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Why do pedestrians get lost? A case study of personal, situational, and environmental factors in greater London

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ABSTRACT

Despite advances in route optimization and navigational technologies, pedestrians still face challenges navigating complex urban spaces. This study aims to identify and quantify the multidimensional factors that influence pedestrian navigation, with the focus on why people get lost. The collected data from an online survey in which 64 participants reported the locations and contextual information of their getting lost events. Building upon literature, expert interviews, and collected data, we identify and quantify 14 environmental, situational, and personal factors influencing pedestrian navigation. We utilize a dual-analytical approach that combines expert-led analytic hierarchy process (AHP) analysis with data-driven regression models to derive distinct weighting schemes for the factors. While the approach based on experts' opinion (i.e. AHP) demonstrates that familiarity, self-orientation skills, and access to reliable navigation tools are the most important contributing factors, data-driven models additionally highlight the significance of environmental complexity, such as angular distance between exits and number of landmarks near decision points. Importantly, expert-led and data-driven methods reveal different but complementary influences on pedestrian navigation, underscoring the value of combining specialist knowledge with insights derived from observed data to improve our understanding and guide the creation of more navigable urban environments.

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KEYWORDS
Pedestrian navigation; urban environments; wayfinding

1. Introduction

Navigating through urban environments poses unique challenges, heightened by individual differences in cognitive abilities and technological familiarity (Coutrot et al. 2022; Epstein et al. 2017). While urban spaces are designed to ease navigation, the diverse nature of human cognition and varying abilities to utilize mobile navigation applications create a spectrum of navigational efficiencies among city dwellers (Sonmez and Onder 2019). Furthermore, it remains a complicated process to create navigational applications suitable for different type of users (Hunter, Anderson, and

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Belza 2016). This disparity raises critical questions about the inclusivity of urban planning and the effectiveness of existing navigational aids, highlighting a significant problem: The need for a deeper understanding of how people interact with and navigate through complex urban spaces, and what main factors lead to people getting lost so we can design both optimal urban planning and supportive assistive technologies. The objective of this study is to identify and assess the importance of personal, situational, and environmental factors that contribute to pedestrians getting lost in Greater London. To achieve this, three research questions are formulated as follows: (1) Which factors are most associated with pedestrians getting lost in Greater London? (2) How do AHP and regression approaches compare in evaluating these factors? (3) What complementary insights do these approaches provide into the phenomenon of getting lost?

Research into human navigation has often focused on route optimization – the strategies individuals employ to travel from point A to point B (Tyagi, Singh, and Singh 2022). However, this approach often overlooks the multidimensional nature and factors of human navigation, which is not merely about finding the shortest path but also involves the complex interplay of cognitive processes, emotional states, and urban environment (Gath-Morad et al. 2022; Hölscher, Brösamle, and Vrachliotis 2012). Our study shifts the focus from route optimization to the phenomenon of getting lost. Extensive research from cognitive psychology, geography, and urban studies has laid the groundwork, revealing how memory, perception, and spatial reasoning affect navigation (Walkowiak et al. 2023). The novel aspect of our research lies in its empirical foundation: a survey in which participants annotated their approximate locations of getting lost while navigating the urban environment. Rather than focusing on route scenarios, it starts with the areas where people had difficulty navigating, providing a different perspective on urban navigability challenges.

In the context of pedestrian navigation, we define ‘getting lost’ as a state of spatial disorientation, essentially a breakdown in wayfinding (the cognitive element of navigation that guides movement) where the traveller becomes uncertain of their location or the correct route to their destination (Darken and Peterson 2002; Montello and Sas 2006). Lynch (1964) observes that even momentary disorientation in a city can provoke anxiety and that the very word ‘lost’ implies ‘much more than simple geographical uncertainty’, carrying overtones of ‘utter disaster’. Also, Lynch (1964) argues that a well-structured, ‘legible’ environment gives people a sense of security by helping them maintain orientation. Hunter, Anderson, and Belza (2016) further define wayfinding as the integration of cognitive and embodied processes in interaction with environmental cues, suggesting that disruptions to this dynamic (i.e. instances of ‘lostness’) can range from minor uncertainties to severe disorientation. Wayfinding research similarly frames lostness as any lapse in navigational awareness, from minor missteps to severe confusion. Montello and Sas (2006) define geographic disorientation (i.e. getting lost) as uncertainty about one’s whereabouts or direction, noting that such disorientation may be long-lasting and serious but is very often minor and temporary. Even brief episodes of being lost are common and can generate anxiety, frustration, or delays (Montello and Sas 2006). Similarly, Darken and Peterson (2002) report that disoriented travellers tend to be ‘anxious, uncomfortable, and generally unhappy’, reinforcing that even short-lived loss of orientation is a significant event in navigation.

Accordingly, this study adopts a broad definition of 'getting lost' that considers both minor wayfinding errors (e.g. a wrong turn quickly corrected) as well as prolonged disorientation. In our survey, participants were instructed to report any instance of losing track of their location or intended route, so both small detours and longer events of confusion were counted as instances of having 'gotten lost'. We also note that, because our study relies on self-reported getting lost events, cultural norms may shape individuals' willingness to acknowledge or disclose disorientation, meaning that self-estimates of getting lost could vary across contexts (Walkowiak et al. 2023).

The focal point of our research is the Greater London region, a metropolitan labyrinth known for its complexity and diversity (Boeing 2019; Maguire, Nannery, and Spiers 2006). By employing a dual-analytical approach, our study compares expert-led evaluations, grounded in analytic hierarchy process (AHP) analysis (Goepel 2018), with data-driven insights derived from Ordinary Least Squares and Ridge Regression techniques. This methodological blend allows us to dissect the nature of urban navigation, examining factors such as urban complexity, self-orientation skills, personal context, and familiarity with the environment. Through this mixed-methods approach, we aim to uncover patterns and discrepancies in urban navigational efficiency and provide the basis for future targeted interventions.

This paper is structured to methodically unfold our findings and their implications. We begin by discussing the data collection process and the key factors considered, detailing the employed methodology – including the AHP and regression analyses – and presenting the results, which include analyses of multicollinearity and the evaluation of estimated weights. Finally, we reflect on the implications of our findings. Through this structured exploration, this study contributes to the interdisciplinary field of spatial cognition and computation, aiming to aid in the development of more navigable urban environments and applications.

2. Data

This research employs two established methods of analysis in parallel, in order to compare 'expert-led' and 'data-driven' analytical approaches to the ease of navigating urban environments. In both cases, a set of 14 factors identified from the established literature concerning navigation ability, urban complexity, and spatial cognition is used to measure environmental, situational, and personal factors which might influence the propensity of an individual to lose their way during a navigation task. These factors were identified through a focused review of relevant literature on wayfinding, disorientation, and spatial cognition in urban environments, complemented by a series of brainstorming discussions among the research team to consolidate and refine the list. This process was exploratory rather than systematic, with the purpose of deriving a comprehensive and practically relevant set of factors. Data relating to incidents where individuals 'got lost' are then divided into two distinct sets: in the former case, expert-led AHP (a structured approach for multi-criteria decision-making problems) is used to establish the relative importance of each factor; in the latter, OLS and Ridge Regression methods are employed to find the optimal weights for each factor. This process is outlined in Figure 1.

