

2025 ANNUAL REPORT



Executive Summary

Personal air pollution exposure is emerging as the missing layer in modern health, wellbeing, and mobility intelligence. In 2025, AirTrack demonstrated that environmental context is essential for understanding human performance, recovery, and daily behaviour, yet almost entirely absent from current digital health and mobility systems.

Across thousands of user journeys, AirTrack data revealed 41% of NO₂ readings and 20% of PM_{2.5} readings exceeded WHO guidelines, underscoring the importance of personalised exposure insights. There were:

- significant differences in exposure across activities and transport modes
- pollution episodes that disproportionately shaped daily exposure
- behavioural patterns in how people navigate polluted environments
- early physiological signals, with daily Heart Rate Variability (HRV) showing a moderate, statistically significant association with daily air quality (cleaner air → higher HRV)
- new modelling opportunities for wearables, insurers, and mobility platforms, where exposure explains a portion of variance which may otherwise be treated as “noise”.

These findings suggest integrating personal exposure data would materially improve health and sleep algorithms, unlock health-optimised routing for navigation platforms, and give employers and insurers a measurable environmental determinant of wellbeing.

A key learning in 2025 was recognising the significance of air quality communication. Thanks to AirTrack’s use of AI, personalised, calm and non-alarming messaging outperformed generic pollution alerts, helping users take practical action and make cleaner choices without anxiety.

Overall, AirTrack’s 2025 data points to a clear conclusion: when environmental information is delivered in a simple, relevant, and personalised way, people naturally choose healthier paths and as an enabler of positive behavioural change.



Top Cities Air Quality Leaderboard

Lowest NO2

- 1 Port Douglas, Australia
- 2 Leeuwarden, Netherlands
- 3 Sitia, Greece
- 4 Andamooka, Australia
- 5 Kristianstad, Sweden

Highest NO2

- 1 Warsaw Poland
- 2 Salt Lake City, USA
- 3 Bologna, Italy
- 4 The Hague, Netherlands
- 5 Brisbane, Australia

Lowest PM2.5

- 1 Setúbal, Portugal
- 2 Auckland, New Zealand
- 3 Andamooka, Australia
- 4 Port Douglas, Australia
- 5 Leeuwarden, Netherlands

Highest PM2.5

- 1 Genoa, Italy
- 2 Mokhotlong, Lesotho
- 3 Monterrey, Mexico
- 4 Brugge, Belgium
- 5 Montemorelos, Mexico

*based on AirTrack journeys (minimum 10 activities), not population averages.



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1. Why Personal Exposure Matters

1.1 The Blind Spot in Health & Mobility Data

Air pollution is one of the strongest environmental determinants of health and performance, yet most digital platforms, wearables, and mobility tools operate without understanding what individuals actually inhale.

Government monitoring networks provide valuable city level information, but they cannot capture the micro-environments people move through every day. Personal exposure can vary dramatically within metres and minutes due to:

- Street layout and “urban canyon” effects
- Traffic density, vehicle mix, and idling patterns
- Choice of route or side street
- Ventilation rate during walking, running, or cycling
- Indoor and in-vehicle environments with poor filtration

Two people living on the same street can experience entirely different pollution levels based on their commute, exercise habits, or indoor ventilation. A runner on a main road can inhale 3–5× higher concentrations than someone on a nearby backstreet. Inside cars, pollutant levels often spike due to trapped exhaust and limited airflow.

This creates profound blind spots across key industries:

- Wearables misinterpret environmental stress as poor sleep, high strain, or overtraining.
- Employers lack visibility into staff exposure during commutes and field work.
- Mobility and mapping platforms optimise only for time, not health.
- Insurers miss a major modifiable determinant of cardiopulmonary risk.

Personal exposure is therefore the missing behavioural and environmental layer required for precision health, performance modelling, and next generation mobility intelligence.

1.2 Core Pollutants and Their Health Effects

AirTrack focuses on a small number of clinically and epidemiologically well established air pollutants that are most relevant to short-term exposure, physical activity, and daily health outcomes (WHO, 2024).

PM_{2.5} (Fine Particulate Matter)

Particles <2.5 µm penetrate deep into the lungs and bloodstream. Linked to:



- Cardiovascular disease
- Reduced lung function
- Cognitive decline
- Premature mortality
- Impaired concentration
- Decreased Productivity

Acute spikes also affect blood pressure, HRV, perceived exertion, and sleep quality and increased perceived effort.

Nitrogen Dioxide (NO₂)

A traffic related pollutant elevated near busy roads. It:

- Irritates and inflames airways
- Exacerbates asthma
- Reduces lung function
- Impairs exercise tolerance
- Cognitive performance

Short-term exposure can reduce exercise efficiency and increase respiratory strain, with downstream effects on fatigue, work capacity, and tolerance for sustained physical tasks. Its extreme street-level variability makes it essential for commute and workplace exposure assessment.

