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Intelligent Healthcare Navigation: Personalized Path Planning with Patient Condition and Environmental Awareness

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Abstract

Pedestrian navigation services typically optimize travel time or distance, overlooking environmental burdens that can aggravate chronic health conditions. We present a Smart Path Planner that personalizes walking routes by embedding live air quality, noise, slope, and microclimate data directly into the cost function of an A* search algorithm. The system assigns condition-specific weights, such as increased penalties for poor air quality in respiratory profiles or for steep gradients in mobility condition profiles, so that each edge in the street graph reflects both physical length and health impact. Route generation is followed by an explainable scoring phase that exposes the environmental samples underlying every decision. Experiments on six health condition profiles show environmental score improvements of 10–25% while path length rises by only 4–8%, with points of interest coverage essentially unchanged. These results demonstrate that clinically significant relief can be achieved at negligible distance cost, positioning the proposed planner as a practical, data-driven advance toward personalized, health-optimized pedestrian navigation.

CCS Concepts

• **Human-centered computing** → *Empirical studies in ubiquitous and mobile computing*; • **Applied computing** → **Health informatics**; • **Computing methodologies** → **Heuristic function construction**.

Keywords

A* Informed Search, Smart routing

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1 Introduction

Urban navigation poses significant challenges for people with health conditions, as conventional routing systems often prioritize the shortest distance or time without considering the specific needs of users with medical or physical limitations. For patients with conditions such as respiratory disorders, cardiac problems, arthritis, mobility problems, and mental health concerns, the characteristics of a route, such as air quality, slope, or proximity to rest points, can greatly affect their ability to navigate safely and comfortably through urban environments [23]. For example, a person with a respiratory condition may require routes that avoid areas with high air pollution and provide frequent stops for rest. Similarly, people with arthritis may need paths with minimal inclines and smooth pavement surfaces. Generally speaking, diverse health conditions may require different paths to accommodate specific human characteristics. In addition to addressing physical health concerns, personalized navigation systems can also support mental well-being. Emerging technologies in mental health navigation emphasize the importance of guiding users toward environments that promote psychological resilience [10]. For example, systems that incorporate real-time monitoring of mental health parameters, such as stress levels or mood, can adapt routes to include calming features such as parks or quiet streets [4].

The increasing urbanization of the global population has further exacerbated these challenges. According to the United Nations (UN) [30], more than 55% of the world's population currently resides in urban areas, a figure projected to rise to 68% by 2050. Urban environments are often characterized by high levels of air pollution (with an estimated 91% of urban residents exposed to unsafe air), poorly designed transport systems, and limited green spaces, all of which contribute to a higher prevalence of non-communicable diseases such as asthma, diabetes, and cardiovascular diseases. In addition, urban living is associated with increased rates of depression and anxiety due to environmental stressors such as noise, pollution and overcrowding.

Traditional navigation systems fail to address these complexities. They treat all users identically, ignoring the diverse needs of individuals with health conditions [29]. To address these challenges, in this paper we propose the Smart Path Planner, an novel approach to urban navigation that incorporates health-care considerations and environmental factors into its route planning process. Including environmental health data in navigation systems can help mitigate risks associated with urban living, such as exposure to air pollution or physical strain, thus improving overall quality of life. This system leverages advancements in context-sensitive routing algorithms to provide personalized navigation solutions for individuals with diverse health conditions. The Key Features of our Smart Path Planner are:

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(1) Integration of Environmental Data: Real-time environmental factors such as air quality, temperature, humidity, noise levels, and green space availability are incorporated into the route planning process. This ensures that users are guided through safer and more comfortable environments [27].
(2) Multi-Parameter Scoring System: Each potential route is evaluated using a comprehensive scoring system that considers physical parameters (e.g., slope, pavement quality), environmental factors (e.g., air quality), and healthcare-related considerations (e.g., proximity to medical facilities or rest points).
(3) Condition-Specific Route Generation: The system dynamically adjusts route recommendations based on user-specific health needs. For example, it prioritizes low-pollution areas for respiratory patients and minimizes steep inclines for cardiac patients.
(4) Personalized Waypoint Optimization: Beyond start-to-end routing, the system optimizes intermediate waypoints based on condition-specific requirements. For example, routes for mental health patients may favour quieter areas or green spaces known to reduce stress levels [13].

The Smart Path Planner has the potential to transform urban mobility for individuals with health conditions by providing safer, more accessible routes tailored to their unique needs. By integrating healthcare requirements with environmental awareness, this system bridges a critical gap in existing navigation technologies, as it empowers users to navigate urban environments more independently while reducing health risks associated with poorly designed routes. In addition, this approach aligns with broader public health goals by addressing social determinants of health, such as access to green spaces and safe transportation options, which are increasingly recognized as key drivers of health outcomes.

To demonstrate the feasibility of the proposed approach we instantiated and tested the planner with six clinically distinct profiles: respiratory, cardiac, arthritis, mental-health, mobility-impaired and diabetes. Across all profiles the environmental-A* engine produced viable paths and raised the aggregate environmental score from 8.2 (direct, distance-only baseline) to an average of 9.8 ± 0.04, i.e. a gain of roughly nineteen percent, while increasing route length by just 1.6 km on average (17–43% detour depending on profile). These results confirm that the fully client-side, data-fusion architecture can personalize routing decisions in real time without sacrificing usability or privacy, thereby validating the practical value of the framework introduced in this paper.