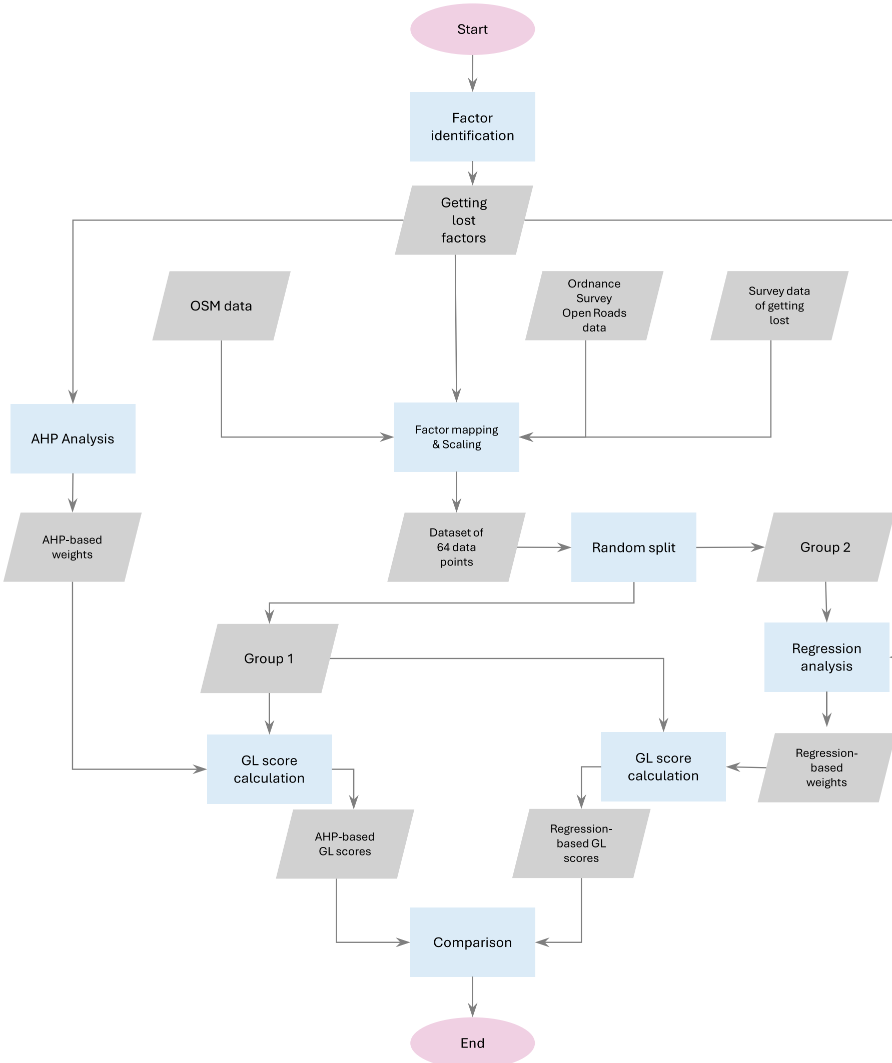

Figure 1. Process flowchart.

2.1. Data collection

To understand how and why individuals lose their way during navigation tasks, it is necessary to observe instances where this occurred. Data relating to specific incidents of getting lost were therefore collected through an online survey administered through the 'Prolific' platform in 2022. To address potential recall bias and enhance the reliability of the collected data, all participants were explicitly instructed at the outset: 'Please do not respond to the survey if you are not certain about the details of your getting lost event'. The sample for the survey was also vetted via 'Prolific': 103 individuals participated in the full survey following a screening of the 400 initial respondents, which excluded participants who offered their recollections of incidents that occurred over a year ago and were therefore likely not reliable. Responses indicating uncertainty or vague recollections were also removed from the dataset. This multi-step vetting process ensured that only recent and reliably remembered events were included in the final analysis.

The one-year recall window was selected in line with established practice in survey methodology, where 12-month reference periods are commonly used for quantitative recall (Bradburn, Rips, and Shevell 1987; Wagenaar 1986). Prior research has demonstrated that critical details for personal events are already subject to significant memory loss after 1 year, with loss rates increasing steeply for longer intervals. This makes a 1-year window an effective balance between sample size and data reliability. To participate in the full survey, the incident described by respondents also needed to have taken place within the 'Greater London Area' (also colloquially described to potential survey participants as 'within the M25') and respondents were required to be generally familiar with London (in other words, they were intended to be undertaking everyday tasks, rather than visiting purely for touristic purposes).

Participants were asked to provide their basic demographic information (age and gender, given in Table 1) and general travel habits (including most frequently utilized forms of transport), in addition to information regarding the location at which they got lost, how they were navigating at the time, and what they considered the relevant factors leading to them losing their way. This was primarily obtained via a combination of ordinal categorical, binary choice, and open-ended questions, but participants were also asked to mark the location at which they got lost on a map (as accurately as they were able to recall). Since this research primarily focuses on examining environmental, situational, and human factors that influence navigation efficiency, with the potential to inform urban design for improved wayfinding, the subsequent analysis does not incorporate demographic variables related to instances of getting lost. The general area in which each respondent reported their incident is given in Figure 2.

Each survey response was assessed for the quality and consistency of the geospatial information provided. As participants submitted both a point on a map and a textual description, the latter was used to verify the former. Participants were aware of the purpose of the survey, and the descriptions they provided were often quite detailed. Therefore, where discrepancies arose, the textual description was given priority, and the geolocated point was adjusted accordingly. If a response was incomplete or could not be reliably interpreted into meaningful geospatial information (which typically occurred where the reported point and textual description were irreconcilably different), the result was excluded from further analysis.

Some participants reported instances of getting lost while driving. While this area is crucial for future research, the decision-making processes during driving may differ from those used in navigating active transportation methods, such as pedestrian navigation

Table 1. Survey participants by age group and gender.

		Gender			
		Female	Male	Prefer not to say	Total
Age group	18–29	28	10	1	39
	30–39	20	11	0	31
	40–49	13	5	0	18
	50–65	9	6	0	15
	Total	70	32	1	103

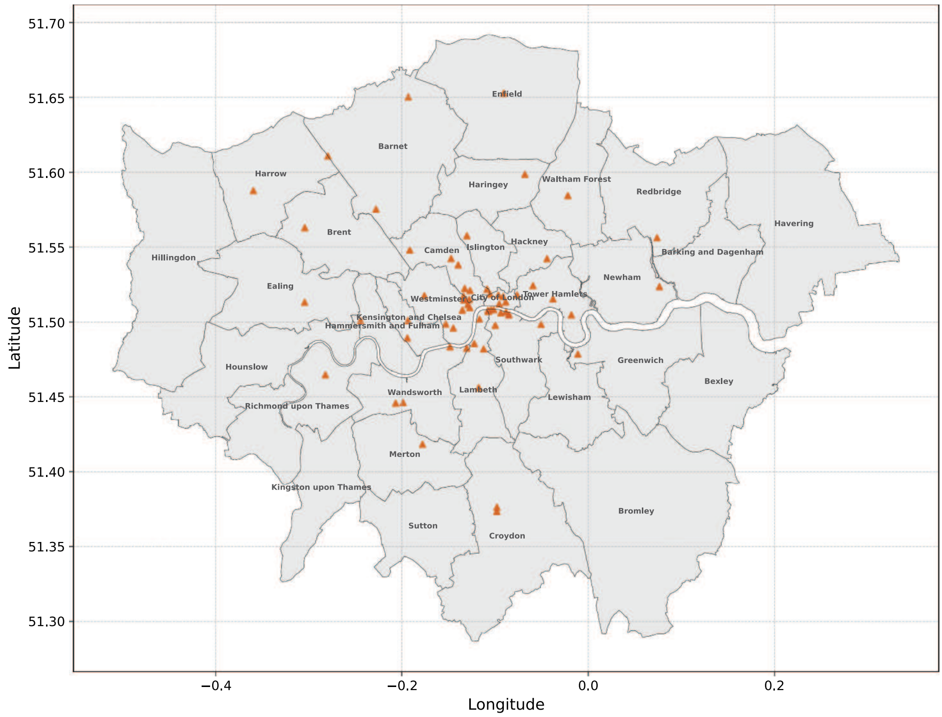

Figure 2. Overview of the getting lost survey points per London Borough.

(Karimi, Jiang, and Zhu 2013). Accordingly, responses where the individual was driving were excluded. In addition, despite the screening of survey participants, several of the subsequently reported experiences were outside of the Greater London Area. These entries were also excluded from the analysis.

The remaining sample consists of 64 data points, each corresponding to a getting lost event. To extract related information from other data sources, each of these points was matched to the nearest junction in the Ordnance Survey (OS) Open Roads dataset by calculating the shortest distance between the observed 'getting lost' location and all available junctions. The geospatial information for each event was thus anchored to its closest junction. This process is illustrated by Figure 3(A).

