales, domestic wood burning significantly impacts $PM_{2.5}$ levels, especially along the north coast and during winter (Welsh Government, 2024). A survey indicated that up to 75 % of households in rural Wales use firewood (Jennifer and James, 2013), raising concerns about indoor air quality, especially in poorly ventilated homes (Khalequzzaman et al., 2011). Socioeconomic and cultural factors such as fuel poverty and traditional hearth-centred gatherings can further elevate exposure risks (Ferguson et al., 2023; Roberts, 2020).

Despite these concerns, rural $PM_{2.5}$ concentrations are often underestimated due to sparse monitoring. The UK's Automatic Urban and Rural Network (AURN) has only about 15 % of its stations in rural areas, which together account for around 15 % of the population but 85 % of the land area (DEFRA, 2017; Ricardo Energy and Environment, 2024). In Wales, around 32 % of the population lives in rural areas, yet only two AURN stations are located there (Edmonds and Green, 2023). This distribution broadly reflects population density but limits understanding of spatial variation in rural air quality. Few studies have assessed rural children's personal exposure, despite distinct pollution sources. While research from countries such as Ghana (Arku et al., 2015), China (Zhang et al., 2018), Bhutan (Wangchuk et al., 2015), and Nepal (Devakumar et al., 2014) linked children's exposure to crop burning and biomass cooking and heating, these findings are not directly transferable to rural UK settings, where energy sources, infrastructure, and housing differ.

Taken together, current research on children's $PM_{2.5}$ exposure focuses heavily on urban contexts, particularly schools and commutes, while overlooking rural contexts and exposure patterns in home environments. This is especially concerning in regions like rural Wales, where specific pollution sources and socio-cultural practices may significantly affect children's air quality exposure. Moreover, the impact of the location of the sensor within homes, and household behaviours, remains unexplored despite their potential importance in shaping children's exposure profiles.

To address these, this study explores schoolchildren personal exposure to $PM_{2.5}$ during a school day in a rural setting using a citizen science method and low-cost sensors, identifying the microenvironments that contribute most to their exposure risks. Specifically, it quantifies $PM_{2.5}$ exposure levels across home, school, and commute settings and evaluate influencing factors including household heating methods such as wood burning and commuting modes such as walking or car travel. By focusing on an understudied population and context, the findings will provide new insights into rural children's air pollution exposure patterns and identify key contributing sources.

2. Method

2.1. Study site

This study was carried out in the Isle of Anglesey, a rural region in North Wales part of a wider data gathering effort led by the Public Map Platform. Unlike urban areas where traffic emissions dominate, Anglesey's air quality could be influenced by factors such as agricultural activities and fuel burning which are the common air pollution sources in rural Wales (Natural Resources Wales, 2021). Additionally, the island has a mix of socio-economic backgrounds with fuel poverty (Williams, 2017), contributing to increased reliance on wood burning for home heating, which is a significant source of $PM_{2.5}$ in the UK (DEFRA, 2020). Cultural practices, such as seasonal bonfires and traditional hearth-centred gatherings, further contribute to intermittent pollution spikes (Roberts, 2020). Apart from these factors, air quality monitoring in Anglesey remains limited, without fixed-site $PM_{2.5}$ monitors performed by the local authority, which underrepresents local variations (North Wales Combined Authorities, 2024). Furthermore, the Isle of Anglesey Statistical Profile (North Wales Regional Partnership Board, 2024) reports that 29.6 % of children live in low-income families, placing them at a higher risk of exposure to poorer indoor air quality (Ferguson et al., 2020). Therefore, by focusing on Anglesey, this study aimed to generate first-hand data on rural children's exposure patterns while exploring the effectiveness of participatory monitoring in a community with unique environmental and cultural characteristics.

Given this background, a household wood burner mapping (Fig. 1) was generated based on energy performance certificate (EPC) records (DLUHC, 2025) for residential properties across the island. These records indicate the heating sources used in each household, allowing identification of those using wood and enabling an exploration of the spatial distribution of household wood burners in the Isle of Anglesey. Areas are shaded according to the proportion of households with a wood burner, with darker colours indicating higher prevalence. It should be noted that only the most recent EPC records were included, and postcode areas with fewer than 10 households were excluded from the mapping. The spatial distribution indicates that higher population appears in coastal areas, where more household wood burners present in these areas, especially in eastern, northern and southern coastal areas.

To assess and compare the potential impacts of wood-burning activities on $PM_{2.5}$ level, we co-operated with two primary schools to pilot this study as shown in Fig. 1, where the teachers were keen to understand the pollution exposure of their pupils. School A is in the largest town on the island, which contains a larger number of postcode zones with low or zero reported rates of households with wood burners. However, this town functions as a key transport hub due to its busy ferry port and its role as the terminus for both highway and rail connections linking regional towns. School A is positioned adjacent to a railway line and a major highway and lies beneath a flight path, making it potentially more exposed to traffic-related air pollution. In contrast, School B is located in a small rural village in north Anglesey with a smaller population, limited vehicle traffic, but higher overall concentration of wood-burning households. The village is surrounded by farmland, which may contribute to particulate emissions from agricultural activities. Neither of the participating schools operates school bus services, meaning all children travel to school via other means such as walking or private transport.