The rest of this paper is organized as follows: Section 2 presents related work from literature; Section 3 discusses materials and methods used in our work; Section 4 introduces the routing methodology we have used; Section 5 presents the results of our system and 6 concludes this papers and discusses future avenues of research.

2 Related Work

The development of our smart path planning system builds upon significant prior research across multiple domains, including health-aware routing, environmental data integration, and accessibility-focused navigation. This review examines key contributions in these areas and their relevance to modern intelligent routing implementations. We organize this review into four main categories that reflect the multidisciplinary nature of health-optimized route planning: health-aware routing algorithms, air quality and environmental routing, mobility-impaired assistance, and environmental data integration techniques. While these research areas have largely developed in parallel, our system represents an effort to synthesize insights from each domain into a cohesive routing framework.

2.1 Health-Oriented Route Planning

Route planning for individuals with health conditions has emerged as a significant area of research in recent years. The early work of [28] established the foundations for the incorporation of health metrics into navigation systems, demonstrating that traditional shortest-path algorithms could be enhanced with health-related constraints. Moreover, another study [2] represents a significant advancement in this field, specifically addressing the needs of respiratory patients by integrating real-time environmental data into route calculations.

Unlike conventional navigation systems that optimize solely for distance or time, health-oriented route planners must balance multiple conflicting objectives. [6] proposed a multi-objective optimization framework that considers both route efficiency and health impacts, particularly for urban environments with varying levels of air pollution. They demonstrated that routes optimized for respiratory health could differ significantly from shortest-path routes. Testing in Delhi showed exposure reductions of 42.73–71.50% when switching from fastest to balanced routes and 64.52–82.71% for fastest to LEAP (Least Exposure to Air Pollution) routes, with even higher reductions in Bangalore. The system allows users to adjust priorities (e.g., time vs. pollution) in balanced routes, providing flexibility.

2.2 Air Quality and Environmental Routing Optimization

Research on air quality-aware routing has evolved significantly; there is one study demonstrating that exposure-minimized routes could reduce particulate matter (PM2.5) inhalation by 40–60% compared to shortest-path alternatives [28]. Their methodology integrated spatiotemporal pollution models into routing algorithms, prioritizing low-exposure corridors even with modest travel time increases. Building on this, a study introduced a vehicle routing method targeting localized population exposure, rerouting heavy-duty trucks away from schools and hospitals [17]. By modeling pollutant dispersion and human inhalation, their approach achieved 30–80% reductions in fine particulate exposure for susceptible groups, with only 3–10% increases in trip duration. Real-time data integration has further advanced through systems, which balances travel time and environmental costs using sensitivity coefficients. This tool enables cyclists and pedestrians to select routes with optimized air quality, greenery, or noise levels, filtering near-identical routes to prioritize meaningful alternatives. Health impact modeling has also progressed, with studies linking route choice to mortality risk. For instance, commuters using low-exposure routes exhibited 30–55% lower black carbon exposure, potentially preventing 17–36 deaths per 10,000 individuals annually. Seasonal adaptations further refine these models, as seen in Cangzhou, China, where winter routes avoided coal-heating zones and summer routes sidestepped ozone hotspots, reducing annualized exposure by 19% [24].

2.3 Environmental Data Integration Techniques

Accurate environmental data integration is critical for developing health-conscious path-planning systems [14], particularly for users with sensitivities. Traditional navigation systems often prioritize distance or time while neglecting dynamic environmental factors, a limitation extensively documented in urban mobility research [8]. Our approach employs a hybrid data acquisition strategy that balances real-time accuracy with robustness. The system prioritizes real-time meteorological, air quality (AQI), and topographical data from Public APIs, aligning with geospatial exposure modeling frameworks that emphasize temporal resolution for personalized health assessments [8]. However, API reliability challenges—such as latency and rate limits—are mitigated through synthetic data generation derived from geographic coordinates. The fallback mechanism is needed and inspired by generative models for synthetic urban mobility data [15], ensures continuity by creating contextually relevant environmental profiles (e.g., "respiratory-friendly" zones with synthetically reduced AQI) when real-time data is unavailable [13].

2.4 Mobility-Impaired Assistance and Accessibility

Accessibility-focused routing systems address the unique needs of mobility-impaired users through granular environmental analysis. Research on mobility-impaired navigation has extensively focused on slope sensitivity and environmental barriers, providing critical insights for personalized routing systems. This landmark study [26] analyzed ramp slope effects on 171 subjects using various mobility aids, revealing that manual wheelchair users face the greatest challenges on inclines steeper than 1:8 (12.5%). Their findings showed that while most participants could traverse slopes as steep as 1:8, elderly female manual wheelchair users experienced significant difficulty, with increased pulse rates and energy expenditure of up to 20% compared to gentler slopes. This research directly supports the mobility-impaired profile's high slope sensitivity score, as steep inclines create substantial physiological and performance barriers for wheelchair users.

