CHAPTER SIX

Pedestrian travel choice behavior and modeling

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Abstract

To develop policies to increase the active mode share, understanding the factors influencing active-mode travel choice behavior, both positively and negatively, is essential. Travel choice behavior research attempts to unravel these behaviors and factors. This chapter provides an overview of pedestrian travel choice behavior research trends. In particular, this chapter discusses (A) which travel choices pedestrians make, (B) which (discrete) choice models can be used to study pedestrians' travel choice behavior, and (C) which factors are known to influence pedestrians' travel choice behavior according to the pedestrian literature.

1. Introduction

To develop policies to increase the active mode share, particularly the share of walking trips, a thorough understanding of pedestrian travel choice behavior is essential. Here, the (pedestrian) travel choice behavior process encompasses all choices individuals make from the moment they start thinking about their travel schedule for the day until the moment they arrive at their last destination.

If we understand when, where, and why people decide (not) to walk, we are better capable of creating policies that effectively change (pedestrians') travel choice behavior and increase the walking mode share. Here, we are interested in the factors influencing travel choice behavior and the (mathematical) relations between the factors. The relationships allow planners, designers, and policy-makers to focus on the most influential factors, while the mathematical description allows them the opportunity to predict pedestrians' travel choice behavior in situations where currently no data or experience exists (e.g., designing new neighborhoods, planning public spaces). The simulation of pedestrian travel choice behavior allows for the proactive planning of pedestrian spaces, where potential designs can be assessed and optimized before they leave the drawing board. Consequently, capturing pedestrians' travel choice behavior in mathematical models is essential to support targeted pedestrian planning and policy-making.

The following chapter provides an overview of travel choice behavior modeling and behavioral findings concerning pedestrians' choices. The chapter is constructed with the following two perspectives in mind. Firstly, the researcher who wants to study the travel choice behavior of pedestrians. Secondly, the perspective of the (traffic) designer, engineer, or spatial planner who wants to design safe and accessible spaces for pedestrians.

To cater to both perspectives, we divided the chapter into three parts. The first section (Section 2) presents a theoretical traffic choice behavior framework. The framework shows the dependencies between pedestrians' choices before and during their trip. Afterward, Section 3 briefly introduces the most popular model types that are often adopted to model the travel choice behavior of travelers and pedestrians in particular. This section focuses on the mathematical description of these models, as well as their main benefits and challenges. This section also identifies example studies that a reader can use to explore each discrete choice modeling method further. Section 4 presents a comprehensive overview of factors uncovered by the model types. In contrast to Section 3, this section focuses on the behavioral findings that have been uncovered using the discrete choice model types introduced before. Sections 3 and 4 can be independently studied.

In combination, the three sections answer the following three questions:

- Which travel choices do pedestrians make?
- Which choice models can be used to quantify pedestrians' travel choice behavior?
- Which factors influence pedestrians' travel choice behavior?

Afterward, Section 5 wraps up this chapter with a brief discussion of the current knowledge gaps concerning pedestrians' travel choice behavior research.

2. Pedestrian travel choice behavior framework

The travel choice behavior of private motorized travelers and public transport passengers has been studied extensively (among others Aveni and Ben-Elia, 2015; Klinger and Lanzendorf, 2016; Essen et al., 2016). Often, these studies aim to identify and quantify people's travel choice behavior to forecast transportation demand under alternative future scenarios. The most common models that coordinate the demand forecast are the trip-based models (i.e., the four-step model) and activity-based models. These types of models simulate travel behavior using four steps. First, the trip demand is computed based on land use distribution within the region. In essence, this step captures how people's activities induce travel. Accordingly, the distribution of trips is determined. Here, either the production of trips is connected to the attraction of trips (macroscopic approach), or the destination of each trip is determined for each activity for each period in time

(microscopic approach). Subsequently, the travel mode and route choice are determined based on the network and trip characteristics. In each consecutive step, the behavior of travelers becomes more detailed; as such, more information regarding the space through which travelers move is required to simulate these travel choices. The demand forecast models identify that travelers make at least four distinct travel choices: activity, departure time, mode, and route choice.

Next to these travel choices, Section 4 will show that there are strong indications that the travel choice behavior of active-mode travelers, such as pedestrians and cyclists, is influenced by more specific details of the infrastructure, such as the number of left-hand turns, the presence of traffic lights along the route, the debris on the road and the gradient of the road. This contrasts with the route choice behavior of private and public transport travelers, which is predominantly influenced by travel time, (transfer) delay, and travel time reliability. In addition, pedestrians have additional degrees of movement freedom (i.e., other trip-chaining possibilities and different usage of the infrastructure) and are influenced differently by the physiological environment and the length of the trip (e.g., physical fatigue and the weather) in comparison with private car and public transport travelers. Therefore, route choice needs to be further detailed to incorporate the additional complexity of pedestrian travel choice behavior.

Most research featuring pedestrian movement behavior divides the most detailed choice level (i.e., route choice) into three additional levels, namely strategic route choice, tactical route choice, and choices related to the operational dynamics (Hoogendoorn and Bovy, 2004). Here, the strategic route choice features the entire route from origin to destination and details the strategy of a traveler within a road network. The tactical route choice identifies travelers' strategy within complex parts of the infrastructure, such as gating systems, large open spaces, and intersections. The operational decisions feature the lowest level of decision-making in which travelers decide how to move (i.e., speed and direction) in the next few seconds while considering the objects and signals from their direct environment. The operational movement choices should also be incorporated into the conceptual framework.

The travel choices mentioned in the four-step model and the choice level model of (Hoogendoorn and Bovy, 2004) can be combined into one theoretical framework that structures the movement decisions of pedestrians regarding the impact of their decisions, see Fig. 1. At each consecutive choice level, the choice behavior becomes more specific. Even though the choices at different levels are related, a hierarchy between the

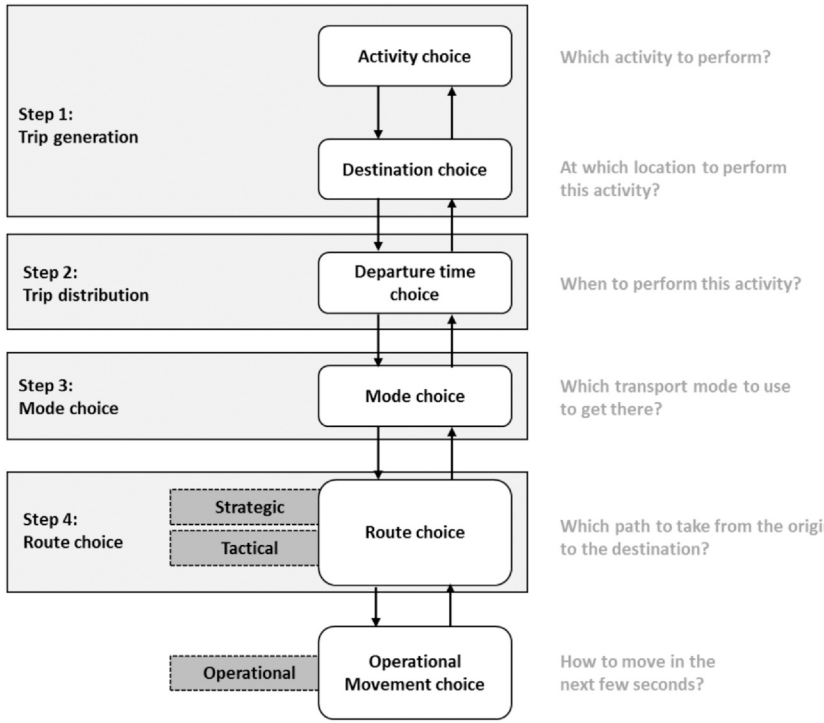

Fig. 1 Conceptual framework of pedestrian travel choice behavior.

choices does not necessarily exist. For example, if you know there are roadworks between you and your intended destination (route choice), you might consider shopping elsewhere or taking a detour. As such, lower-level choices might influence higher-level choices and vice versa.

When studying the literature, you'll quickly learn that each researcher describes the choice levels mentioned above slightly differently. Table 1 provides an overview of potential word combinations used in pedestrian literature to describe the travel choice levels. Please note that this overview does not attempt to be comprehensive, but it provides insight into the wide variety of descriptions used to describe the six types of choices pedestrians make on a day-to-day basis.

It is interesting to note that the upper part of Table 1 featuring the higher-level travel choices is relatively sparse. This is not to say that no research has been performed on these topics. Most research regarding this topic does not explicitly target pedestrian travel choice behavior. Instead, it features all types of travelers, irrespective of their mode of transport.

Table 1 Examples of phrases used to describe pedestrian travel choice behavior.

Choice	Examples of choices recorded in literature
Activity choices (AC)	No. of shops to visits Activity scheduling at train stations Activity scheduling in airports
Departure choices (Dep)	—
Destination choices (Des)	Lunch location
Mode choices (MC)	Satisfaction with walking trips Reason (not) to walk Perceived quality of (walking) mode Propensity to walk Route fidelity
Route choices (RC)	Route choice in street network Perceived satisfaction with route Perceived (lack of) accessibility Walkability neighborhood Design treatment preferences of streets Crossing location and route Route selection at signalized intersections
Operational choices (OC)	Waiting location on platform Current speed choice Lateral positioning

3. Modeling travel choice behavior

To unravel pedestrians' travel choice behavior and the relationships between factors influencing pedestrians' travel choice behavior, researchers have adapted a variety of choice models. A basic understanding of the various choice model types is essential to understand pedestrians' travel choice behavior better and, more importantly, to determine which travel choice model one can adopt to unravel a particular pedestrian travel choice. In addition, this knowledge helps us to put the findings presented in Section 4 in perspective and understand why certain influential factors are more studied (and thus accounted for by city planners) than others.

Travel choice models essentially predict the outcome of a travel choice given a set of discrete alternatives. Depending on the particular choice level, the alternatives of a travel choice feature destination locations,

moments of the day, modes of transportation, or routes between origin and destination. What all choice models have in common is that they predict a discrete outcome, the travel choice, based on a set of continuous and/or categorical variables describing factors that could potentially influence the discrete outcome.

The modeling techniques can be split into models founded in economic and psychological theories, so-called choice models, and (non-)parametric algorithms that 'learn' directly from the data, so-called machine learning approaches. Data-driven machine learning approaches, such as Support Vector Machines (SVM), Random Forest (RF), XGBoost, and artificial neural network (ANN) models, are more and more frequently adopted to simulate travel choice behavior (e.g., Ali, 2024; Jin et al., 2024; Taamneh et al., 2024). Even though researchers have recorded occasions where machine learning algorithms outperform choice models, the explainability of most machine learning models is still very limited (Kashifi et al., 2022). As explainability is key to understanding why people make choices, we have chosen to focus this overview of choice modeling methods on the more formal discrete choice models.