2.2. Study design

To assess students' daily personal exposure to $PM_{2.5}$, the study incorporated both school-based stationary monitoring and individual personal monitoring. Stationary indoor air quality sensors were installed in each participating school to continuously monitor $PM_{2.5}$ concentrations within the classroom environment during school hours. To capture exposures outside of school, a rolling-based personal monitoring

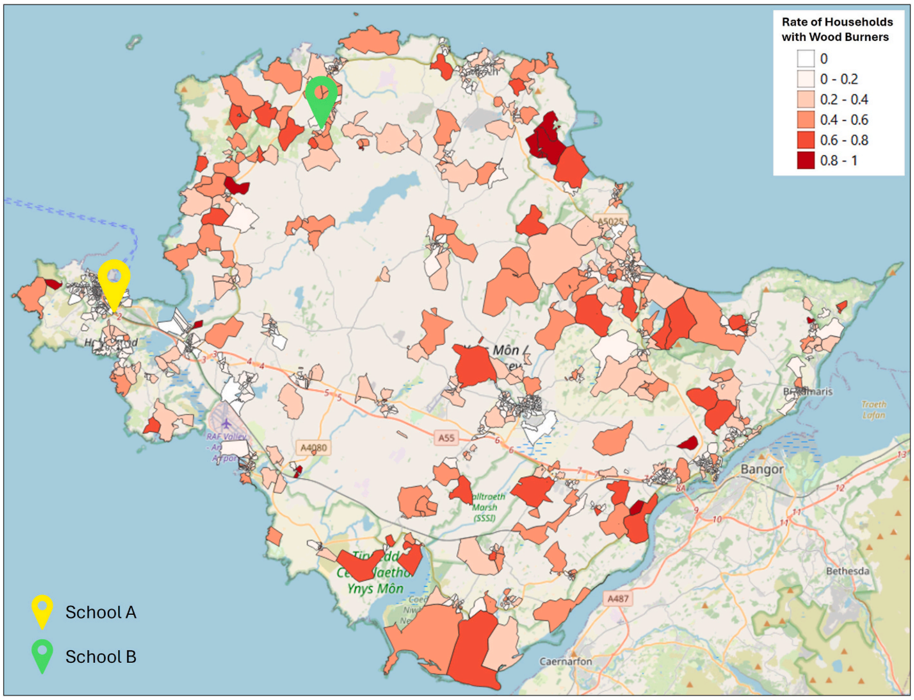

Fig. 1. Distribution of household wood burners in Anglesey by postcode based on EPC records and locations of Pilot Schools. Darker shading indicates a higher number of households using wood burners within each postcode area. Postcode regions with fewer than 10 EPC records were excluded from the map.

approach was implemented. This involved equipping a rotating group of students with portable air quality monitors to measure their exposure levels during non-school hours as illustrated in Fig. 2. The study engaged 53 children aged 8–11 years (Year 4 - Year 6) from the two participating schools and was conducted between November and March 2024 to evaluate their personal exposure in the cold season.

Prior to data collection, teachers and students received a briefing that outlined the objectives of 'personal monitoring', introduced the equipment, and explained the procedures. Teachers informed parents and obtained their consent for student participation as per UK research ethics requirements in both English and Welsh. Meanwhile, trained bilingual field staff, referred to as "mappers" due to their role in collecting and organizing spatial or participatory data as part of the Public Map Platform project, were responsible for managing the devices and delivering the introduction and reflection sessions in schools (Hutchinson and McVey, 2025). Due to limited resources and school scheduling, each session involved five students, enabling effective learning and meaningful discussion. Different groups participated on different days, allowing data collection under varied conditions and locations, thereby enhancing the overall representativeness of the dataset. Mappers visited each school up to four times per week over a three-week period, repeating the same procedure with different participants.

The rolling-based personal air pollution measurement included three stages: briefing, data collection and visualisation, and reflection. At the start of each session, mappers met with the participating students to provide age-appropriate information about the air pollution sources and health impacts, describe the equipment and measurement process, and assist students in attaching the devices to their backpacks. Pre-surveys were conducted to collect participants' basic information for data

Fig. 2. Child-carried $PM_{2.5}$ monitoring during non-school hours. The image on the left taken by the mappers shows a student in this study wearing a backpack equipped with portable monitors. (Source: Vecteezy.com).

identification detailed in Table 1 using an online survey tool - KoboToolbox platform (Das, 2024). To ensure data quality, mappers provided clear guidance such as avoiding heat sources, not turning off the devices, not obstructing air inlet and outlet, and keeping backpacks in bedrooms during home hours. Care was taken to deliver instructions using simple, clear language suited to the students' academic level and experience in Welsh or English as appropriate.

The personal measurement period lasted from 3:00 p.m. (after the school day) until 9:00 a.m. the following morning. During this time, the students carried the monitoring devices as they went about their usual activities. Data collected at 1-min intervals were automatically uploaded to the cloud. After the monitoring period ended, school staff collected and charged the devices in preparation for the next session. Researchers then downloaded and conducted preliminary analysis of the data to create individualised result sheets. These included summary statistics including average, minimum, and maximum $PM_{2.5}$ levels, time-series graphs of $PM_{2.5}$ variation, and spatial exposure maps generated by QGIS highlighting pollution hotspots.

On the following school day, mappers returned to school in the afternoon to conduct the reflection session. They presented each student with their result sheet and helped them complete a time-activity log. Mappers and teachers then facilitated a discussion based on the result sheet and time-activity log, exploring each student's exposure journey, including potential sources of pollution, peak exposure periods, and ways to reduce personal exposure. Additional contextual information such as travel modes, home heating practices, and where the backpack was kept overnight was also collected by mappers through a post-survey using the KoboToolbox.

Table 1
Summary of data collected, parameters measured, tools used, and collection details for school-based and personal PM2.5 monitoring.

Category	Parameters	Devices/ Tools	Additional Information
Indoor PM2.5 at School	- PM2.5 concentration	AirGradient	- Time interval: 1-min - Monitoring period: Continuous (24/7)
Personal PM2.5 Exposure	- PM2.5 concentration	AirBeam3	- Time interval: 1-min - Monitoring period: 3:00 p.m.-9:00 a.m. (following day)
Location	- Longitude and Latitude	TKMARS GPS	- Time interval: 1-min - Monitoring period: 3:00 p.m.-9:00 a.m. (following day)
Demographic	- School name - Student initials - School Year - Gender	KoboToolbox	- Collected during Personal Monitoring Introduction Session (Pre-survey)
Daily Routine (non-school hours)	- Time-activity patterns	Activity Log sheet	- Collected during Personal Monitoring Reflection Session (Post-survey)
Environmental and Behavioural Context	- Commute mode - Home heating practices - Backpack location at home - Student Observations (What/when/where did they see/smell)	KoboToolbox	- Collected during Personal Monitoring Reflection Session (Post-survey)

2.3. Air quality sensors and data analysis

2.3.1. Device selection and specifications

The AirGradient One indoor sensor (AirGradient, Thailand, Plantower PMS5003, https://www.airgradient.com/indoor/) was selected for school-based stationary monitoring of $PM_{2.5}$ level. This sensor was chosen for its reliable performance, ease of use, compact size, robustness, low cost, and low noise as reported by Chatzidiakou et al. (2023), ensuring high data quality while minimizing classrooms disruption. The specification of the AirGradient One is listed in Table A in Appendix A. This sensor has an on-sensor LEDs to display readings for air pollutants including $PM_{2.5}$. The sensors transmit data when they are connected to WiFi and plugged into a standard mains power socket. The AirGradient company provides an online platform that receives and visualises data at 1-min intervals. A guide on how to access the platform and understand the data presented was provided to the teachers from the participating schools to access and understand the data.