2.2. Factors associated with getting lost

In accordance with 14 categories identified from existing research, the following information was extracted from the survey data or supplementary data sources for each of the 64 points. The inclusion of any particular category should not be interpreted as confirmation of its importance in navigating urban environments but rather that there is a theoretical or empirical reason to consider the extent to which it may have an influence:

2.2.1. Number of exits

Interpretation: More exits at a junction make it easier for an individual to get lost. Burns (1998) refers to this concept as 'navigational degrees of freedom'. O'Neill (1991) expands

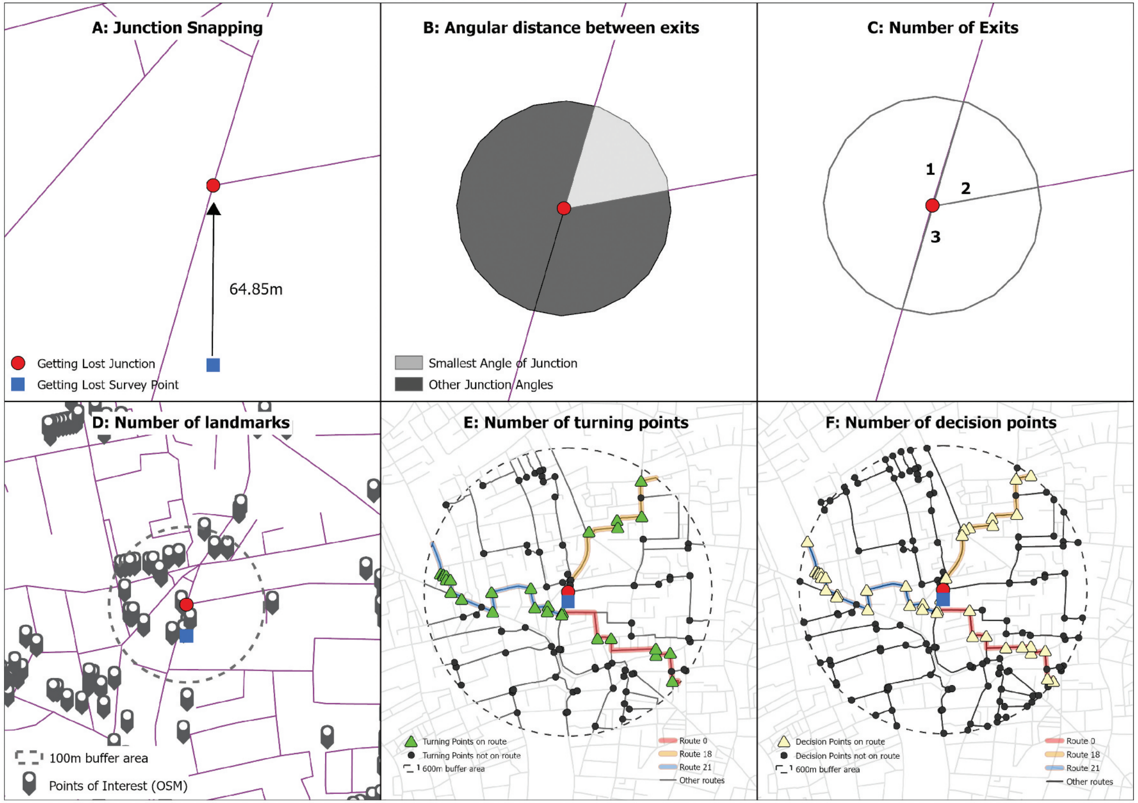

Figure 3. Illustrations of the complexity of spatial methodologies. Illustration of city complexity measures for a dummy point. 3A: The snapping of the point at which a survey respondent reported getting lost to the nearest junction on the road network. 3B: The calculation of the smallest angle between two roads at the junction of the snapped point. 3C: The identification of the number of exits at the junction of the snapped point. 3D: The number of landmarks identified within a 100 m buffer of the snapped point. 3E: The number of turning points on the route between the edge of a 600 m buffer and the snapped point. The specifics of some routes (given in blue, orange, and red) are highlighted for illustrative purposes, but routes and turning points (given in black) from all intersections with the buffer are considered. 3F: The number of decision points on the route between the edge of a 600 m buffer and the snapped point. As for 3E, the route and decision points between each intersection with the buffer and the snapped point are considered.

this general principle into his ‘Inter Connection Density’ measure, which demonstrated that greater complexity was connected to lower performance in navigating between two locations.

Measurement: The number of exits on the junction, as indicated by OS Open Roads. Only the junction itself is considered; turnings or branches after the junction are not included.

2.2.2. Angular distance between exits

Interpretation: Smaller angles between exits make exits more difficult to differentiate and, therefore, make it easier for an individual to get lost. Sadalla and Montello (1989), for example, show the difficulties demonstrated by test subjects in estimating angles when moving along a pathway.

Measurement: The minimum angle between any two adjacent exits at a junction”., as indicated by OS Open Roads.

2.2.3. Pedestrian flow

Interpretation: Areas with heavy pedestrian traffic make it easier for an individual to get lost. The findings of Langer and Saegert (1977), for example, highlight that crowdedness may influence the performance of individuals in carrying out tasks.

Measurement: Manually assessed using Google Street View Imagery (SVI), scored on a cale of 1–5 (with 1 being the lightest pedestrian flow and 5 being the heaviest pedestrian flow). The locations and corresponding scores for pedestrian flow are reported in Appendix B.

Note: We do not use SVI as a real-time source for quantifying pedestrian and transportation flow by counting the number of pedestrians or vehicles present. Instead, contextual information provided, such as commercial density (e.g. shops and cafés), and the width and continuity of pavements are used to infer pedestrian flow; the number of traffic lanes, visible signage, intersection complexity, and road hierarchy are considered in estimating transportation flow. Additionally, as London is a location with which we are highly familiar, we complemented the SVI-based assessment with direct local knowledge when ambiguity arose. The evaluation of pedestrian flow (as well as vehicle flow follows) is subjective to the author knowledge and the intepretation of visual information contained within SVIs avialable at each getting lost location.

2.2.4. Transportation flow

Interpretation: Areas with heavy vehicle traffic make it easier for an individual to get lost. There is evidence that navigating transport infrastructure can be a barrier to pedestrians, particularly when there is a high volume of traffic (Anciaes and Jones 2016). Measuring pedestrian and transportation flows are subject to the exact time when an individual got lost. However, given the available data, synchronising the two is impossible. This is because neither the survey participants reported their precise time of getting lost, nor the available pedestrian/transportation flow data could provide fine-grained temporal frequency data that aligns with it. Therefore, despite acknowledging the uncertainty caused by this, the best approximation could be achieved through the interpretation of the visual information contained in the available SVIs at each location where a person gets lost.

Measurement: Manually assessed using SVI, scored on a scale of 1–5 (with 1 being the lightest transportation flow and 5 being the heaviest transportation flow).

2.2.5. Visibility

Interpretation: Lower visibility areas are more difficult to navigate and, therefore, make it easier for an individual to get lost (Gath-Morad et al. 2024). This draws on ideas from Kubat et al. (2012), who suggest that users in unfamiliar urban environments tend to follow visually connected routes.

Measurement: Self-reported score (on a scale of 1–5, with 1 being 'Not relevant' and 5 being 'Highly relevant') by survey respondents, in relation to the category 'Limited visibility' for the question 'Which of the following made you get lost (please rate by relevance)?'

2.2.6. Number of decision points

Interpretation: Routes involving a higher number of decision points are more complicated and, therefore, make it easier for an individual to get lost. Burns (1998) outlines that a decision point is essentially any point at which an individual encounters uncertainty along their route. Having more instances of uncertainty increases the number of choices made by the individual and may, therefore, increase the likelihood of an individual eventually making an incorrect choice.

Measurement: The mean number of decision points for simulated routes terminating at the point at which the survey respondent got lost. Decision points were defined as the number of 'maneuvers' on each route, as calculated by the 'Project OSRM' routing engine (Luxen and Vetter 2011) which utilizes OSM data. Origins of the simulated routes were all intersections between a 600 m buffer around the getting lost point and the OSM road network, which were subsequently snapped to the nearest junction.

Note: The 600 m distance is based on Transport for London's estimate that the average Londoner walks 1.2 km per day (Transport for London 2018) and reflects that survey trips were typically one-way rather than round trips. This provides a suitable estimate of the distance walked by respondents, regardless of any additional modes of transport used.

2.2.7. Number of landmarks

Interpretation: Landmarks make it easier for individuals to navigate, so a lack of nearby landmarks makes it easier for an individual to get lost. There is notable literature regarding the interaction between landmarks and navigation. An overview is given by E. Chan et al. (2012) and Yesiltepe et al. (2021).