Ozone (O₃)

A secondary pollutant formed by combining NO_x, VOCs and sunlight. It:

- Irritates lung tissue
- Reduces exercise performance
- Increases respiratory symptoms
- Interacts with heat stress in summer

Ozone exposure has been linked to reduced aerobic capacity and increased physiological stress, particularly in warm conditions, which may limit sustained performance and productivity during outdoor activity or heat-exposed work.



1.3 Why Dose Matters

Health impacts depend not just on concentration but on the inhaled dose. Ventilation increases 2–3× when walking, 5–6× when running, and even higher during intense training. As a result:

- a jog at “moderate” pollution can result in a high dose of air pollution
- a short exposure at peak traffic can be similar to a long period of background pollution
- indoor or in-vehicle environments may have high exposure but lower dosage.

Platforms relying solely on ambient concentration underestimate the physiological load. AirTrack instead models personal dose using movement, ventilation, and exposure dynamics, aligning with modern toxicology, epidemiology, and exercise physiology.

1.4 Why we use the Air Quality Health Index (AQHI)

People are exposed to, and therefore breathe in, mixtures of pollutant dosages, not individual components. Our AQHI provides a simple, health-based measure reflecting the combined short-term impact of $PM_{2.5}$, NO_2 and O_3 based on an approach originally developed in Canada (Environment and Climate Change Canada (ECCC) & Health Canada (2023)). This makes it more informative for daily decisions than pollutant specific thresholds or annual guidelines. AQHI allows AirTrack to translate complex environmental science into a clear, personalised health indicator, supporting better decisions across wearables, mobility platforms, and employer wellbeing programmes.

2. AirTrack Data Insights

In 2025, AirTrack analysed more than 108,000 activities and generated over 117,000 GPS-linked exposure points. Across this dataset, 20% of $PM_{2.5}$ readings and 41% of NO_2 readings exceeded WHO (2021) 24-hour guidelines, highlighting the importance of personal exposure insights in daily decision making. This section presents key insights from the 2025 AirTrack dataset, summarising global patterns in air quality and how exposure varies by location and activities.

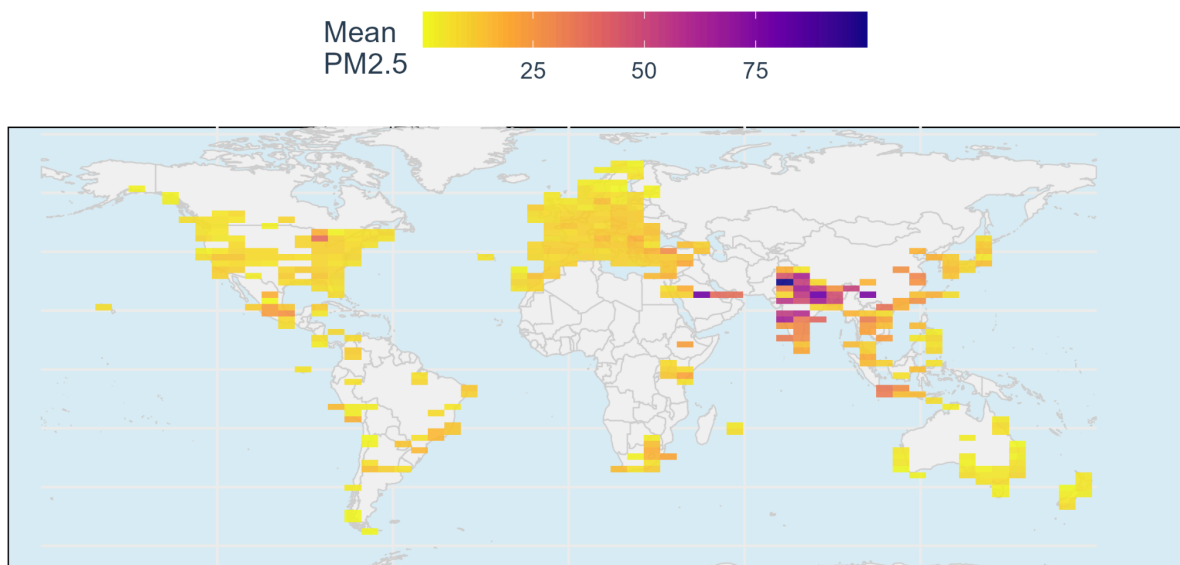
2.1 Global Dataset

The global footprint of AirTrack journeys allows us to map real-world pollution exposure across more than 100 countries. Figure 2.1 shows the average $PM_{2.5}$ exposures

encountered along AirTrack journeys in 2025. Each coloured grid cell represents an area where users travelled and exercised, with colour intensity reflecting the mean pollution exposure level recorded there. Because AirTrack data is activity-based rather than population-based, the map highlights locations where users were active, not a complete global pollution surface.