For the personal monitoring, since primary school children do not typically have smartphones, devices needed to operate independently, without relying on other electronic equipment. This was necessary to reduce both the complexity and labour intensity of data collection. To ensure the devices were suitable for children to carry, they also had to be compact, lightweight, and wearable. To meet these criteria, the AirBeam3 (https://www.habitatmap.org/airbeam/) and TKMARS GPS Tracker were selected to gather personal $PM_{2.5}$ concentrations and location data respectively during personal measurement period. The AirBeam3 has been performance-tested by Air Quality Sensor Performance Evaluation Centre (AQMD, 2022). Specifications for both devices are provided in Table A in Appendix A. Both devices are equipped with a cellular unit with a SIM card slot, allowing data to be unloaded to the cloud via a cellular connection. This enables remote monitoring and retrieval without the need for local intervention.

Experimental testing conducted prior to deployment showed that the AirBeam3 offers a standby time of up to 20 h on a full charge when collecting and transmitting data at 1-min intervals via a 4G cellular connection. This is sufficient to cover non-school hours. However, while the device is weather-resistant, it is not fully weatherproof. Hence, during the introductory session, students were instructed by teachers and mappers to keep the devices away from water, excessive moisture, and direct heat sources to minimise the risk of compromising data accuracy and prevent potential damage to the equipment. To ensure data reliability, sensor calibration was conducted prior to the measurement period to maintain the accuracy of the $PM_{2.5}$ measurements collected throughout the study. Appendix B provides the calibration results.

2.3.2. Data collection

For stationary monitoring, the AirGradient sensor logged data at a 1-min interval and uploaded data to the cloud automatically. For personal monitoring, the AirBeam3 sensor and a GPS tracker were securely attached to each student's backpack. Both $PM_{2.5}$ concentrations and GPS location data were recorded at 1-min intervals to provide a balanced temporal-spatial resolution while preserving battery life. To support real-time data logging and uploading without requiring a smartphone, SIM cards were installed in both AirBeam3 sensors and GPS trackers, enabling automatic transmission of data to the cloud during the measurement period. In instances where the device lost connectivity, data were stored locally in the internal memory and automatically uploaded once the connection was restored. All logged data were encrypted to maintain participant anonymity and protect sensitive information in the event of device loss or theft. The AirBeam3 and GPS tracker were each powered by their own dedicated battery units. A total of five AirBeam3 monitors and five GPS trackers were used in the study. Table 1 summarizes the data collected, tools used, and collection details for PM2.5 monitoring in this study.

2.3.3. Data preparation and analysis

After completing each measurement session, encrypted data collected during each personal measurement cycle and school indoor fixed measurements during school hours were downloaded from the cloud to a secure university server immediately after each session was completed. Once downloaded, the data were decrypted and imported into a central database for further processing and analysis. The process of sensor data retrieval, processing, and analysis is illustrated in Figure C (Appendix C).

Personal exposure data from the AirBeam3 sensors ($PM_{2.5}$ levels) and the GPS trackers (location data) were merged using matching timestamps in Python. One-minute data from personal monitoring and 1-s data from school indoor fixed sensors were aggregated into 5-min averages to construct a full daily exposure profile for each student. However, some data loss occurred, mainly due to device battery depletion or power-offs during measurements, leading to incomplete profiles. Positional errors also happened when students did not carry their backpacks while moving between microenvironments. To ensure data quality, raw data were filtered to exclude invalid measurements based on the following criteria: 1) $PM_{2.5}$ data covered less than 90 % of the monitoring period; 2) data from the home or commute environments were entirely missing; or 3) sensors were left in a location without the student (e.g. left in a car while the student was at home). Invalid measurements were repeated when possible or otherwise excluded from the study. Valid data were then used to calculate mean daily $PM_{2.5}$ exposure levels, which were grouped by participating schools.

To provide a more detailed analysis of exposure contexts, the 1-min data points were categorized into three main environments: "school," "home," and "commute" based on GPS data. The "home" category was further subdivided based on the location of the student's backpack within the home, including bedroom, kitchen, living room, hallway/near the door, and other areas, reported by children in the post-surveys. The "commute" category was broken down by mode of transport including walking or travelling by car in this study. Average $PM_{2.5}$ exposure were then calculated for each of these categories to better understand variations in students' exposure across different environments and activities.

Two exposure metrics were used for exposure assessment, including time-weighted exposure concentration and cumulative exposure. The time-weighted exposure concentration represents the average PM2.5 concentration adjusted for the duration spent in each microenvironment (in $\mu g/m^3$). Cumulative exposure reflects the total amount of PM2.5 encountered over the exposure duration (in $\mu g{\cdot}min/m^3$). Additionally, the inhaled PM2.5 dose was calculated (in μg), which refers to total mass of PM2.5 inhaled during the monitoring period, incorporating both concentration and breathing rate.

3. Results

3.1. Participation statistics

A total of 53 children participated, and 94 % of them collected valid data, a testament to the value of community science. In total, about 853 h of PM2.5 data were collected through personal monitoring. Pre-surveys and post-surveys were collected for all 50 children who collected valid $PM_{2.5}$ data, using the KoboToolbox platform. Table 2 shows the information of the participants from pre- and post-surveys who collected valid sensing data for the personal measurement. Analysis of the surveys showed that the student population was evenly split by gender, with males and females each accounting for 50 %. Travelling by car was the most common mode of commuting, reported by 76 % of the students. Additionally, 32 % of the participants indicated that they use a fuel burner or have a fireplace at home.