Measurement: As outlined by E. Chan et al. (2012), landmarks for the purposes of navigation have been conceptualised in a number of ways. In this instance, the number of OSM points of interest within a 100 m buffer is employed as a proxy. Using this proxy, we argue that the quantity of landmarks might not make a direct significant difference, but it does increase the possibility that one of these landmarks can be of use to the lost individual. An illustration of this process is given in Figure 3D.

2.2.8. Self-orientation skills

Interpretation: Individuals with poorer self-orientation skills will get lost more easily. Walkowiak et al. (2023), for example, demonstrate different navigation abilities across individuals.

Measurement: This factor is measured through an open-ended question included in the survey where a large proportion of participants have provided discussion on their self-orientation skills either at the moment of getting lost or in the long term. The open-ended question acts as the basis of the factor measurement, which is constructed as follows: 'In your own words, please briefly describe what happened when you got lost. Why do you think you lost your way?' Four experts independently evaluated each response and assigned a score between 0 and 1, with 0 indicating the poorest and 1 the strongest orientation skills. The final score for each respondent was calculated as the average of the four expert ratings. For cases where no response was provided or where orientation ability could not reasonably be inferred, a neutral score of 0.5 was assigned to retain the observation.

2.2.9. Personal context

Interpretation: Tired or distracted individuals will get lost more easily. Burns (1998), for example, reports 'distracted attention' as the second most commonly reported cause of survey respondents losing their way.

Measurement: The mean self-reported score across two categories for the survey question 'Which of the following made you get lost (please rate by relevance)?'; 'I was tired' and 'Other distractions (mobile phone, listening to music, etc)'. Scored on a scale of 1–5, with 1 being 'Not relevant' and 5 being 'Highly relevant'.

2.2.10. Number of turning points

Interpretation: Routes involving a higher number of turning points are more complicated and therefore make it easier for an individual to get lost. This aligns with Bailenson, Shum, and Uttal (1998)'s idea of 'road climbing', in that people may favor longer, straight road segments (particularly when starting a route) even if this involves travelling further, due to cognitive effort of identifying optimal routes.

Measurement: Same as the method for *Number of decision points*, but number of 'turns' were counted instead of number of 'maneuvers'. A turn must be a maneuver, but a maneuver would not necessarily be a turn; meaning that this category reflects the number of positive actions required to navigate a route (whereas *Number of decision points* reflects the number of active and passive, such as 'continue', actions combined).

2.2.11. City/smaller scale complexity

Interpretation: Areas with complex layouts make it easier for an individual to get lost. Stanitsa, Hallett, and Jude (2023), for example, note that spatial complexity is generally regarded as related to success in reaching a destination.

Measurement: The 'orientation entropy' for the appropriate London borough (as defined by OpenStreetMap (2022)), utilizing OSMnx (Boeing 2017), and adapted from the method outlined in (Boeing 2019).

2.2.12. Access to reliable map

Interpretation: This factor includes all forms of external aids or tools used to support navigation in the urban environment, the accuracy of the information they provide, and the reliability of access to these aids at critical moments. We use a broad definition of 'map' to include not only traditional paper or digital maps, but also wayfinding kiosks, handwritten or verbal directions, and routing applications. This reflects the diverse ways in which urban navigators access spatial information. A loss of access, inaccurate information, or interruption of service (e.g. due to technical issues or ambiguous instructions) may all increase the risk of getting lost. For instance, Groves (2011) highlights GPS positioning errors in 'urban canyons'.

Measurement: Binary classification.

2.2.13. Familiarity

Interpretation: Individuals are less likely to get lost on routes with which they are familiar, so a less familiar route will make it easier for an individual to get lost. O'Neill (1992) and Piccardi, Risetti, and Nori (2011) argue for the importance of environmental familiarity in navigation tasks.

Measurement: Self-reported score (0–100, with 0 being not familiar and 100 being very familiar) by survey respondents, in relation to the question 'How familiar were you with the route that you were on when you got lost?'

2.2.14. Name similarity

Interpretation: Streets with similar names may cause confusion and therefore make it easier for an individual to get lost. The problem of similar-sounding street names is discussed in depth by K. Chan, Vasardani, and Winter (2015).

Measurement: Binary classification, where 1 signifies two similarly named roads within a 100 m buffer of the getting lost point. Similarity was determined by the Levenshtein distance, with a threshold score of 0.7.

Each factor outlined in Section 2.2 is normalized between 0 and 1 on the basis of observed values before use in regression analysis or weighted sum calculations. Boolean variables retained their original value at zero or one, while continuous variables were min-max scaled using the observed sample range. This approach enables comparability across all factors and eliminates the influence of differing original scales on the derived weights.

3. Methodology

3.1. Analytic hierarchy process

In Section 2.2, we identified 14 factors that may influence pedestrian navigation and contribute to a getting lost event. However, determining the relative importance of each factor requires further analysis. In this work, we address the evaluation of the weights of getting lost factors using AHP. AHP is a structured approach for multi-criteria decision-making problems. It decomposes complex problems into a hierarchy of more easily comprehended sub-problems, each of which can be analyzed independently. Through a mathematical process, AHP subsequently synthesizes these comparisons to assign a numerical weight to each factor, representing the relative importance of the factor in contributing to the outcome.

We applied AHP to assess the impact of various factors on their contribution to a getting lost event. This involves conducting pairwise importance comparisons of the 14 factors, detailed in Section 2. To implement our AHP analysis, an online AHP survey was used which included all 14 factors and generated 91 pairwise comparison questions accordingly, covering all possible pairwise combinations of these factors (Goepel 2018). Four researchers with expertise in geospatial data science, urban studies, and navigation were invited to complete the online survey, by choosing which factor in each pair they believed was more important in getting lost events and then assigning a priority level to their choice based on their knowledge and judgment. To assess the intercoder reliability among the four experts on the 14 factors, we computed Krippendorff's Alpha (α) for interval data (Krippendorff 2018). The results of this analysis are provided in Appendix A. The total sum of the weights assigned to all factors equals one. This means each individual weight reflects the specific percentage that the factor contributes to the likelihood of a getting lost event. For our further analysis, we used the average score of each factor, calculated by taking the mean of the scores given by all four experts.

The online tool utilized for this research was AHP-OS. A full explanation of the specific implementation and underlying mathematics is outlined in Goepel (2018). AHP-OS utilizes the method of Alonso and Lamata (2006) for calculating the consistency ratio. For this article, the weighted geometric mean aggregation of individual judgments is selected for group aggregation.

3.2. Analysis

3.2.1. General description

Our dataset, comprising 64 data points, was randomly split into two even-sized groups for further analysis. The rationale for splitting the dataset was to ensure a fair evaluation of the weighting schemes. One-half of the data was used to derive weights via regression methods, while the other half was reserved for applying these weights and for testing purposes. This approach allows for a more robust comparison between expert-driven and data-driven weighting methods. For the first group, we computed the getting lost score for each data point. This process involved calculating the weighted sum of the individual factor scores, using the weights provided by experts through AHP analysis, as outlined in Section 3.1. Conversely, for the second group, instead of using the expert-provided AHP weights, we applied two distinct regression models to derive alternative sets of weights directly from the survey data. During this process, the target getting lost scores were uniformly set to one across all data points, and their individual factor scores were used for generating alternative weight sets. This approach was designed to evaluate different weighting schemes, potentially providing a more accurate reflection of each factor's contribution to the getting lost event. The next step involved applying the derived weights from the data points of the second group to the first group. This led to the recalculation of the getting lost scores for the first group using these new weights from the regression models. The final stage of our analysis involves a comparative review of the getting lost scores of the first group, comparing those derived from AHP weights (expert-led) with those obtained from the second group's regression models (data-driven).

In addition, we conducted both multicollinearity and correlation analyses on the getting lost matrix derived from the AHP approach, in order to further reveal the inter-relationships among the factors. Multicollinearity arises when two or more factors in a regression model exhibit linear dependence, meaning that one factor can be predicted to a certain degree of accuracy using the others. Although multicollinearity does not necessarily reduce the overall predictive power of a model (O'brien 2007), it can impede the accurate estimation of individual regression coefficients. To quantify the degree of collinearity, we calculated the Variance Inflation Factor (VIF) for all 14 factors in Group 1, using it as an established indicator of multicollinearity.