Even so, several regional patterns emerge:

- elevated exposures are visible across areas of India, China, and Southeast Asia, reflecting recognised global $PM_{2.5}$ hotspots
- moderate levels are observed across much of Europe and the eastern United States
- lower exposures are evident in parts of the Southern Hemisphere (e.g. New Zealand and Argentina).



Data Source: AirTrack 2025

Figure 2.1: $PM_{2.5}$ AirTrack exposure data during 2025 Note: This map represents where AirTrack users travelled and were exposed, not a global pollution surface.

Figure 2.2 visualises daily $PM_{2.5}$ levels as an *Air Quality Barcode* throughout 2025. Each vertical stripe shows the daily mean exposure of AirTrack users, allowing seasonal variation to be seen clearly:

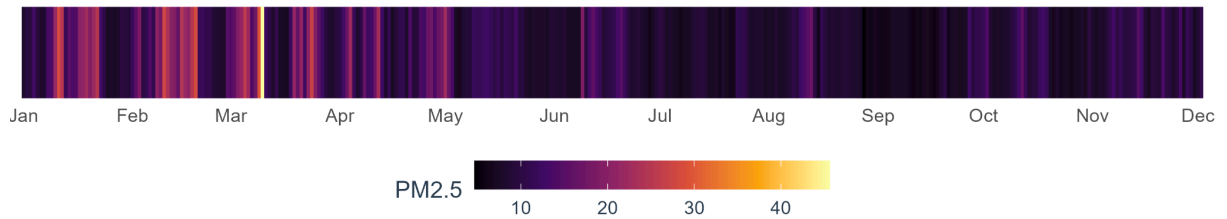
- winter months (Jan–Feb, Nov–Dec) show more frequent dark bands, reflecting typical winter pollution episodes driven by temperature inversions, heating demand, and reduced atmospheric mixing



- summer (Jun–Aug) is generally cleaner, with fewer high pollution days and greater dispersion
- spring and autumn exhibit short, intense episodes linked to regional stagnation, weather driven events, or wildfires.

2025: The Air Quality Barcode

Daily average PM_{2.5} concentration across the year



Data Source: AirTrack 2025

Figure 2.2: The Air Quality Barcode (2025 PM_{2.5}) showing exposure across AirTrackers

2.2 Exposure Across Activities

Figure 2.3 presents the time-weighted average exposure to NO₂ and PM_{2.5} across the most common activity types logged by AirTrack users. For NO₂, which is closely associated with road traffic:

- cycling, running, and walking show the highest exposures, reflecting frequent use of roadside or urban routes
- hiking records substantially lower levels, consistent with cleaner, non-urban settings
- e-cycling also shows reduced NO₂ exposure, likely due to longer, more suburban or off-road trips.

For PM_{2.5}, which is more regional in nature:

- walking, running, and cycling again show the highest exposure values, reflecting time spent in urban environments
- hiking and other leisure activities show lower PM_{2.5} levels
- e-cycling records the lowest exposures.

