A PERSONALIZED TRIP PLANNER FOR VULNERABLE ROAD USERS

FINAL REPORT

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EXECUTIVE SUMMARY

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1 INTRODUCTION

Mobility is an essential component of quality of life. Vulnerable Road Users (VRUs), here defined as individuals with mobility issues such as elderly persons or wheelchair users, recognize mobility is demanding and may be discouraged from participating in social activities. In novel environments, and even familiar ones, VRUs encounter a range of obstacles impeding easy navigation and access to locations (Ding et al., 2007). Existing designs of built environments and public transportation systems do not entirely fulfill the needs of people with disabilities in terms of mobility and accessibility (Poldma et al., 2014). According to a survey among wheelchair users, a narrow sidewalk, steep slope, bad weather, and sidewalk surface traversability are examples of outdoor obstructions for their navigation (Meyers et al., 2002). Specific standards are presented by the Americans with Disability Act (ADA) and Architecture Barriers Act, to increase the accessibility to urban structure facilities of VRUs. However environmental barriers still limit the accessibility of the urban areas and public transportation systems for VRUs, which affects the quality of their life. Identifying and avoiding inaccessible places in the current pavement network as a short-term solution instead of redesigning urban transportation and sidewalk networks as a long-term solution can accelerate helping VRUs (Ferrari et al., 2014).

In recent years, the usage of online navigation systems has increased (Ding et al., 2007). Online responses based on user preferences can contribute to finding the best routes (Safi et al., 2015). Although current navigation systems find the shortest path, pedestrians are interested in having a more accessible path than the shortest distance from origin to destination (Alfonzo, 2005). For example, a very narrow sidewalk in a recommended shortest path from routing services is inaccessible for people with mobility impairments. People with disabilities have different physical conditions and demands, which must be considered in route navigation. The preferences and needs of individuals with disabilities may differ from other pedestrians; a designed routing system should facilitate users to have a customized route. A system with greater accessibility for VRUs might increase their participation in social and outdoor activities. A range of sidewalk network factors can affect the preferences of users with disabilities. The related works of literature agreed on four factors that significantly influenced users' path choice, especially those in wheelchairs: width of sidewalk segments, distance to the destination, slope, and surface type (Kasemsuppakorn et al., 2015; Inada et al., 2014; Izumi et al., 2007). These studies assumed a static individual's preference framework in calculating an optimal path to the destination, with no provision for en-route changes to preference. To summarize, this paper develops a new framework to fill the above gaps with the following contributions. First, the new trip planner accommodates the various road and trip characteristics to improve the safety and efficiency of mobility for people with disabilities who walk and use transit in urban and suburban environments. Second, a hybrid adaptive routing system uses real-time route information and copes with unexpected sidewalk conditions en-route. Third, dynamic trip planning incorporates changing preferences and the interaction effect between sidewalk variables and weather conditions contributing to a path choice. The structure of the

remainder of this paper is as follows: the literature review section provides a review of some related work for navigation and routing services, including VRU's preferences. The method section outlines the adaptive, personalized routing systems for mobility-impaired users. The evaluation section includes the implementations results and analysis of the complexity of the developed model in various real-world scenarios.

2 LITERATURE REVIEW

Significant efforts have been applied to studies for route planning and wayfinding for people with disabilities. A few studies attempted techniques that integrated personalized routing with static en-route user preferences, environmental barriers, and other factors such as sidewalk slope.

2.1 Wayfinding based on network information and personal preferences

Pedestrian navigation systems have considered users' physical and mental conditions influencing the choice of sidewalk path. Typically, Dijkstra's algorithm was used on pedestrian networks with identified non-traversable routes (Izumi et al., 2007). A pedestrian navigation system that incorporates experience-centric and computer-centric approaches provides a more robust solution; meeting individuals' impairment demands (Karimi et al., 2014). Considering several sidewalk accessibility factors, a weighted approach was developed for scores of factors and impedance levels of different sidewalk segments to find the optimal path choice (Inada et al., 2014). This is similar to the wheelchair routing technique called Absolute Restriction Method based on users' preferences(Kasemsuppakorn et al., 2015). Although this approach suggests the optimal path close to the user's preferred route compared to the shortest path, it does not accommodate the importance of sidewalk variables changing by time and the interaction effect between the factors contributing to a path choice. The OpenStreetMap sidewalk database has been investigated considering mobility-impaired users to assess its suitability for navigating wheelchair users (Mobasheri et al., 2017). While the study suggested the static sidewalk condition information from OpenStreetMap is acceptable, it does not consider how real-time information of sidewalk conditions can improve navigation for wheelchair users.

2.2 Collaborative wayfinding approach

Studies considering collaborative wayfinding for persons with disabilities are limited. A wayfinding client/server system called RouteChecker was designed to provide a personalized, collaborative route for VRUs (Völkel and Weber, 2008). Sidewalk network information was considered for a personalized route with a weighting approach to enable users with disabilities to set the importance of sidewalk factors (Hashemi and Karimi, 2017). The above studies on wayfinding for VRUs lack adaptiveness and often fail to address the personalized preferences of VRUs changing over time in estimating the users' utilities. This research presents an adaptive and personalized routing model as a part of a mobility assistant program called Vulnerable Road Users' Personalized Optimum Dynamic routing (VRUPOD). Table 1 highlights our developed VRU Mobility Framework compared to previous studies.

Table 1: Model Category in VRU Mobility Framework

Author (Year)	Model Category			
	Static Linear	Interaction Effect	Dynamic	Adaptive
Izumi et al. (2007)	✓			
Völkel and Weber (2008)	✓			
Karimi et al. (2014)	✓			
Inada et al. (2014)	✓			
Kasemsuppakorn et al. (2015)	✓			
Mobasheri et al. (2017)	✓			
Hashemi and Karimi (2017)	✓			
This research		✓	✓	✓

The static normative approach developed in the previous studies is only satisfactory when conditions of intermediate nodes in the network are consistent, a constant rate of change occurs per each change of the link condition, and the same fixed routes are valid every day regardless of the user preference. Recalculating the static path without modeling other essential characteristics (discussed below) does not appropriately reflect vulnerable road users' personal preferences and value of time. There is a significant limitation for routing models with static parameters: First, the changes in preferences by time en-route must be considered. Second, the optimal sidewalk path's determination should accommodate information of unexpected sidewalk conditions (e.g., non-traversable segments). The stochasticity and time of available information regarding the non-traversable segment's location (crowd-sourced) must be considered at the current stage before the next decision is made. Such environments are different from deterministic and static environments where sidewalk segment costs are fixed. In such cases, the standard shortest path algorithms such as Dijkstra and A* search are myopic and will fail to find the minimum cost path (Hall, 1986). Also, there is an inefficiency to take a detour because it can not adapt to the environment's changes. Third, the interaction effect between sidewalk variables such as the slope, surface type, and the weather condition can limit the accessibility of sidewalk segments and must be considered. A formulation of the joint utility function addresses the dynamic user preference-based metric and the interaction effect of the sidewalk segment factors. A reinforcement learning framework (Sutton and Barto, 1998; Mao and Shen, 2018) is adopted to compute the optimal policy accounting for the learning process of adaptively accommodating unexpected sidewalk conditions based on real-time crowd-sourced information.

3 APPROACH AND METHOD

The adaptive personalized routing considers the sidewalk network as a graph in which nodes represent sidewalk intersection and edges represent sidewalk segments. In the VRU mobility problem, we develop the cost function to address the preferences of the user changing by time and the interaction effect between sidewalk factors contributing to a path choice.

3.1 Vulnerable Road User Mobility Assistance Platform

The ongoing Vulnerable Road User Mobility Assistance Platform (VRUMAP) by (Owens and Miller, 2018) enables users to save personal information relevant to transportation needs (e.g., stamina and ability to traverse uneven terrain). Figure 1 shows VRUMAP combining personal

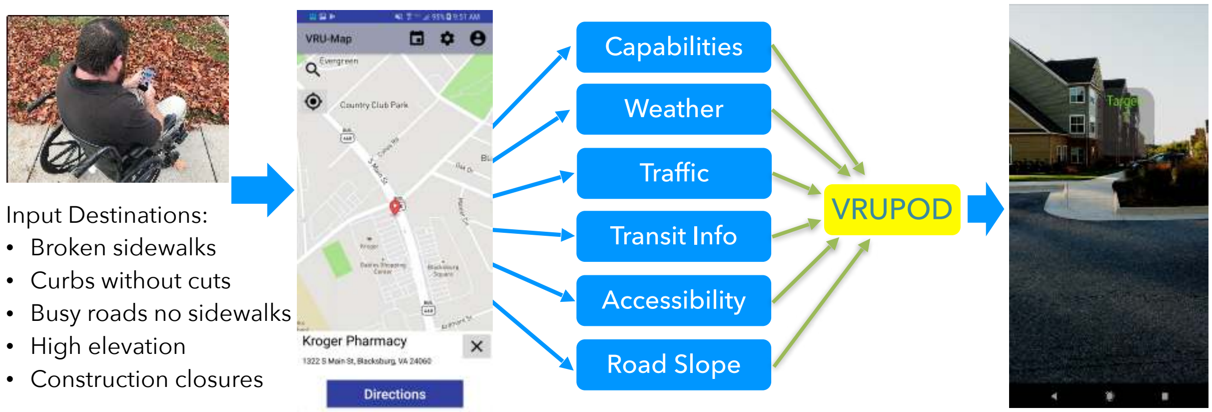


Figure 1: Vulnerable Road User Mobility Assistance Platform (VRUMAP) and the Role of VRUPOD

information with publicly-available information about route nodes, elevation changes, weather, traffic, multimodal transit, etc., along with crowd-sourced information about route impediments (e.g., construction), facilities, and rest opportunities to provide personalized route guidance for users. Currently, the app is being developed for both Android and iOS smartphone platforms using Android Studio and Swift, respectively, with supplemental coding using, Java, and database management software including local SQL databases and Firebase's Cloud Firestore for crowd-sourcing capabilities (Owens and Miller, 2018). Maps are sourced from the open-source platform Mapbox, with routing being implemented using custom code.

As shown in Figure 2, routes are developed using a series of location nodes, with weights for segments between nodes being associated with positive or negative valences depending on information present in the public and crowd-sourced datasets combined with individual needs and capabilities. For example, a segment with a steep elevation change or stairs would have a strong negative weighting for a person who uses a wheelchair, while crowd reported accessible restroom facilities may have a positive weighting if the user prefers more frequent restroom access. In this paper, we focus on the demonstration of the VRUPOD method, tested in various simulated environments, while VRUMAP is still under development phase. Currently, ongoing visual recognition work in VRUMAP automatically recognizes traffic warning signs and tracks the edges of the sidewalks through a machine-learning algorithm. These images show the recognized signboards such as the yield sign, construction sign, detour sign, and traffic cone, which are possible obstacles for wheel-

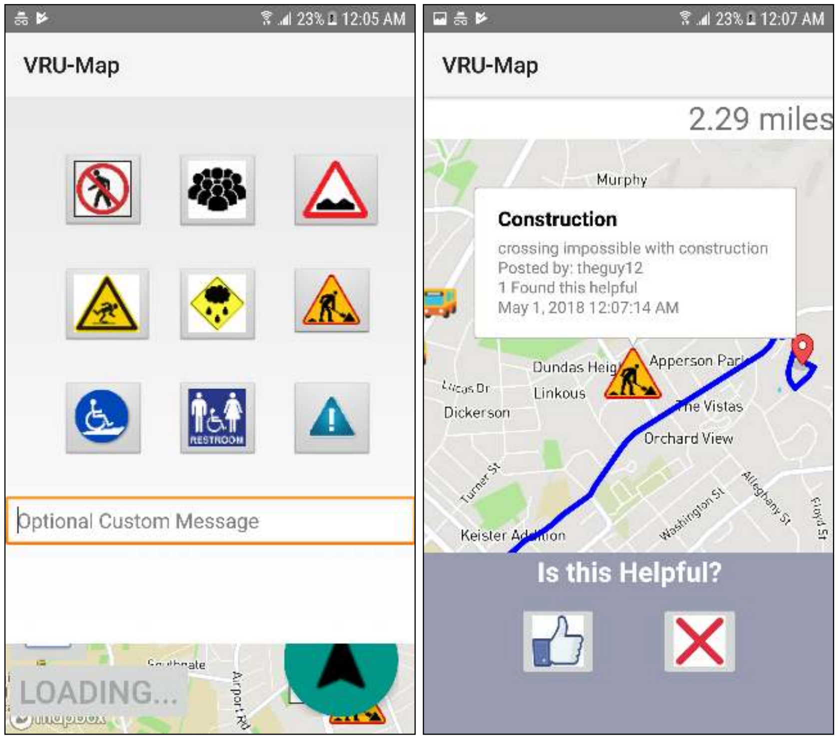


Figure 2: Prototype Crowd-Source Interface of VRU

chair users detected in real-time. While this paper focuses on presenting the VRUPOD method, the full wayfinding capability will be possible by incorporating visual recognition works.