Participant feedback underscored the value of engagement. Children were enthusiastic about gathering their own data by carrying the sensors on backpacks during non-school hours, often describing the opportunity to collect their own data as the most exciting and enjoyable part of the study. Teachers also reported that the study increased awareness of air quality issues within the school leading them to open windows more resulting, anecdotally, in improved pupil engagement.

Table 2
Information of the participants from surveys who collected valid data (n = 50).

	Parameter		Overall Result	School A	School B
Demographics Information	School year	4	42 %	64 %	0 %
		5	28 %	24 %	35 %
		6	30 %	12 %	65 %
	Gender	Male	50 %	52 %	47 %
	Ethnicity	Welsh	100 %	100 %	100 %
Transportation	Car		76 %	76 %	76 %
	Walk		24 %	24 %	24 %
Other Influences	Adult smoking		12 %	12 %	12 %
	Having fuel burner and/or fireplace		32 %	21 %	53 %

3.2. Daily $PM_{2.5}$ personal exposure pattern

Participating children's personal $PM_{2.5}$ levels varied during the day across both schools. Fig. 3a shows the time-series of 5-min mean $PM_{2.5}$ concentrations for all monitored children in Anglesey, with individual traces in grey and the average in red. Results showed that the average daily mean $PM_{2.5}$ exposure across all participants was 6.5 $\mu g/m^3$, though individual daily means reached as high as 43.5 $\mu g/m^3$, with 12 % experiencing levels above 15 $\mu g/m^3$. Clear peaks in $PM_{2.5}$ levels, which could reach over 600 $\mu g/m^3$, were observed during the evening hours, typically between 18:00 and 22:00 as illustrated in Fig. 3b. Morning peaks were less prominent but still present for some individuals. It is worth noting that a few children's time-series also showed sharp spikes during the late-night and early morning hours (00:00–04:00), In addition to nighttime spikes, elevated $PM_{2.5}$ levels were also observed between 07:00 and 09:00.

To better understand the contribution of different microenvironments to children's $PM_{2.5}$ exposure, the analysis incorporated both pollutant concentration and time spent in each setting. The data were categorized into three main settings: home, school, and commute, with the commuting period further divided into morning and afternoon segments to capture directional differences in exposure. As shown in Fig. 3c and Table D, on average, across all participants, exposure levels were 8.2 $\mu g/m^3$ in the home, 1.7 $\mu g/m^3$ morning commute, 5.7 $\mu g/m^3$ afternoon commute, and 2.6 $\mu g/m^3$ school.

Based on GPS data and time-activity logs, children spent most of their day at home (67 %) primarily sleeping, followed by time at school (29 %), where most activities occurred indoors, and commuting (4 %) (Table D). Consequently, home environments produced the highest mean cumulative exposure of 7644.2 $\mu g\ min/m^3$. Fig. 3c shows the box plot of cumulative PM2.5 exposure across the three microenvironments. When accounting for inhalation rates associated with activity levels in each setting, dose estimates revealed that children inhaled an average of 71.7 μg of PM2.5 per day, with the home accounting for the largest proportion (77 %) of total exposure, followed by the school (13 %) and commute (10 %) (Table D).

It should be noted that outliers were retained in the exposure analysis to reflect the full range of conditions encountered during the monitoring period. This allows for a more comprehensive assessment of both typical and extreme $PM_{2.5}$ pollution events that could affect children's health even if such events are infrequent.

3.3. Personal exposure comparison by schools

Fig. 4a presents violin plots showing the distribution of daily average $PM_{2.5}$ exposure concentration and average concentrations across home,