We subsequently performed regression analyses using both OLS and Ridge Regression on the data points in Group 2, yielding two distinct sets of weights. These regression-derived weights, along with the initial AHP-derived weights, were each applied to the data points in Group 1, resulting in three corresponding sets of getting lost scores for Group 1. To evaluate the statistical significance of differences among these three sets of scores, we first conducted the Shapiro–Wilk test (Shapiro and Wilk 1965) to assess the normality of the getting lost score distributions under each weighting scheme. Based on the results of these normality tests, we proceeded to conduct pairwise comparisons using both the t-test (for normally distributed data) and the non-parametric Wilcoxon signed-rank test as a robustness check for cases where normality could not be assumed.

Whilst the weights calculated by the OLS and Ridge regression techniques (discussed in Section 4.2) may be negative, the weights derived from the AHP analysis must be positive. For particular factor, we therefore transform the values for each data point to account for directionality. This is outlined in Table 2. A value of 1 for any given factor would imply that an individual was more likely to get lost.

3.2.2. Getting lost score of Group 1

For each data point in Group 1, we calculated the weighted sum of AHP weights and scaled factor values, resulting in the getting lost score for each data point as follows:

$$\mathbf{S_1} = \mathbf{X_1}\omega_{ahp} \tag{1}$$

Where $\mathbf{S_1}$ denotes the score matrix for getting lost of Group 1. $\mathbf{X_1}$ is a 32×14 matrix, where each row represents a data point and each column corresponds to one of the 14 factors. ω_{ahp} is a known column vector of dimension 14×1, containing the weights derived from our expert-led AHP online questionnaire, as described in Section 3.1.

3.2.3. Weights estimation of Group 2

Group 2’s analysis aims to identify a distinct set of weights. These weights were optimized to maximize the overall getting lost scores for Group 2, indicating a higher likelihood of

Table 2. Factor transformations and interpretation.

Factor	Direction
ID1: Number of Exits	x
ID2: Angular distance between exits	$1-x$
ID3: Pedestrian Flow	x
ID4: Transportation Flow	x
ID5: Visibility	x
ID6: Number of decision points	x
ID7: Number of Landmarks near decision points	$1-x$
ID8: Self-orientation skills	$1-x$
ID9: Personal context	x
ID10: Number of turning points	x
ID11: City/Smaller scale complexity	x
ID12: Access to reliable map	x
ID13: Familiarity	$1-x$
ID14: Name similarity	x

getting lost events occurring. The overall getting lost score matrix of Group 2 is calculated as follows:

$$\mathbf{S_2} = \mathbf{X_2}\omega_2 \tag{2}$$

Where $\mathbf{S_2}$ represents the getting lost score matrix for Group 2, with dimension 32×1, each element corresponding to the aggregated getting lost score for one of the 32 data points. The matrix $\mathbf{X_2}$ encapsulates the individual factor scores for each data point in Group 2. It is a 32×14 sized matrix, where each row corresponds to a data point, and each of the 14 columns represents one of the identified factors affecting the likelihood of getting lost. The vector ω_2 is the weight vector to be optimised. It contains the weights for the 14 factors and is determined such that, when applied to $\mathbf{X_2}$, it maximizes the getting lost scores in $\mathbf{S_2}$.

Given that each factor in our dataset is normalized to the range [0,1], and the sum of the 14 factor weights is constrained to one, the maximum possible getting lost score for any data point is capped at one. Since all data points from both Group 1 and Group 2 are derived from real-life instances of getting lost, it is reasonable to anticipate that the weighted sum of each data point's factors would approximate this maximum value at one. Therefore, to optimize the set of factor weights in a way that maximizes the likelihood of a getting event, we structured the maximized $\mathbf{S_2}$ matrix as an all-ones matrix, denoted as $\mathbf{S_{max}}$. This approach aligns with our theoretical maximum, allowing us to effectively gauge the optimal combination of weights that correspond to the highest likelihood of getting lost based on our dataset.

In our study, we applied the Ordinary Least Squares (OLS) and Ridge Regression (RR) as two regression models to determine the optimal set of weights for the factors in Group 2. This approach is framed as an optimization problem, aiming to minimize the mean squared error (MSE) between the desired maximum getting lost scores and the scores calculated through the explored weights. Mathematically, the optimal weights maximizing the getting lost score can be expressed as follows:

$$\hat{\omega}_{2_{OLS}} = arg\,min_{\omega_2}\left(\frac{1}{N}\sum_{i=1}^{N}\left(\mathbf{S_{max}} - \mathbf{X_2}\omega_2\right)^2\right) \tag{3}$$

$$\hat{\omega}_{2_{RR}} = arg\,min_{\omega_2}\left(\frac{1}{N}\sum_{i=1}^{N}\left(\mathbf{S_{max}} - \mathbf{X_2}\omega_2\right)^2 + \lambda|\omega_2|_2^2\right) \tag{4}$$

Where (3) and (4) represent the identified weights by using OLS and RR, respectively. Here, $\hat{\omega}_2$ represents the estimated weights vector that minimizes the MSE. $\mathbf{S_{max}}$ is the matrix of desired maximum getting lost scores for Group 2, and $\mathbf{X_2}$ is the matrix constituted by individual factor scores. The optimization process adjusts the weights ω_2 to find the best fit between the predicted scores $\mathbf{X_2}\omega_2$ and the desired getting lost scores $\mathbf{S_{max}}$. Compared with OLS regression in (3), the Ridge regression model in (4) introduces a regularization term. This term is the sum of the L2 norm of the weights, denoted as $\parallel \omega_2 \parallel_2^2$. The symbol λ denotes the regularization parameter, which serves to reduce the risk of overfitting and enables more effective handling of multicollinearity in the model.

Furthermore, we incorporated one additional constraint condition into the optimization procedure to ensure the validity and applicability of our model. The condition is expressed as $\sum_{i=1}^{14} \hat{\omega}_{2i} = 1$, mandates that the aggregate of all identified weights in the vector $\hat{\omega}_2$ must equal one. This condition, where the sum of all weights equals 1, ensures that each weight reflects the proportion of its corresponding factor in the overall model.

4. Results

4.1. Multicollinearity and correlation

As shown in Table 3, several factors exhibit relatively high VIFs, particularly those with values exceeding the commonly used threshold of 5. These factors include the number of exits, angular distance between exits, pedestrian flow, number of landmarks near decision points, number of decision points, and number of turning points.

To further examine the relationships between these factors, a correlation matrix was constructed, as detailed in Figure 4. The results reveal a strong correlation between several pairs of factors. Notably, the number of exits and the angular distance between exits exhibit a correlation coefficient of 0.87. Pedestrian flow is correlated with the number of landmarks, with a coefficient of −0.68, and the number of decision points and the number of turning points show a correlation coefficient of 0.96.

4.2. Expert-led and data-driven weights

In our analysis, we applied both OLS and Ridge regression techniques to determine the weights of factors in Group 2. The outcomes of this analysis are presented in Figure 5, and the blue bar chart represents the AHP weights of Group 1, as specified in Section 3.1. Additionally, the weights of Group 2 derived through OLS and Ridge regression are depicted as orange and magenta bar charts, respectively.

To identify an appropriate penalty parameter λ for the Ridge regression model, we employed Ridge trace analysis (Hoerl and Kennard 1970; McDonald 2009). This technique plots the estimated regression coefficients against a sequence of λ values. When λ is small, the coefficients can fluctuate substantially, but as λ increases the curves gradually flatten,

Table 3. Variance inflation factor (VIF) for each getting lost factor. (VIF greater than five is indicated in bold.)