Most discrete choice models are based on the theory of random utility maximization (RUM). This theory assumes that people are rational creatures who optimize the utility of their choices. People are likelier to choose an alternative with a higher utility than an alternative with a lower utility. RUM also assumes that each individual is aware of all choice alternatives and can make tradeoffs between alternatives based on a set of quantifiable attributes.

Below, the most relevant discrete choice model types are briefly described to quantify the choice behavior of pedestrians: the binary logistic model (BN - Section 3.2), the Multinomial Logit model (MNL - Section 3.3), the Pathsize Logit model (PSL - Section 3.4), the Nested Logit model (NL - Section 3.5), the Mixed Logit model (ML - Section 3.6), the Latent Class Choice Model (LCCM - Section 3.7), and the Ordered Logit model (OL - Section 3.8). In addition, Section 3.1 introduces the Odds Ratio (OR). While this is formally not a discrete choice model, it is often used to analyze the impact of attributes on choice behavior.

This section provides an overview of each model's fundamentals and main assumptions. For each model type, a limited set of example studies is identified that showcase the implementation of this model type to quantify and understand pedestrian travel choice behavior. The goal of the examples is not to be comprehensive but rather to provide a starting point for

interested readers who want to learn about the implementation of this model type for pedestrian travel choice modeling. Please note that the behavioral findings uncovered by means of each model type are discussed in more extensively in Section 4.

You'll see that the mathematical complexity increases rapidly throughout this section. Please note that only when adopting a specific discrete choice model for a modeling project is it essential to understand all of its details thoroughly. In those cases, the reader is also advised to read the underlying more fundamental papers featuring each particular model type. At the same time, we hope this high-level overview can provide preliminary insights into the various choice model types and their capabilities and allow you to make an informed choice regarding which model type to apply to which modeling challenge. To aid your search, an overview of model capabilities in relation to the travel choice levels is provided in Section 3.9.

3.1 Odds ratio

The most straightforward way to quantify the impact of a factor (also called attribute, variable, or feature) on a pedestrian's travel choice is by using the Odds ratio. In essence, odds ratios measure the association between an exposure and an outcome. An odds ratio identifies to what extent an outcome is more likely in case of exposure to a given factor.

The odds ratio is computed by (Eq. 1). Here, exposure $N_{exposed\ cases}$ represents the number of pedestrians that were exposed to a factor in a given scenario and made a choice, $N_{unexposed\ cases}$ the number of pedestrians that were not exposed to a factor but still made that choice, $N_{exposed\ non-cases}$ the number of pedestrians that were exposed to the factor but made a different choice, and $N_{unexposed\ non-cases}$ the number of pedestrians that were not exposed and made a different choice.

$$OR = \frac{N_{exposed\ cases} \times N_{unexposed\ cases}}{N_{exposed\ non-cases} \times N_{unexposed\ non-cases}} \tag{1}$$

The odds ratio can be used to compare the relative odds of the occurrence of a certain outcome of interest (e.g., the likelihood of catching a disease or the probability that a route is being chosen). As the odds ratios are normalized, the OR can be used to compare the impact of factors on the outcome. The reader is referred to (Szumilas, 2010) for a more thorough explanation of the use of odds ratios.

In pedestrian travel choice research, odds ratios are mainly applied in route choice behavior research and pedestrian crash risk modeling. The

odds ratio is often combined with a more sophisticated modeling method, such as binary logit. For instance, (Dessing et al., 2016) and (Lee and Lee, 2021) adopted it to compute the impact of environmental factors on children's route to school. (Dhoke and Choudhary, 2024) studied pedestrian compliance behavior under time pressure at signalized intersections. And (Sasidharan and Menéndez, 2014) used odds ratios to explain pedestrian crash injury severity.

3.2 Binary logistic regression (or binary logit regression)

Odds ratios are often computed for each factor, also called feature, separately. That is, the impact of each factor is determined without considering the impact of other factors that potentially play a role simultaneously. However, often factors are not (entirely) independent. For instance, the presence of other pedestrians is partly correlated with the width of pedestrian footways. Both factors are also known to influence pedestrian's route choice behavior. Using an odds ratio, we cannot establish which factor, i.e., pedestrian presence or path width, is most influential.

One of the models that can capture the relative importance of factors is the Binary logistic regression model. In this case, we model the outcome as a response to a group of predictor variables using one of the generalized linear model types. The dependent variable in a binary logistic regression model has two levels, e.g., yes or no, sick or not sick, and chosen or not chosen.

The binary logistic regression model models the logit-transformed probability of the outcome as a linear relationship with several predictor variables (see Eq. (3) and (2)). Here, $P(i)$ refers to the probability of choosing alternative i, β_{ASC} represents the alternative specific constant, β_v are the relative weights of the various variables x_v, and ε_i the unexplained variability.

$$P(i) = \frac{e^{U_i}}{1 - e^{U_i}} \tag{2}$$

$$U(i) = \beta_{\mathrm{ASC}} + \sum_{v} \beta_v \, x_v + \varepsilon_i \tag{3}$$

The main assumptions of the binary logistic regression model are that the observations are independent of each other and that the independent variables are also independent of each other. That is, the variables are not highly correlated. Correlated variables introduce multicollinearity, which might lead to skewed or misleading results.

As a result of the binary nature of the dependent variable, the binary logistic model is often applied in mode choice modeling and operational choice behavior at crossings. In the case of mode choice, most studies model a One-vs-Rest classification task, such as the propensity to walk (e.g., walking or adopting any other mode of transport). For instance, (Hadid et al., 2024) studied the willingness to walk to access public transit and (Dogmusöz, 2024) quantified the environmental factors that influence the willingness to walk on a campus. In the case of operational choice research, especially decision-making near signalized intersections and unsignalized crossings is the main focus. For example, (Yanfeng et al., 2010) studied the impact of traffic conditions and road design on the choice to cross the road. Similarly, (Patra et al., 2020) quantified the impact of road crossing time on the willingness to detour via a safer bridge.

3.3 MultiNomial logit model (MNL)

Not all choices come in binary pairs. In some cases, they come in nominal sets of more than two, such as mode choice (e.g., car, bus, bike, or walking), route choice (e.g., which of the potential routes between origin and destination does one take) or operational choices (e.g., at what location on the bus platform do I wait for the bus). Here, nominal means that there is no inherent natural order in the choice alternatives. The bus is not measurably "better" or "worse" than the car.

The multinomial logit model (MNL) is one of the simpler discrete choice models that can handle multiple choice options. It is rooted in the RUM theory and assumes that people optimize the utility of their choices. They are more likely to choose an option with a high utility than an option with a lower utility.

The MNL models the probability of a choice given a finite set of unordered alternatives. Here, the probability $P_n i$ represents the probability that an individual chooses alternative i (see Eqs. (4) and (5)).

$$P(i) = \frac{\exp(U_i)}{\sum_{j \in C_n} \exp(U_j)} \tag{4}$$

$$U_i = \beta_{ASC,i} + \sum_{v} (\beta_v \, x_{v,i}) + \varepsilon_i \tag{5}$$

Here, $V_{(i)}$ represents the systematic part and ε_i the random part of the utility of alternative i. C_n is the choice set available to participant n, and β_v a

vector of model parameters. β_{ASC} is the alternative specific constant, representing the general bias of participants for a particular alternative i relative to another (reference) alternative.

This model has one important property: the independence of irrelevant alternatives (IIA). IIA is a concept used in economics and decision theory to describe that when a third irrelevant alternative is introduced in the choice set, the relative preferences between the existing two alternatives should not change.

In addition to this property, three key assumptions are made in the MNL model. Firstly, the random component ε_i of the utilities of the different alternatives are independent and identically distributed (IID) with a Gumbel distribution. IID implies that there are no unobserved factors affecting a specific subset of utilities in the choice set. Secondly, various individuals will respond homogeneously to the attributes across alternatives. This implies that there is no taste variation in the population. Thirdly, the error variance-covariance structure of the alternatives is identical across individuals. In essence, all users use the same logic to quantify the utility of the alternatives.

Many researchers have adopted the MNL to study pedestrian travel choice behavior. For instance, (Ton et al., 2019) developed a mode choice model that explicitly accounted for walking and cycling trips, and (Madsen, 2021) developed an MNL model to explain the shopping behavior in a small Dutch city. (Basu et al., 2023; Liu and Neisch, 2023), and (Broach and Dill, 2016) developed pedestrian route choice models. Antonini et al. (2006) developed an operational choice model that determines the speed and orientation in the next time step. The diversity of the topics illustrates the flexibility of the MNL model.

3.4 Path size Logit model (PSL)

The MNL model assumes that all choices are equally likely and that the choice probabilities of alternatives are not correlated. Yet, in some cases, this is not entirely true. For instance, in the case of route choice, two routes between origin A and destination B can partially overlap. In addition to the similarity in characteristics of the alternatives, the fact that two potential routes are intertwined might create additional benefits or risks concerning reliability and/or accessibility. If one of the two routes is unreliable, for instance, due to a traffic jam, the other is still available at very limited rerouting costs. And if the overlapping part of a route is well-designed for pedestrians, the utility of both routes might increase. Depending on the choice level, the overlap might increase or decrease the utility of the overlapping alternatives.

A set of extensions to the MNL model has been developed to deal with the partial spatial overlap. The Path size logit model proposed by (Ben-Akiva and Ramming, 1998) is one of the most popular of these extensions in the traffic engineering field, which accounts for the route overlap by including a correction term within the deterministic part of the route utility function. Here, we display the formulation as depicted in (Frejinger et al., 2009) (see Eqs. (6)–(9)). The path size discount factor *PS* is adopted as one of the characteristics of the route.

$$P(i) = \frac{\exp(U_i)}{\sum_{j \in C_n} \exp(U_j)} \tag{6}$$

$$U_i = \beta_{ASC,i} + \sum_{\nu} (\beta_\nu \, x_{\nu,i}) + \beta_{PS_i} \, PS_i + \varepsilon_i \tag{7}$$

$$PS_i = \sum_{\alpha \in A_i} \frac{l_\alpha}{l_i} \frac{1}{M_{\alpha,i}} \tag{8}$$

$$M_{\alpha,i} = \sum_{i \in C_n} \delta_{\alpha i} \tag{9}$$

Similarly to the MNL, ε_i represents the random part of the utility of alternative i. C_n is the choice set available to participant n, β_ν a vector of model parameters, and β_{ASC} is the alternative specific constant. In addition to the generic MNL formulation, A_i is the set of links on path i, l_α is the length of link α, and l_i is the length of path i. $M_{\alpha,i}$ is the number of paths in choice set C_n that use link α. $\delta_{\alpha i}$ is the link-path incidence, which equals 1 if path i contains link α and 0 otherwise.