3.2 Sidewalk accessibility factor selection

In this paper, some common factors used for individuals with disabilities routing are described in Table 2. The accessibility of each pedestrian segment for users with disabilities in this paper is defined by five parameters: width, length, slope, sidewalk surface type, and weather condition. The width, length, slope, and surface type factors come from (201) and have been used in (Hashemi and Karimi, 2017), (Kasemsuppakorn et al., 2015), and (Sobek and Miller, 2006). Additionally, inclement weather conditions may affect the traversability of sidewalk segment when applied to the slope and surface parameters of a sidewalk (Cooper et al., 2012). The ADA standard determines acceptable sidewalk parameters as follows: the width of the sidewalk should have minimum clearance at 3 feet. Any sidewalk width less than 3 feet does not meet the minimum requirement for the mobility of users with disabilities. However, sidewalks can be constructed wider than this. The length of a sidewalk section is the distance between the start node and end node. Sidewalk surfaces must be stable, solid, and resistant to slide. Materials that are often used in sidewalk surfaces are concrete, asphalt, stone, brick, and gravel. The most common form of sidewalk material in the United States is concrete, the second material is asphalt (Huber et al., 2013).

Table 2: Sidewalk Parameter Selection Criteria for VRU

	Sobek and Miller (2006)	Kasemsuppakorn and Karimi (2009)	Kasemsuppakorn et al. (2015)	Hashemi and Karimi (2017)	This research
Width	✓	✓	✓	✓	✓
Length	✓	✓	✓	✓	✓
Slopes	✓	✓	✓	✓	✓
Steps		✓	✓		
Surface Type		✓	✓		✓
Surface Condition		✓	✓	✓	
Sidewalk Traffic	✓	✓	✓	✓	
Curb Cut Feature	✓		✓		
Ramps Feature	✓				
Uneven Surface		✓			
Weather condition					✓

Each sidewalk parameter (x) is normalized $(\widehat{x})$, and the weight of each factor (x) is calculated regarding wheelchair user choices and preferences by using the Analytic Hierarchy Process (AHP) method (Hashemi and Karimi, 2017). An overview of the VRUPOD system is described in Figure 3.

In this paper, we model the VRU mobility problem as the adaptive routing problem with real-time information of the network and present the formulation as a Markov decision process (MDP) (Rambha et al., 2016). A Q-learning framework (Sutton and Barto, 1998) is provided to solve the optimal routing strategy. A MDP models a sequential decision-making problem with five elements: decision epochs, a set of possible world states $s \in S$, a set of possible actions $a \in A$, reward function, and state transition probability. A *policy* is a function $\pi(s) : S \longrightarrow A$ that maps

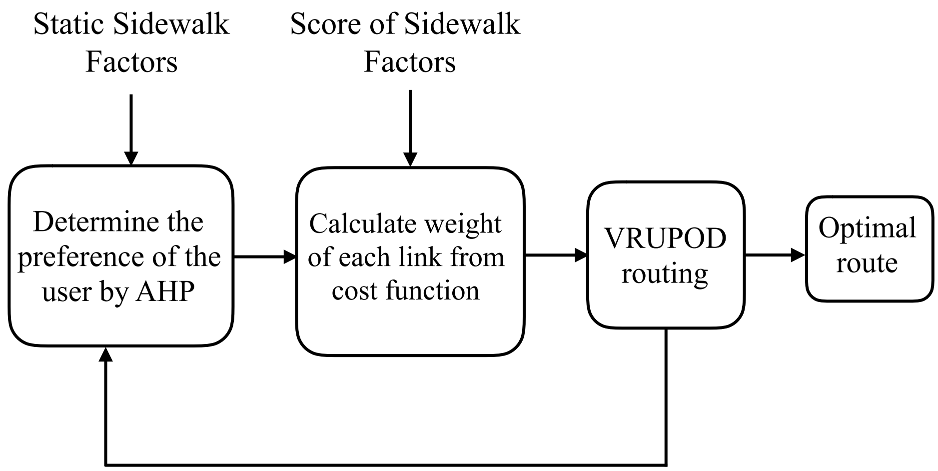


Figure 3: A VRUPOD Model for Vulnerable Road Users

the current state to an action, and optimal policy is the best possible action. The MDP can be solved using a Dynamic Programming method for problems where it is possible to develop the environment with the exact state transition probability and rewards. However, in most real-world problems, such as integrating real-time crowd-sourced information on sidewalk segments' traversability status, we cannot precisely develop the environment. In such cases, the Q-Learning algorithm can solve the MDP, where the rewards and transition functions are unknown. The Q-learning algorithm investigates all likelihoods of state-action pairs and estimates the long-term reward received by applying an action in a state.

Consider the sidewalk network as a graph *G=(N,E)* where $n \in N$ is the set of nodes and $e \in E$ is the set of edges. A VRU can move from *n to* n' if an edge connects the two nodes. The objective of this work is to find the path or strategy that minimizes the total cost in a given origin-destination pair (n_o,n_d). Equation 1 is used to calculate the dynamic and personalized cost $C_{(e)}(t)$ of each sidewalk segment based on parameters that define sidewalk segment accessibility for VRU.

$$C_{(e)}(t) = W_w(t)S_{w(e)} + W_l(t)S_{l(e)} + W_s(t)S_{s(e)}S_{wc(e)} + W_{sf}(t)S_{sf(e)}S_{wc(e)}, \tag{1}$$

where $S_{w(e)}$, $S_{l(e)}$, $S_{s(e)}$, $S_{wc(e)}$, $S_{sf(e)}$ are scores for width, length, slope, weather condition, and surface type of each segment used instead of actual values which are different in range. In order to obtain the score of each factor the actual values are normalized using Equation 2. Let *x* be the actual value of each parameter, S (normalized) or the score of the factors we calculate as:

$$S = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{2}$$

W_w, W_l, W_s, W_{sf} are weights for width, length, slope and surface type. The values of weights for each parameter are calculated using the AHP method. In the AHP method the summation of weights is equal to one (Equation 3).

$$W_w(t) + W_l(t) + W_s(t) + W_{sf}(t) = 1 \tag{3}$$

Traversability status of each sidewalk segment at time *t*, given by the traversable segment status vector is *H(t)*=$\{h_1(t), h_2(t), h_3(t), \ldots, h_{|E|}(t)\}$, based on real-time crowd-sourced information from VRUMAP.

Binary classification is used to determine the traversability of the sidewalk segments. We impose a threshold $\kappa_{(e)}$ for each sidewalk segment to determine whether the segment is traversable or not. If $\kappa_{(e)}$, updated real-time by crowd-sourced information (e.g., information from VRUMAP) is greater than or equal to the threshold value, then the sidewalk segment is considered non-traversable (1), otherwise the sidewalk segment is considered traversable (0). Other studies have successfully followed a similar approach(Chavez-Garcia et al., 2018; Wang et al., 2009; Hewitt et al., 2017; Papadakis, 2013). A considerable reduction in computational complexity is observed when using binary classification, allowing for a more detailed analysis of terrain portions of more interest (Papadakis, 2013).

$$h_{(\mathrm{e})} = \begin{cases} 1 & \text{non} - \text{traversable} & \text{if } \kappa_{(e)} \geq 4 \\ 0 & \text{traversable} & \text{if } \kappa_{(e)} < 4 \end{cases}$$

In this sequential decision-making framework, the states $s \in S$ of the VRU at each decision stage k are defined as $s = (n_k, t_k, H(t_k))$. At the current location $n_k \neq n_d$ (n_d is the destination node), the pedestrian must decide on which adjacent node to travel. The information available at this stage includes the current time t_k and the traversable segment vector $H(t_k)$. There is a tradeoff between the number of segments to monitor and resulting projection accuracy by monitoring two segments ahead of the VRU's current location. If E^1 and E^2 are the set of first and second successor segments respectively from the VRU's current location, then a state s_k is defined as

$s_k = \left(n_k, t_k, H^{E^1 \cup E^2}(t_k)\right)$ where $H^{E^1 \cup E^2}$ represent the traversability statuses of the set of first and second successor segments from the VRU's current location. The goal is to determine the optimal policy, $\pi^*(s_k)$, showing which segment the pedestrian must select. In this paper, the expected return starting at s, taking action a and following π is $Q^{\pi}(s, a)$. The optimal policy $\pi^*(s)$ for $s \in S$ is thus given by:

$$\pi^*(s) = \underset{a}{\operatorname{argmax}} Q^*(s, a) \tag{4}$$

3.3 Reinforcement learning

We adopt Q-learning to obtain the optimal policy. At the current stage of the decision process, the agent will receive a reward; the sidewalk segment's estimated cost $C(n, n')$ comprising of the sum of $C_{(e)}(t)$ and a fixed penalty (0 if traversable and very large number if non-traversable) defined by the traversability status of the segment. As discussed, the cost function $C_{(e)}(t)$ accommodates the time-varying preferences of the VRU and the interaction effects between the sidewalk factors contributing to a path choice. Utilizing its current knowledge of the environment (the estimated Q-function so far), the agent will choose the state's best action while accommodating exploration through the Boltzmann exploration strategy. Using the Boltzmann exploration strategy, the relative Q-values weigh the probabilities of taking different actions. We highlight that the system's state at this stage includes the traversability status of the first and second successor sidewalk segments from the agent's current location. This component of the state model allows us to integrate the crowd-sourced information for sidewalk segment conditions, as shown in Figure 2. The new action will allow the environment to change into a new state, with the agent receiving a new reward. The state-action pair value is then revised to consider the response. The revision rule in each state is:

$$Q(s, a) = (1 - \alpha) Q(s, a) + \alpha \left[r' + \gamma \max_{a} Q(s', a) \right] \tag{5}$$

where (s, a) is state-action pair, α the learning rate, r' is the reward that agent will receive and turn into new state s', and γ is a discount factor. The adaptive personalized routing for the VRU mobility problem can then be determined by using the final Q-table after a sufficient number of iterations and convergence, providing the optimal action to take at each possible state. The VRUPOD model is shown in Algorithm 1, with additional details provided in the evaluation section.