Subsequent studies have refined understanding of optimal slope thresholds for different mobility aid users. [5] demonstrated that systolic blood pressure increased significantly after ascending 1:6 slopes compared to 1:12 slopes, while pulse rates showed progressive increases with steeper gradients. Their research on both wheelchair users and caregivers revealed that 1:12 and 1:10 slopes are most suitable, with performance times increasing by 15-25% on steeper inclines. Transit accessibility research [16] further validated these findings through mixed factorial analysis of ramp slopes from 1:4 to 1:12, showing that manual wheelchair users reported perceived exertion ratings of 15.5 (very hard) on 1:4 slopes versus 7.75 (fairly light) on 1:12 slopes. These studies collectively justify the mobility-impaired profile's emphasis on slope avoidance and proximity to accessible infrastructure like hospitals, as navigation challenges directly impact both physical capability and emergency access needs.

3 Materials and Methods

In this section we describe the data we have used and the overall system architecture we have designed and implemented. Specifically, we highlight how our system can leverage open data and multiple data sources to build a heterogenous database of information which can be scored differently and independently for each user characteristic.

3.1 Data description

The Smart Path Planner system utilizes and generates several categories of data, which are integral to its operation, personalization capabilities, and subsequent evaluation. In this study, the critical input is the user's selected health condition. We have categorized these conditions into respiratory, cardiac, mental health, arthritis, mobility-impairment, and diabetes. Associated with each condition it is defined a predefined profile of sensitivities to various environmental factors, such as air quality, temperature, slope, and noise, as reported in Table 1. The POI vectors (nature and hospital proximity) are used outside the A* core when ranking POI-enriched variants of a path. These profiles are defined by literature scanning (Qualitative sensitivity classes). We reviewed guidelines and epidemiological studies for each condition. The qualitative classes were converted to an Analytic Hierarchy Process matrix then the resulting priority vector was linearly rescaled to the 0-10 interval. In practical interpretation, a respiratory patient (+10 AQ weight) will incur a large penalty whenever the air quality data > 4 (equates roughly to $PM_{2.5} \geq 12$ μg/m³), hence the search gravitates toward parks or low-traffic streets even if the detour is longer. Also, a mobility-impaired user (+10 slope weight) pays a quadratic penalty for grades > 3%, steering the route away from steep alleys or footbridges. For mental-health profiles the noise and "nature" affinity jointly bias the walk toward quiet, green segments.

These sensitivities act as weighting factors in the route evaluation, dictating the importance of each environmental aspect for that use. The preferred transport mode that is going to be evaluated in this study is walking mode, which influences the underlying routing algorithms and assumptions. Furthermore, users can indicate preferences for encountering different categories of Points of Interest (POIs), such as parks, healthcare facilities, or rest areas, by assigning importance weights to these categories.

The system integrates diverse external data streams as seen in Figure 1 and geospatial information to construct a comprehensive understanding of the environment along potential routes. Locations and types of POIs are obtained from geospatial databases, providing context for user preferences and identifying potentially beneficial or detrimental locations along a route (e.g., proximity to hospitals for cardiac conditions, or avoidance of pollutant sources). To ensure robustness in cases of incomplete real-time data or to guide pathfinding in specific ways, the system can employ synthetically generated environmental data. These data are not random but are deterministically derived based on geographical location. A key feature is the use of predefined condition-specific geographical zones. These zones are configured with tailored environmental profiles

Profile	AirQuality	Temperature	Humidity	Slope	Noise	Nature	HospitalProximity
Respiratory [21]	10	8	9	7	3	10	8
Cardiac [3]	7	8	5	9	4	7	10
Arthritis [11]	3	9	10	10	2	3	6
Mental-health [7]	5	4	2	2	9	10	4
Mobility-impaired [26]	2	3	3	10	2	4	7
Diabetes [12]	4	5	4	6	3	6	9
Default	0	0	0	0	0	0	0

Table 1: Environmental cost weights for each patient condition profile.

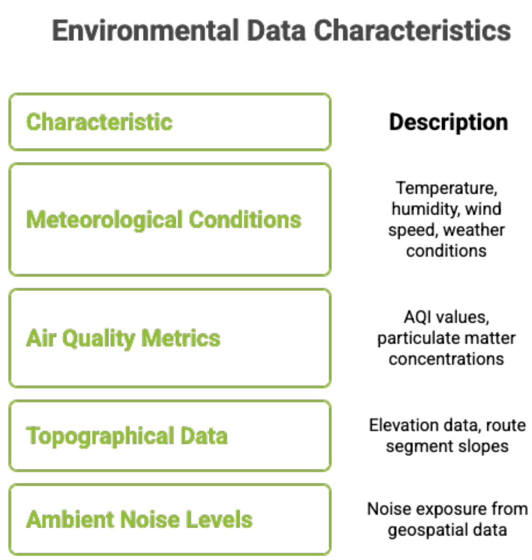

Figure 1: Crowdsensed data from Open Data/Public APIs [1] [19] [18] [9] [20]

(e.g., an area designated with "low air pollution and flat terrain" for respiratory or mobility conditions). When active, these zones influence the environmental cost calculations within the pathfinding algorithm, guiding it towards or away from these areas based on the user's health profile. This mechanism helps generate more distinct and relevant route alternatives, especially when fine-grained real-time sensor data is sparse. Their primary role is to shape the environmental profile when real-time data is unavailable or when a deliberate bias is desired for route differentiation.