Air Pollution Exposure by Activity

Time-weighted average exposure for PM_{2.5} and NO₂

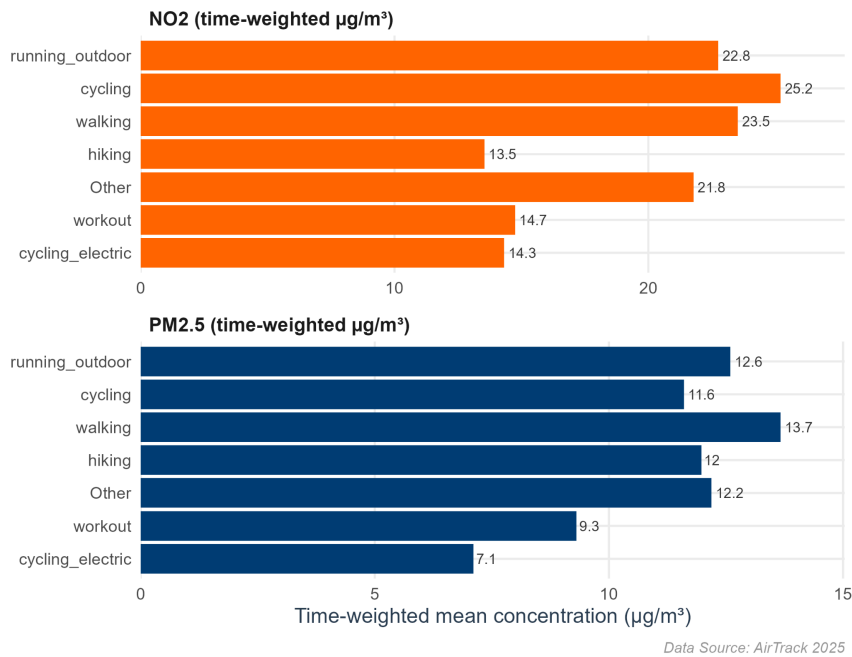


Figure 2.3: NO₂ (top) and PM_{2.5} (bottom) time weighted exposure (µg/m³) by activity

2.3 Route-based Insights and Behaviour Change

AirTrack's routing engine enables users to compare their usual route with a cleaner alternative, quantifying the expected difference in inhaled dose. Although this feature was launched in the latter part of 2025 and dataset growth is ongoing, early examples already illustrate substantial benefits. Figure 2.4 shows screenshots of typical AirTrack cleaner routes, where exposure is reduced by 18–21%.

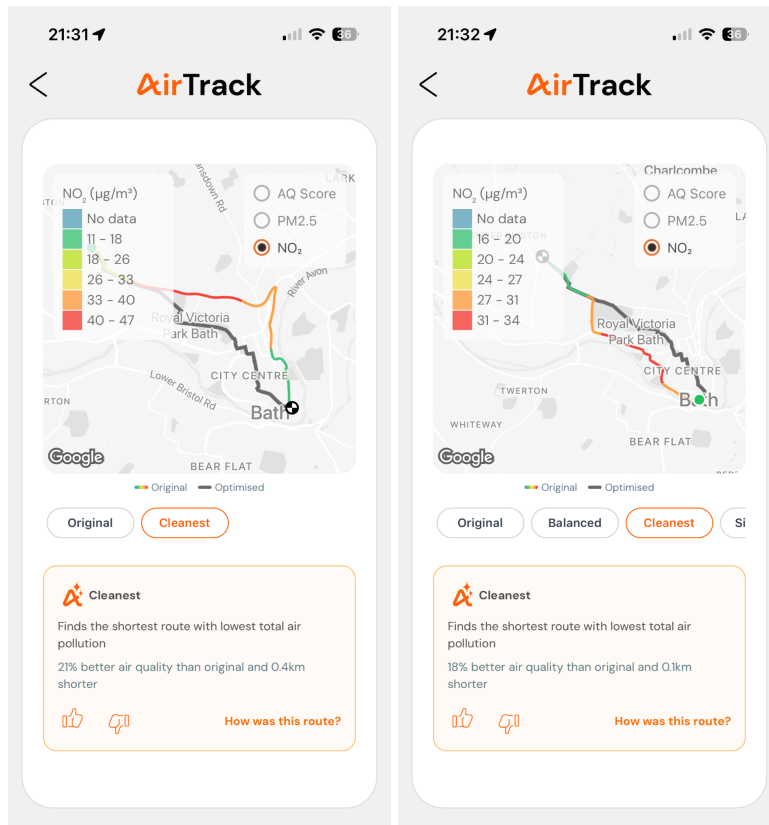


Figure 2.4: Screenshots of AirTrack cleaner route comparison (18–21% better air quality)

In October 2025, AirTrack identified potential average NO₂ reductions of 47% through cleaner routing, rising to 57% in November and remaining substantial at 38% in December – based on similar length routes. These route level insights highlight the capacity of personalised exposure information to influence behaviour. With continued data collection, AirTrack will quantify the extent to which users actively choose cleaner routes when viable alternatives are available.

2.4 Case study: Project Salt Run's ultra-distance run through India

Hannah Cox is an AirTracker who is running 100 marathons in 100 days across India. Over the course of approximately 1,160 hours (~48 days), more than 160,000 high-resolution exposure points were recorded and subsequently aggregated to 1-minute means for analysis (Figure 2.5). The interactive map can be accessed:

<https://storage.googleapis.com/airtrack-pdn-public-assets/salt-run/pollution-route.htm>