How does the path size discount factor work? If a route is entirely standalone, PS_i is 1 and $ln(1) = 0$. Consequently, no discount is applied to standalone routes in the PSL. In the case of two identical paths, a discount of $ln(\frac{1}{2}) \approx -0.6931$ is applied. In general, when two or more routes share a link, the PS factor drops below 1 (i.e., $PS_i < 1$), and its natural logarithm becomes negative (i.e., $ln(PS_i) < 0$). The more routes make use of a link, the larger the discount of the route. Given a positive PS parameter value β_{PS_i}, such as found by (Sevtsuk and Basu, 2022), the utility function discounts for the shared use of the link by decreasing the utility of each route that uses the link.

Unsurprisingly, the PSL is predominantly used to model route choices. Two nice examples of its application are found in (Sevtsuk et al., 2021) and (Lue and Miller, 2019). The first study by Sevtsuk et al. (2021) adopt both

MNL and PSL models to study route choice preferences in San Fransisco. In the latter study, Lue et al. (2019) quantified pedestrian route choice behavior in Toronto using the PSL model. A nice benefit of calibrating both MNL and PSL models on the same dataset is that one can also analyze the impact of the overlap on the choice behavior.

3.5 Nested MNL (N-MNL/NL)

In contrast to route choices, the extent of the overlap between alternatives and/or correlation between alternatives cannot always be explicitly quantified. For instance, the choice to take the car for a particular trip is not correlated with the choice to take the bus for that same trip. However, someone who is likely to take the bus might also be more likely to consider a tram or metro for the same trip. The NL model relaxes the IIA assumption by grouping the alternatives that are potentially more correlated in so-called nests or groups to allow nests of alternatives to be more similar to each other in an unobserved way.

The mathematical formulation of the NL model, which was originally introduced by (McFadden, 1977), is slightly different from the standard MNL model. In this case, the total probability of an individual selecting alternative i is given by Eq. (10). Here, $P(g)$ represents the probability that an individual selects nest g, and $P(i|g)$ identifies the probability that alternative i is selected within nest g.

$$P(i) = \sum_{g \in G} P(g) \times P(i|g) \tag{10}$$

In essence, the probability of choosing an alternative is the product of the probability that an individual selects a specific nest and the probability of choosing a particular alternative within that nest. The first part of this product, i.e., the probability of individual n selecting a nest g, can be computed by (11) and (12). Here, $\beta_{ASC,g}$ is the nest-specific constant, and β_v is the coefficient for variables x_g that describe nest-specific differences in characteristics.

$$P(g) = \frac{\exp\left(\frac{U_g}{\lambda_g}\right)}{\sum_{g' \in G} \exp\left(\frac{V_{g'}}{\lambda_{g'}}\right)} \tag{11}$$

$$U_g = \beta_{\mathrm{ASC},g} + \sum_{v} (\beta_v \, x_{v,g}) + \varepsilon_g \tag{12}$$

The second part of this product, i.e., the probability that an individual selects alternative i within nest g, is given by Eqs. (13) and (14). Here, $\beta_{ASC,i}$ is the alternative specific constant for alternative i, β_v represents the parameters featuring variable v of the alternative i.

$$P(i|g) = \frac{\exp(U_i)}{\sum_{j \in C_g} \exp(U_j)} \tag{13}$$

$$U_i = \beta_{\text{ASC},i} + \sum_v (\beta_v \, x_{v,i}) + \varepsilon_i \tag{14}$$

One essential assumption of the NL model is that alternatives can only belong to one nest at a time at each level. Thus, walking can, for instance, not be part of the 'active-mode' nest and the 'not-powered modes' nest. This can sometimes create friction in the model formulation.

Which nesting structures to try is up to the discretion of the modeler. One can impose one specific structure based on a hypothesis or search over a set of possible nesting structures. This is also directly one of the main challenges of an NL model. The number of potential nesting structures quickly explodes with the number of nesting layers and choice alternatives. One does not always have the computational power to test all possible structures. At the same time, only testing a subset of potential structures also means one cannot guarantee one has found the optimal nesting structure.

The cross-nested logit (CNL) model is an extension of the NL model, which allows alternatives to be part of multiple nests. Especially for mode choice analysis, this model can sometimes provide more natural nesting structures. The reader is referred to (Ben-Akiva and Bierlaire, 1999) for an introduction to the CNL model.

Over the years, the NL model has been mainly applied in mode-choice research in the broader transportation field. Initially, the NL model was predominantly used to determine how people choose between the car, bus/tram/metro, and train for commuting trips. Recently, some studies have also applied the NL model with more extensive alternative sets, including walking and cycling alternatives. For instance, (Ton et al., 2020a) adopted, among other models, the NL model to identify the determinants of commuter mode choice in the Netherlands. One completely different application of the NL model is presented in (Haghani et al., 2015a), who adopted the NL model to study exit choice behavior, where exits on the same side of the building were grouped in nests.

3.6 Mixed logit (ML)

In most cases, individuals make similar choices on similar choice tasks. The Mixed Logit model accounts for the correlation between subsequent choices of participants, which allows for random taste variation across individuals and the correlation of unobserved factors over time. Accounting for the correlation between choices of the same individual is essential to model the choice behavior captured in stated choice experiments, where participants repetitively set slightly different choice scenarios. The original ML model description can be found in (McFadden and Train, 2000).

Underneath, we adopt the ML model formulation proposed by (Hensher and Greene, 2003). We assume that an individual chooses between i alternatives in a set of choice situations T. The utility of each alternative i is evaluated by each individual n in choice task t is represented by Eq. (15).

$$U_{n,i} = \beta_{ASC,n,i} + \sum_{\nu} (\beta_{\nu,n}\, x_{\nu,n,i,t}) + [\varepsilon_{n,i,t} + \eta_{n,i,t}] \tag{15}$$

Here, $\varepsilon_{n,i,t} + \eta_{n,i,t}$ the random part of the utility of alternative i for participant n in task t. $\eta_{n,i,t}$ is a random term with a mean of zero whose distribution is dependent on the alternatives and individuals and $\eta_{n,i,t}$ is a random term with zero mean that is IID over alternatives.

It is called a "mixed" logit because the choice probability is a mixture of logits. The conditional probability $L_{n,i}$ (i.e., one of the logits) for choice i is accordingly given by Eq. (16):

$$L_{n,i}(\beta_n|\eta_{n,i}) = \frac{\exp(U_{n,i,t})}{\sum_{j\in C_{n,t}} U_{n,j,t}} \tag{16}$$

When integrating the conditional probability $L_{n,i}$ over all values of $\eta_{n,i}$ and weighted by the density of $\eta_{n,i}$, it becomes the unconditional choice probability (see Eq. (17)).

$$P_{n,i}(\beta_q|\Omega) = \int_{\eta_{n,i}} L_{n,i}(\beta_n|\eta_{n,i})\, f(\eta_{n,i}|\Omega)\, \eta_{n,i} \tag{17}$$

Here, Ω are the fixed parameters of the distribution and f the mixing distribution. Any probability density function can be used to describe the distribution of the coefficients of the population. Often, a normal

distribution is applied, predominantly for its simplicity. Each β_n is associated with an alternative attribute and has both mean and standard deviation.

The mixed logit model is adopted more and more frequently to study pedestrian movement behavior. We have seen multiple applications over the years. Using random parameters in a discrete choice model allows for a flexible and very insightful model specification. For instance, (Beaulieu and Farooq, 2019) used an ML to predict the location choice of pedestrians, (Anciaes and Jones, 2018) estimated the preference for varying types of pedestrian crossing facilities, (Dui, 2025) used the ML model to study the impact of light on the route choice behavior of pedestrians in a maze. In addition, (Lovreglio et al., 2016) studied exit choice behavior during building evacuations using a similar modeling approach.

3.7 Latent class choice model (LCCM)

In contrast to the ML model, which assumes the entire population displays heterogeneity regarding decision-making, the latent class choice model hypothesizes that the heterogeneity in the dataset is due to two or more segments within the population that showcase distinct choice strategies. The population can be segmented into clusters with different decision-making protocols and preferences by means of class-specific utility equations for each class.

The LCCM estimates separate logit models for each population segment to capture this behavior. Knowledge regarding potential segments in the choice behavior of the population allows policymakers to understand the population's behavior better and enables them to target specific segments of the population more specifically by means of interventions. For instance, (Ton et al., 2020b) establishes that there are different segments in the Dutch population, some of which are more inclined to consider walking as a mode of transport than other segments. To increase the walking mode share, it might be more effective to target network planning and infrastructure design interventions at the segments of the Dutch population that are already willing to consider walking.

In the LCCM, the probability $P_t(i)$ that an individual chooses alternative i for task t is the product of (1) the probability $P(i, t|s)$ that an

individual chooses alternative i in choice task t given that this individual is part of segment s and (2) the probability $P(s|z_n)$ that this individual is part of segment s (see Eqs. (18)–(20)).

$$P_t(i) = \sum_{s=1}^{S} P(i,\ t|s)\ P(s|z_n) \tag{18}$$

$$P(i,\ t|s) = \frac{\exp(U_{i,t|s})}{\sum_{j \in C_{n,t}} \exp(U_{j,t|s})} \tag{19}$$

$$U_{i,t|s} = \beta_{ASC,i,t|} + \sum_{v} (\beta_v x_{v,i,t|s}) + \varepsilon_{i,t} \tag{20}$$

The probability $P(s|z_n)$ that an individual belongs to segment s is modeled using Eq. (21). z_n represents an individual-specific characteristic and γ_s and γ_k parameters of the class membership function for classes s and k. In the LCCM, only the ASC parameters are random variables to capture the distribution of the left-right bias within each segment.

$$P(s|z_n) = \frac{\exp(\gamma_s z_n)}{\sum_{k=1}^{S} \gamma_k z_n} \tag{21}$$

The latent class choice model is still gaining traction in the pedestrian research field. This is most likely because an LCCM is quite data-hungry, and quite large and informative datasets are required to estimate an LCCM. Most pedestrian travel choice datasets are not comprehensive enough to calibrate an LCCM. Yet, a few applications of the LCCM have been presented. For instance, (Haghani and Sarvi, 2016) has identified classes of pedestrian crowd evacuees, and Duives & van Beek (2025) identified classes within the pedestrian population that react differently to light conditions. (Lee et al., 2019) adopts the LCCM to model the impact of travel context and spatial cognition on the perceived walkability of streets. Lastly, (Hossain et al., 2021) presents a nice application of combined departure time-mode choice modeling, showing that pedestrians prefer mid-day alternatives over other departure time choice alternatives.