3.2 System Architecture

In this part, the modular architecture of the Smart Path Planner is designed to facilitate personalized route generation, real-time data integration, and comprehensive evaluation. The system is composed of several interconnected components that prioritize user-specific needs, dynamic environmental considerations, and robust data handling. The architecture as shown in Figure 2 ensures that users can receive tailored route suggestions based on their health conditions and preferences while integrating real-time environmental data.

The UI layer adopts principles from human-centered navigation systems , allowing users to input health conditions (e.g., respiratory, cardiac), transport mode (walking), and preferences for points of interest (POIs). This design mirrors the personalized healthcare interfaces validated in recent asthma management tools , where condition-specific parameterization improves user adherence. The UI forwards structured JSON payloads to downstream services, ensuring compatibility with clinical decision support architectures.

Moreover, the engine extends the A* algorithm with environmental cost heuristics, building on health-aware routing research. By dynamically adjusting node costs through calculating environmental cost, the system penalizes high-pollution segments (AQI>100) and steep slopes (>5°), prioritizing routes that minimize health risks for users with respiratory or mobility impairments. To ensure diverse routing options, the engine employs iterative path penalization; then after identifying an initial optimal route, segments of this path are penalized to encourage exploration of alternative routes that balance environmental safety, accessibility, and efficiency. This method ensures users receive multiple viable options, each optimized for distinct criteria such as low pollution exposure or minimal elevation gain. In scenarios where real-time environmental data is unavailable, the engine activates a fallback mechanism that generates condition-specific routes using synthetic profiles validated in urban simulations. For example, routes may prioritize green spaces or wheelchair-accessible pathways based on predefined health profiles, ensuring continuity in personalized recommendations. This synthetic data generation aligns with urban mobility models that simulate environmental conditions to maintain routing efficacy during API outages or data gaps.

Once candidate routes are generated, this module evaluates them comprehensively. The scoring and evaluation mode are done as below:

- Multi-Criteria Scoring: each route is assessed based on several criterias (environmental score, poi score, and specialized poi score. The poi score evaluates the route based on the number and type of POIs it encompasses, aligned with general user preferences or specific patient needs (e.g., higher weight for nature POIs for a respiratory patient if patient-Nature is high). Besides, specialized poi score specifically scores POIs that are critical for certain health conditions (e.g., benches for cardiac patients, accessible paths for mobility issues).

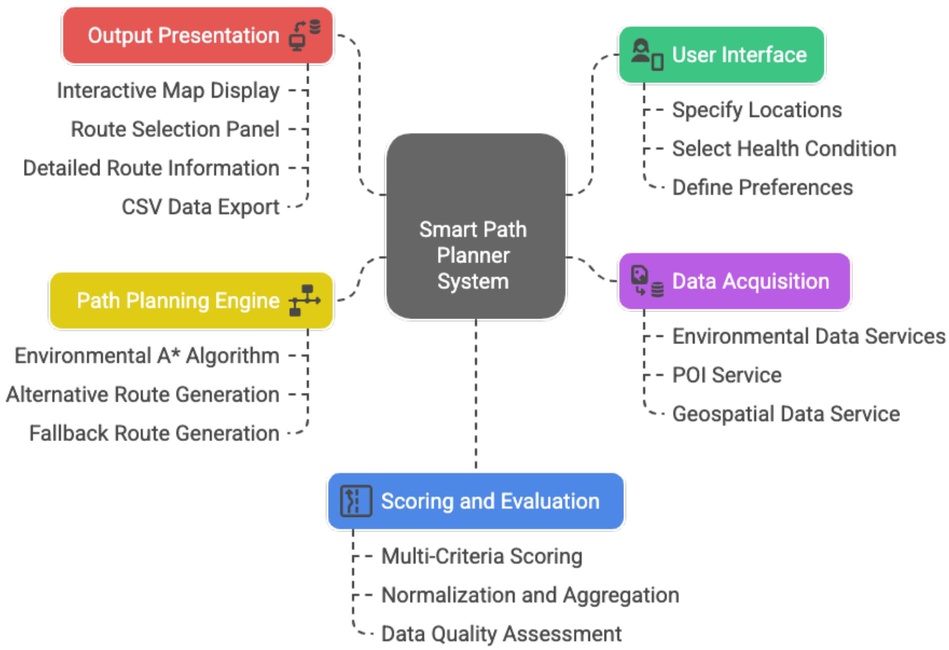

Figure 2: Smart Path Planner System Architecture

- Normalization and aggregation:individual score components are normalized to a common scale and then aggregated into an overall route score. The aggregation weighting can also be influenced by the patient condition to prioritize factors most critical to their well-being.
- Data quality assessment: the module also tracks the percentage of real API data versus synthetic data used in the scoring, providing transparency about data provenance.