Algorithm 1 Q-learning for VRUPOD method

```
Let Θ = α[−C(n, n′) + max_{a′} Q(s′, a′)]
Input: G = (N, E), destination n_d, learning rate α
Output Q-function for VRUPOD to n_d
Initialize: Q(s, a)    0, ∀s ∈ S, ∀a ∈ A(s)
for each way finding do
    s    initial state
    while s[0] ≠ n_d do
        Select node a ∈ A(s)
        Travel to node n′ = a
        Perceive new state s′ = (n′, t′, H(t′))
        Accept cost of segment C(n, n′)
        Q(s, a)    (1 − α)Q(s, a) + Θ
        s    s′
    end while
end for
Return Q
```

3.4 Analytic Hierarchical Process (AHP)

We use the AHP to decide with multiple objectives and criteria by determining how important a parameter or object is than another. In the developed method, weights are obtained for each factor of sidewalk using a 4×4 matrix A which is the pairwise comparison matrix. Each cell of matrix (a_{ij}) in row i and column j denote how much more important factor i is than factor j.

$$A = \begin{pmatrix} 1 & a_{01} & a_{02} & a_{03} \\ 1/a_{10} & 1 & a_{12} & a_{13} \\ 1/a_{20} & 1/a_{21} & 1 & a_{23} \\ 1/a_{30} & 1/a_{31} & 1/a_{32} & 1 \end{pmatrix} \tag{6}$$

The importance of factors is assessed on a range from 1-9 where 1 means parameter i and j are of equal importance, and 9 means factor i is far more important than factor j. If factor 1 is five times more important than factor 2, then factor 2 is one fifth as important as factor 1.

Generally, $n(n-1)/2$ comparisons are required in which diagonal elements are equal to 1, and the other elements will simply be the reciprocals of the earlier comparisons. The AHP method uses a comparison matrix, assigns a weight to each pedestrian parameter, and computes the weight of each factor based on the preferences of users. To calculate the weight of each parameter for individual VRUs in this paper a survey dataset based on the ADA standard is used Kasemsuppakorn et al. (2015). Each survey question includes a comparison of the importance of two parameters. The importance of each parameter is defined using five levels: extremely, very strongly, strongly, moderately and no difference. According to the user's survey responses, a binary comparison matrix can be built. The weights that are obtained from the AHP method are used in the developed cost function to determine the weight of each segment of the sidewalk. In the developed VRUPOD method a sidewalk width that is less than ADA standards is considered as level 0 and is pruned from the network. The five surface types are ranked based on field surveys where level 1 indicates the best and most accessible, and level 5 indicates the worst condition.

$$\text{Surface Type} = \begin{cases} \text{Concrete} & 1 \\ \text{Asphalt} & 2 \\ \text{Brick} & 3 \\ \text{Cobblestone} & 4 \\ \text{Gravel} & 5 \end{cases}$$

Weather condition ranges from level 1 to 5, where level 1 (sunny) indicates the best weather condition and level 5 (Extreme snow) the worst weather condition to accurately reflect the interaction effects between the surface type and slope with the different severity of the weather.

$$\text{Weather Condition} = \begin{cases} \text{Sunny} & 1 \\ \text{Moderate Rain} & 2 \\ \text{Moderate Snow} & 3 \\ \text{Extreme Rain} & 4 \\ \text{Extreme Snow} & 5 \end{cases}$$

This paper presents a numerical example for sunny, rainy, and snowy in the moderate cases of the weather condition for illustrative purposes.

4 DATA PREPARATION

To evaluate the usefulness of the developed method and calculate a cost for each sidewalk segment, the Boston sidewalk inventory is used, which includes width, length, slope, and sidewalk surface type. Table 3 shows a sample database characteristic of the Boston sidewalk inventory. SWD_ID indicates a unique ID associated with each sidewalk segment, Width indicates the average width of the sidewalk, Length shows the length of the sidewalk, Slope shows average cross slope (perpendicular to the path of travel) in degrees, Mat shows primary sidewalk material (CC- Cement Concrete, BC - Bituminous Concrete). The weather condition information is assumed to be provided through online web-based data set such as Open Weather Map. We assume that VRUs experience the same and consistent weather condition throughout his/her short trip. For instance, if the weather is sunny at the origin, it will be sunny during the trip and at the destination.

Table 3: Sample Boston Sidewalk Inventory Database

SWD_ID	Width	Length	Slope	Mat
15739	4	931.9775324	3.9	BC
5439	8	282.649369	3.8	BC
4777	17.5	1662.671837	0.8	BC
4778	17	1561.205981	1.8	BC
4779	18.5	1791.473169	0.7	BC
4949	15.2	1416.268866	2	CC
4948	15.5	1226.37165	1.5	CC
5476	12	312.5817051	3.9	CC
5475	14	306.143638	3.9	CC

4.1 Simulated Participants

The VRU database that is simulated in this paper includes five participants who are new in the environment of study (Kasemsuppakorn et al., 2015). This includes the dataset collected through a field survey for five participants with one female and four males between 20 to 40 years old. The demographics of the participants in this dataset are age, gender, disability type, wheelchair make and model, most concern parameter, and their fitness level. The level of fitness scales from one to ten and determines the VRUs' degree of tiredness and endurance in different sidewalks slopes. The four male participants have a perceived fitness level greater than 5 while the female has a low perceived fitness level (level 2). Based on the sidewalk inventory information and preferences of the user, the VRUPOD path planning model finds the optimal policy and chooses the best route for each user.

5 RESULTS AND DISCUSSIONS

The performance of the VRUPOD method is highlighted by comparing against the following traditional models and their objectives.

Static Minimum Cost (SMC): By appropriately adjusting the VRU mobility problem, we use the Dijkstra algorithm to minimize the path cost while the user's preferences are set at the beginning of the trip.

Dynamic Minimum Cost (DMC): By appropriately adjusting the VRU mobility problem, we use the Dijkstra algorithm to minimize the time-dependent path cost by varying user preference at predefined trip duration or time steps. The DMC model will recalculate the current network's shortest path and recommend the new path to the user when there is a non-traversable segment en-route from the origin to the destination.

Shortest Path (SP): Use the Dijkstra algorithm to find the minimum distance from the origin to the destination.

Figure 4: A Real-World Depiction of the Sidewalk Network used for Evaluating the Developed Model (Source: Google Maps)

A case study is carried out on a simulated mid-size network ($\approx 1000 ft \times 600 ft$) represented as an 8×8 grid (see Figure 4) and in a time frame [0-30 minutes] of user's trip and five time steps. The preferences of users may change in each time step in the DMC and VRUPOD method. There are 81 nodes and 144 segments in the case study network, and we assume that we have complete real-time information on all the segments. In the case study, the sidewalk network is considered as a graph in which nodes represent sidewalk connections and edges represent sidewalk segments, the cost of each segment calculated according to the function $C_{(e)}(t)$. The location of the non-traversable segment is randomly changed for all the scenarios between the runs in the simulation. If there is a time window [0-30 minutes] and a stage represented by a unit of time, then the decisions of a traveler who is in the first stage and encounters an unexpected construction can be different from another traveler who is in the fifth stage and encounters an unexpected construction. As the user approaches the destination, the decisions of the user can be varied to reflect the traveler's preference change and a desire to arrive at the destination more quickly instead of taking detours based on their initial preferences. For instance, a traveler who has covered about 70 percent of a trip may, because of tiredness and other considerations want to reach the destination with minimal detours as possible. This can be accomplished by varying the weights assigned to the parameters such as length.

Figure 5 shows an illustrative example of a route suggestion that is not accessible for people with disabilities. The line (blue) shows the original static route that is the shortest path from A to the transit stop, the line (red) shows the detour option 1 with a high slope when there is a non-traversable segment in the VRU's route in rainy weather. The line (green) shows detour option 2 that takes a long detour with a walking shelter to avoid the rain. VRUPOD will guide VRUs toward option 2, by finding the tradeoff between taking a long detour (exploration) and taking the originally known route (exploitation). While the advantage of VRUPOD will depend on the quality and when the information concerning unexpected events are known (crowd-sourced), this paper focuses on demonstrating a new VRU mobility framework by formulating the VRUPOD.

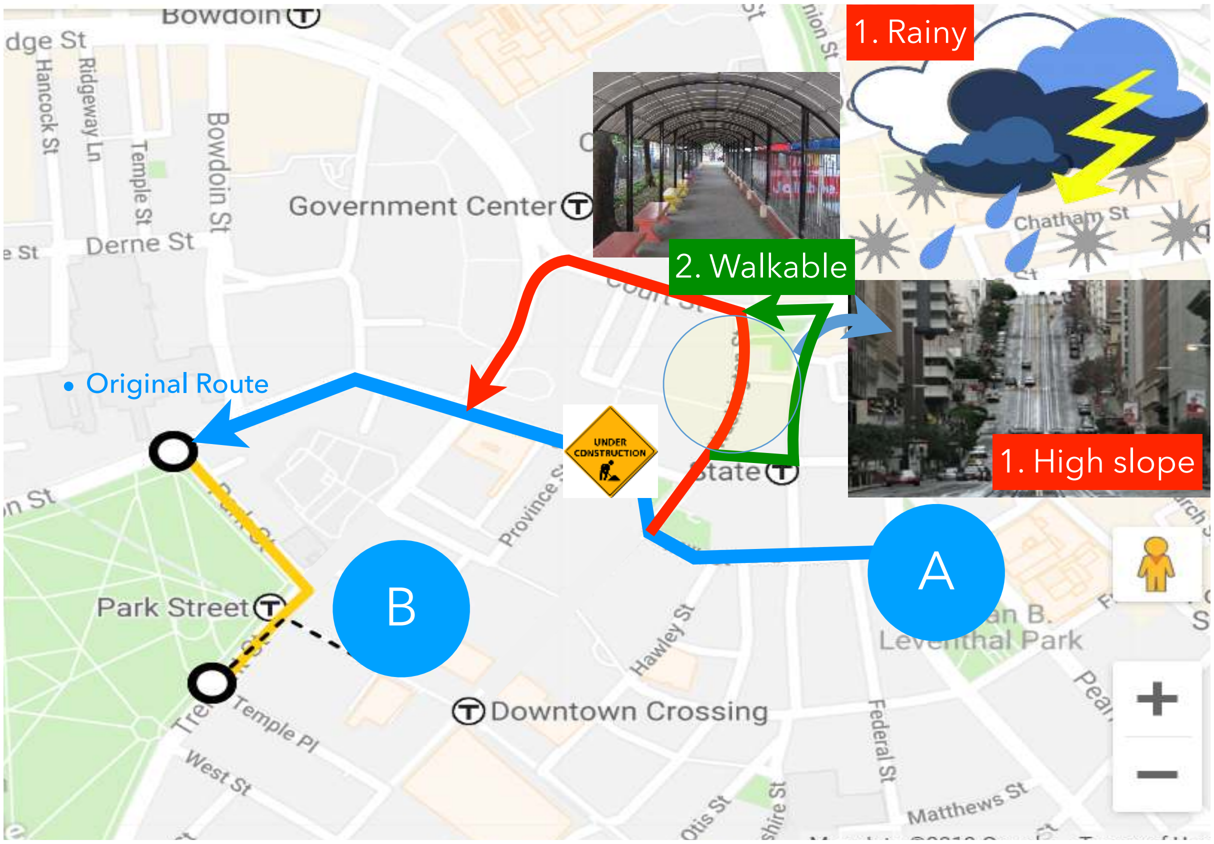
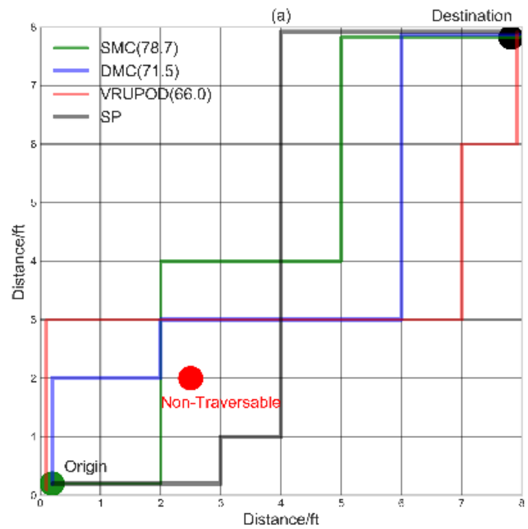
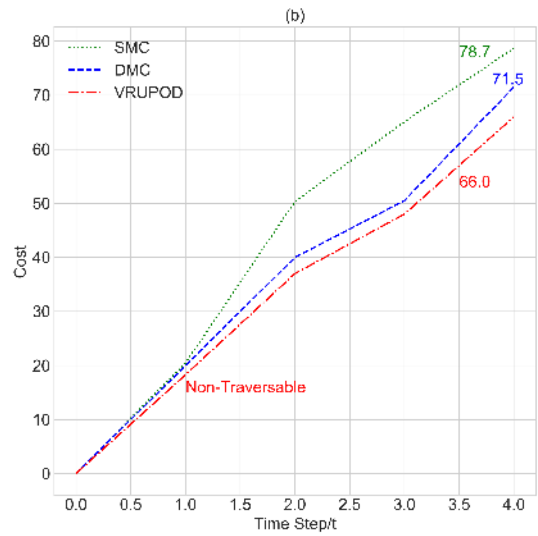