Features	VIF
ID1: Number of Exits	**15.69**
ID2: Angular distance between exits	**22.88**
ID3: Pedestrian Flow	**5.76**
ID4: Transportation Flow	4.48
ID5: Visibility	2.16
ID6: Number of decision points	**42.19**
ID7: Number of Landmarks near decision points	**4.87**
ID8: Self-orientation skills	2.46
ID9: Personal context	2.15
ID10: Number of turning points	**37.20**
ID11: City/Smaller scale complexity	1.65
ID12: Access to reliable map	2.73
ID13: Familiarity	4.73
ID14: Name similarity	2.08

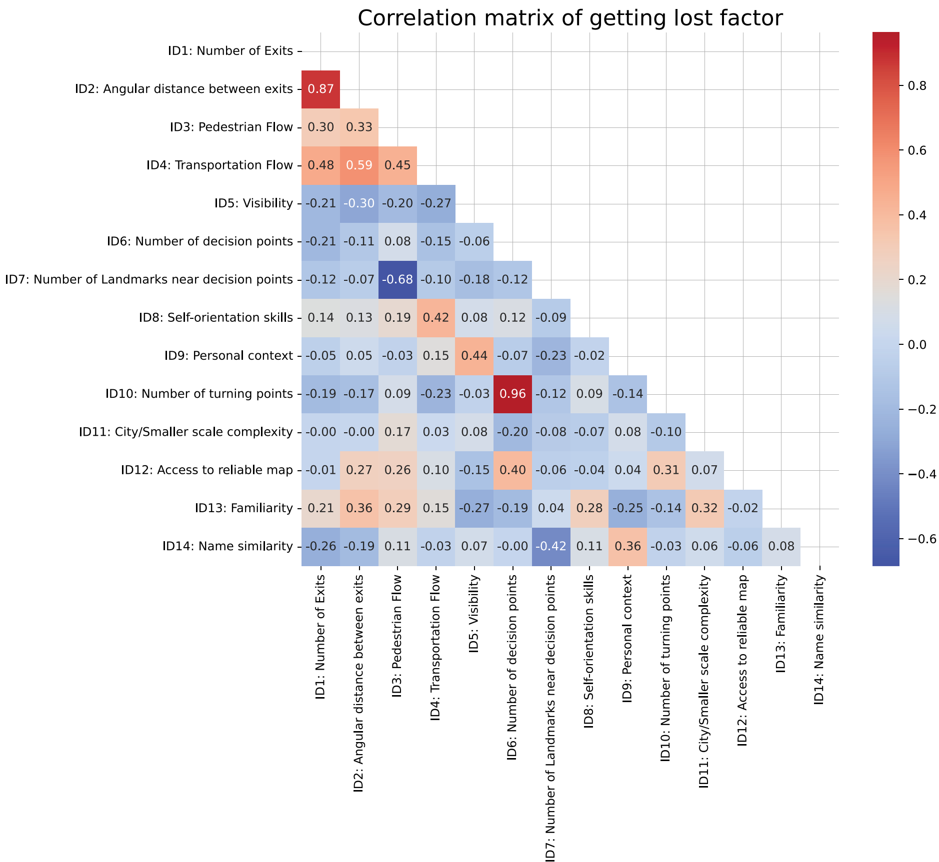

Figure 4. Correlation matrix among the 14 factors.

indicating that the estimates become less sensitive to further increases in λ. We selected $\lambda = 0.4$ because, as shown in Figure 6, the slopes of the coefficient paths begin to stabilise around this value. This suggests that the shrinkage is sufficient to control variance without introducing excessive bias. The variances of the weights estimated through OLS and Ridge regression were 0.416 and 0.009, respectively.

4.3. Getting lost scores under different weighting schemes

We applied the weights estimated from OLS and Ridge regressions back to the data points of Group 1 and recalculated their getting lost scores using these new sets of weights. The mean and variance of getting lost scores for the data points in Group 1 are reported in Table 4. Both weights from OLS and Ridge regression produced higher getting lost scores compared to the original AHP scores in Group 1. OLS had an average score of 0.94, while Ridge regression had an average of 0.76, compared to AHP's 0.59. Among the three weighting methods, the getting lost scores derived from OLS weights exhibited the greatest variance at 0.07, in contrast to substantially lower variances for weights from AHP and Ridge, at 0.01 and 0.03, respectively.

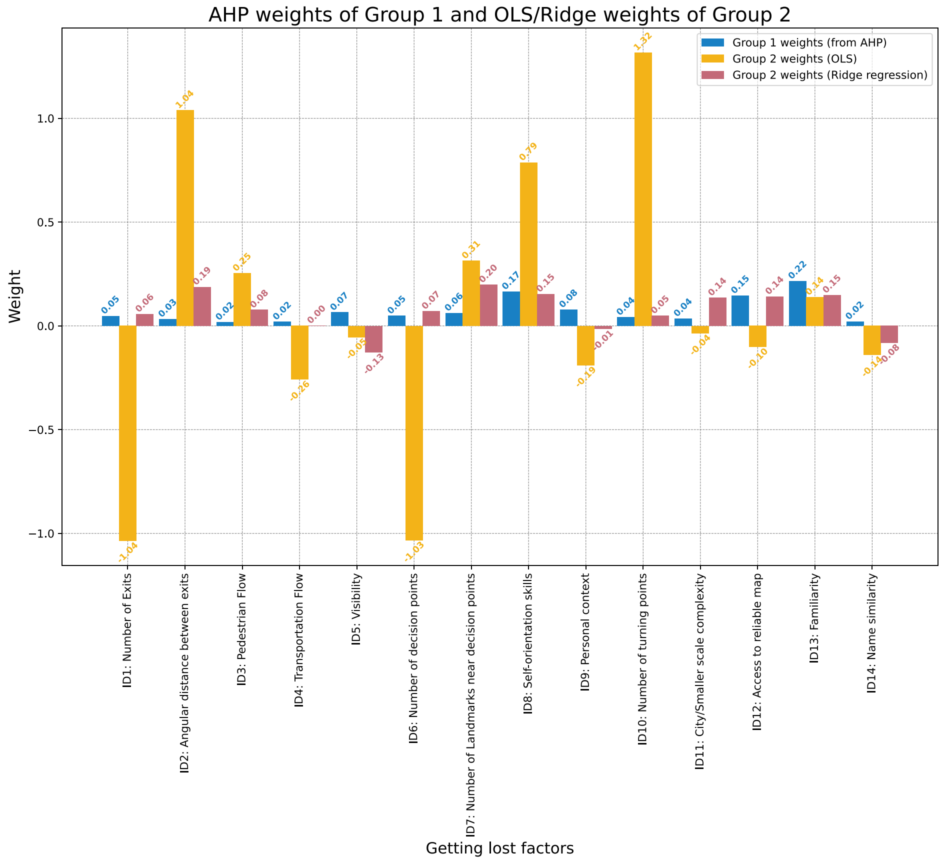

Figure 5. Weights from AHP analysis (on group 1), OLS, and RR (on group 2).

The results of the Shapiro–Wilk normality test are summarized in Table 5. For the AHP-weighted getting lost scores, the W statistic is 0.97 with a p-value of 0.571. For the OLS-weighted scores, the W statistic is 0.98 with a p-value of 0.682. For the Ridge-weighted scores, the W statistic is 0.94 with a p-value of 0.083. To further assess and visualize the normality condition, Q–Q plots are presented in Figure 7. The Q–Q plot for the AHP-weighted scores displays points that largely align with the theoretically normal line, while the Q–Q plots for the OLS- and Ridge-weighted scores show greater deviations from normality.

The results of both the t-tests and Wilcoxon tests are presented in Table 6. For all comparisons between the AHP, OLS, and Ridge weighting methods, the p-values were found to be less than 0.001. These results indicate statistically significant differences in the getting lost scores derived from the three weighting methods.

5. Discussion and conclusion

Navigating through complex urban areas remains challenging for pedestrians, even with the assistance of optimized routes provided by advanced navigational tools, due to the complex interplay of various factors that impact pedestrian navigation and

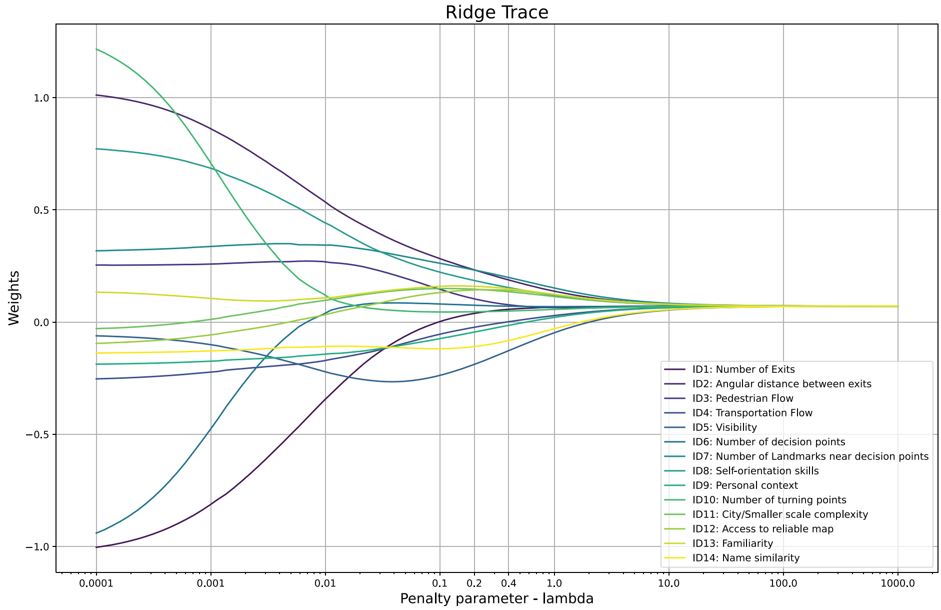

Figure 6. Variation of estimated weights with respect to penalty parameter.