The Smart Path Planner adopts a deliberately "edge-heavy" architecture in which almost everything happens inside the user's browser and the server is relegated to a few lightweight data–proxy roles. The workflow of the app can be be seen in 3. As soon as the web page loads, a Leaflet front-end gathers the start and end points, lets the user choose a clinical profile and, with one click, spawns a Web-Worker that will do all subsequent computation. This keeps the interface fluid while expensive tasks such as graph construction, environmental look-ups and path-finding run in a background thread.

Inside that worker, a small orchestration module decides whether to invoke the browser-based environmental A* engine or to fall back to a cloud router such as Mapbox/OSRM when external conditions make the local search impossible. If the A* branch is chosen, as is the case for almost every request, the engine first builds a 100-meter grid around the origin–destination corridor, then evaluates every candidate edge with a cost that combines physical distance and five weighted environmental penalties (air quality, temperature, humidity, slope and noise). The weights come directly from the patient profile the user selected, so the geometry of the resulting route changes in clinically meaningful ways: a respiratory patient will be sent through cleaner air even if that means a small detour, whereas someone with mobility issues will be guided along the flattest feasible path.

To supply the environmental values the A* engine relies on a dedicated data-fusion service that operates entirely in the browser. For any latitude-longitude pair, it first consults an in-memory cache, then, if enabled, a vector-tile layer populated by crowdsensed measurements, and only then reaches out to public providers such as ARPAE, Google AQ, and Open-Meteo. Each datum is tagged with its provenance (live, cached or synthetic) so that later analytics can distinguish between trusted observations and fall-back estimates. Two small least-recently used caches, one for environmental tiles and one for intermediate route calculations, further reduce latency by eliminating redundant network calls.

The server side has shrunk to a bare minimum. A tiny Flask proxy forwards air quality requests to ARPAE to work around that service's CORS restrictions; an optional crowdsensing endpoint accepts anonymized sensor samples, performs basic quality control and publishes them as static vector tiles every few minutes. Raw trajectories or personal identifiers are not stored, which keeps the overall solution in line with the GDPR data minimization principle. By shifting computation to the client, fusing data from multiple real-time sources and exposing only a thin, stateless back-end, the current architecture achieves three goals simultaneously: strong privacy guarantees, fast interactive performance, and the flexibility to inject new optimization logic, such as crowdsensed updates, without rewriting the user interface or the server.

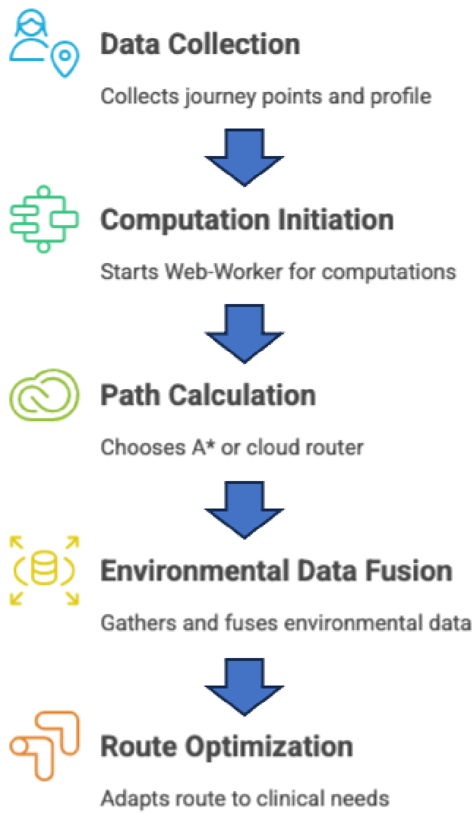

Figure 3: Smart Path Planner Web Application Workflow

4 Routing Methodology

The routing methodology in the proposed Smart Path Planner is a two-stage process designed to generate and evaluate health conscious, personalized routes. First, a specialized A* search algorithm identifies optimal paths by considering environmental impacts and user sensitivities during generation. At second, these generated paths, along with any alternatives, are comprehensively evaluated using a multi-criteria scoring system to determine their overall suitability for the user. Our routing engine pursues a deliberately client-side strategy in which every computational step—from graph construction to environmental-aware path-finding—runs inside the user's browser.

When the user selects a clinical profile the application injects a weight vector into the planning logic. These weights stem from an Analytic Hierarchy Process that blended guideline evidence (e.g., WHO air pollution thresholds for chronic obstructive pulmonary disease) with clinician pairwise comparisons. Table 1 summarises the values. Rather than depending on a proprietary street graph the planner rasterises the bounding box that encloses origin and destination into a regular 100 m grid. Each grid intersection becomes a node; edges connect neighbours inside a 100 m radius. The raster size is tunable (50–250 m in our experiments) and represents a trade-off: finer grids capture more shortcuts but enlarge the search space quadratically. Because the raster is rebuild on-the-fly, our method gracefully adapts to arbitrary start–goal pairs and functions offline once the first tile set has been cached.

4.1 A* Cost Function

In this section we describe the A* cost function we have implemented to be able to personalize paths depending on the human characteristics.