3.8 Ordered Logit (OL)

In some cases, the order of the alternatives matters. For instance, when choosing departure times, the order of the alternatives has a meaning. Adjoining alternatives are more correlated than alternatives that are spaced

further apart. In a perception survey, the same is true for the ordered answers, such as 'very safe,' 'safe,' 'unsafe,' and 'very unsafe'.

The ordered logit model (OL) is developed to deal with an observed ordinal dependent variable y_i. This model is also known as the proportional odds model or parallel regressions model. The OL model assumes that the response variable y_i is actually a function of another latent variable y'_i that is not measured.

$$y'_i = \beta_{ASC,i} + \sum_{v} \beta_v x_{v,i} + \varepsilon_i \tag{22}$$

Here $\beta_{ASC,i}$ is the alternative-specific constant for categories i and j, β_v are the coefficients for the explanatory variables $x_{v,i}$ that influence the realized value of v for alternative i for an individual, and ε_i is a random disturbance term with a standard logistic distribution.

The value of the observed variable y_i depends on whether or not the latent variable y'_i has crossed a particular threshold τ_j. Yet, as y'_i is a latent variable, one cannot directly observe it. However, one can only establish when y'_i crosses the thresholds τ_j, as the response to the observed variable y_i changes when one crosses a threshold.

The observable answer to the question y_i, the participants' choice is given by:

$$y_{n,i} = j \quad \text{if} \quad \tau_{j-1} < y_i^* \leq \tau_j \tag{23}$$

Please note that the distances between the thresholds τ are unequal. The probability that pedestrian n selects alternative j is accordingly given by:

$$\begin{aligned} P(i, j) &= P(y_i = j) = P(\alpha_{j-1} < y_i^* \leq \alpha_j) \\ &= F(\alpha_j - x_i\beta) - F(\alpha_{j-1} - x_i\beta) \end{aligned} \tag{24}$$

The functional form of F is the standard logistic cdf (see Eq. (25)).

$$F(z) = \frac{\exp(z)}{1 + \exp(z)} \tag{25}$$

Similarly to the MNL model, the OL model also assumes IIA. That is, the probability of choosing an alternative is independent of the introduction of one new irrelevant alternative and does not affect the relative odds of choosing between any two alternatives. In addition, the OL model adopts the parallel slopes assumption. The estimated coefficients β_v of the independent variables are constant across the alternatives.

The OL model is an interesting model to apply for a wide range of applications, among which, the modeling of departure time choice, time spent at activities, or perception ratings. For instance, (Campisi et al., 2020) applied it to understand the willingness to adopt micro-mobility services in Palermo, (Bellizzi et al., 2018) studied air transport passengers satisfaction, and (Mahdi and Esztergár-Kiss, 2024) analyzed the factors that increased time spent at leisure activities using an OL model. To the author's knowledge, no researchers have adopted the OL model to study pedestrian travel choice behavior yet. Few researchers adopted the OL model to quantify pedestrian traffic safety and crash risk. For instance, (AlKheder, 2023) quantified the impact of the built environment on pedestrian traffic safety.

3.9 Which model is applied to which travel choice?

The characteristics of the classification task can guide us in determining which discrete model type is best suited. For instance, research has established that modes of transport are correlated in one or more (overlapping) nests. Consequently, a model that can handle the correlation between choice alternatives is required to model mode choice behavior.

Table 2 presents an overview of the assumptions regarding the correlation between responses and alternatives, and the type of variables (e.g., binary, multiple-choice, nominal, and ordinal). Based on this categorization, we established which choice levels can (or should) be modeled by means of which model category. In our assessment, we use the model descriptions presented in the previous subsections.

Undoubtedly, the pedestrian travel choice literature contains studies that adopt a model type that is identified with a "—" in Table 2 for a particular choice level. It is up to the researcher's discretion to determine whether violating the main modeling assumptions results in unrealistic results. In some cases, minor violations of the assumptions can still provide potentially interesting preliminary results. Especially when working with limited datasets, the more complex discrete choice model types (e.g., NL, ML, LCCM) might be challenging to estimate.

4. Factors influencing pedestrian travel choice behavior

A lot of research has been performed on pedestrian travel choice behavior. Over the years, many distinct factors have been identified that

Table 2 Overview of discrete choice modeling options per choice level, where 'x' identifies that the model type can handle these assumptions, variable types, and choice levels, and the '—' identifies that the model type is originally not designed to handle data featuring these assumptions, variable types, and choice levels.

	OR	BL	MNL	PSL	NL	ML	LCCM	OL	OGEV
Correlation assumptions									
Individuals' responses	—	—	—	x	—	—	—	—	—
Alternatives in the same nest	—	—	—	—	x	x	—	—	—
Individuals in the same segment	—	—	—	—	—	x	x	—	—
Consecutive ordered alternatives	—	—	—	—	—	—	—	x	x
Type of variables									
Binary	x	x	x	x	x	x	x	x	x
Multiple choices (≥3)	—	—	x	x	x	x	x	x	x
Nominal	x	x	x	x	x	x	x	x	x
Ordinal	—	—	—	—	—	—	—	x	x
Choice levels									
Activity scheduling	—	—	x	—	x	x	x	x	x
Departure time choice	—	—	x	—	—	—	—	x	x
Destination choice	—	—	x	—	x	x	x	x	x
Mode choice	x	x	x	—	x	x	x	—	—
Route choice	x	—	(x)	x	—	—	—	—	—
Operational choices	—	—	x	—	x	x	x	—	—
Perception/satisfaction	—	—	—	—	—	—	—	x	x

influence the travel choice behavior of active-mode travelers. This section provides an overview of these factors, the signs of their influence, and a map of them to the relevant travel choice level.

The research efforts featuring the travel choice behavior of pedestrians have increased rapidly in the last two decades. To the author's knowledge, a limited number of overviews have been put forward concerning pedestrians' travel choice behavior. Four of these overview studies provide an

overview of the empirical findings. (Papadimitriou et al., 2015) studied the work featuring the crossing behavior of pedestrians. (Duives et al., 2015) looked at the studies regarding the operational dynamics of pedestrians. (Basu et al., 2022) presents a comprehensive overview of factors associated with pedestrian route choice. Lastly, (Ogilvie et al., 2007) gives an overview of the impact of interventions to promote walking. In the following section, we will incorporate most of their findings. While we do not pretend to be comprehensive, we try to provide an overview of the most essential findings.

While (Ton et al., 2019) identify that pedestrian and cycling travel choice behavior are not the same, they are reasonably similar. Compared with the research efforts featuring pedestrian travel choice behavior, cyclists' travel choice behavior has been studied more thoroughly in the last few decades. The author expects that some empirical findings featuring cyclists' travel choice behavior also apply to pedestrians' travel choice behavior. That is why we will incorporate some findings featuring cyclists' travel choice behavior in this overview. We hope that these gaps in the pedestrian travel choice literature will soon be solved.

Within the pedestrian choice behavior literature, seven categories are distinguished. These categories relate to the characteristics of the individual 4.1, the social network surrounding the individual 4.2, the destination environment 4.3, the structure of the built environment 4.4, the physiological/natural environment 4.6, the trip 4.5 and the actions that the government has implemented 4.7. Each of these classes is discussed in a separate section below.

4.1 The characteristics of the individual

Five subcategories of the literature feature characteristics of the individual, namely factors related to their socio-demographic and economic characteristics, physical abilities, current state of being, perceptions and beliefs regarding various modes of transport, and intentions about upcoming activities. The findings regarding these subcategories are discussed below.

4.1.1 Socio-demographic factors

Table 3 presents an overview of socio-demographic factors that influence pedestrians' travel choice behavior. In the contemporary pedestrian travel choice literature *age* and *gender* are often identified as influential factors for a range of travel choices, predominantly mode and route choice. The literature illustrates that the effect of age is non-linear and culturally

Table 3 Socio-demographic factors that influence pedestrian travel choice behavior, where N = Negative, P = Positive, ? = both positive and negative, NL= non-linear relationships. AC, Dep, Des, MC, RC, and OC refer to the six travel choice levels.

	AC	Dep	Des	MC	RC	OC	
Age	NL	.	NL	NL	NL	NL	Berrigan 2002, *Heinen 2010*, Panter 2010, Hankey 2012, Dijkstra 2014, Gehrke 2014, Hamre 2014, Kim 2014, Cantillo 2015, *Duives 2015a*, Kamargianni 2015, Karl 2015, Bode 2016, Cabrera 2016, Chen 2016, Clifton 2016, Cervero 1996, Hong 2016, Kruechten 2016, Zhiming 2016, Scheiner 2019, Hatamzadeh 2020, Gupta 2022, Abdulhussein 2024
Gender	NL	.	NL	NL	NL	NL	Berrigan 2002, Panter 2010, McDonald 2012, Dijkstra 2014, Gehrke 2014, Hamre 2014, Kim 2014, Lindeloew 2014, Cantillo 2015, *Duives 2015a*, Karl 2015, Bode 2016, Cabrera 2016, Chen 2016, Cervero 1996, Hong 2016, Singh 2016, Zhiming 2016, Scheiner 2019, Hatamzadeh 2020, Seong 2021, Gupta 2022, Abdulhussein 2024
Education level	.	.	.	P	NL	.	Berrigan 2002, Zahran 2008, *Heinen 2010*, Gehrke 2014, Rathnayake 2015, Zhiming 2016
Education level parents	.	.	.	N	.	.	Panter 2010
Ethnicity	.	.	NL	NL	.	NL	Berrigan 2002, Maley 2010, Hankey 2012, *Duives 2015a*
Ethnicity of parents	.	.	.	NL	.	.	Aarts 2013
Personal income	.	.	.	?	.	.	Gehrke 2014, Hamre 2014, Hong 2016, Ton 2019, Gupta 2022, Abdulhussein 2024
Employment	.	.	NL	P	.	.	Hankey 2012, Hong 2016
Occupation	.	.	.	?	.	.	Aarts 2013, Lindeloew 2014, Danalet 2016, Ton 2019b, Seong 2021

dependent. For instance, older individuals and children display more safety-oriented route choice behavior than adults. Similarly, older individuals find other factors important than younger individuals when making mode and destination choices. The effect of age is, by definition, non-linear. In general, men were found to walk slightly more than women. In addition, the empirical findings regarding the choice behavior of various age groups and/or genders point in different directions depending on where and when the studies are performed. Here, the interpretation of safety is often identified as one of the explanatory factors for the conflicting results in the literature.