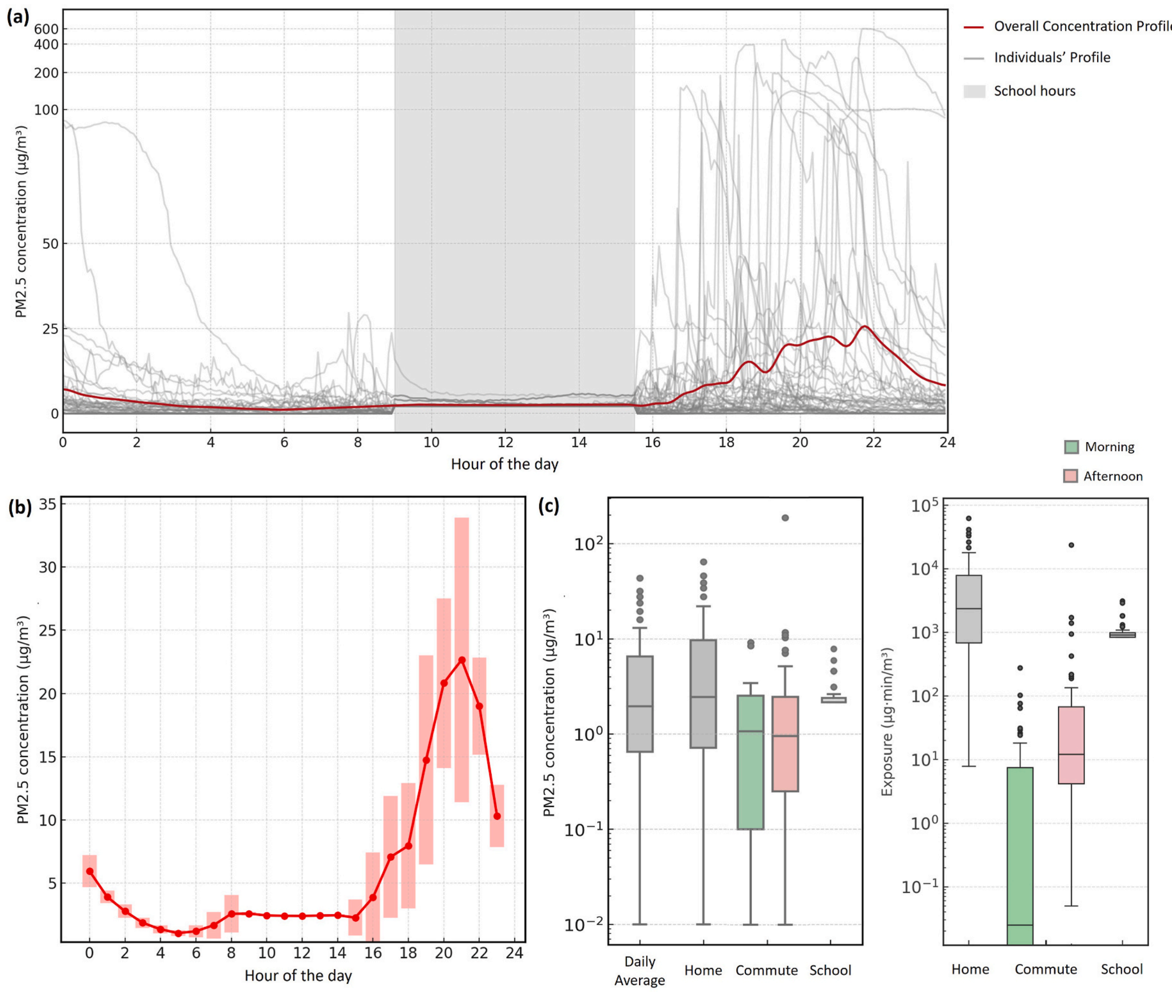

Fig. 3. (a) Individual and overall 5-min average PM2.5 concentration profiles across a 24-h period. The grey lines represent individual participants' profiles, and the red line shows the overall mean concentration profile. Shaded areas indicate school hours (approximately from 9:00 a.m.–3:30 p.m.); (b) Diurnal variation graph of hourly average PM2.5 concentrations across all participants. The red line shows the mean concentration for each hour, while the shaded bars represent the variability (±1 SD); (c) Box plots of PM2.5 exposure concentrations and cumulative exposure in each microenvironment. It illustrates participants' daily average personal exposure, and average exposure at home, at school, and during commutes separated by morning and afternoon periods. The y-axis is log-scaled to better visualise the wide range of exposure levels. Grey dots represent outliers, indicating instances of high concentrations and exposure levels.

commute, and school, for the two participating schools. Children from School A and School B experienced similar overall $PM_{2.5}$ exposure pattern, despite their different environmental settings. Notably, students at School B experienced slightly higher $PM_{2.5}$ exposures and more variability across all microenvironments, especially within the home setting. Post-survey data as shown in Table 1 indicate that one key difference between the two schools lies in the prevalence of household fuel-burning appliances. Approximately 53 % of students at School B reported having a wood burner and/or fireplace at home, compared to 21 % at School A. This suggests that indoor biomass combustion is likely a significant contributor to higher $PM_{2.5}$ exposure.

These patterns are consistent with the fuel burner mapping as shown in Fig. 4b, which demonstrate higher concentrations of wood burner use in residential areas near School B. Fig. 4c further supports this observation, presenting a box plot of the percentage of households with fuel burners in children's residential areas by postcode. On average, approximately 8 % of households in the residential areas of children from School A have a fuel burner, compared to 29 % in the areas of children from School B. It can be seen that both values underrepresent actual percentage of households with wood-burning appliances reported in the surveys, suggesting more frequent residential burning activity than indicated by EPC data alone. It is also important to note that the presence of a burner does not equate to regular burning activity.

3.4. Distribution of mean $PM_{2.5}$ level in home environments

Which room to place sensor within the home affects pollution measurement data. According to post-survey responses, backpack placement in the home environment varied: 20 % left in the bedroom as mentioned in the instruction, 26 % left them in the kitchen, 10 % in the living room, 36 % near doors or hallways, and 8 % in other locations. Fig. 5 presents a violin plot illustrating the distribution of average $PM_{2.5}$ exposure concentrations across various sensor placements within households. As shown, $PM_{2.5}$ concentrations in kitchens and near doorways or hallways exhibited the greatest variability and highest peak values, with maximum mean levels exceeding 30 $\mu g/m^3$ in kitchens and reaching over 60 $\mu g/m^3$ in hallway areas. These spaces are likely subject to pollution bursts from cooking, proximity to wood-burning stoves, or the accumulation of pollutants due to specific features of the home's layout and floor plan causing limited ventilation near doorways or hallways.

In contrast, $PM_{2.5}$ levels in bedrooms and living rooms were more moderate and consistent, showing narrower distributions and lower peaks. This suggests that these spaces may offer more stable air quality conditions, potentially due to less activity, better isolation from