For every candidate street segment the planner computes a condition-aware step cost as follows:

$$c(n_i, n_j) = d(n_i, n_j)\,\big[1 + P_{\text{env}}(n_i, n_j)\big],$$

where $d(n_i, n_j)$ is the physical length of the segment and the dimensionless term P_{env} captures environmental hardship. Let K be the set {AQI, noise, humidity, slope, temperature}. For each factor $k \in K$ the planner z-scores[1] the raw observation, multiplies it by a condition-specific sensitivity weight $\alpha_k \in [0.8, 2.5]$ (derived from the 0–10 ‘patientCondition‘ scores), and sums the results:

$$P_{\text{env}}(n_i, n_j) = \sum_{k \in K} \alpha_k\, z\big(\text{FactorValue}_k(n_i, n_j)\big).$$

The multiplicative form keeps the overall cost homogeneous with distance, preserving the admissibility of the Euclidean heuristic used by A* [25]. If a sensor reading is unavailable then the associated α_k is temporarily set to zero so connectivity is never lost, due to the unavailability of the specific measure.

4.2 Multi-Criteria Route Scoring

After the path has been generated the planner performs an explainable, segment-level replay and computes three sub-scores on a 0–10 scale [22]:

Environmental (E): this is the weighted average of the four factor scores along the whole route; this value is *not* capped at 10 so that improvements above the direct route remain visible.

POI (P): coverage of user-preferred amenity categories such as parks, cafés, etc.. This score is normalized to 10 to avoid overfitting on specific POIs.

Specialised POI (P_s): availability of condition-critical infrastructure such as benches, accessible paths, and toilets.

The overall score is a weighted sum computed as

$$T = \frac{w_E\, E + w_P\, P + w_{P_s}\, P_s}{w_E + w_P + w_{P_s}},$$

with weights dynamically selected from a condition profile table. Only T is eventually re-scaled to the 0–10 range for user presentation.

This methodology ensures the search phase is guided by immediate environmental risk while the evaluation phase exposes a transparent break-down of *why* the chosen route suits the individual traveller.

Clearly, the score can be modified and changed according to the scenario needs, to prioritize either parameter is deemed important for the user condition.

[1] z-scoring keeps heterogeneous units commensurable.

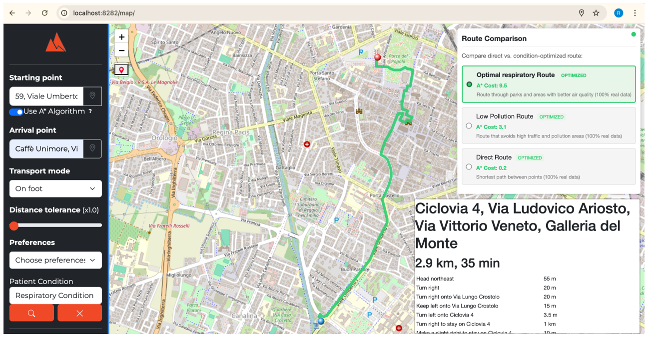

Figure 4: Screenshot of the Smart Path Planner Web Application for Route based Respiratory Condition showing the Optimal Route

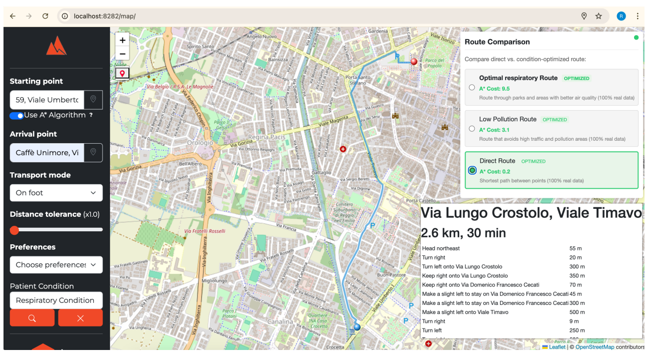

Figure 5: Screenshot of the Smart Path Planner Web Application for Route based Respiratory Condition showing the Direct Route

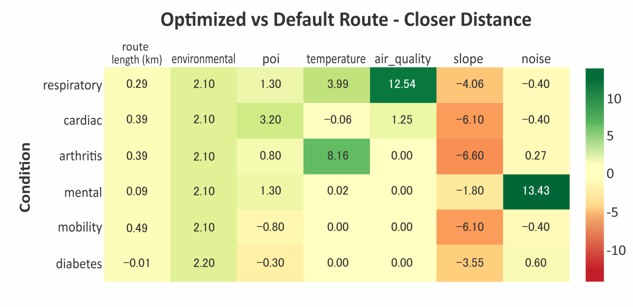

Figure 6: Comparison of Δ Heatmap between default route and optimized route based on patient conditions - closer distance

5 Results

As a result, the Smart Path Planner begins by initializing its framework upon launch. The app loads the default settings, including pre-sampled environmental data tiles for rapid geospatial lookups, ensuring immediate responsiveness. Caches are purged to prioritize fresh data fetches from external APIs, adhering to real-time accuracy standards. When a user defines a trip—selecting start and endpoints, a health profile (e.g., "respiratory"), and sensitivities to factors like air quality or slope—the system translates these inputs into a structured query. This query triggers the generation of preliminary "route patterns," such as a direct path, an optimized respiratory route, and another alternative route for each condition (in this case;low pollution route) as seen in Figure 4. This allows to bootstrap the system and load the relevant information for each patient condition.