Table 4. Mean and variance of getting lost scores for group 1 by weights from both OLS and RR.

Method	Mean GL Score	Variance
AHP	0.59	0.01
OLS	0.94	0.07
Ridge	0.76	0.03

Table 5. Results of the Shapiro–Wilk test for normality on group 1 getting lost scores under different weighting schemes.

Weighting Scheme	Shapiro-Wilk Statistic	p-value
AHP	0.97	0.571
OLS	0.98	0.682
Ridge	0.94	0.083

often lead to confusion. In this work, we identify a list of factors that may cause pedestrians to get lost in urban areas, as well as their relative contributions by generating weighting systems from both expert-led and data-driven methods. Potential multicollinearity and correlation are revealed from the identified factors, leading us to employ both unregularized and regularized regression models to produce factor weights. We find that the scores for getting lost, calculated from both expert-led and data-driven methods, demonstrated distinct but complementary influences on pedestrian navigation.

Our findings from the correlation analysis are consistent with the elevated VIFs. For example, an increase in the number of exits at a junction typically corresponds to a decrease in the angular distance between these exits. Similarly, areas with a greater number of points of interest are likely to attract more pedestrians, and itineraries with

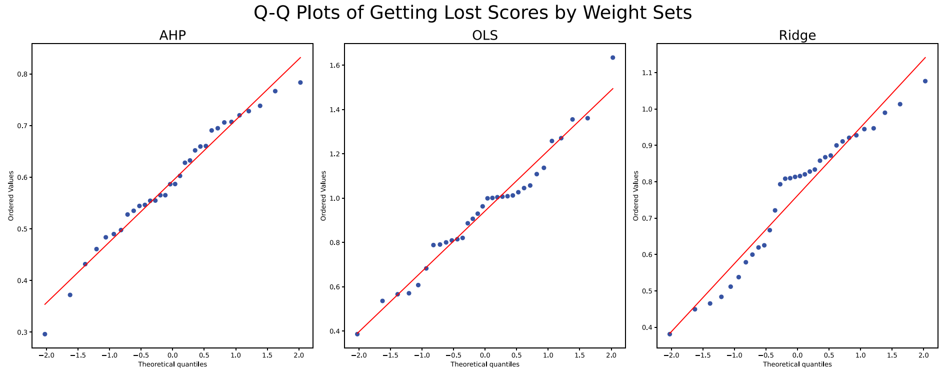

Figure 7. Q–Q plot of getting lost scores under different weighting schemes.

Table 6. Results of t-tests and Wilcoxon tests between three weighting methods.

Test	Comparison	Statistic	p-value
t-test	AHP vs. OLS	−8.8	6.0×10^{-10}
t-test	AHP vs. Ridge	−7.7	1.13×10^{-8}
t-test	OLS vs. Ridge	5.0	2.06×10^{-5}
Wilcoxon test	AHP vs. OLS	9.0	1.5×10^{-8}
Wilcoxon test	AHP vs. Ridge	22.0	2.5×10^{-7}
Wilcoxon test	OLS vs. Ridge	57.0	3.2×10^{-5}

a higher number of decision points may lead to an increased number of turns, explaining the strong correlation observed between these two factors. The presence of multicollinearity and correlation among factors highlights the need to utilize regularization techniques to achieve more stable and interpretable results estimates.

The OLS model produces the highest average getting lost score, but also the greatest variance, indicating differences across scores and possible overemphasis of certain factors. In contrast, Ridge regression produces more balanced and consistent estimates, with variance lower than OLS and a mean score between those of AHP and OLS. By effectively mitigating multicollinearity, Ridge regression not only achieves lower variance and higher scores than AHP but also generates a weight distribution similar to expert-led estimates, underscoring its effectiveness in modelling getting lost events.

Our analysis revealed that the choice of three weighting schemes significantly influences the computed getting lost scores, as confirmed by both parametric and non-parametric significance tests. However, to answer the fundamental question—*Why do pedestrians get lost?*—we need to examine the factor weights produced by each method and their substantive interpretation. For the expert-led AHP approach, the most important factors identified were familiarity with the environment, self-orientation skills, and access to reliable navigation aids. This reflects the expert view that people-centric factors are decisive in determining the likelihood of getting lost. Familiarity represents an individual's personal knowledge of the area, while self-orientation skills capture their ability to navigate effectively in confusing environments. In addition, experts emphasise that external navigational support – such as maps or mobile navigation applications – can further strengthen a pedestrian's ability to find their way. By contrast, the OLS model places the greatest positive weights on the angular distance between exits, number of turning points, and self-orientation skills. This indicates that the model considers the structural complexity of the route – such as how many choices a pedestrian must make and how many possible paths are available at a junction – as major determinants of getting lost. While self-orientation skills still play a significant role, the prominence of environmental factors suggests that the complexity of the urban layout may strongly influence navigation outcomes. However, the presence of negative weights for certain factors points to potential issues of multicollinearity and overfitting, which can lead the model to overestimate or underestimate the true importance of some variables. Also, it is noticeable that several pairs of highly correlated factors show opposite coefficient signs, such as the number of exits versus the angular distance between exits and the number of decision points versus the number of turning points. OLS still provides an overall unbiased fit to the data but multicollinearity inflates coefficient variance, making individual weights unstable and sometimes counterintuitive. The regularized Ridge regression model, on the other hand, provides a more balanced interpretation. The most influential factors include number of landmarks near decision points, angular distance between exits, familiarity and self-orientation skills. Similar to the OLS-derived weighting scheme, Ridge regression assigns relatively greater importance to the underlying complexity of the urban environment. Ridge regression reduces the magnitude of negative weights, thus offering more stable and generalizable estimates. This suggests that, compared to OLS, Ridge regression, as a data-driven method, is more capable of identifying the key contributors to getting lost while mitigating the distortions introduced by highly correlated factors in the dataset. The weighting schemes from expert-led AHP and regression models are distinct yet complementary in explaining pedestrian navigation: experts emphasised human-centric factors such as familiarity and self-orientation skills, whereas the regression models placed more weight on the environmental complexity around the getting lost locations. This difference may be explained by the fact that the AHP questionnaire was completed independently of the survey data, leading experts to consider general scenarios of getting lost, while the regression models were fitted to specific contextual information provided by the survey responses.

Taken together, the findings suggest that pedestrians become lost mainly due to two main strands of reasons. From a static view given by experts, individual reasons account for the largest share of getting lost events, while location-specific analysis from regression methods emphasises the environmental complexities. Three mechanisms of decision density, environmental complexity, and external support consistently emerge as central across methods, even though their relative weights differ between expert-led and data-driven approaches. By contrast, factors such as name similarity or transportation flows were less influential, reflecting that salience, timing, and perception may matter more than simple presence or quantity. Rather than providing definitive effect sizes, our analysis acts as an empirical case study of Greater London that illustrates how different factors contribute to pedestrians getting lost. The results highlight patterns – such as the importance of decision density, environmental complexity, and orientation support – that warrant further testing with richer data and in other contexts. While our study captures the *state* of being lost at specific locations, future work that incorporates itineraries and dynamic traces could help clarify the processes by which pedestrians gradually become disoriented.