Figure 5: An Illustrative Example of the Advantage of the VRUPOD Considering Accessibility

The results of three scenarios are presented for sunny, rainy, and snowy weather conditions. For each scenario, a path cost comparison is made for SMC, DMC, and VRUPOD method to assess the performance. In our developed framework for sidewalk segment cost, the weather score influences the segment's cost through interaction with the surface type parameter. In effect, slick sidewalk surfaces (due to rain and snow) will significantly increase the segment's overall cost, thus impacting VRUs optimal route choice.

Figure 6 , 7 and 8 show a comparison of four models for the same origin-destination (OD) and obstacle location in sunny, rainy and snowy weather conditions. A path cost comparison is done for SMC, DMC and VRUPOD to assess the performance. As mentioned earlier, weather conditions can affect the accessibility of the sidewalk. Slick sidewalk surfaces due to rain and snow greatly impact wheelchair users. The preference for the sidewalk slope parameter is different for sunny, rainy and snowy weather.

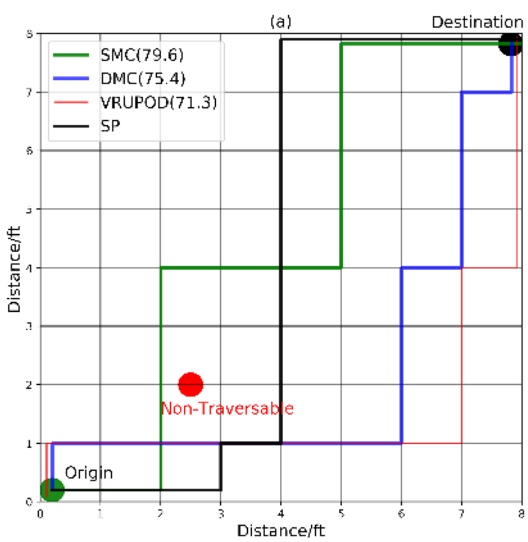


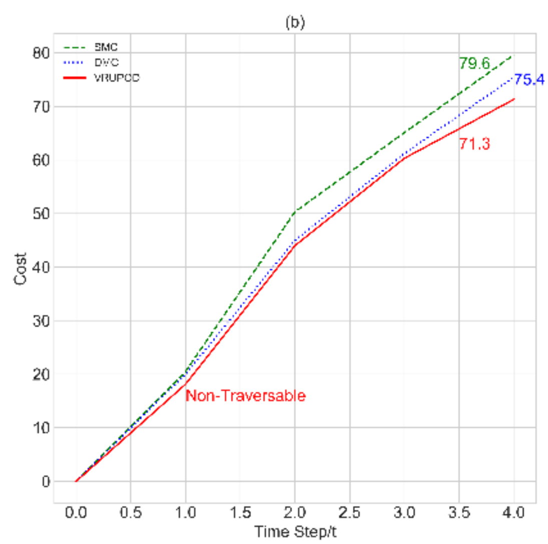


(a) Path graph for four models

(b) Cost graph for three models

Figure 6: Comparison of Four Models for Same OD and Obstacle Location and Cost of Three Models by Time Step in a Sunny Weather

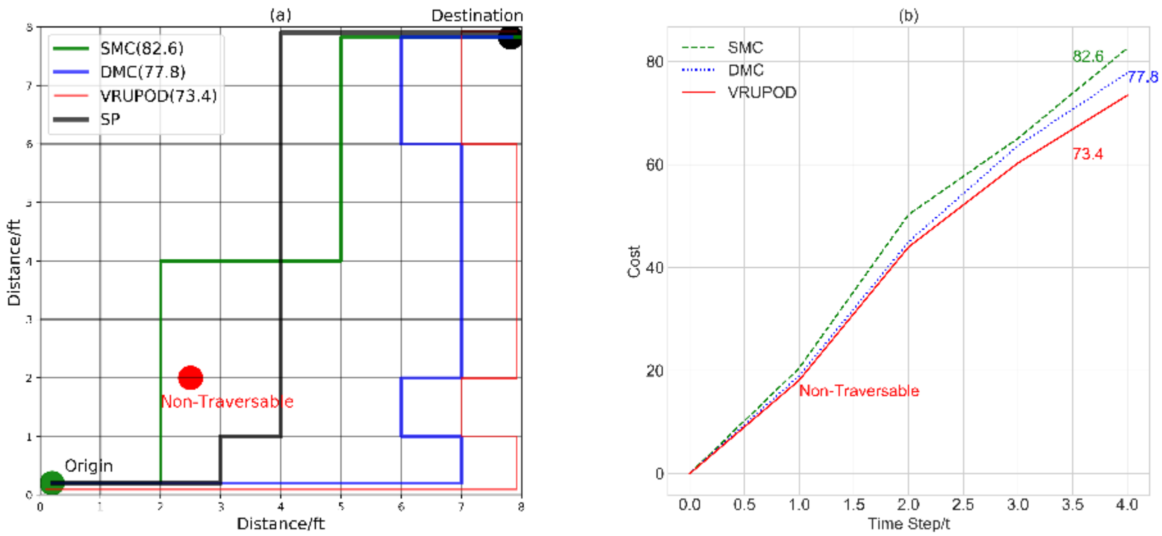




(a) Path graph for four models

(b) Cost graph for three models

Figure 7: Comparison of Four Models for Same OD and Obstacle Location and Cost of Three Models by Time Step in a Rainy Weather



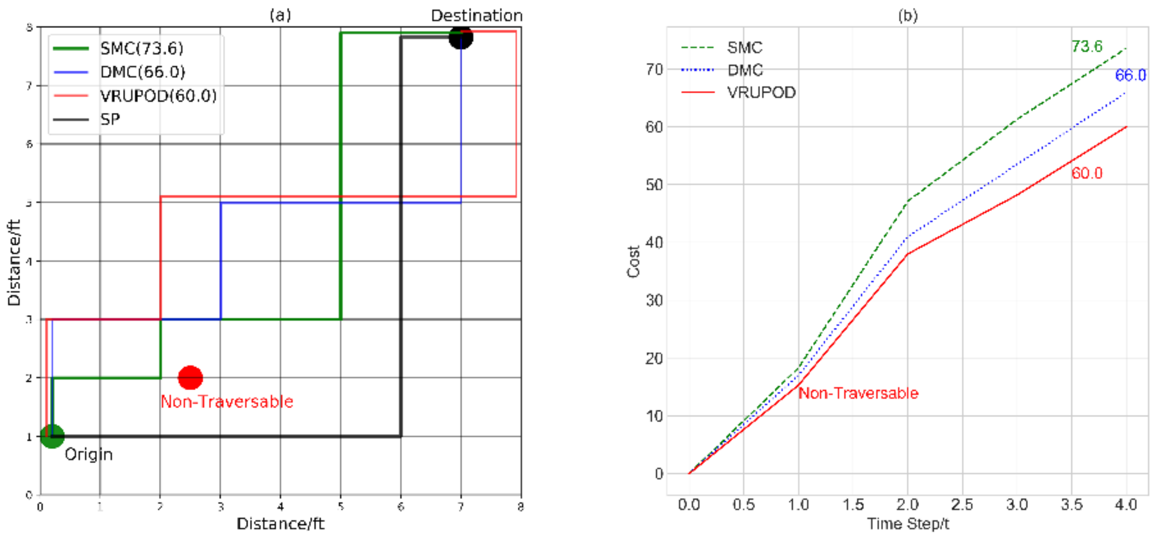
(a) Path graph for four models

(b) Cost graph for three models

Figure 8: Comparison of Four Models for Same OD and Obstacle Location and Cost of Three Models by Time Step in a Snowy Weather

In sunny weather, the sidewalk is not slick so VRUs can traverse a higher slope while a normal or average slope will be preferred for rainy and snowy conditions. Path cost for the SP is the same in sunny, rainy and snowy weather. Looking at each time step, VRUPOD has less steep increase in the cost, most of them occurred during time step 1-2, where the location corresponding to the non-traversable link resulting in increasing the cost of the path. Cost evaluation reveals the superiority of the VRUPOD to the other models. VRUPOD has a lower total cost when compared with the SMC and the DMC. This can be attributed to the fact that the VRUPOD policy is based on comparing Q values of the nearby segments to decide which way to go. Ultimately, integrating the two successor segments from the VRU's current location into the state model definition allows the Q-function to perceive the effect of their decision much early to decide the best segment to select at the current stage of the trip. Cost evaluation reveals the superiority of the VRUPOD over the other models. VRUPOD has a lower total cost averaging 12% and 5% less compared with the SMC and the DMC.