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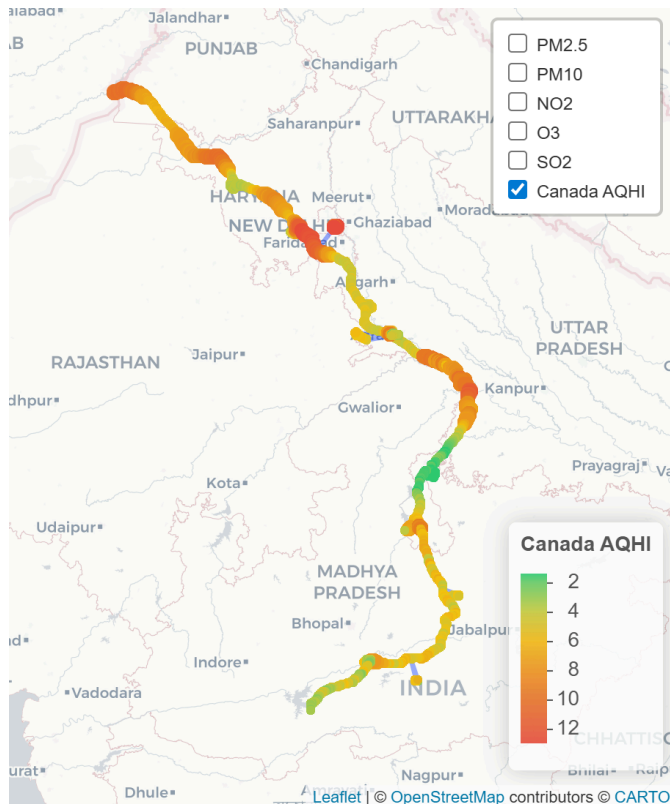


Figure 2.5: Hannah Cox's [Air Quality exposure](#) whilst running through India (AQHI).

Across the full duration of the run, Hannah has been exposed to consistently elevated levels of particulate and traffic-related air pollution. Mean $PM_{2.5}$ exposures were $72.7 \mu\text{g}/\text{m}^3$, nearly five times the WHO 24-hour guideline ($15 \mu\text{g}/\text{m}^3$), with peak values exceeding $300 \mu\text{g}/\text{m}^3$. Exposure to PM_{10} followed a similar pattern, with a mean concentration of $133 \mu\text{g}/\text{m}^3$ and maxima above $400 \mu\text{g}/\text{m}^3$, reflecting frequent proximity to road traffic, resuspension, and regional dust sources. NO_2 , a marker of combustion and traffic emissions, showed a mean concentration of $24.1 \mu\text{g}/\text{m}^3$, with short-duration peaks above $80 \mu\text{g}/\text{m}^3$, particularly when passing through or near large urban areas. O_3 exhibited a contrasting pattern, with higher concentrations during more rural sections of the route, consistent with photochemical formation and titration effects in urban environments. The AQHI averaged 5.7 over the run, corresponding to a moderate to high health-risk category, with values frequently exceeding 9–11 during the most polluted segments.

The time-series analysis below (Figure 2.6) highlights pronounced spatial and temporal variability in exposure. Elevated $PM_{2.5}$, PM_{10} , and NO_2 concentrations were sustained during extended periods in northern India, particularly around the Indo-Gangetic Plain, where regional background pollution and urban emissions combine. In contrast, central



stretches of the route show clearer reductions in particulate concentrations, accompanied by relative increases in ozone, a classic urban–rural pollution gradient.

Despite this variability, high exposure was the norm rather than the exception. $PM_{2.5}$ concentrations exceeded the WHO 24-hour guideline (used here as a reference threshold) during over 96% of the run time, while NO_2 exceeded its WHO 24 hour guideline value more than 34% of the time, underscoring the chronic nature of exposure experienced during prolonged outdoor activity in these environments. $PM_{2.5}$ and PM_{10} were strongly correlated ($r \approx 0.80$), while ozone showed a negative correlation with NO_2 . AQHI was most strongly correlated with $PM_{2.5}$ ($r \approx 0.92$), confirming that regional fine particulate matter was the dominant driver of overall health risk during the run.