In addition to age and gender, various other socio-economic factors have also been identified. While higher levels of *education* and *employment* are often associated with higher levels of walking, a higher personal *income level* is related to lower levels of walking. At the same time, walking is also positively correlated with *being retired* and *unemployed* in other contexts. Potentially, the latter two correlations are a side effect of having more time on your hands and a smaller travel budget.

4.1.2 Physical abilities of the individual

The research featuring the impact of an individual's physical capabilities on their travel choice behavior is slim (see Table 4). Research indicates that individuals who have the *physical ability* to walk, are *fit*, and have a low *BMI* are more likely to walk. Similarly, individuals who have reduced physical abilities are less likely to walk for a trip.

Table 4 Physical capability factors influencing pedestrian travel choice behavior, where N = Negative, P = Positive, ? = both positive and negative, NL= non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
Reduced phys. ability	.	.	.	N	.	NL	Cabrera 2016
BMI/weight status	.	.	.	N	.	.	Panter 2010
Familiarity with route	.	.	.	.	P	NL	Kim 2014, Hofinger 2016
Experience	.	.	.	.	NL	.	Zhiming 2016

We expect that physical abilities also play a role in route choice. For instance, visually impaired individuals will adopt different routes than healthy individuals. Similarly, individuals with stability disorders, such as older individuals with walkers, will adopt routes with smooth surfaces and smooth transitions between road and pedestrian infrastructures.

4.1.3 Current state of the individual

Besides individuals' socio-economic background and capabilities, their current state also influences their travel choices. In literature, a limited set of factors is found regarding the effect of the current state of the individuals on their travel choices (see Table 5). At the level of mode choice, the positive influence of *motivation* is mentioned. Moreover, the possibility of guiding a child during transport positively correlates with the choice to walk. In addition, *motivation* and *time constraints* also influence a pedestrian's route choices. For instance, when rushing towards a train station, the most direct route is preferred, while on the way back home, an easy-going, less crowded route might be preferred.

The remainder of the factors identified in this category influence the operational choice behavior of pedestrians. Examples of these factors are *step length*, *step frequency*, *body rotation*, *headway*, *interaction behavior*, and *carrying baggage*; each of which influences the velocity of the pedestrians on the very short-term.

Empirical research does not mention whether the individual's current state also influences activity, departure, and/or destination choices. Yet, we do not expect this to be the case.

4.1.4 Ownership of transportation vehicles

Many studies illustrate that car and moped ownership negatively influence the choice to walk (see Table 6). The negative impact of car/moped ownership might be due to the possibility of making other choices if one owns a car. In the Netherlands, there are suggestions that bicycle ownership also negatively influences the choice to walk (e.g., Ton et al., 2020b). When a bicycle is available, one is less likely to walk for short-distance trips. In other countries, bicycle ownership is often positively correlated with the choice to walk. Yet, one needs to be careful in interpreting the direction of this relationship, as bicycle ownership can also result from a preference for active mode use in general. If people are more active, they are potentially more inclined to walk and ride a bicycle and thus own a

Table 5 Factors related to the current state influencing pedestrian travel choice behavior, P = Positive, ? = both positive and negative, NL= non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
Motivation	.	.	.	?	?	NL	Bode 2013, Dachner 2016, Hofinger 2016, Zhang 2016,
Hurry	.	.	.	.	.	.	Bernhoft 2008
Baggage	.	.	.	.	NL	NL	Chen 2016, Singh 2016
Self-organisation	.	.	.	.	.	NL	Mai 2016
Body rotation	.	.	.	.	.	NL	Feliciani 2016
Travelling speed	.	.	.	.	.	NL	Chen 2016, Zeng 2016, Zhang 2016
Headway	.	.	.	.	.	NL	Duives 2016, Mai 2016, Zeng 2016
Interaction behaviour	.	.	.	.	.	NL	Kruechten 2016, Nicolas 2016
Interaction angle	.	.	.	.	.	NL	Duives 2015a, Duives 2016
Sight angle	.	.	.	.	.	NL	Duives 2016
Step length	.	.	.	.	.	NL	Zeng 2016
Step frequency	.	.	.	.	.	NL	Feng 2016
Acceleration	.	.	.	.	.	NL	Antonini 2006
Entrance point	.	.	.	.	NL	.	Zacharias 2001, Hofinger 2016

Table 6 Factors related to ownership influencing pedestrian travel choice behavior, where N = Negative, P = Positive, ? = both positive and negative, NL= non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
Cars per household member/car ownership	.	.	N	N	N	.	Eash 1999, Walton 2007, Guo 2009, Maley 2010, Aarts 2013, Gupta 2022
Access to car	.	.	.	N	.	.	Panter 2010, Hamre 2014, Hatamzadeh 2020
Use car share	.	.	N	.	.	.	Maley 2010,
Access to/ownership bike	.	.	.	?	.	.	Hamre 2014, Ton 2020, Gupta 2022
Home age	.	.	.	NL	.	.	Berrigan 2002
Transit subscription	.	.	.	N	.	.	Ton 2019
Driving license	.	.	.	P	.	.	Seong 2021

bicycle. Hence, it is difficult to determine the direction of causality between walking, cycling, and bicycle ownership.

Only the influence of ownership of transportation vehicles on mode choice is described in the literature. Yet, ownership is postulated to influence activity scheduling and destination choice behavior. For instance, if one does not have access to a bike, one might not visit the restaurant in the densely populated city center with minimal parking options and limited public transit in the evening but instead opt for the restaurant in the outskirts where one can always park the car. Similarly, if one owns a bicycle but no car, the destinations one can visit are restricted to the distance one can reasonably travel by bike.

4.1.5 Goal orientation and habits

Literature indicates that the *goals* that individuals are aiming to achieve within their current tours influence their higher-level decisions, such as activity, departure time, and destination choices (see Table 7). This effect is mainly described for the shopping and dining behavior of pedestrians. Yet, we expect similar effects for other motives, such as commuting, going to school, and grocery shopping. Moreover, the number of activities in the

Table 7 Factors related to goal orientation and habits influencing pedestrian travel choice behavior, where N = Negative, P = Positive, ? = both positive and negative, NL= non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
No. stops in CBD	NL	.	.	.	.	.	Saarloos 2010
Planned stops	NL	.	.	.	.	.	Saarloos 2010
Purchase stops	NL	.	.	.	.	.	Saarloos 2010
Type of activities	NL	NL	NL	.	.	.	Han 2010, Dijkstra 2014, Clifton 2016
Type of destination	.	.	NL	NL	.	.	Eash 1999, Danalet 2016
Habit to walk	.	.	.	P	.	.	Ton 2019a

intended list of activities is found to influence mode choice decisions. The more stops, the more likely a person is to choose a flexible transport mode that can carry baggage, such as a car or a bicycle.

Interestingly enough, *walking habit* is also found to influence our mode choice behavior. The more a person walks on average, the more likely it is that the current trip is also made on foot. Also, in this case, the causality and underlying cause of this relationship are difficult to establish. It might be because people like to be active, like to walk, or because they are 'captured' pedestrians without other means of transport.

4.1.6 Perception and beliefs

Quite some studies have identified factors that capture the perception and beliefs of travelers regarding the use of the chosen mode. Many factors have been identified that positively influence the perception of a mode of transport (see Table 8). Among others, the following factors have been mentioned: the *habit* to use the mode, the good match of the transport mode with the *lifestyle* of the individual, *pleasurability*, *fun*, *(in-)convenience*, *comfortability*, and the *relaxing effect* of using the mode.

Besides perception, the literature illustrates that beliefs and attitudes towards the distinct modes influence travel choices. While *awareness of the ecological consequences* of active modalities are found to increase the

Table 8 Individual factors related to *personality and perception* that influence pedestrian travel choice behavior, where N = Negative, P = Positive, ? = both positive and negative, NL= non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
Willingness to pay	NL	.	.	.	.	.	Rathnayake 2015
Conviviality	.	.	.	.	P	.	Moura 2017
Perception of danger	.	.	.	N	.	.	Panter 2010
Car safety attitudes	.	.	.	N	.	.	Dill 2014
Risk-taking behavior	.	.	.	.	.	NL	Papadimitriou 2016
Positive attitude w.r.t. walking	.	.	.	P	.	.	Dill2014, Ton 2019b
Habit to walk	.	.	.	?	.	.	Walton 2007, Hong 2016, Ton 2019a
Pleasurability	.	.	.	P	.	.	Lindeloew 2014
Fun	.	.	.	P	.	.	Florez 2014
Convenience	.	.	.	P	.	.	Florez 2014, Moura 2017
Comfort	.	.	.	.	P	.	Koh 2013a, Moura 2017
Convenience to go by car	.	.	.	N	.	.	Walton 2007
Avoidance of confusion	.	.	.	P	.	.	Florez 2014

likelihood of walking, the *perception of danger and safety* and a positive *attitude towards driving* are found to decrease this likelihood.

4.2 The social surroundings

People rarely make choices without considering social norms and the behavior of other individuals in their social network. Based on the literature, factors related to the social environment of individuals can be divided into three categories: the household, the inner circles of acquaintances, and the neighborhood where the individual resides (see Table 9). Below, the factors regarding the three categories are elaborated upon separately.