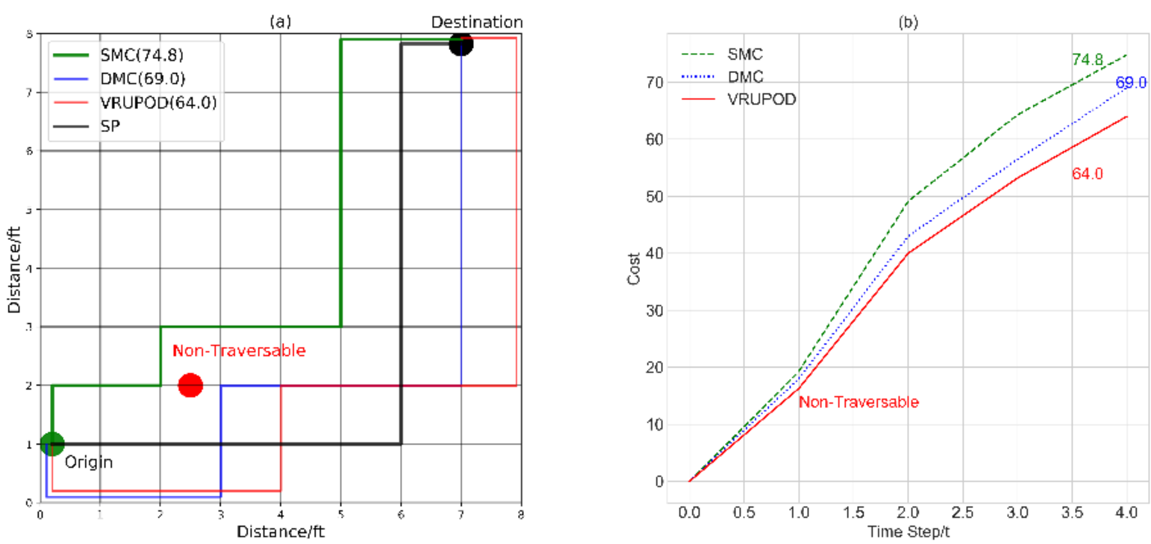
To further investigate the VRUPOD path selection we change the location of the origin and destination, while keeping the obstacle location and network size the same as Figure 6 and compare



(a) Path graph for four models

(b) Cost graph for three models

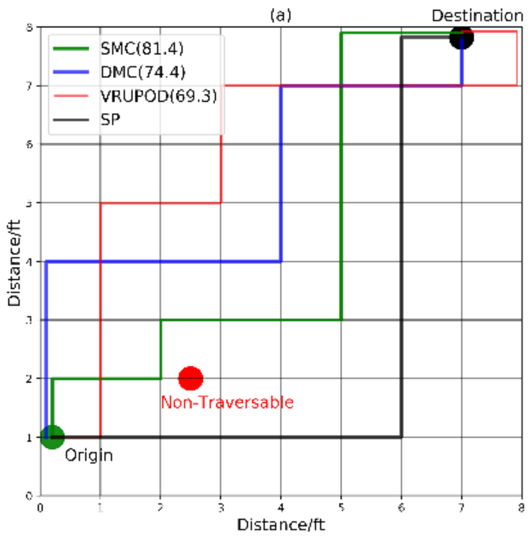
Figure 9: Comparison of Four Models for OD Change and Same Obstacle Location and Cost of Three Models by Time Step in a Sunny Weather



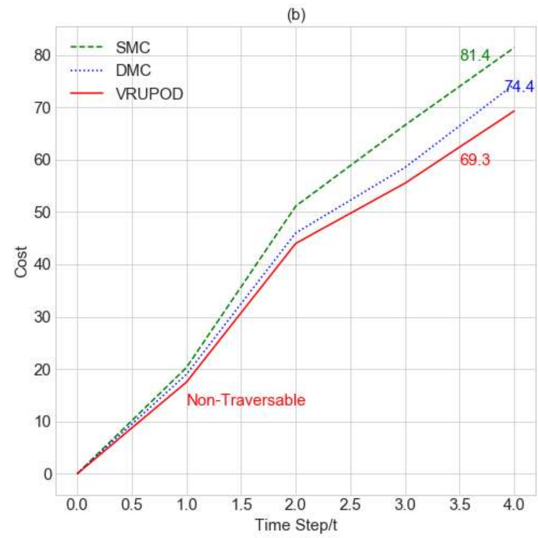
(a) Path graph for four models

(b) Cost graph for three models

Figure 10: Comparison of Four Models for OD Change and Same Obstacle Location and Cost of Three Models by Time Step in a Rainy Weather



(a) Path graph for four models



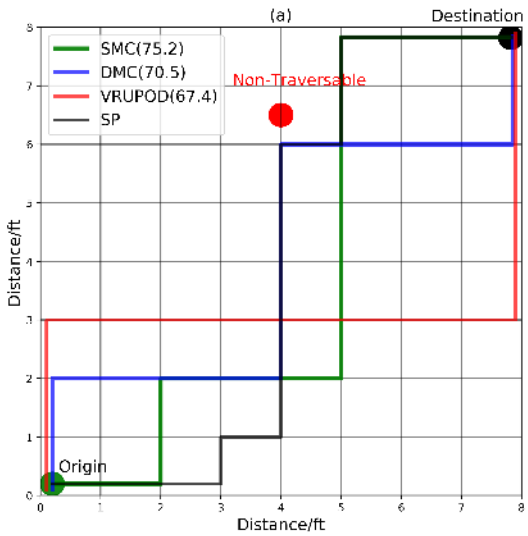
(b) Cost graph for three models

Figure 11: Comparison of Four Models for OD Change and Same Obstacle Location and Cost of Three Models by Time Step in a Snowy Weather

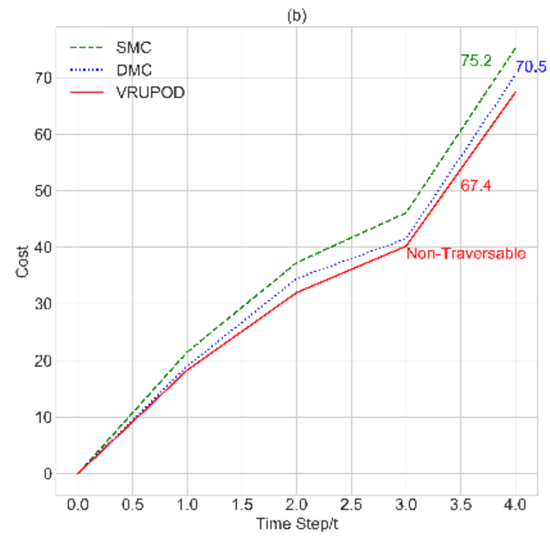
with the three different methods (see Figures 9, 10 and 11). The results for sunny, rainy, and snowy weather show that VRUPOD finds the most optimal routes with minimum cost, averaging 15% and 7% less total cost compared to SMC and DMC. Looking at each time step, VRUPOD has a less steep increase in the cost, mostly occurring during time steps 1-2, where the location corresponding to the non-traversable segment results in increasing the cost of the path. The Q function is directly updated based on the information gathered by exploring all possible scenarios in the pedestrian network. The best routing policy can then be determined from the Q function.

Lastly, in Figure 14 (scenario 3), we change the obstacle location later in VRU's trip in sunny, rainy, and snowy weather conditions and compare the path and cost of the VRUPOD method with the other three methods (plots for sunny and rainy omitted). The developed VRUPOD method directs the user to a route with a lower total cost, averaging 10% and 5% less total cost compared to SMC and DMC. Looking at each time step, VRUPOD has a less steep increase in the cost, mostly occurring during time steps 3-4, where the location corresponding to the non-traversable segment increases the cost of the path.

As discussed above, this can be attributed to the fact that the VRUPOD policy is based on comparing

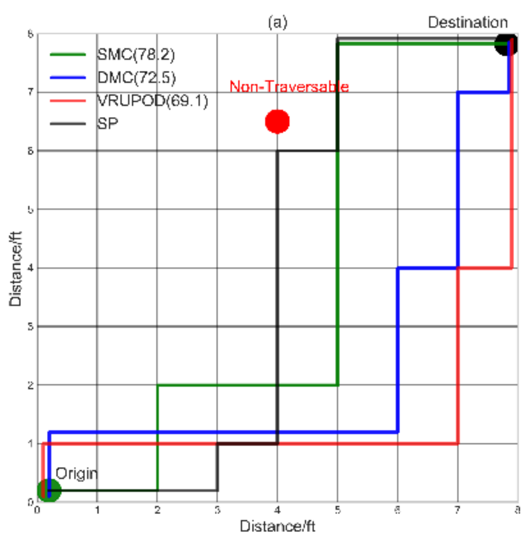


(a) Path graph for four models

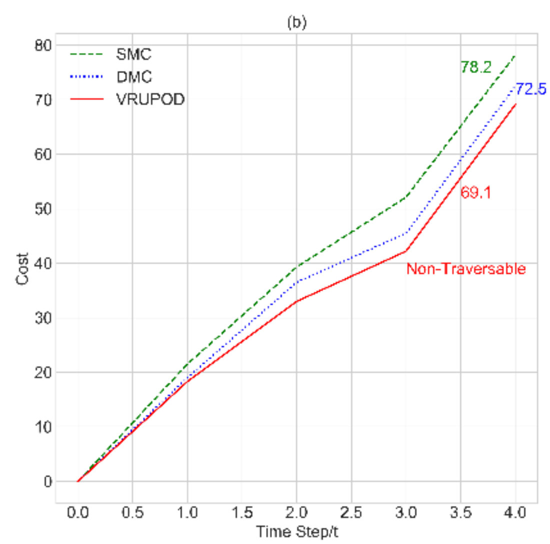


(b) Cost graph for three models

Figure 12: Comparison of Four Models for Same OD and Change Obstacle Location and Cost of Three Models by Time Step in a Sunny Weather

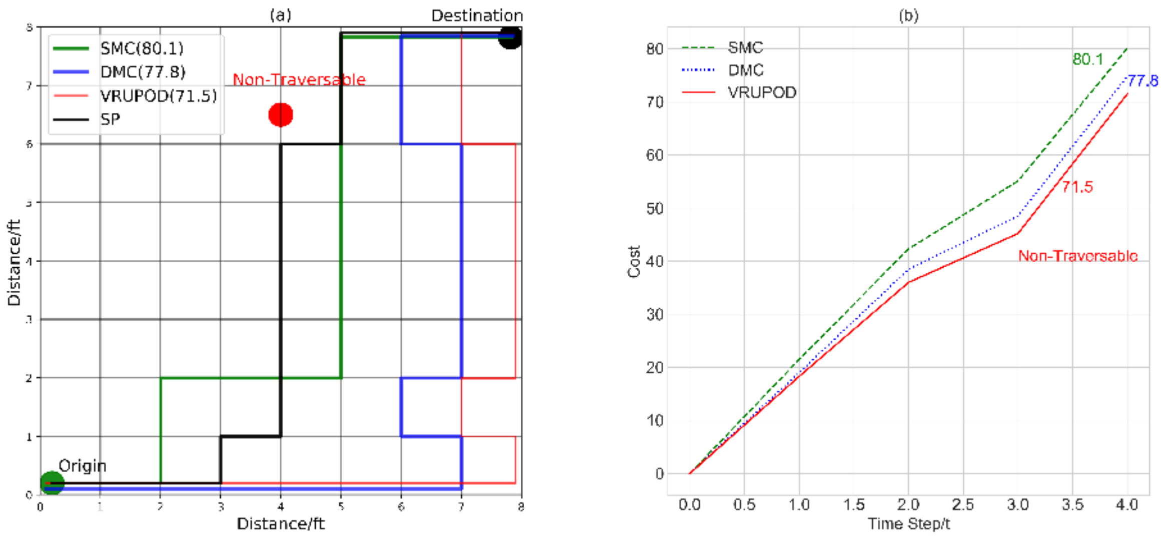


(a) Path graph for four models



(b) Cost graph for three models

Figure 13: Comparison of Four Models for Same OD and Change Obstacle Location and Cost of Three Models by Time Step in a Rainy Weather



(a) Path graph for four models

(b) Cost graph for three models

Figure 14: Comparison of Four Models for Same OD and Change Obstacle Location and Cost of Three Models by Time Step in a Snowy Weather

Q values of the nearby segments to decide which way to go. The Q-values are obtained at convergence, having accommodated all possible scenarios of obstacle locations. In all three scenarios, the VRUPOD solution for sunny weather consistently reported a lower total cost than VRUPOD solutions for rainy and snowy weather conditions. This is expected since the increase in the cost of sidewalk segments during sunny weather conditions is lower compared to the sidewalk segment cost during rainy and snowy conditions. In general, this affects the accessibility of the sidewalk, impacting the optimal route choice and the total cost to get to the destination.