There are several limitations in this work, which also suggest directions for future research. Methodologically, our regression models revealed issues of multicollinearity, with some factors highly correlated, which complicates the interpretation of individual factor weights and produces negative weights in the OLS model. Although Ridge regression helps mitigate these distortions, the presence of unstable or counterintuitive weights highlights the challenges of disentangling highly interrelated urban navigation factors. This reflection is important for interpreting our findings and indicates that further methodological refinement is needed, for example by exploring alternative modelling strategies that can better handle multicollinearity. A further limitation concerns the measurement of self-orientation skills, which are difficult to define and measure directly. In this study, we therefore relied on secondary proxies from open-ended questions. Future work should address this by designing a more sophisticated survey platform that enables participants to systematically evaluate their orientation skills, for example, through the Santa Barbara Sense of Direction Scale (Hegarty et al. 2002). Another limitation is that, while our survey collected the reported location at which respondents became lost, it did not include detailed itinerary information that could provide a richer context for the entire wayfinding process. As revealed by Grübel et al. (2019), the inaccuracy of pedestrians' mental maps versus the true environment can lead pedestrians to follow incorrect itineraries, ultimately causing them to get lost over time. Accordingly, future research should develop survey platforms that allow participants to capture both the locations at which they became lost and their itineraries, thereby yielding more comprehensive contextual information on getting lost events. In addition, some of the getting lost factors are subjectively evaluated, including visibility, pedestrian, and vehicle flow. This limitation highlights the need for approaches that can quantitatively measure these factors in the future. Finally, our findings are based on a case study of the Greater London Area. However, cultural norms and urban context may shape the experience of getting lost. Thus, future studies should examine the extent to which our findings generalise to other cities or cultural settings.

To conclude, across all weighting methods, self-orientation skills, familiarity and access to reliable maps or tools consistently emerge as leading contributors to pedestrians getting lost. Notably, expert-led weights place greater emphasis on people-centric factors, such as familiarity and self-orientation skills, whereas data-driven models, particularly OLS, highlight structural features of the environment, such as the angular distance between exits. The Ridge regression results offer a middle ground between these perspectives, balancing personal and environmental influences. Additionally, the elevated weights assigned to factors like city or local-scale complexity in the regression models suggest that environmental complexity is a significant, data-driven risk for disorientation, potentially underestimated by experts. This divergence further underscores the value of integrating both expert knowledge and data-driven analysis to gain a comprehensive understanding of the factors that contribute to pedestrian getting lost events in urban environments.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A. Intercoder reliability (krippendorff's α for interval data)

To quantify agreement among the four expert coders on the 14 factors, we computed Krippendorff's Alpha (α) for interval data (Krippendorff 2018):

$$\alpha = 1 - \frac{D_o}{D_e},$$

where D_o is the observed disagreement and D_e is the disagreement expected by chance.

Observed disagreement. Let $i = 1, \ldots, N$ index items (factors), $c = 1, \ldots, K$ index coders (experts), and $x_{ic} \in \mathbb{R}$ be coder c's weight for item i (missing values allowed), normalized at zero to one. Denote by $C_i \subseteq \{1, \ldots, K\}$ the set of coders who rated item i, with $m_i = |C_i|$. Using the squared Euclidean distance for interval data, the observed disagreement is the average pairwise squared difference within each item, aggregated over items:

$$D_o = \frac{\sum_{i=1}^{N} \sum_{\substack{c,c' \in C_i \\ c<c'}} (x_{ic} - x_{ic'})^2}{\sum_{i=1}^{N} \binom{m_i}{2}}.$$

Expected disagreement. Let $M = \sum_{i=1}^{N} m_i$ be the total number of observed ratings, and $\{z_u\}_{u=1}^{M}$ the pooled set of all ratings across items and coders. The expected disagreement is defined analogously as the average pairwise squared difference between two ratings drawn at random (without replacement) from this pooled distribution:

$$D_e = \frac{\sum_{\substack{u<v \\ u,v \in \{1,\ldots,M\}}} (z_u - z_v)^2}{\binom{M}{2}}.$$

Result and interpretation. The outcome of AHP analysis across four experts (coders) and 14 factors (items) are illustrated in Table A1.

Applying the above to our data (four coders, 14 items) yields $\alpha \approx 0.69$, indicating a moderate level of agreement.

Table A1. AHP weights derived from expert evaluation.

Factor	Expert 1	Expert 2	Expert 3	Expert 4
ID1: Number of Exits	0.0260	0.0430	0.0370	0.0919
ID2: Angular distance between exits	0.0300	0.0246	0.0132	0.0919
ID3: Pedestrian Flow	0.0125	0.0128	0.0161	0.0284
ID4: Transportation Flow	0.0125	0.0140	0.0197	0.0275
ID5: Visibility	0.0853	0.0281	0.0675	0.0875
ID6: Number of decision points	0.0640	0.0306	0.0381	0.0555
ID7: Landmarks near decision points	0.0494	0.0875	0.0380	0.0655
ID8: Self-orientation skills	0.1428	0.1553	0.1446	0.1545
ID9: Personal context	0.0128	0.1715	0.1262	0.0979
ID10: Number of turning points	0.0393	0.0262	0.0278	0.0779
ID11: City/Smaller scale complexity	0.0681	0.0214	0.0554	0.0144
ID12: Access to reliable map	0.1776	0.1006	0.1588	0.1020
ID13: Familiarity	0.2582	0.2522	0.2449	0.0904
ID14: Name similarity	0.0215	0.0322	0.0127	0.0147

Appendix B. pedestrian and vehicle flow assessment

To enhance transparency in how pedestrian and vehicle flow were assessed, we provide here both a geographic visualisation of the assigned scores and a set of illustrative examples from Google Street View (SVI).

A. Geographic visualisation of scores Figure A1 shows the spatial distribution of the manually assigned pedestrian and vehicle flow scores across the London study area.

B. Illustrative SVI examples Figure A2 presents example SVI images illustrating how scores were assigned. Four categories are shown (0, 0.25, 0.5, 1.0), each represented with one pedestrian-flow image and one vehicle-flow image, to demonstrate the visual cues used for evaluation.

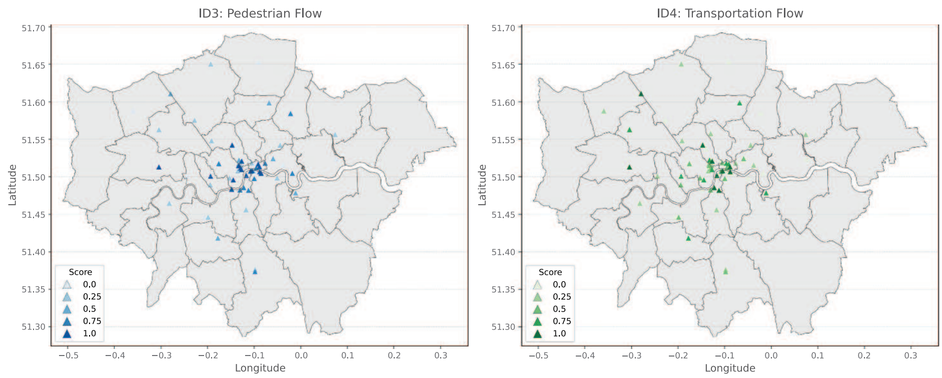

Figure A1. Geographic distribution of pedestrian flow (ID3) and vehicle flow (ID4) scores in London.

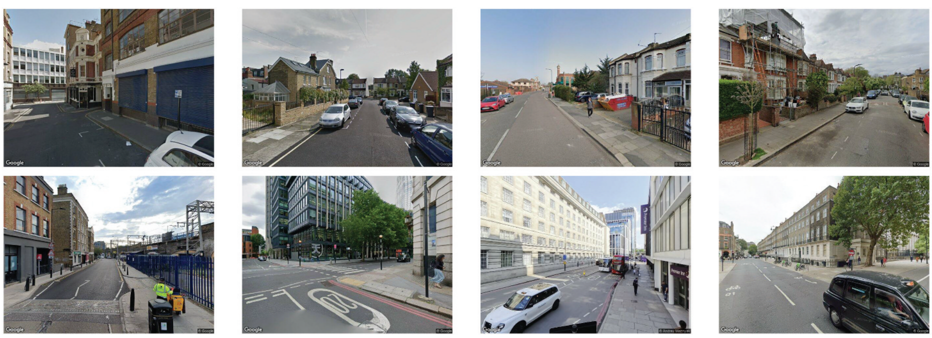

Figure A2. Illustrative SVI images used for assigning pedestrian flow (ID3) and vehicle flow (ID4) scores. Two representative images are provided for each scoring category (from left to right: 0, 0.25, 0.5, 1.0).