Table 9 Factors related to the social surroundings that influence pedestrian travel choice behavior, where N = Negative, P = Positive, ? = both positive and negative, NL= non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
The household							
Household size	P	.	.	P	N	.	Guo 2009, Clifton 2016, Tian 2017, Ton 2020b
Children in the household	.	.	N	N	.	.	Maley 2010, Hamre 2014, Hatamzadeh 2020, Seong 2021
Nr. of siblings	.	.	.	P	.	.	Aarts 2013, Ton 2022b
Amount of workers in the household	P	.	.	P	.	.	Eash 1999, Tian 2017
Parent(s) commute by car	.	.	.	N	.	.	Scheiner 2019
Household income	.	.	.	N	.	.	Tian 2017, Seong 2021
The acquaintances							
Friends, family, classmates bike / walk	.	.	.	P	.	.	Handy 1996, Panter 2010
Significant others 'stimulate'	.	.	.	P	.	.	Panter 2010a,
Walking in groups	.	.	.	.	N	NL	Kim 2014, Bode 2016, Cabrera 2016, Feng 2016, Gorrini 2016, Huang 2016, Kruechten 2016, Shahhoseini 2016, Zhao 2016

(continued)

Table 9 Factors related to the social surroundings that influence pedestrian travel choice behavior, where N = Negative, P = Positive, ? = both positive and negative, NL= non-linear relationships. (*cont'd*)

	AC	Dep	Des	MC	RC	OC	
The neighborhood							
Coexistence	.	.	.	.	P	.	Moura 2017
Social cohesion	.	.	.	P	.	.	Aarts 2013
Sense of community	.	.	.	P	.	.	Panter 2010
Herding	.	.	.	.	P	.	Bode 2013, Haghani 2016, Zhu 2016
Socially safe	.	.	.	P	.	.	Aarts 2013
Safe from crime	.	.	.	P	P	.	Handy 1996, Cantillo 2015, Pratiwi 2015, Olojede 2024
Single-family homes	P	.	.	P	.	.	Tian 2017, Seong 2021

4.2.1 The Household

At a household level, generally, three factors are identified, being the *household income*, the *household size*, and the *number of workers* in the household. Regarding the first of these factors, positive and negative trends have been reported concerning the choice to cycle. The latter two factors predominantly negatively influence the choice to walk. Surprisingly, a positive relation between the number of siblings and the propensity to walk was found in two Dutch studies. In this respect, the author assumes that the *number of children* in the household is a proxy for household size. Presumably, the significant influence of the latter two factors (i.e., household size and number of workers) might be related to the increasing number of activities in the trip chain of household members and a flexible mode of transport that allows for trip chaining. Which mode this is very context-dependent.

4.2.2 The acquaintances

The literature is unequivocal on the influence of acquaintances on the travel choice behavior of the individual. The proportion of the *general population*, *colleagues*, *classmates*, *friends*, and *family* who walk or cycle positively influence the choice to walk or cycle. In the study by (Heinen et al., 2011), this is called a subjective norm within the circle of acquaintances. Moreover, if there is a *significant other* who uses active modes of transport to travel to work, or one is stimulated to use an active mode of transport, the probability that an individual will use an active mode of transport for other trips increases. The studies do not indicate whether this influence on the adaptation of a particular mode is the result of similar personalities in one household, a lack of other modes in the household, or whether the significant other influences the choice actively. As could be expected, literature also indicates that if the *car is used by parents* for short-distance trips and a child or adolescent can *rely on others to drive* them, the child is less likely to walk.

4.2.3 Neighbourhood

The factors featuring the influence of other individuals in the neighborhood, which are mentioned in the literature, are all related to safety and associated with lower levels of walking. Among others, these factors relate to *social safety* and the possibility that *crimes* are committed. Besides that, factors that provide an indication of neighborhood cohesion (i.e., *coexistence*, *social cohesion*, and *sense of community*) were found to influence the choice to walk (and cycle) positively. The prevalence of one movement direction (a.k.a. herding) is often identified as an influential factor.

Table 9 indicates that factors related to the effect of the social surroundings of the individual were mainly studied in the context of the mode and route choice behavior. Interestingly, household size and the number of children in the household are positively related to the choice to walk. At the same time, household size is negatively influencing route choice, suggesting that people prefer routes through streets with a lower household density. This while friends, family and significant others that stimulate walking are positively influencing the choice to walk. Similarly, safe neighbourhoods with social cohesion are also found to increase pedestrian demand.

At the same time, the influence of the social surroundings on activity choice, destination choice, departure choice, and operational walking dynamics is undetermined. Whether the influence of the household or the circle of acquaintances on the choice to walk are non-existent or have not yet been determined cannot be said based on the hitherto literature.

4.3 The destination environment

This category entails all arrangements facilitated by the destination environment, rules enforced at the destination environment, and infrastructure present at the destination location of pedestrians (see Table 10). Almost all studies detailing the impact of the destination environment focus on commuter travel (i.e., the work and school environment). Here, a distinction can be made between two sources of influence, namely primary and secondary working conditions.

4.3.1 Primary working conditions

This category consists of the workplace conditions regulated via employment contracts and/or school regulations, for example, *working hours* and the *sector* in which one works. With respect to pedestrian travel choice behavior, little is known. Yet, we can borrow some insights from bicycle behavior research. (Buehler, 2012) and (Hansen and Nielsen, 2014) show, in agreement with (Heinen et al., 2010), that individuals who *work overtime and/or work part time* are less likely to cycle. At the same time, individuals who work in the public sector are more likely to cycle to work. Whether this is due to increased awareness regarding sustainability and health, social norms, or nice facilities for pedestrians at the destination is not directly clear from the literature.

Table 10 Destination environment factors that influence active-mode travel behaviour, where N = Negative, P = Positive, ? = both positive and negative, NL= non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
Car parking free	.	.	.	N	.	.	Hamre 2014
Accessibility to work	.	.	.	NL	.	.	Munshi 2016
Kilometer allowance	.	.	.	N	.	.	Ton 2020b
Transit subsidies	.	.	.	P	.	.	Hamre 2014
Walk/cycle subsidies	.	.	.	P	.	.	Hamre 2014
Type of restaurant	.	.	NL	.	.	.	Danalet 2016

4.3.2 Secondary working conditions

This category of working conditions relates to all the arrangements and facilities that employers or schools provide as a service to their employees or students. Most of the studies that mention secondary working conditions and focus on active travel behavior are concerned with the mode choice of cyclists. Besides facilities for cyclists, employers and schools also provide facilities for public transit users and car drivers. Some studies find that if there are *free car parking spaces near the workplace*, individuals are less likely to walk. However, if the employer provides *transit commuter subsidies* or subsidies to walk and/or cycle, the likelihood that people cycle or walk increases. Moreover, limitations on the car parking capacity at the destination are positively related to the choice to walk.

4.4 The built environment

The current literature on pedestrian travel choice behavior supports the notion that the built environment greatly impacts pedestrian travel choice behavior. Four categories of built environment factors have been identified: physical objects in the built environment, aesthetics of the built environment, the network structure, and the region characteristics. Here, the first category refers to the objective evaluation of the road infrastructure, while the second category refers to the subjective evaluation of the built environment. The last two categories relate to the characteristics of the transportation network and the characteristics of the regions through which individuals travel.

4.4.1 Road infrastructure

Most studies that detail the influence of factors that describe the road infrastructure refer to mode and route choice (see Table 11). Regarding mode choice, several factors seem to hinder the pedestrians along the route, among others *(illegal) parking* along the route, *stairs* on the route, steep road *gradients*, *uneven pavement* and *wide streets* with a lot of heavy traffic. Also *dog dirt* is, unsurprisingly, also in this context identified as negatively influencing pedestrian route choice.

Many factors have been identified that positively influence the choice to walk, among others, the presence of *sidewalks*, *presence of separation* between transportation modes, the *pavement condition*, the *lighting condition* and the type and number of (signalized) *crossing opportunities*. Along this line, all road infrastructure that improves the safety experience of pedestrians is expected to impact the choice to walk positively, pedestrian demand, and route choice. Surprisingly, (Aarts et al., 2013) also identify the positive influence of *debris*, and *trash* on the pavement on pedestrian mode choice. Yet, this study also indicates that these findings might be explained by the increased awareness of avid pedestrians concerning these issues.

4.4.2 Aesthetics

Several studies have researched the effect of aesthetics, i.e., the evaluation of the subjective characteristics of the built environment, on pedestrian travel choices (see Table 12). Many positive influences have been identified, such as the presence of *vegetation*, a nice *view*, *transparent facades*, *shops*, *dwellings on the ground floor*, and *trash cans*. All of which provide entertainment for pedestrians on their route. Also, some barriers are recorded, namely *blind walls*, *litter* on the street, and the presence of *urban furniture* or *parks*. Here, urban furniture and parks score negatively because of negative safety implications for certain societal groups.

4.4.3 The network structure

The structure of the network over which pedestrians move is mentioned in some studies, mainly concerning mode and route choice (see Table 13). The factors mentioned are generally either related to *connectivity* or *accessibility* of the transportation network.

Within the first group of factors (connectivity), among others, the *distance between crosswalks*, *intersection density*, and *road density* are identified.

Table 11 Road infrastructure factors that influence active-mode travel behaviour, where N = Negative, P = Positive, ? = both positive and negative, NL = non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
(Illegal) parking on route	.	.	N	N	.	.	Barros 2015, Waerden 1998, Olojede 2024
Stairs on route	.	.	.	N	.	.	Barros 2015
Gradient street	.	.	N	N	N	.	Walton 2007, Borst 2009, Gomez 2010, Guo 2009, Kim 2014, Barros 2015, Clifton 2016a
Width of street	.	.	.	P	.	NL	Barros 2015, Kamargianni 2015
Width of sidewalk	.	.	.	P	P	X	Guo 2009, Rodriguez 2009, Guo 2013, Kim 2014, Duives 2015a, Yanagisawa 2016, Scheiner 2019, Basu 2022
Bottleneck length	.	.	.	.	.	NL	Duives 2015a
Type of street	.	.	.	NL	.	.	Hankey 2012, Barros 2015, Papadimitriou 2016
Angle of corridor	.	.	.	.	.	NL	Duives 2015a
Dedicated infrastructure	.	.	.	P	.	.	McCormack 2011, Muhs 2016
Facilities	.	.	.	NL	.	.	McCormack 2011, Hankey 2012, Pratiwi 2015,
Presence sidewalk	.	.	.	?	P	.	Handy 1996, Bernhoft 2008, Rodriguez 2009, Abdulhussein 2024, Olojede 2024

(continued)

Table 11 Road infrastructure factors that influence active-mode travel behaviour, where N = Negative, P = Positive, ? = both positive and negative, NL = non-linear relationships. (*cont'd*)

	AC	Dep	Des	MC	RC	OC	
Degrees of separation	.	.	.	.	P	.	Pratiwi 2015
Sidewalk fence	.	.	.	P	P	.	Kim 2014, Abdulhussein 2024
Lighting conditions	.	.	.	P	P	.	Bernhoft 2008, Barros 2015, Pratiwi 2015, Moura 2017
Sidewalk quality	P	.	.	P	P	.	Bernhoft 2008, Borst 2009, Gomez 2010, Segadilha 2014, *Duives 2015a*, Rodriguez 2015, Tian 2017, Scheiner 2019
Litter on streets	.	.	.	.	N	.	Borst 2009, Rodriguez 2015
Debris/glass on the road	.	.	.	P	.	.	Aarts 2013
Dog dirt on road	.	.	.	N	.	.	Aarts 2013
Trashcans	.	.	.	P	P	.	Rodriguez 2009, Kim 2014
Presence of urban furniture	.	.	.	N	.	.	Barros 2015
Ramps on-off pavement	.	.	.	.	P	.	Borst 2009
Signalized crossing	.	.	.	P	NL	.	Sisiopiku 2003, Heinen 2010, Kim 2014, Cantillo 2015, Rodriguez 2015, Borst 2009, Krom 2022, Abdulhussein 2024
Pedestrian crossings	.	.	.	P	P	.	Borst 2009, Rodriguez 2009, Kim 2014, Rodriguez 2015, Scheiner 2019, Olojede 2024