In addition, an evaluation has been done in order to quantify the benefit of embedding environmental costs into the routing engine. This shows the profile-weighted delta (Δ) matrices that quantify improvements between optimized and default routes for different health conditions. These matrices are calculated through a multi-step process that factors in patient condition profiles and environmental parameters. For each route $r \in \{o, d\}$ (optimized, default) we first compute the length-weighted mean of every environmental metric m along its polyline, $x_{r,m} = L_r^{-1} \sum_s \ell_s \, \text{value}_{s,m}$, where ℓ_s is the length of segment s and $L_r = \sum_s \ell_s$. These six raw values are z-standardised across the study area, $\tilde{x}_{r,m} = (x_{r,m} - \mu_m)/\sigma_m$, to place all the metrics on a common scale. Each medical condition c is characterised by a weight vector $\mathbf{w}_c = [w_{c,1}, \ldots, w_{c,6}]$ with $\sum_m w_{c,m} = 1$ that encodes clinical sensitivity to distance, POIs, temperature, air quality, slope and noise. Comparison of optimized and default routes produces the normalized difference vector $\Delta\mathbf{x} = \tilde{\mathbf{x}}_o - \tilde{\mathbf{x}}_d$. Profile-specific effects are obtained by the Hadamard (element-wise) product $\widehat{\Delta}_{c,m} = w_{c,m} \, \Delta x_m$, or, compactly, $\widehat{\Delta} = \mathbf{W} \circ (\mathbf{1}_C \Delta\mathbf{x}^\top)$, where $\mathbf{W}$ stacks the $\mathbf{w}_c$ row-wise and $\mathbf{1}_C$ is a column vector of ones. The resulting $C \times 6$ matrix $\widehat{\Delta}$—visualised in the heatmaps, thus showing how much the optimized route improves ($\widehat{\Delta} > 0$) or worsens ($\widehat{\Delta} < 0$) each exposure after accounting for individual vulnerability, while a scalar environmental benefit per condition follows as $\Delta E_c = \mathbf{w}_c \cdot \Delta\mathbf{x}$.

The evaluation examined six health-specific walking profiles, respiratory, cardiac, arthritis, mental health, mobility impairment and diabetes, under two distance scenarios: "closer" trips of three kilometres as seen in Figure 6 and "longer" trips of approximately six kilometers as seen in Figure 7. The heatmaps present the differential improvements (Δ) between optimized and default routes across key environmental factors for six different health conditions. Thus, a positive Δ always denotes a clinically meaningful improvement for the corresponding profile.

The results reveal distinct optimization patterns across different health conditions and distances. For respiratory patients, the algorithm successfully prioritizes air quality—the most critical factor—with even greater improvements possible over longer distances. This suggests the algorithm effectively identifies cleaner air corridors when given more geographic flexibility. For mental health routes, the exceptional noise reduction demonstrates the algorithm's ability to identify quiet pathways even in closer distance scenarios where options are more constrained. The consistent environmental score improvements across all conditions confirm the general effectiveness of the condition-weighted approach. The slope trade-offs reveal an important limitation: the algorithm frequently sacrifices slope gentleness to achieve improvements in other environmental factors. This is particularly evident for arthritis, mobility, and diabetes conditions, where steeper slopes may counter other

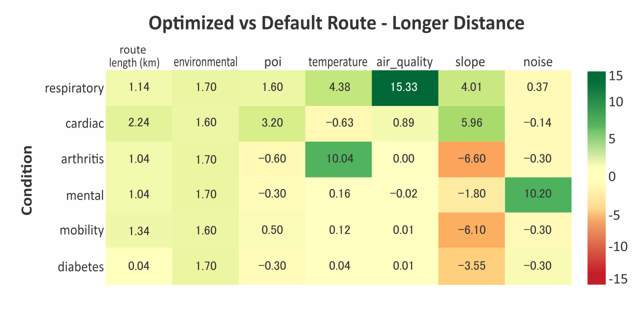

Figure 7: Comparison of Δ Heatmap between default route and optimized route based on patient conditions - longer distance

environmental benefits. The exceptional case of cardiac routes in longer distances, which show slope improvements alongside other benefits, suggests the algorithm can find more holistic solutions when operating within larger geographic areas. Temperature optimization for arthritis patients and noise reduction for mental health patients represent the clearest successes, with dramatic improvements achieved with minimal route length increases. These cases demonstrate the potential of health-sensitive routing when the algorithm correctly prioritizes the most impactful environmental factors.