Table 4 shows the summary of results estimated for the different weather conditions, origin-destination location, and obstacle location (including the results from the omitted plots). The percentage improvement is estimated for VRUPOD compared to SMC (A%) and DMC (B%), respectively, and shown in the table as **A–B**. Some possible design considerations and architecture have been proposed to help the final development of a personalized navigation system for wheelchair users (Ding et al., 2007). While the work (Ding et al., 2007) proposed using the standard shortest path algorithms such as Dijkstra, equivalent to the SMC and DMC models, this approach will not adequately accommodate the stochastic nature of unexpected non-traversable segments. Our results

Table 4: Summary of results for different scenarios

		OBSTACLE	METHOD			
COND.	$O \nleftrightarrow D$	LOCATION	SMC	DMC	VRUPOD	% AVG IMP.
Sunny	$(0,0) \nleftrightarrow (8,8)$	$(2,2) \nleftrightarrow (3,2)$	78.7	71.5	66.0	**16–7**
	$(0,1) \nleftrightarrow (7,8)$	$(2,2) \nleftrightarrow (3,2)$	73.6	66.0	60.0	**18–9**
	$(0,0) \nleftrightarrow (8,8)$	$(4,6) \nleftrightarrow (4,7)$	75.2	70.5	67.4	**10–4**
Rainy	$(0,0) \nleftrightarrow (8,8)$	$(2,2) \nleftrightarrow (3,2)$	79.6	75.4	71.3	**10–5**
	$(0,1) \nleftrightarrow (7,8)$	$(2,2) \nleftrightarrow (3,2)$	74.8	69.0	64.0	**14–7**
	$(0,0) \nleftrightarrow (8,8)$	$(4,6) \nleftrightarrow (4,7)$	78.2	72.5	69.1	**12–5**
Snowy	$(0,0) \nleftrightarrow (8,8)$	$(2,2) \nleftrightarrow (3,2)$	82.6	77.8	73.4	**11–5**
	$(0,1) \nleftrightarrow (7,8)$	$(2,2) \nleftrightarrow (3,2)$	81.4	74.4	69.3	**15–7**
	$(0,0) \nleftrightarrow (8,8)$	$(4,6) \nleftrightarrow (4,7)$	80.1	77.8	71.5	**11–8**

in Table 4 show that VRUPOD, which integrates unexpected non-traversable segments location information, provides considerable improvement in performance than the SMC and DMC models.

A number of trips are conducted with the starting node (0,0) as the origin to the ending node (8,8) as the destination to show how adaptive routing path suggestions are affected by different scenarios of user preferences. We use survey records (Kasemsuppakorn et al., 2015) of the preferences of four distinctive users and estimate each sidewalk parameter's weight using the AHP approach. As the trip progresses, we gradually increase the weight for sidewalk length while proportionally decreasing the weight for the other sidewalk parameters (e.g., slope and surface type). We use this approach to simulate a realistic time-varying preference. To summarize, the ratings (0-10 scale) of the four user's preference data are described as follows; User1: High rating for slope and surface type compared to width and distance; User2: High rating for width and distance of sidewalk compared to slope and surface type; User3: High rating for surface type and width compared to distance and slope. User4: High rating for sidewalk distance compared to width, slope, and surface type.

In Figure 15, the results show the different path options that are suggested by the VRUPOD method. In general, the total score for any given parameter (e.g., sidewalk width, slope, etc.) for the optimal

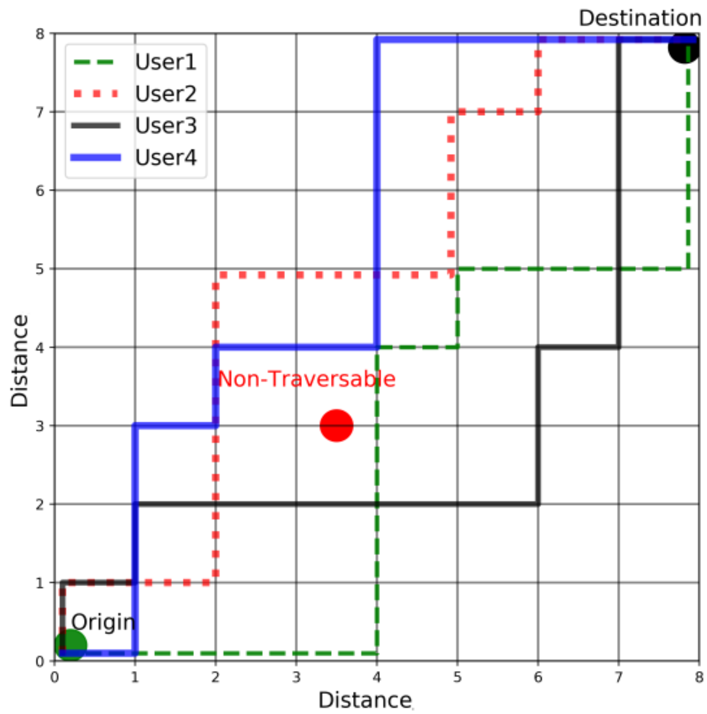


Figure 15: Shows How the Preference of Users Affects the Path Suggestion from the VRUPOD Method

path directly correlates with the user's preference ratings. For instance, the sidewalk segments forming the path recommended for User1 will have more segments with a lower elevation than for User2.

We conduct a Monte Carlo simulation with 100 scenarios of origin-destination and obstacles randomly placed at various locations in the grid to evaluate the robustness of the developed model. We summarize the results for estimated path cost for VRUPOD and DMC through a boxplot. Figure 16 shows a lower mean cost for VRUPOD than DMC. We observe a similar interquartile range for VRUPOD and DMC with a slightly narrow range for VRUPOD than DMC. The policies generated by VRUPOD (q-learning model) inherently accommodates the effect of random obstacle location and thus improves its performance compared to the DMC.

Furthermore, we assess the total average score for parameters such as sidewalk surface type and average slope for the optimal path from the VRUPOD method. The calculated quantities from the VRUPOD method are compared with the shortest path in two tests. In the first test, sidewalk surface

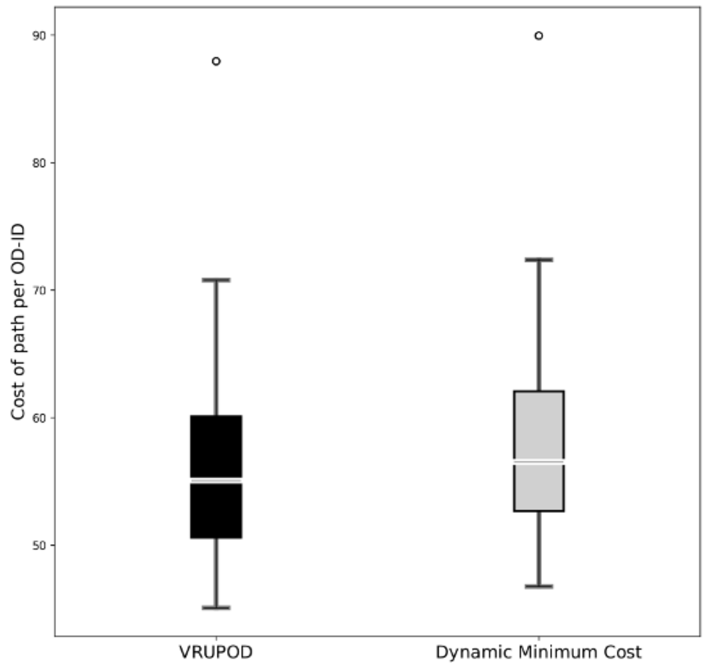


Figure 16: Boxplot of Monte Carlo Simulation Results for Path Cost Based on Routing Policies from the VRUPOD Method and DMC Method

type is the most critical parameter; the lower the sidewalk surface type score, the better the sidewalk path. In the second test, the sidewalk slope is the most important factor; the lower the sidewalk slope score, the better the sidewalk path. Figures 17 and 18 represent the comparison graphs: average surface type and average slope, respectively. As shown in Figure 17, 85.71% of routes recommended by the VRUPOD method have the lowest average sidewalk surface type score. In the second test, as shown in Figure 18, 71.42% of routes recommended by VRUPOD have the lowest average sidewalk slope score. The observed improvement is expected since VRUPOD considers the parameters' weight and finds the path with a minimum expected cost, reflecting those weights (preferences) rather than the shortest path. This observation supports the results from Figure 15, suggesting that the optimal path directly correlates with the user's preference ratings.

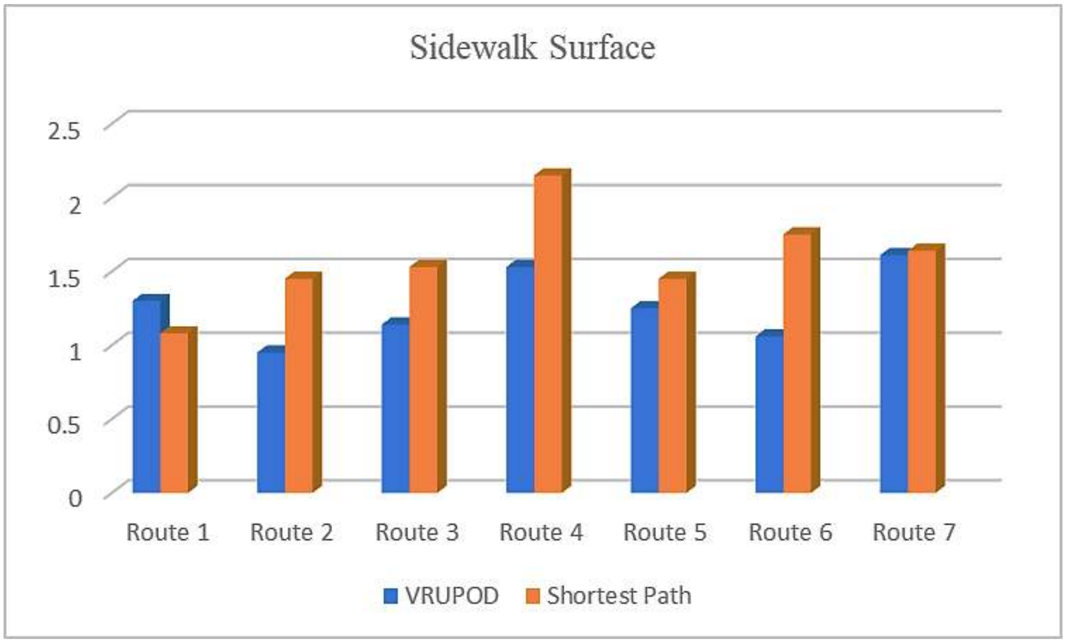


Figure 17: The Average Sidewalk Surface Type Score Comparison Between VRUPOD and Shortest Path

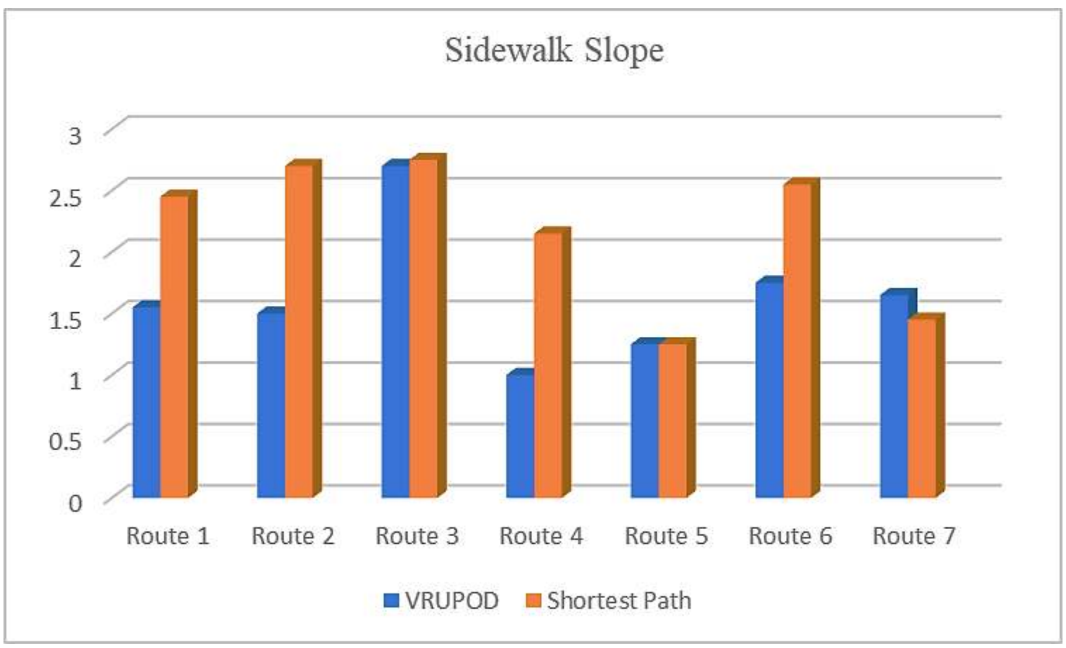


Figure 18: The Average Sidewalk Slope Score Comparison Between VRUPOD and Shortest Path

Finally, a quantitative assessment of the computational complexity of Algorithm 1 is provided for pedestrian networks of various sizes. The mean and standard deviation of the CPU time for 5 experiments is reported. The processor specification used for implementation is 2.9 GHz 6-Core Intel Core i9, 32 GB RAM.