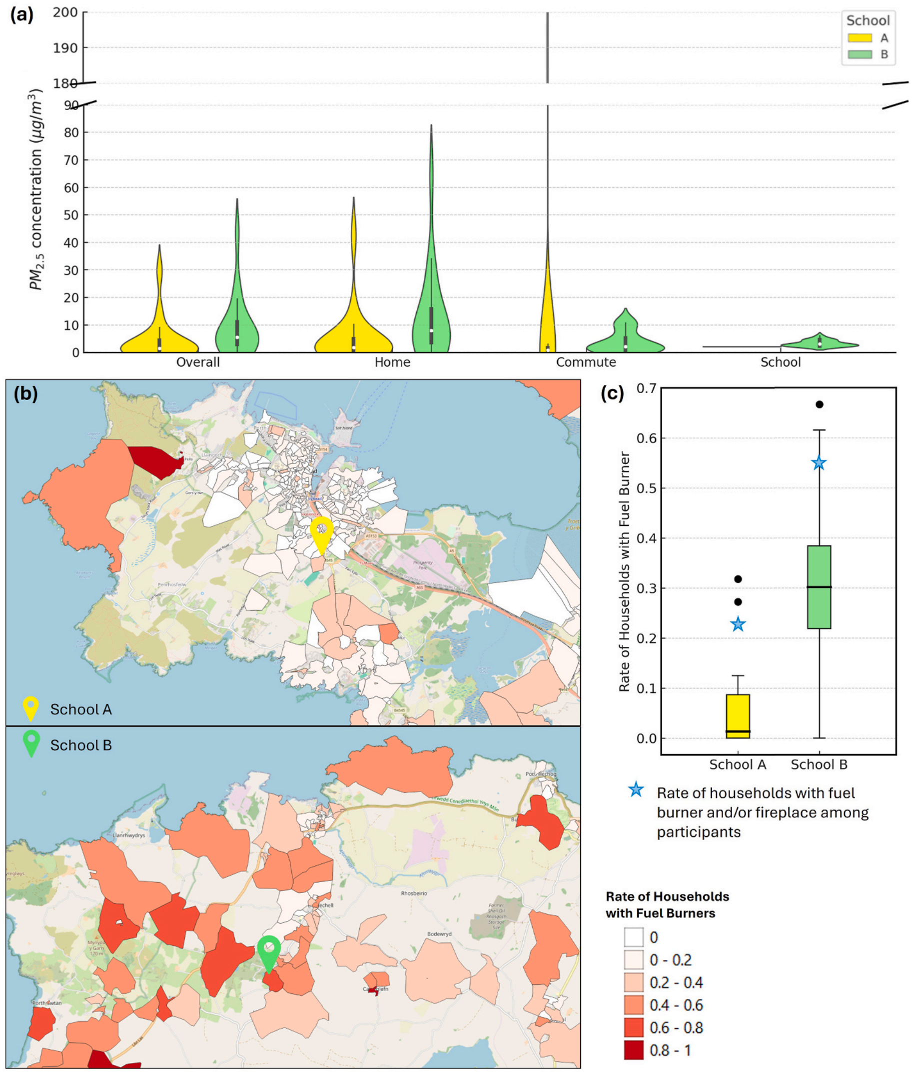

Fig. 4. (a) Violin plot of daily mean PM2.5 exposure concentration and average PM2.5 across different microenvironments (home, commute, school), compared between the two participating schools; (b) Maps showing the spatial distribution of households with wood burners in areas surrounding two schools; and (c) Box plot showing the proportion of households with wood burners in children's living areas compared across schools. The blue star indicates the proportion reported by students through the post-survey.

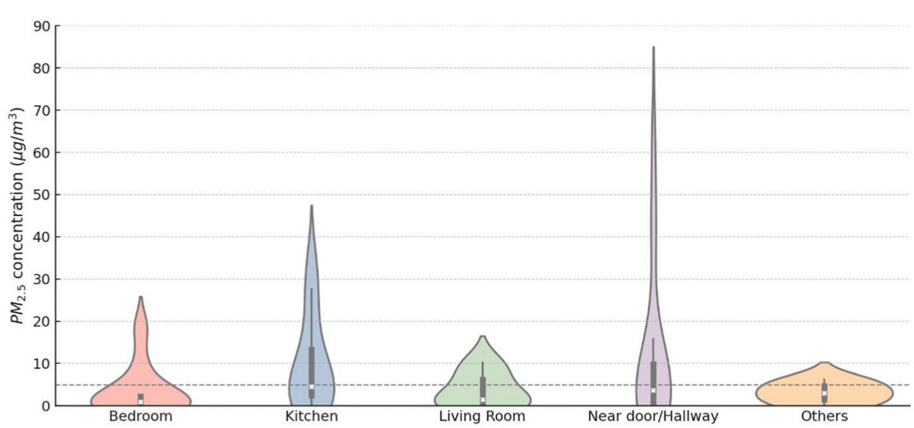

Fig. 5. Violin plot of average PM2.5 exposure concentration in different sensor placements within households.

pollution sources, or more frequent changes in air flow to refresh polluted indoor air. However, since the placement of sensors in home environments was decided by the children, cases involving wood burning may not be fully represented in these rooms. For instance, in one household using wood fuel for heating, the child placed the sensor in the hallway, which did not capture pollutant levels within the bedroom.

3.5. Distribution of mean $PM_{2.5}$ level during commute

According to post-survey results, 76 % of participating children travelled between home and school by car, while 24 % walked. As shown in Fig. 6a and Table D, car travel is associated with statistical meaningful and more variable $PM_{2.5}$ concentrations and longer exposure duration than walking. This suggests that children commuting by car may experience more prolonged and fluctuating pollution levels. One likely contributing factor, based on post-survey responses, is that some parents smoke inside the car without opening windows, which can cause elevated $PM_{2.5}$ within the vehicle space. Fig. 6c shows an example of a student's car commute during which adult smoking was reported, reinforcing the impact of such in-vehicle behaviours on exposure levels.

In contrast, children who walked to school experienced lower and more stable $PM_{2.5}$ levels in a shorter period, with most values falling below 5 μg/m^3. However, one extreme exposure concentration of 187 μg/m^3 was recorded along a route that passed through a busy high street as shown in Fig. 6b. Based on OpenStreetMap data and children's post-survey observations, this route included proximity to open kitchens in restaurants and bakery shops, where bursts of pollutants from intensive cooking activities, especially during peak hours, are likely contributors to elevated $PM_{2.5}$ concentrations. However, the total commuting period represents only about 4 % of the day. Therefore, while high momentary concentrations during commuting provide useful insights into pollution sources and behavioural influences, their contribution to overall daily exposure remains relatively limited (5 %).

4. Discussion

This study adopted a citizen science approach, that students carried portable air quality and GPS sensors in their backpacks, recorded observations of pollution sources, and participated in pre- and post-surveys and reflection activities. This combination of low-cost sensing and participatory engagement not only supported collection of individual-level data across diverse real-life settings but also enhanced environmental awareness among participants. These findings align with previous studies demonstrating that participatory monitoring can enhance children's understanding of air quality and promote behavioural reflection on pollution sources (Otu et al., 2024; Varaden et al., 2021). Feedback from pupils and teachers further indicated that such engagement can promote meaningful behavioural changes, such as more frequent window opening, which may have secondary benefits for indoor air quality and pupil wellbeing. Moreover, the study appeared to stimulate discussions among parents, encouraging greater awareness of local pollution sources and everyday behaviours contributing to them (Ballantyne et al., 2001). Beyond these, the approach also contributed to the democratization of environmental monitoring and air quality information, especially in resource-limited rural areas (Oyola et al., 2022).