Type of crosswalk	.	.	NL	.	Sisiopiku 2003
Traffic safety	.	?	P	.	Gomez 2010, Panter 2010a, Aarts 2013, Moura 2017, Tzouras 2024
Presence subway station or railway line	.	.	P	.	Kim 2014
Presence of busroute	.	.	P	.	Borst 2009, Hankey 2012, Kim 2014
Presence of buslane	.	.	P	.	Kim 2014
Pedestrian Index	.	P	.	.	Clifton 2016
Walkability index	.	NL	.	.	Panter 2010, Panter 2010a, McCormack 2011
Accident hotspot	.	.	N	.	Scheiner 2019

Table 12 Factors related to aesthetics that influence active-mode travel behavior - part 3, where N = Negative, P = Positive, ? = both positive and negative, NL = non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
Aesthetics	.	.	.	NL	P	.	Guo 2009, Panter 2010a, McCormack 2011, Koh 2013a, Verhoeff 2014, Lopez 2021, Olojede 2024
Type of wayfinding signs	.	.	.	.	.	NL	Dachner 2016, Kuenzer 2016, Hofinger 2016
Illumination route	.	.	.	.	.	NL	Dachner 2016
Presence of vegetation - greeneries	.	.	.	P	P	.	Handy 1996, Sisiopiku 2003, Zahran 2008, Borst 2009, Aarts 2013, Segadilha 2014, Pratiwi 2015
Presence of water	.	.	.	NL	.	.	Aarts 2013
Trees	.	.	.	P	P	.	Bafatakis 2014, Kim 2014, Barros 2015,
Open space	.	.	.	.	P	.	Guo 2013
Site view / scenery	.	.	.	.	P	.	Pratiwi 2015
Visibility	.	.	.	.	.	NL	Zhiming 2016
Presence of street lamps	.	.	.	.	P	.	Dachner 2016, Olojede 2024
Information about service	.	.	.	.	P	.	Dachner 2016, Zhu 2016
Colour of signs	.	.	.	.	P	.	Kunzer 2016

Visibility of route	.	.	.	.	P	.	Haghani 2015, Haghani 2016, Natapov 2016
Overview	.	.	.	.	P	.	Bernhoft 2008
Height of the ceiling	.	.	.	.	P	.	Verhoeff 2014
Facade transparency	.	.	.	.	P	.	Moura 2017
Interesting facades	.	.	.	P	.	.	Handy 1996, Ton 2019b, Olojede 2024
Dwellings on the first floor	.	.	.	.	P	.	Borst 2009
Concrete barriers	.	.	.	.	NL	.	Sisiopiku 2003
High walls	.	.	.	N	N	.	Borst 2009, Barros 2015
Abandonned buildings	.	.	.	.	P	.	Rodriguez 2015
Presence of park	.	.	P	.	NL	.	Borst 2009, Clifton 2016a

Table 13 Network characteristics that influence pedestrian travel choice behavior, where N = Negative, P = Positive, ? = both positive and negative, NL = non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
Accessibility	.	.	.	N	.	.	Lindeloew 2014
Non-motor. accessibility	.	.	.	P	.	.	Eash 1999
Transit accessibility	.	.	.	P	P	.	McCormack 2011, Hamre 2014, Pratiwi 2015, Muhs 2016, Seong 2021
Transit stops	.	.	.	.	N	.	Rodriguez 2015, Seong 2021
Employment accessibility	.	.	.	P	.	.	Muhs 2016
Miles of freeway nearby	.	.	.	N	.	.	Clifton 2016
Dist. to transit stop	.	.	.	P	.	.	Eash 1999
Non-residential land use	.	.	.	P	.	.	Muhs 2016
High rise buildings	.	.	.	N	.	.	Aarts 2013
Intersection density	.	.	.	.	NL	.	Guo 2009, Guo 2013, Muhs 2016
Busy intersections	.	.	.	N	.	.	Handy 1996
Dist. between crosswalks	.	.	.	N	.	.	Barros 2015
Road density	.	.	.	P	.	.	Rodriguez 2009
Connectivity	.	.	.	NL	P	.	Gomez 2010, Panter 2010a, McCormack 2011, Muhs 2016, Moura 2017, Olojede 2024

Generally, pedestrians evaluate highly connected networks with frequent crossing facilities best.

A second group of factors focuses more on the accessibility of the region. Among others, the *accessibility of motorways* and *public transport* are identified as influences on the travel choice behavior of pedestrians. Depending on the interpretation of accessibility and the country in which the study was performed, accessibility of these other modes influences the likelihood of choosing to walk positively or negatively. Interestingly, transit accessibility is often positively associated with the pedestrian mode share. Potentially, because the space surrounding public transit hubs are designed to accommodate pedestrians on the first- and lastmile of their trips.

4.4.4 Region characteristics

Also, the neighborhood through which a pedestrian walks is found to influence their travel choice behavior (see Table 14). The literature mainly mentions the impact of region characteristics on pedestrian mode and route choice. Often, the *density of population*, *households*, *employment opportunities*, and *activity spaces* (i.e., retail, schools, industry, parks) positively influence the choice to walk.

The land use type also influences the decision to walk and a pedestrian's route choice. Generally, areas with a *diverse land use* and a high number of *retail services* attract more pedestrians. Moreover, some of these studies identified the diversity of land use as a factor that nudges people to walk instead of cycle. Salon (2016); Pucher et al. (2011), and (Cervero and Radisch, 1996) find more pedestrian demand within the central business districts, which generally have a very diverse land use. Moura et al. (2017), furthermore, identifies that the presence of *landmarks and office buildings* increases the walkability of an area.

A last group of studies has identified factors that increase the likelihood of choosing a certain destination. Amongst other findings, pedestrians are more likely to commute to regions with a *high population and employment density*. One exception to this rule is identified by (Clifton et al., 2016), who illustrates that pedestrians are less likely to walk towards destinations in regions with lots of *industry*. This study identifies *social safety* as the driver for the lower propensity to walk.

4.5 Trip characteristics

The characteristics of the trip itself also influence the travel choice behavior of pedestrians (see Tables 15 and 16). Most obviously, the *distance*, free-

Table 14 Region characteristics that influence pedestrian travel choice behavior, where N = Negative, P = Positive, ? = both positive and negative, NL = non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
Population density	.	.	.	NL	NL	.	Zahran 2008, Rodriguez 2009, Panter 2010a, McCormack 2011, Hankey 2012, Hamre 2014, Muhs 2016, Gupta 2022
Residential density	.	.	.	P	.	.	Muhs2016, Berjisian 2019, Seong 2021
Household density	.	.	P	.	.	.	Clifton 2016a
Household income neighbourhood	.	.	.	.	P	.	Hankey 2012, Rodriguez 2009
Median home value	.	.	.	P	.	.	Zahran 2008
Industry density	.	.	N	.	.	.	Clifton 2016a
Activity density	P	.	.	.	.	.	Tian 2017
Employment density	.	.	P	P	.	.	Zahran 2008, McCormack 2011, Muhs 2016, Clifton 2016a, Tian 2017, Berjisian 2019, Gupta 2022
Retail/shops/services	.	.	.	P	P	.	Borst 2009, Koh 2013a, Guo 2013, Verhoeff 2014, Barros 2015, Borgers 2014, Seong 2021
Land use diversity	.	.	.	P	P	X	Rodriguez 2009, Panter 2010a, McCormack 2011, Hankey 2012, Kim 2014, Muhs 2016, Munshi 2016, Moura 2017, Gupta 2022, Olojede 2024

Recreation land use	.	.	.	NL	.	.	McCormack 2011
Region type	.	.	.	NL	.	.	Berrigan 2002, Panter 2010, *Pucher 2010*, Salon 2016
Neighbourhood type	.	.	.	P	.	.	Cervero 1996, McCormack 2011, Salon 2016
Air pollution	.	.	.	N	.	.	Zahran 2008
Existence of landmarks	.	.	.	.	P	.	Moura 2017
Public meeting place density	.	.	.	.	P	.	Moura 2017
Public park density	.	.	.	P	P	.	Gomez 2010, Rodriguez 2015
Conspiciousness	.	.	.	.	P	.	Moura 2017
Crime in neighbourhood	.	.	.	.	?	.	Hankey 2012

Table 15 Trip factors that influence active-mode travel behavior – part 1, where N = Negative, P = Positive, ? = both positive and negative, NL = nships.

	AC	Dep	Des	MC	RC	OC	
Distance/proximity	.	.	N	NL	X	.	Waerden 1998, Maley 2010, Panter 2010, Saarloos 2010, Aarts 2013, Florez 2014, Hamre 2014, Wang 2015, Chen 2016, Munshi 2016, Muhs 2016, Clifton 2016a, Scheiner 2019
Travel time	.	.	.	N	N	.	Bernhoft 2008, Zahran 2008, Guo 2009, Gehrke 2014, Florez 2014, Abdulhussein 2024
Waiting time	.	N	.	.	.	.	Raveau 2014, Han 2010
Time of day	.	NL	NL	.	NL	NL	Raveau 2014, Danalet 2016, Han 2010
Day of week	.	.	.	.	.	NL	Zhao 2016a
Costs - PT/car	.	.	P	N	.	.	Heinen 2010, Raveau 2014, Karl 2015
Destination type	.	.	.	NL	.	.	Cervero 1996, Antonini 2006
No. of transfers	.	.	.	.	N	.	Raveau 2014
Directness of route	.	.	.	.	P	.	Borgers 2014, Verhoeff 2014
Complexity of route	.	.	.	.	N	.	Li 2006, Broach 2012, Borgers 2014
Repetition of part of route	.	.	.	.	N	.	Borgers 2014
Feasibility (time - space)	.	.	.	N	.	.	Lindeloew 2014