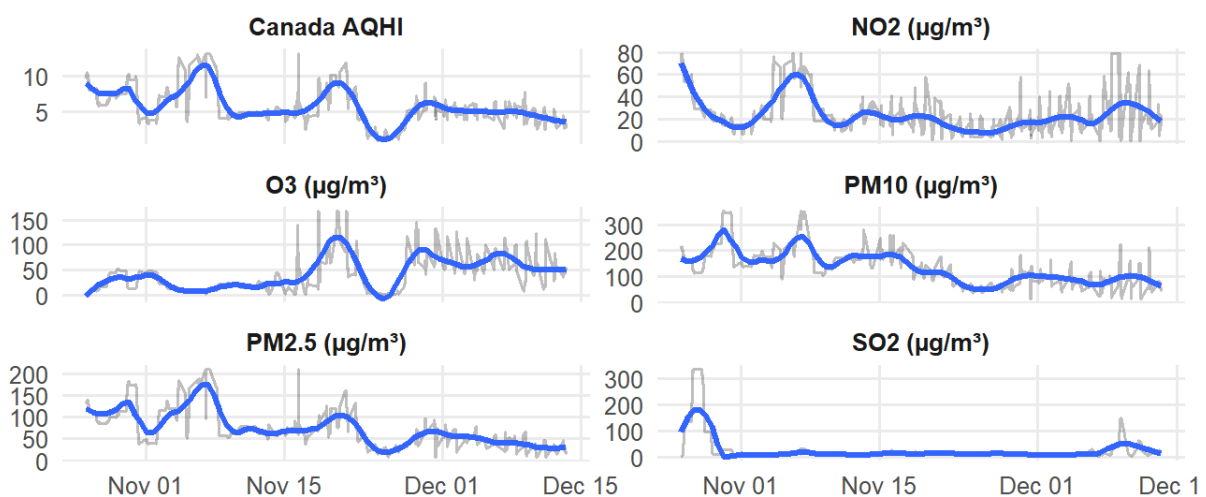


Figure 2.6: Hannah Cox's exposure during the first half of 100 day x 100 marathon challenge through India

3. Physiological Impacts: Early Signals from AirTrack

Physiological signals are directly influenced by air pollution (Jeong, 2025). A substantial portion of day-to-day variance in HRV, resting heart rate, sleep quality, and recovery scores is environmental, but currently treated as unexplained “noise.” Inhaled pollutants trigger systemic inflammation and oxidative stress, impairing autonomic balance. This suppresses HRV and elevates resting heart rate, two core components of readiness and recovery models (Wang et al. 2025). Airway irritation leads to subclinical respiratory events that can fragment sleep and disrupt deep and REM sleep ratios. Wearables may misattribute these disruptions to stress, alcohol, or poor habits..



A key focus for AirTrack in 2025 was beginning to explore how personalised air pollution exposure relates to physiological recovery. Using always-on HRV measurements collected through AirCoach and paired with AirTrack's real-time environmental data, we conducted an initial exploratory analysis to assess whether day-to-day differences in air quality influence autonomic function. Although this work represents an early stage of our scientific roadmap, the results are encouraging.

3.1 Daily air quality shows a relationship with HRV

Across 11,000+ HRV readings from two users over 64 user-days, we observed that worse air quality (higher AQHI) was associated with lower daily average HRV, with a moderate and statistically significant correlation ($r \approx -0.28$, $p \approx 0.02$). When HRV and AQHI were averaged by user and by day (Figure 3.1), a meaningful pattern emerged: HRV tended to be higher on days with cleaner air and lower when pollution levels were elevated. To avoid confounding effects such as age, fitness, or baseline HRV differences between individuals, we analysed each user relative to their own daily average. This within-person approach ensures that the observed relationships reflect day-to-day changes in air quality rather than differences between users.

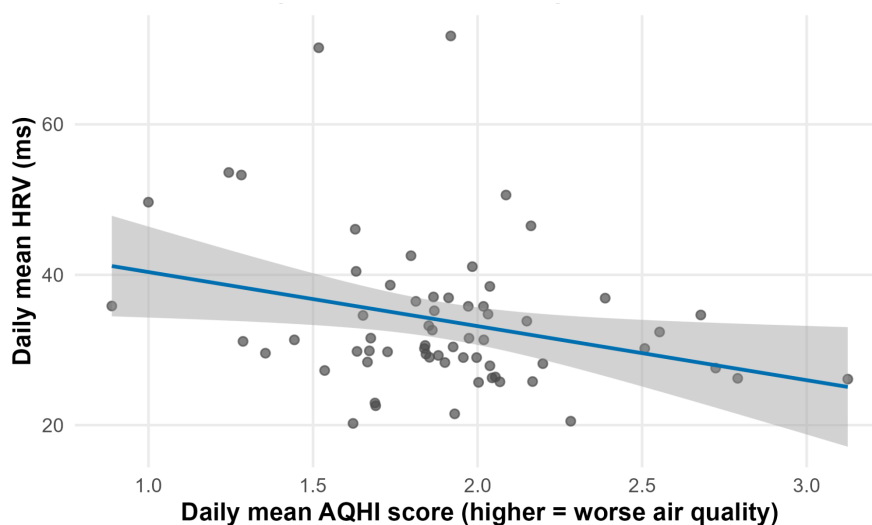


Figure 3.1: Daily mean HRV vs Daily Mean AQHI

This aligns with established scientific literature showing that air pollution can reduce parasympathetic activity and impair recovery. Importantly, we were able to detect this relationship even with:

- a very small sample (two early AirCoach users)
- limited indoor air quality representation
- and highly variable minute-level HRV data



The fact that a daily level signal still emerges suggests that AirTrack’s personalised exposure modelling is already capturing physiologically relevant environmental variation.