4.1. Overview of exposure patterns

Over recent decades, many personal air quality studies have examined primary school children's exposure to pollutants such as UFP and BC (Alvarez-Pedrerol et al., 2017; Dirks et al., 2016; Edwards and Whitehouse, 2018; Ryan et al., 2015), with fewer focusing specifically on PM2.5. Existing PM2.5 studies often measure exposure only during school hours or commuting periods or are conducted in rural contexts within developing countries (Arku et al., 2015; Varaden et al., 2021; Zhang et al., 2018). This gap largely reflects the logistical challenges of collecting full-day personal exposure data from children, including securing school and parental consent, and maintaining children's engagement (Varaden et al., 2021). These challenges are even more

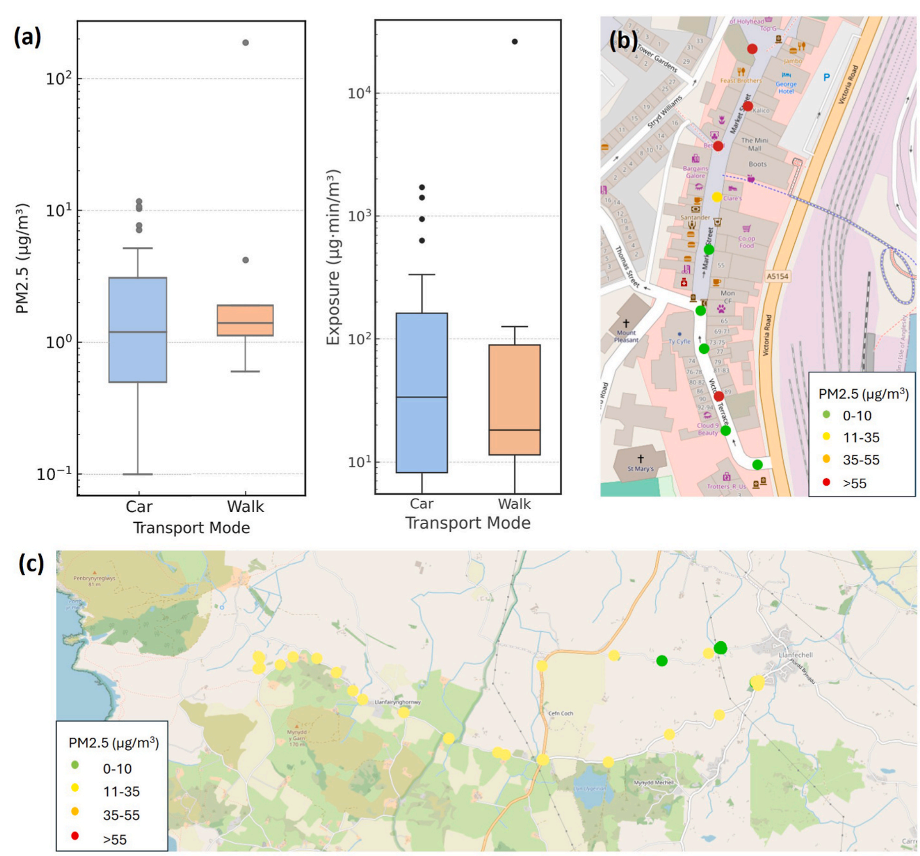

Fig. 6. (a) Box plot of average PM2.5 exposure concentration and cumulative exposure by different transportations during commutes and examples of high concentration maps by (b) walking in high street and (c) car.

apparent in resource-limited rural areas. Moreover, there is a common assumption that major indoor pollution sources, such as solid fuel use, are uncommon in developed countries, leading to limited investigation of children's exposure in rural settings across high-income regions. A major strength of this study is its ability to generate personal exposure estimates across an entire school day, enabling direct comparisons between home, school, and commuting environments in a rural, high-income setting. Importantly, the data were specific to the participating children and their local context, which helped foster a sense of engagement and ownership among both pupils and the school community.

Personal monitoring results revealed that daily mean $PM_{2.5}$ exposure concentration across all participating children was below the WHO 24-h guideline of 15 μg/m^3 (WHO, 2021). However, some children experienced daily averages exceeding this limit, highlighting that although overall exposure appeared acceptable on average, individual variability and high peaks warrant concern. Among three microenvironments, the home environment contributed the most to children's inhaled $PM_{2.5}$ dose (77 %), approximately double the proportion reported in the study from Ghana (Arku et al., 2015). This difference may be partly due to the current study taking place in winter, when children spent longer period indoors and households relied more heavily on heating. As a result, indoor sources such as cooking and wood burning (reported by around one-third of participants) combined with reduced ventilation, led to higher and more persistent PM2.5 levels, particularly at night (Figs. 3 and 18:00–04:00). These findings align with rural studies elsewhere (Devakumar et al., 2014; Wangchuk et al., 2015; Zhang et al., 2022), though the extended nighttime elevations observed here suggest prolonged wood combustion for heating rather than short cooking periods. Beyond practical heating needs, such practices may also reflect cultural and social preferences for warmth and comfort within the home (DEFRA, 2020).

Average school-time $PM_{2.5}$ concentration (2.6 μg/m^3) was lower than those reported in the SAMHE project (>4.5 μg/m^3) (Handy et al., 2025), suggesting effective indoor air quality management in the rural Welsh schools examined. During commutes, children experienced higher PM2.5 concentrations than at schools. This is in line with findings from the BREATHE London (Varaden et al., 2021) and Toxic School Run (Edwards and Whitehouse, 2018) studies in the urban areas, which identified commuting periods as key exposure windows. However, unlike BREATHE London, where higher concentrations occurred during morning commutes, this study found afternoon commutes to be more polluted. This discrepancy may reflect lower local pollution-generating activities in the early morning in this rural context.

Children in this study spent 67 % of their day at home, 29 % at school, and 4 % commuting, comparable to patterns reported from similar studies in Ghana (Nyarku et al., 2019) and Bhutan (Wangchuk et al., 2015). When time spent in each microenvironment is considered, commuting accounts for the smallest fraction of overall daily exposure. It highlights that, while commuting environments may exhibit short-term peaks in PM2.5, their limited duration results in a relatively minor contribution to overall daily exposure.