Table 5: Quantitative assessment of the computational complexity of VRUPOD

Pedestrian network size (nodes, edges).	CPU time (s) (mean, std)
(25 , 41)	(9005.3, 502.7)
(81, 144)	(10980.9, 1770.1)
(121, 220)	(13007.1, 1997.5)
(24725, 20881)	(–, –)

The computational time for VRUPOD increases with the increase in size of the pedestrian network. The system state space is a subset of the Cartesian product of the number of nodes, the time periods of interest, and the number of segments being monitored from the VRU's location. Thus, the network size is one of the essential considerations that affect the size of state space. For cases with large state spaces, this leads to a high computational time since the state space must be explored to determine the optimal action at each state. This will make VRUPOD unattractive for real-world adoption. However, we make a case for the applicability and scalability of VRUPOD. Most pedestrians and VRU are limited by an acceptable total walking distance/time Atash (1994). Therefore, we can restrict the pedestrian network size utilized in VRUPOD for each routing decision. One approach to restricting the pedestrian network size will be to utilize the shortest distance from the VRU's origin to destination as a radius for generating a circular spatial region. The center for the circular spatial region will be the VRU's origin. The pedestrian network in this region can then be generated and utilized in Algorithm 1. By restricting the pedestrian network size, we can overcome the performance constraints resulting from large pedestrian networks.

6 CONCLUSIONS AND RECOMMENDATIONS

Prior work has focused on wayfinding with static parameters related to the sidewalk for people with disabilities, however, wayfinding with static parameters might be impractical in real world situations. Routing with static parameters is only applicable when the same fixed route and the same conditions of the route are valid every day. This paper provides a VRUPOD model incorporating dynamic parameters in wayfinding for VRUs. The method developed in this paper uses the information that is collected from traveling on the sidewalk network and updates the best decision values. Thus if an unexpected event happens on the sidewalk the VRU can reroute. Individuals with disabilities also can explore unfamiliar places through the VRUPOD method. The optimal policies based on VRUPOD find the most accessible route adaptively. The technique is a personalized wayfinding since users with disabilities choose the importance of parameters affecting the sidewalk by the AHP method. A case study is carried out on a mid-size network to show the performance of different methods in recommending the path to individuals with disabilities. VRUPOD outperforms the shortest path, static minimum cost and dynamic minimum cost methods in terms of suggested path cost. VRUPOD recommends an accessible path incorporating unexpected events. The average sidewalk surface type score and average slope score for routes recommended by VRUPOD are the lowest as well. For future work, we will investigate a scalable heuristic approach to overcome the limitation of reinforcement learning regarding the size of the sidewalk network to provide computationally efficient solutions. Also the extension of this research is looking at integrating data from machine vision with mounted cameras on wheelchairs, which will clearly identify the surface condition.

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APPENDIX

Publications, presentations, posters resulting from this project

1) Darko J., Folsom, L., Pugh, N., Park, H., Shirzad, K., Owens, J., Miller, A., Adaptive Personalized Routing for Vulnerable Road Users. IET Intelligent Transport System (Under Review)

2) Darko, J., Park, H., A Multimodal Public Transit Routing for Vulnerable Road Users Considering Risk-Preference, International Conference on Transportation and Development 2021 American Society of Civil Engineers. June 8-10, 2021

3) Shirzad, K., Darko J., Folsom, L., Pugh, N., Park, H., Owens, J., Miller, A., A Personalized Trip Planner for Vulnerable Road Users. Proceedings of the 100th Annual Meeting of Transportation Research Board (TRB2021), # 21-02068, Washington, DC, January 2021

4) Darko, J., Park, H., Multimodal Public Transit Routing considering Travelers' Risk-Preference, Proceedings of the 100th Annual Meeting of the Transportation Research Forum (TRF2021), # 154, April 2021.

5) Darko, J., Park, H., Chow, J., Vulnerable Road User Personalized Optimum and Dynamic, 8th International symposium on transport network reliability (INSTR), Stockholm, Sweden, June 16-18, 2021.

6) Darko, J., Park, H. Modeling and Assessing the Impact of a Traveler's Preference on Transit Route-Choice Behavior. North Carolina Department of Transportation Research & Innovation Summit-2020. 2nd Place Poster Competition Winner. https://www.hsrc.unc.edu/ncdot-ri-summit/virtual-poster-gallery/darko-ncat/

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Sidewalk inventory data

1	SWK_ID	MATERIAL	SWK_WIDTH	SWK_SLOPE	DAM_LENGTH	DAM_WIDTH
2	1	OT	7	2.2	15	5.5
3	2	CC	6	2.5	101	6
4	3	CC	6	3	97	6
5	4	CC	6	5	30	6
6	5	CC	5.5	1.8	25	5.5
7	6	CC	6.5	3.6	68	6.5
8	7	CC	6.5	1.8	152	6.5
9	8	CC	7	3.7	86	7
10	9	BC	5	4.7	1400	5
11	10	CC	9.5	0.7	5	9.5
12	11	CC	7	4.8	23	7
13	12	CC	7	4.4	34	7
14	13	CC	4.5	1.2	31	4.5
15	14	BC	0	0	0	0
16	15		6.5	2.3	20	6.5
17	16	CC	7.5	5.4	80	7.5
18	17	CC	7	3.1	155	7
19	18	CC	6.5	3.4	90	6.5
20	19	CC	6.5	0.3	125	6.5
21	20	CC	6.5	2.6	80	6.5
22	21		7	1.5	10	6
23	22	CC	6	6.1	22	6
24	23	CC	6	7.1	22	6
25	24	BR	9.5	6.1	165	9.5
26	25	BR	9.5	3.1	150	9.5
27	26	GB	9	1.7	20	8
28	28	CC	8	3.5	206	8
29	29	CC	8	2	187	8
30	24506	CC	10	1.3	204	10
31	24507	CC	7.5	2.8	30	7.5
32	24508	CC	6	0.3	28	6
33	24509	CC	7.5	3.1	35	7.5
34	24510	CC	5	1.1	100	5
35	24511	BC	4.5	3.2	1133	4.5
36	24512	CC	7.5	8.5	60	7.5
37	24513	CC	6.5	3.3	5	6.5
38	24514	CC	11.5	3.8	140	11.5
39	24515	CC	9.5	2.9	150	9.5
40	24516	CC	8.5	5.9	20	8.5
41	24517		6	3.9	30	6.5
42	24518	CC	9.5	6.7	142	9.5
43	24519	BC	7.5	2.9	216	7.5
44	24520	CC	6.5	3.3	20	6.5
45	24521	CC	5.5	14.1	45	5.5
46	24522	CC	6.5	6.1	75	6.5
47	24523	CC	6	5.8	35	6
48	24524	CC	6.5	4.5	40	6.5

49	24525	CC	5	6.1	55	5
50	24526	CC	5	1.7	10	5
51	24527	CC	6.5	3.4	30	6.5
52	24528	CC	7	4.2	75	7
53	24529		6.5	5.9	550	30
54	24530	CC	5	2.8	55	5
55	24531	BC	4.5	9.1	2060	4.5
56	24532	BC	5	6.5	2060	5
57	24533	CC	6.5	3.1	50	6.5
58	24534	CC	7.5	4.1	20	7.5
59	24535	CC	6.5	2.8	35	6.5
60	24536	CC	6.5	2.8	25	6.5
61	24537	CC	7	1.9		4.5
62	24538	CC	6	2.2	152	6
63	24539	CC	0	0	90	9.5
64	24542		20	1.8	50	20.5
65	24543	CC	7.5	6.2	70	6
66	24544		6	0.8	20	6
67	24545	BC	7	5.1	320	7
68	24546	CC	0	0	100	0
69	24547	CC	5	0	0	0
70	24548	CC	4	0	10	0
71	24549	CC	0	0	20	0
72	24550	CC	4	0	0	0
73	24551		0	0	0	0
74	24552	CC	7.5	2.1	477	7.5
75	24553	CB	14	0.3	18	14
76	24554	CC	7.5	6.1	50	7.5
77	24555	CC	7.5	0.2	35	7.5
78	24556	OT	6	0	0	0
79	24557	CC	7.5	0.8	45	7.5
80	24558		0	0	0	0
81	24559		0	0	0	0
82	24560	BC	5.5	4.2	173	5.5
83	24561	CC	7.5	4.1	0	7.5
84	24562	CC	5	2.6	515	5
85	24563		0	0	0	0
86	24564		0	0	0	0
87	24565		8	0.2	30	6
88	24566		8	2.3	10	10
89	24567	BC	4	2.6	1147	4
90	24568	CC	6.5	3.5	50	6.5
91	24569	CC	7.5	2.4	40	7.5
92	24570		7	2.4	25	5
93	24571	CC	8	0.5	40	5
94	24572	CC	0	0	0	0
95	24573		0	0	0	0
96	24574	CC	6	1.1	10	6

97	24575		6.5	9.5	20	6.5
98	24576	CC	6	2.1	10	6
99	24577	CC	5	0.3	60	5
100	24578	BC	5.5	5.6	100	5.5
101	24579		7	1.4	10	6
102	24580		6	1.9	10	6
103	24581	CC	7.5	2.3	191	7.5
104	24582	CC	7	2.1	98	7
105	24583	CC	7	2.8	167	7
106	24584	CC	7.5	2.8	15	7.5
107	24585	CC	10	0.3	10	10
108	24586	CC	10	8.8	50	10
109	24587	CC	0	0	30	10.5
110	24588	CC	10	3.9	0	10
111	24589	CC	9	0	15	0
112	24590	CC	10	3.5	15	10
113	24591	CC	8	3.6	40	8
114	24592	CC	5	4.8	20	5
115	24593	CC	7.5	3.3	20	7.5
116	24594	CC	6	5.3	85	6
117	24595	CC	7	6.1	40	7
118	24596		8	1.5	10	16.5
119	24597		8	2.2	20	7.5
120	24598	CC	9	0.5	O	9
121	24599		8	3.2	2641	3.5
122	24600	CC	8.5	0.8	15	8.5
123	24601	CC	6	4.1	100	6
124	24602	CC	6.5	3.3	68	6.5
125	24603	CC	6.5	3.3	68	6.5
126	24604	CC	6	5	25	6
127	24605	CC	7.5	4.1	165	7.5
128	24606		7	3.1	10	
129	24607	CC	6.5	3.7	0	6.5
130	24608	CC	8	0.4	40	8
131	24609		0	0	0	0
132	24610	CC	6	1.3	0	6
133	24611	CC	6	4.5	30	6
134	24612	CC	6	3.7	20	6
135	24613	CC	5	3.6	5 2	5
136	24614	CC	4	4.5	0	0
137	24615	BC	7	2.9	185	7
138	24616	CC	5.5	6.9	12	5.5
139	24617	CC	7.5	0.6	124	7.5
140	24618	CC	5.5	3.9	75	5.5
141	24619	CC	5	1.2	65	5
142	24620	CC	5	6.2	70	5
143	24621	CC	7.5	3.3	15	7.5