3.2 Early signs of individual-level sensitivity?

We also examined whether individuals showed lower HRV on days when *their own* exposure was worse than their personal average (3.2). This within-user analysis focuses on how each individual responds to day-to-day variation in air quality.

The early dataset shows a subtle downward trend, indicating that HRV may dip on higher-exposure days. However, this effect is not yet statistically robust – an expected outcome given the limited sample size, possible lag-time between exposure and effect and early-stage model inputs. With more users, longer longitudinal coverage, and improved indoor air quality inference, we expect these within-person relationships to strengthen and become clinically interpretable.

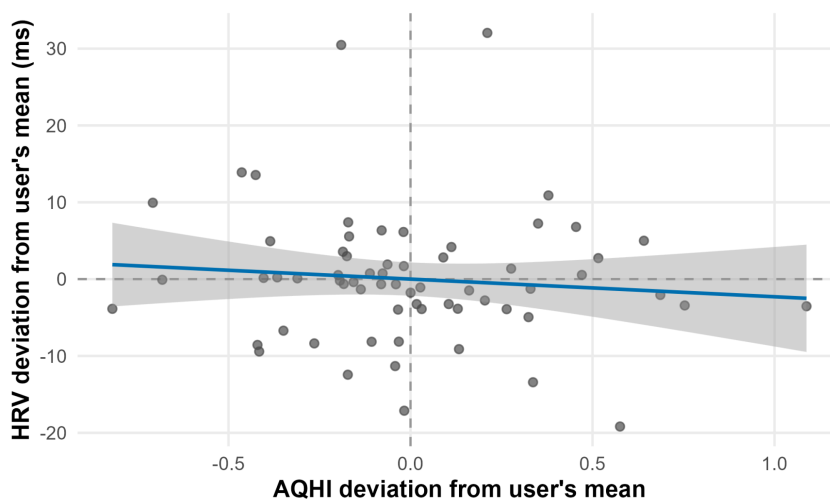


Figure 3.2: HRV deviation from user’s mean vs user’s AQHI

3.3 Looking ahead

Together, these analyses illustrate the emerging capability of AirTrack to detect meaningful physiological responses to environmental exposure. At the day level, we observe a consistent link between cleaner air and higher HRV. At the individual level, early signals suggest that personal fluctuations in exposure may influence recovery, although larger datasets and further analysis are required to account for potential confounders.

These findings provide an encouraging foundation for AirTrack’s expanding scientific programme as we move into 2026, with upcoming clinical pilots, workplace studies, and



enhanced exposure-dose modelling set to deepen our understanding of how air quality affects human physiology.

4. Air Quality Communication

4.1 Communicating Air Quality in a Relatable Way

Throughout development, AirTrack has prioritised non-alarming communication to avoid increasing anxiety while still enabling informed decisions. Appropriately communicating air quality is essential for AirTrack to tackle health inequalities and improve accessibility to clean air (Schute et al., 2025). One of the clearest lessons from AirTrack’s 2025 data is that people engage when it is relatable, simple, and visual.

Our audience of over 2800 users is global and diverse: 57.5% male and 42.5% female, spanning all ages from 18 to 65+. While our largest user bases are in the United Kingdom, we have users in over 100 countries worldwide. Their profiles vary widely – athletes, commuters, parents, data enthusiasts, and clinical users alike – which makes crafting the right message a real challenge. Each group interprets air quality differently, and a single style of communication rarely resonates across all users. That’s why relatability and clarity are so important: people engage most when information reflects their own routines, decisions, and environments.

Most public air quality information is designed for cities by local authorities. But users respond far more strongly when exposure is framed in ways that reflect their own lived experience: cleaner backstreets, commuting patterns, ventilation during movement, and the specific activities that shape their daily dose. Personalised insights consistently outperform regional averages or colour-coded alerts.

We also learned that people increasingly want new, constructive content. They need to understand the problem from multiple angles – what it means globally, and what it means personally. Users don’t just want warnings; they want both a general understanding of the issue and clear, specific guidance on what they can do. This shift toward empowering communication is exactly why simplicity and positivity matter.

4.2 Why Personalised Insights Drive Engagement

AirTrack’s AI post-activity notifications have become one of our most powerful communication tools. They are personal, actionable, and encourage small, achievable adjustments—whether that’s taking a quieter route, changing direction with the wind, or moving a workout indoors on high-pollution days. Importantly, they focus on reinforcing



positive behaviours and maintaining activity rather than discouraging it. Feedback from users shows they value highly specific and personalised data, often comparing results and expecting the summary to be precise. We've now refined our notifications to a point where they enjoy a 100% approval rate among users.