4.2. Influence of wood burning

The influence of domestic wood burning on children's $PM_{2.5}$ exposure became evident when comparing the two schools, with biomass combustion appearing to outweigh traffic proximity as a main exposure driver. Although School A is located near major transport infrastructures, including a ferry port, railway, highway, and flight path, students there recorded lower $PM_{2.5}$ levels during both commuting and school hours than those from School B. In contrast, children from School B, where more domestic wood burning appliances were reported, experienced higher and more variable $PM_{2.5}$ levels, particularly at home. This suggests that indoor biomass combustion is a key contributor to elevated exposure and may also affect nearby outdoor air quality.

Comparison between student reports and EPC records (Fig. 5) revealed that wood burning may be more widespread than official data suggest, as EPC assessments typically omit decorative stoves. The local mapper team and Roberts (2020) further indicated that wood use is often motivated by cost savings, with timber widely available on the island. Socioeconomic data from 2019 Ordinary National Survey (ONS, 2023) further support this. School B is located in a more rural area with lower average household net income, where reliance on biomass fuels may reflect both fuel poverty and affordability pressures. However, cultural norms, especially in more rural areas, may also reinforce their continued use. Together, these factors highlight how economic, environmental, and social contexts interact to shape household energy choices and underscore the need for targeted investigations addressing both fuel poverty and cultural drivers of wood burning.

4.3. Influence of sensor placement in the home

Sensor placement within the home played a significant role in shaping exposure data. Although children were instructed to place their backpacks (equipped sensors) in their bedrooms, only 20 % adhered to this protocol. As shown in Fig. 5, this resulted in notable variation in home-based measurements, highlighting the sensitivity of personal exposure estimates to sensor location. Similar observations were reported by Devakumar et al. (2014), who assessed the exposure levels across different indoor microenvironments in rural households.

These patterns reflect the fact the participants, particularly in the home environment, did not always carry the sensor with them, even when guidance was provided. In many cases, children left the sensors in fixed locations based on household routines, parental habits, or where they believed pollution sources might be present. As a result, the placement of the sensor within the household strongly influences the monitoring results, with notable variation in PM2.5 concentrations observed across different indoor spaces. These findings highlight the real-world challenges of deploying personal monitoring protocols with young participants in dynamic household environments and emphasise the need to account for sensor placement behaviours when interpreting personal exposure data.

4.4. Role of adult behaviours in shaping Children's exposure

Findings from this study suggest that children's exposure to air pollution is largely determined by adult behaviours within the household, consistent with observations by Barnes et al. (2004). While children's daily activities influence short-term variations, adults' heating, ventilation, and lifestyle practices exert the greatest overall impact on indoor PM2.5 levels. Household heating decisions, particularly the use of wood-burning stoves and open fires, strongly shaped nighttime and household concentrations. Adults' choices about when to light or refuel stoves, and whether to ventilate during or after combustion, directly influenced pollutant persistence indoors. Similarly, cooking without adequate extraction and indoor or in-vehicle smoking generated short-term peaks and some of the highest levels observed.

These findings emphasise that children's exposure arises primarily from adult-controlled environmental conditions rather than from their own behaviour. Interventions should therefore focus on raising awareness and encouraging behaviour change among parents and caregivers to effectively reduce children's exposure to indoor air pollution in rural settings.

4.5. Limitations and future work

These findings reinforce the critical role of behavioural and contextual factors in shaping personal exposure, particularly in rural settings. Parental habits such as indoor smoking and choice of household heating practices emerged as key determinants of children's exposure, often outweighing the influence of environmental infrastructure like roadways or transport hubs. However, this study has several limitations. Reliance on self-reported data, including post-survey responses and time-activity logs, introduces potential recall bias, especially among younger participants. The short, single-day monitoring period also limited the ability to assess seasonal or weather-related variability. Furthermore, the small sample size and limited geographic scope, with participants drawn from two schools, limit the generalisability of findings to other rural areas. Lastly, while contextual data helped identify likely pollution sources, source-specific quantification (e.g. distinguishing between cooking, smoking, or wood burning) was not feasible.

Future research should expand the geographic coverage to include diverse rural settings and socioeconomic contexts. Longer monitoring periods and integration of quantitative sensor data with qualitative family insights could enhance understanding of exposure dynamics. As the Public Map Platform evolves, linking these datasets to environmental, social, and economic layers will enable more granular spatial analysis. Strengthening parental engagement and exploring educational and behavioural spillover effects among students will also be critical for supporting community-led air quality action.

5. Conclusion

This study examined children's exposure to $PM_{2.5}$ across home, school, and commute environments in a rural Welsh context, using personal air quality monitors carried by children from two primary schools in Anglesey as part of the Public Map Platform project. Through a citizen science approach, it gathered detailed, real-world exposure data across different microenvironments. Results showed that children's highest and most variable PM2.5 exposure occurred within home environments, where indoor sources such as wood burning and smoking were major contributors. Although overall average exposure concentrations remained below WHO guidelines, short-term peaks, sometimes exceeding 600 $\mu g/m^3$, highlighted the influence of household activities on indoor air quality. Sensor placement within homes was also found to significantly affect recorded concentrations, underscoring the sensitivity of personal monitoring data to participant behaviour and the methodological challenges of deploying sensors with young children. Overall, the results demonstrate that adults' heating, ventilation, and smoking practices have a greater impact on children's exposure than the children's own activities or location. Importantly, it also shows that participatory data collection using wearable sensors is feasible and effective with primary-aged children, producing data in a real-world setting.

CRediT authorship contribution statement

Shuangyu Wei: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zhiwen Luo:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Simon Lannon:** Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization. **Tania Sharmin:** Writing – review & editing, Project administration, Funding acquisition. **Joseph Smith:** Investigation, Data curation. **Hanbin Zhang:** Writing – review & editing, Validation. **Flora Samuel:** Writing – review & editing, Project administration, Funding acquisition.

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Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.128291.

Data availability

Data will be made available on request.

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