144	24622	CC	6.5	2.8	45	6.5
145	24623	CC	6.5	7.8	20	6.5
146	24624	CC	5	3.1	120	5
147	24625		0	0	0	0
148	24626	CC	5	3.2	0O	0
149	24628		9.5	1	50	9.5
150	24629	CC	7	3.5	30	7
151	24630		8	0.2	30	7
152	24631		9	1.1	10	7
153	24634	CC	0	0	0	0
154	24635	BC	0	0	0	0
155	24636	CC	8	2.6	10	0
156	24637		9	0.3	30	9
157	24639	CC	0	0	0	0
158	24640		9.5	1.5	O	O
159	24641	CC	9.5	4 .9	0	0
160	24643	CC	7.3	3.2	90	7.3
161	24644	CC	6	3.2	31	6
162	24645	CC	7	3.5	83	7
163	24646		9	5.7	20	9
164	24647		9	0.7	17	9
165	24648		10	4.3	40	9
166	24649		8	1.6	46	8
167	24650	CC	7.5	1.5	110	7.5
168	24651	CC	6.5	3.8	50	6.5
169	24652		9	4.7		9
170	24653		7	4	20	6.5
171	24654		7	4.1	40	6.5
172	24655		7	4.9	30	6
173	24656		6	3.2	30	6
174	24657	CC	6.5	7	50	6.5
175	24658	CC	9	2.8	30	9
176	24659	CC	7	2.1	77	7
177	24660	CC	7	3.2	0	7
178	24661	CC	6	1.8	40	6
179	24662	CC	6	4.2	0	0
180	24663	CC	6	2.8	250	6
181	24664	CC	7	2.4	10	7
182	24665	CC	6	2.8	9	6
183	24666	CC	6	2.4	10	6
184	24667	CC	8	2.6	60	9
185	24668	CC	6	3.2	20	6
186	24669	CC	6	2.2	60	6
187	24670		9	4.6	30	9
188	24671	CC	9	3.3	16	9
189	24672	CC	9	3.5	10	9
190	24673	CC	7	4.7	0	0
191	24674	CC	7	2.5	0	7

192	24675	CC	6	3.2	34	0	
193	24676	CC	7	2.3	0	7	
194	24677	CC	6	1.7	15	6	
195	24678	CC	6	2.7	18	6	
196	24679	CC	7	2.8	40	7	
197	24680	BR	8	2.3	26	8	
198	24681		7	2.4	20	7	
199	24682	CC	10	3.2	40	10	
200	24683	CC	10	2.4	40	10	
201	24684	CC	10	4.2	60	10	
202	24685	CC	10	3.4	20	10	
203	24686	CC	10	2.5	10	10	
204	24687	CC	10	3.5		10	
205	24688	CC	7	2.2	67	7	
206	24689		0	0	0	0	
207	24690		8	0.9	40	6.5	
208	24691	CC	4	3.7	47	4	
209	24692	CC	0	0	0	0	
210	24693	CC	3	6.5	366	3	
211	24694	BC	3	4.5	0	3	
212	24695	CC	7	5.9	289	7	
213	24697		7.4	3	10	7.4	
214	24698	CC	7.5	3.8	0	7.5	
215	24699	BC	3	2.9	630	3	
216	24700	CC	7	3.2	46	7	
217	24701		0	0	0	0	
218	24702	CC	7	2.3	133	7	
219	24703	CC	5	2.8	20	5	
220	24704	CB	10	1.1	45	10	
221	24705	CC	6	6.1	10	6	
222	24706	CC	0	0	0	0	
223	24707	CC	8	2.5	11	8	
224	24708		10	0.5	O	O	N
225	24709	CC	6	1	100	5.5	
226	24710	BR	8	2.5	0	4	
227	24711	CC	10	3.9	10	1	
228	24712		0	0	0	0	
229	24713		0	0	0	0	
230	24714	BC	5	0.4	815	5	
231	24715	CC	7.5	5.2	0	0	
232	24716		0	0	0	0	
233	24717	CB	7.5	5.3	0	0	
234	24720	CC	4	15.8	328	4	
235	24721	BC	5	2.9	0	5	
236	24724	BR	12	4.5	15	6	
237	24725	CC	6.5	3.7	5	6	
238	24726	CC	6.5	2.3	86	6.5	

239	24727	CC	7	2.4	20	8
240	24728	CC	6	8.2	130	6
241	24729	BC	5.5	7.9	93	5.5
242	24730		7	0.9	10	4
243	24731	CC	5	0.1	40	5
244	24732	BC	6	1.9	555	6
245	24733		6	1.5	30	6
246	24734	CC	4	4.5	80	1
247	24736	CC	7.5	2.5	111	7.5
248	24737	CC	6.5	3.6	50	6.5
249	24738	BC	5.5	1.6	1013	5.5
250	24739	CC	4	3	40	4
251	24740	CC	5	2.2	10	5
252	24741		0	0	0	0
253	24742		5	2.1	10	0
254	24743	CC	5.5	2.6	15	5.5
255	24744	CC	6.5	4.5	14	6.5
256	24745		10	1.8	40	6
257	24747	CC	6	1.7	55	6
258	24748		7	4.9	191	6
259	24749	BC	0	0	0	0
260	24750	BC	0	0	0	0
261	24751	BC	0	0	0	0
262	24752	BC	0	0	0	0
263	24754	BC	4.5	1.4	796	4.5
264	24755	CC	10	3.6	60	10
265	24756	CC	5.5	15	20	5.5
266	24757		0	0	0	0
267	24758	CC	0	0	0	7
268	24759	CC	10	2.2	1400	10
269	24760	CC	10	2.6	42	10
270	24761	CC	6.2	1. 7	120	6. 2
271	10741	CC	0	0	20	10
272	17860	CC	12	2.3	30	11.5
273	17860	CC	12	2.3	25	11.5
274	5599	CC	40	2.2	0	0
275	22471	CC	0	0	0	0
276	21932	BR	6	1.4	5	5
277	21932	BR	6	1.4	0	5
278	22116	GB	44	2.7	0	0
279	22116	GB	44	2.7	0	0
280	22116		44	2.7	0	0
281	22116		44	2.7	0	0
282	23095	CC	6	6.6	128	6
283	22181	CC	11.5	3.6	35	11.5
284	24518	CC	9.5	6.7	142	9.5
285	22221	GB	12	4.1	63	12

286	22221	GB	12	4.1	0	0
287	22221	GB	12	4.1	0	12
288	5600	GB	40	1.1	0	0
289	16531	CC	5.5	4.9	54	3.5
290	23132	CC	11.5	3.8	0	O
291	22160	CC	13	0.4	18	13
292	23091	CC	12	0.1	18	12
293	23091	CC	12	0.1	18	12
294	23091	CC	12	0.1	18	12
295	5505	BR	48	0.2	0	0
296	5505	CC	48	0.2	0	0
297	17286	BR	30	1.2	0	11.5
298	17286	BR	30	1.2	0	11.5
299	17289	BL	16.5	2.5	0	16.5
300	17289	BR	16.5	2.5	5	16.5
301	17286	BR	30	1.2	0	11.5
302	17289		16.5	2.5	5	16.5
303	17286	BR	30	1.2	4	11.5
304	17291	BR	20	3	20	22
305	17289		30	0.9	20	16.5
306	24362	CC	1l	1.9	90	
307	24362	CC	1l	1.9	90	
308	24362	CC	1l	1.9	90	
309	22848	CC	14	1.8	80	0
310	23811	CC	6	0.6	0	0
311	23811	CC	6	0.6	0	0
312	4647	BR	25	0.6	0	0
313	4647	CC	25	0.6	0	0
314	18460	CB	34.5	5.2	453	34.5
315	18460	CB	34.5	5.2	453	34.5
316	18460	CB	34.5	5.2	453	34.5
317	18460	CB	34.5	5.2	453	34.5
318	24627	CC	30	2.3	631	15
319	24632	CC	16	2.1	845	16
320	24627	CC	30	2.3	631	15
321	18460	CB	34.5	5.2	453	34.5
322	24627	CC	30	2.3	15	15
323	24632	CC	16	2.1	32	16
324	24633	CB	21	11.1	1045	11.5
325	24633	CB	21	11.1	1045	11.5
326	24633	CB	21	11.1	1045	11.5
327	6220	CC	6.5	2.6	110	6.5
328	24633	CB	21	11.1	1045	11.5
329	6220	CC	6.5	2.6	110	6.5
330	24633	CB	21	11.1	1045	11.5
331	24633	CB	21	11.1	1045	11.5
332	18460	CB	34.5	5.2	453	34.5

333	18460	CB	34.5	5.2	453	34.5
334	9188	CC	10.5	2.4	115	10.5
335	1398	CC	22	3.2	0	22
336	1398	BR	22	3.2	0	22
337	23153	CB	28.5	2.5	90	8.5
338	23153	CB	28.5	2.5	90	8.5
339	23153	CB	28.5	2.5	90	8.5
340	23153	CB	28.5	2.5	90	8.5
341	23612	CB	14.5	2.6	0	0
342	24638	CC	10	2.6	92	10
343	23612	CB	14.5	2.6	0	0
344	17876	CC	9.5	5.8	311	9.5
345	17876	CC	9.5	5.8	311	9.5
346	17876	CC	9.5	5.8	311	9.5
347	17876	CC	9.5	5.8	311	9.5
348	16922	CC	6.5	3.9	555	6.5
349	16922	CC	6.5	3.9	555	6.5
350	6515	CC	7	0.6	72	7
351	9674	CC	19	0.2	9	19
352	22165	CC	43	8.3	0	43
353	22166	CC	14	5.2	0	14
354	22166	CC	14	5.2	0	14
355	22165	CC	7.5	4.2	6	7.5
356	22166	CC	7	4.4	203	7
357	16001	BR	7.5	3.5	3	7.5
358	4539	CC	7.5	1.2	15	6
359	8783	CC	9.5	3.6	112	9.5
360	18948	BR	21	2.8	0	21
361	18948	BR	21	2.8	0	21
362	23819		12	3.4	22	6
363	21914	CC	12	1.8	35	5
364	23819	BR	12	3.4	5	6
365	16957	BR	6.5	7.5	45	6.5
366	16968	BR	5	4	30	5
367	22169	CC	5.5	5.4	11	5.5
368	16968	OT	9	5.1		9
369	16968	OT	9	5.1		9
370	17496	CC	5	2.8	26	5
371	22170	CC	5	2.2	26	5
372	22152	CC	7.5	1.5	5	7.5
373	22152	CC	5.5	0.4	16	5.5
374	22170	BR	11.5	2.3	20	11.5
375	22170	CC	5	7.2	15	5
376	16968	CC	9	2.9	5	9
377	16502	CC	6.5	1.3	0	6.5
378	15393	CC	9.5	1.6	0	9.5
379	23812	CC	0	0	0	0

Figure 19: (Boston sidewalk inventory data. (Source: `https://data.boston.gov/dataset/sidewalk-inventory`)