Simplicity is another strong driver. People prefer one simple health-based signal rather than multiple pollutant numbers. This is why AQHI and AirTrack's exposure summaries resonate: they translate complex environmental science into practical guidance that users can apply instantly.

4.3 Behaviour Change Driven by Better Communication

Across 2025, we've started to observe how behavioural shifts are triggered by improved communication: runners choosing quieter routes, commuters adjusting departure times, weekend cyclists moving into parks, indoor workouts replacing outdoor sessions on high-pollution days, and employers recognising exposure as part of wellbeing. It is evident that different audiences benefit from different framing. For example:

- **athletes** respond to performance and cardiovascular load
- **clinical users** require clarity and reassurance
- **general users** respond to simple, personalised storytelling, especially on social platforms.

MJ, an AirTrack user, shared: "It's proper science. The data is so helpful – the visual maps and stats make it easy to see which routes have cleaner air. It's helped me understand air pollution during my runs and adjust the route or timing to reduce my exposure."

Traditional media tends to cover air pollution episodically rather than continuously, largely because the topic is technically complex and difficult to communicate in an engaging way. AirTrack has the potential to fill this gap by making exposure personal, visual, and actionable.

A core lesson from 2025 is simple: people need pollution understanding. Calm, personalised communication transforms air quality data from background noise into a daily decision-making tool. And that is where AirTrack creates real value.

5. Impact and Future Applications

AirTrack's 2025 dataset shows that personal exposure analytics can now deliver practical, measurable value across employers, charities, health platforms, and mobility



systems. Early enterprise pilots demonstrate strong engagement, particularly via AirCoach Leaderboards, and clear behavioural shifts such as cleaner route selection, adjusted commuting times, and reduced exposure during training. These early insights form the foundation for three high-impact product lines: AirTrack, AirTrack Enterprise/Ascent, and the AirAware API.

5.1 AirTrack (Individuals)

AirTrack provides personalised exposure insights, cleaner route guidance, and post-activity summaries that turn complex environmental data into actionable feedback. In 2026, this will expand to include:

- 24/7 environmental physiology insights through AirCoach (linking air quality with HRV and recovery).
- indoor and in-vehicle exposure inference
- trigger detection for asthma and long-term conditions, helping clinicians and patients understand symptom and exposure relationships.

5.2 AirTrack Enterprise/Ascent

Pilots with Arcanys and Asthma + Lung UK show how organisations can use exposure analytics to inform wellbeing strategies and quantify pollution risk during commutes and training. In 2026, Enterprise customers will benefit from:

- cohort dashboards showing group-level exposure trends, high-risk periods, and hotspot corridors
- exposure-adjusted wellbeing metrics, enabling teams to understand how environmental conditions affect recovery and productivity
- behaviour-change intelligence, identifying where cleaner routes, adjusted start times, or indoor alternatives can reduce exposure by 20-50%.

For employers, this creates a new measurable dimension of duty of care; for charities, it supports safer training and better health outcomes.

5.3 AirAware API

The AirAware API converts AirTrack's modelling and insights into scalable infrastructure for partners. This is where your *largest commercial upside* sits. In 2026 we will focus on three core integrations:

1. Mobility & Routing Platforms (Clean Route Engine)

API endpoints will allow transport providers and mobility apps to offer



“health-optimised routing,” reducing inhaled dose by up to 50% with minimal time penalty. This supports:

- cycling and running route selection
- multimodal commute planning
- city planning and micromobility strategies.

2. Wearables & Digital Health (Environmental Physiology Layer)

Exposure adjusted HRV, sleep and recovery modelling provides:

- more accurate readiness scores
- environmental confounder detection
- personalised recommendations when pollution is affecting performance.

Wearables currently treat environmental variation as noise; AirAware API turns it into an explainable input.

3. Insurance & Population Health (Exposure Adjusted Risk Models)

Insurers and health platforms can integrate exposure metrics to:

- identify high-risk commutes or neighbourhoods
- personalise health nudges and prevention programmes
- improve actuarial modelling using objective environmental determinants.

6. Conclusion

The 2025 findings show that personalised exposure insights are measurable, actionable, and increasingly essential to wellbeing, performance, clinical care, and mobility planning. By combining route optimisation, wearable linked physiology, and scalable API infrastructure, AirTrack and the AirAware ecosystem are positioned to become the default environmental intelligence layer for individuals, employers, health systems, and global mobility platforms. In parallel with product and commercial development, AirTrack is committed to scientific transparency and independent validation. Detailed analyses from our exposure datasets have been prepared and submitted for peer-reviewed publication.

Personalised environmental intelligence is no longer a ‘nice to have’; it is becoming a prerequisite for accurate health, performance, and mobility modelling.

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