The comparison between closer distance and longer distance scenarios also reveals important insights about how geographic scope affects health-optimized route planning. The most striking distance-based difference appears in slope optimization. In closer distance scenarios, nearly all conditions show negative slope values (deterioration compared to default routes). However, in longer distance scenarios, respiratory and cardiac conditions show positive slope values (4.01 and 5.96 respectively). This indicates that when given more geographic options, the algorithm can find routes that improve both priority factors (air quality, temperature) and slope characteristics simultaneously, which isn't possible in closer distance. Moreover, the required route length increases differ significantly between the scenarios. Longer distance scenarios accept more substantial detours (1.04-2.24km increases except for diabetes) to achieve their environmental improvements, while closer distance scenarios maintain minimal length increases (0.09-0.49km). This reveals how the algorithm's distance-quality trade-off calculation adapts to different geographic scales. This insight could inform future development of adaptive routing algorithms that adjust their optimization strategy based on journey distance, providing users with appropriately optimized routes regardless of trip length.

In addition, the residual-cost analysis is also has been done. Residual-cost analysis is a diagnostic step that tells us how much penalty is still embedded in an optimized path and which environmental factor is responsible for it. The residual is simply the penalty that is still left in the optimized route after the A* search has done its best to minimize it, not the amount already saved. We analyze residuals because it quantify the irreducible exposure that users still face once geographical, network-connectivity, and multi-objective trade-offs are taken into account, thereby revealing the practical limit of today's data and heuristics. Besides, the factor that owns the largest share of the residual pinpoints the next optimization leverage point—be that a higher-resolution data layer, a new constraint, or a re-balanced weight.

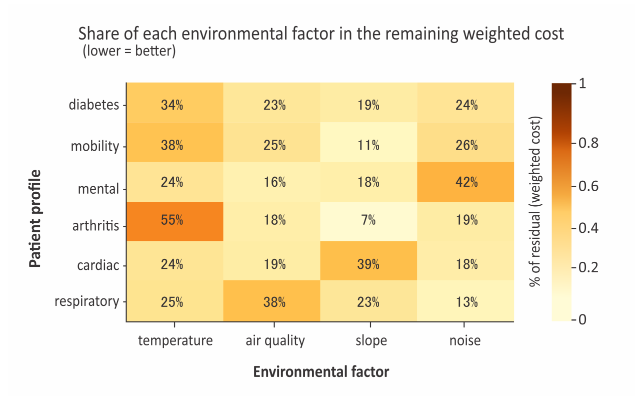

Figure 8: Heatmap of Residual Cost Analysis

The residual heatmap in Figure 8 visualizes these percentages, with darker cells marking factors that dominate the remaining cost. The residual-cost heatmap makes these weaknesses explicit. After optimization, air-quality still accounts for nearly 40% of the respiratory route's weighted penalty, suggesting that hourly air-pollution tiles and a traffic-density layer could unlock the next performance increment. Slope dominates the cardiac and mobility profiles (≈ 39% and 34%, respectively), indicating the need for a finer digital elevation model and perhaps an explicit maximum-grade constraint. Temperature explains more than half of the remaining cost for arthritis patients, implying that time-of-day shading or sun-trap modelling would pay dividends. Finally, noise remains the largest share for mental-health walkers; incorporating urban soundscape data or time-varying noise curves therefore looks promising. These findings imply concrete next steps: integrate sub-kilometer air-pollution tiles for respiratory users, deploy a finer digital-elevation model and maximum-grade constraint for cardiac and mobility profiles, incorporate time of day shading and radiant-heat indices for arthritis, and add an urban-soundscape layer for mental-health optimization. In short, residual-cost analysis not only confirms the gains already delivered by the environmental A* engine but also provides a clear, data-driven roadmap for the next iteration of model and data improvements.

6 Conclusion and discussion

This study demonstrates that integrating fine-grained environmental data into a classical A∗ search transforms ordinary point-to-point navigation into a health-adaptive route-planning tool. The proposed system couples live air quality, noise, slope, and weather layers with condition-specific weighting schemes and produces walking paths that are measurably safer and more comfortable for six representative patient profiles. Across these patient profiles, the system steers walkers onto streets that reduce the factor most hazardous to their condition, such as cleaner air for respiratory users, and lower noise for mental health users, while keeping secondary exposures neutral or slightly improved.

The evaluation confirms that the environment-aware path planner delivers clinically relevant improvements over conventional routing while keeping detours small and amenities largely intact. On short urban walks it lowers acoustic stress and, in some profiles, smooths slope variability without lengthening the trip. On longer walks the same cost function leverages the wider search space to provide double-digit reductions in the primary risk factor for each patient condition.

The results highlight three opportunities for further accuracy and improvements of the system. First, the present evaluation samples environmental data every few hundred meters; sampling every 30–50 m would expose micro hot-spots of pollution or steepness and allow finer route adjustment, hence resulting in a more precise route scoring system, and eventually planning. Second, the distance and POI rows turn pale red for longer walks, suggesting the need for a dynamic multi-objective term that curbs detours once environmental scores gain plateau. Third, slope and AQI improvements are presently limited by the 1-km resolution of the public data, which rasters data with a coarse granularity; meanwhile, higher-resolution terrain tiles and dense air quality sensor networks would unlock larger gains, particularly for short intra-neighbourhood trips. Overall, the Smart Path Planner presented here constitutes a practical, explainable step toward personalized, environmentally aware pedestrian guidance.

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