Table 16 Dynamic trip factors influencing active-mode travel behavior - part 2, where N = Negative, P = Positive, ? = both positive and negative, NL = non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
Trip purpose	.	.	.	NL	.	.	Handy 1996, Karl 2015
Crowdedness	.	.	.	.	P	X	Pratiwi 2015, Crociani 2016, Dalbalmath 2016, Duives 2016, Zhang 2016, Zhu 2016, Olojede 2024
Congestion/density of flow	.	N	.	.	N	N	Antonini 2006, Zhang 2013, Shaha 2013,Verhoeff 2014, Zhang 2014, *Duives 2015a*, Chen 2016, Corbetta 2016, Crociani 2016, Dalbalmath 2016, Haghani 2016, Nicolas 2016, Wang 2016, Yanagisawa 2016, Zeng 2016, Zhang 2016, Zhu 2016a, Ziemer 2016
Capacity policy	.	P	.	.	.	.	Han 2010
Capacity	.	.	NL	.	.	.	Pratiwi 2015, Danalet 2016
Traffic volume	.	.	.	?	?	.	Handy 1996, Bernhoft 2008, Borst 2009, Guo 2013, Koh 2013a, Papadimitriou 2016, Olojede 2024
Heavy traffic	.	.	.	N	.	.	Lindeloew 2014
Traffic noise (safety)	.	.	.	.	P	.	Borst 2009
Speed difference	.	.	.	.	.	?	Seer 2014
Herding	.	.	.	NL	NL	.	Bode 2013, Li 2013, Haghani 2016, Zhu 2016

(continued)

Table 16 Dynamic trip factors influencing active-mode travel behavior - part 2, where N = Negative, P = Positive, ? = both positive and negative, NL = non-linear relationships. (*cont'd*)

	AC	Dep	Des	MC	RC	OC	
Flow situation	.	.	.	.	.	X	Feliciani 2016, Mai 2016, Shahhoseini 2016, Duives 2015a, Gorrini 2016, Huang 2016, Kuenzer 2016
Current direction	.	.	.	.	.	NL	Antonini 2006, Duives 2015a, Corbetta 2016, Mai 2016
Alignment	.	.	.	.	.	NL	Zhao 2016a
Angular deviation	.	.	.	.	N	.	Borgers 2014

flow *travel time* negatively influence the choice to walk. In addition, *time of day* at which the choice is made is also found to influence pedestrians' mode and route choice behavior. The impact of the time of day and the purpose of the trip is very dependent on the categorization that the researchers apply.

A second group of factors relates to pedestrians' wayfinding strategies, among others, the *complexity* of the route and the number of *turns*. For cyclists, previous experiences are also found to influence their route choice behavior. We expect similar effects to hold for pedestrians. Negative experiences regarding road works on a pedestrian path tend to be kept in mind for a long time.

A third set of influential factors relates to the expected *barriers along the route*. Pedestrians dislike detours, congestion, heavy traffic, and transfers within the public transit system. Interestingly enough, also in this case, routes that are perceived to be 'more safe' have a higher likelihood of being adopted.

Next to the more static trip characteristics, some factors change during the day, for instance, the crowdedness of a route. Yet, a clear trend with respect to crowding and congestion cannot be established. The effect of traffic volume is very dependent on the researchers' interpretation of this factor. Where (Haghani et al., 2015b) finds a negative effect because crowding is interpreted as additional delay, (Borst et al., 2009) finds a positive effect of *traffic volume* and *traffic noise* because crowding also improves the (social) safety of routes.

A second set of dynamic factors impacts the traffic safety perception of routes. This group of factors comprises, among other things, the *traffic conditions*, the *proportion of heavy traffic*, and the *number of trucks and buses* along a route. In general, higher traffic demand and higher levels of heavy traffic are negatively correlated with route choice.

4.6 The physiological and environmental characteristics

In contrast to most vehicular modes of transport, pedestrians are affected by the state of their physiological environment (see Table 17). They are less protected from their environment by means of windscreens, roofs, and heating installations. Thus, one would expect a lot of empirical evidence relating pedestrians' departure time, mode, route, and operational choice behavior to weather conditions. Yet, even though this seems to be a logical factor to consider, not much research features the impact of pedestrians' physiological environment.

Table 17 Physiological environment factors and governmental actions that in- fluence active-mode travel behavior – part 6, where N = Negative, P = Positive, ? = both positive and negative, NL = non-linear relationships.

	AC	Dep	Des	MC	RC	OC	
Temperature	.	.	.	P	N	?	Aultman-Hall 2009, Hankey 2012,
Humidity	.	.	.	.	.	.	Aultman-Hall 2009
Bad weather conditions	.	.	.	N	.	.	Walton 2007, Rodriguez 2009, Heinen 2010, Kamargianni 2015
Bicycle season (summer)	.	.	.	P	.	.	Hamre 2014
Rain	.	.	.	N	N	.	Aultman-Hall 2009, Hankey 2012, Duives 2015a
Wind	.	.	.	.	.	NL	Duives 2015a

Literature shows that the season and the overall climate influence the decision to walk (and cycle). Less walking has been recorded in climates with high or very low temperatures and much precipitation. Investigating shorter time spans, the negative effects of *rain*, *wind*, *high temperatures*, and *extreme weather conditions* have been identified.

4.7 Governmental actions

This last category examines the effect of factors involving governmental actions to stimulate pedestrian demand (see Table 18). Very limited research correlates targeted governmental interventions with pedestrian travel choice behavior. Yet, we can take inspiration from the research on cyclist travel choice behavior.

A first group of studies has researched the effect of programs that improve the *safety of cyclists*, the *accessibility to bicycles*, and encourage people to cycle more. The existing research shows that all these programs positively influence the cycle mode share in the short term. The long-term effects have not been investigated in any of the mentioned studies.

A second group of studies looked at implementing *laws that improve the safety of cyclists*. These studies have reviewed the effect of *cycling helmet laws*, *bicycle lighting*, and a *ban on side-by-side cycling*. Mixed results are found,

Table 18 Governmental actions that in- fluence active-mode travel behaviour, where N = Negative, P = Positive, ? = both positive and negative, NL = non-linear relationships.

Safety course	P	Kamargianni 2015
Environmental non-profits	N	Zahran 2008
Walk organizations		Zahran 2008

which depend on the country and culture of the population studied. Laws that influence the lifestyle of people (i.e., cycling helmets and side-by-side cycling ban) are found to influence the cycling mode share negatively.

A third group of studies illustrates that the *presence of lobby groups* in the region that advocate sustainability and active mode travel enhances the cycling mode share. Similar effects are expected regarding pedestrian demand by the author, yet have not been identified in the literature.

This overview of governmental actions to increase cyclist demand shows that they are most effective at stimulating people to ride their bicycles more and potentially for longer distances. Similar effects are expected for targeted governmental interventions aimed at increasing pedestrian demand. Especially the programs that improve pedestrian traffic safety might result in a higher pedestrian demand. Examples of such programs are traffic education in schools, the Safe Routes to School program, the Bike Bus, and targeted infrastructure interventions that decrease the speed limits in neighborhoods.

5. Synthesis pedestrian travel choice behavior

The section asked three questions concerning pedestrian travel choice behavior:

- Which travel choices do pedestrians make?
- Which models can be used to model pedestrians' travel choice behavior?
- Which factors influence pedestrians' travel choice behavior?

Sections 2 to 4 have formulated an answer to these three questions.

First, Section 2 showed that pedestrians make six types of choices during the day: activity choices, destination choices, departure time choices, mode choices, strategic route choices, and operational route choices. These choice levels have a logical ordering based on the timescale at which decisions must be made, yet lower-level choices can influence higher-level choices and vice versa.

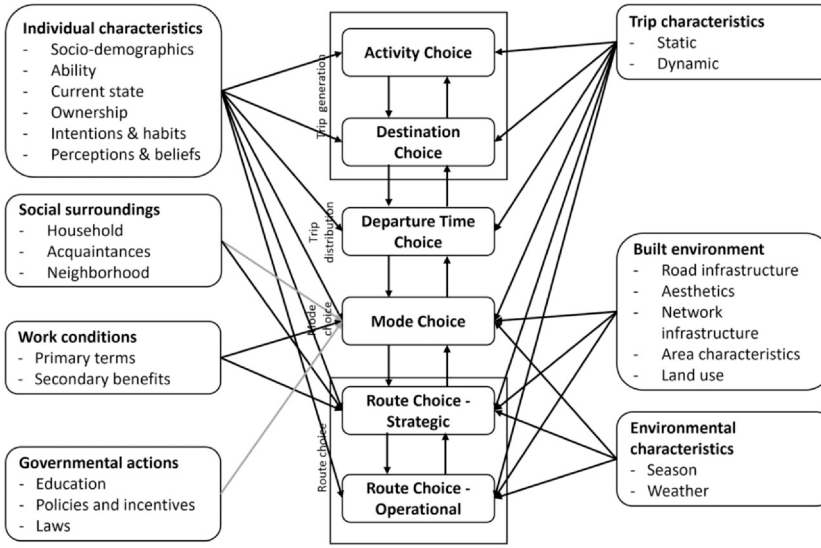

Fig. 2 Illustration of the factors influencing the pedestrian travel choice behavior, in which the arrows indicate the presence of evidence regarding the relationship between a factor category and a travel choice level.

Accordingly, Section 3 presented a vast array of discrete choice models that can be used to study pedestrian travel choice behavior. Each discrete choice model type makes assumptions about pedestrians' choice behavior and should be applied to a subset of travel choice behavior problems.

Lastly, Section 4 showed that we can leverage these models to unravel pedestrian travel choice behavior. In particular, this section indicated that numerous factors influence the travel choice behavior of pedestrians. Fig. 2 visualizes the factors discussed in the previous sections and schematically illustrates the relations between these factors and the travel choice levels mentioned in the theoretical framework.

As one can see, the factors influencing pedestrian travel choice behavior are very diverse. Some, such as road infrastructure characteristics, are spatially very detailed, while others, such as area characteristics, describe aggregate spatial features of neighborhoods. Similarly, some categories cluster factors that influence travel choice behavior in the next few seconds, while others (e.g., season) remain stable for relatively long periods. If Section 4 shows one thing, it is that, probably even more so than car and public transport travel choice behavior, the travel choice behavior of pedestrians is influenced by factors that occur on a very short time scale and high level of spatial detail. Smooth tiles on the footpath and street lanterns

can invite people to walk more. Similarly, closed facades and parked cars can negatively influence pedestrian demand.

When we examine the many factors mentioned in the literature, four pivotal determinants of pedestrian travel can be deduced. These are:

- Enforcement of physical and social safety while walking
- The time needed to walk
- The effort and discomfort involved when walking
- The rewards the individual receives for walking

These four pivotal determinants are complemented in pedestrians' travel choice decisions. That is, pedestrians try to minimize travel time and effort and maximize their rewards while ensuring a reasonable level of safety. The socio-demographic characteristics of people, their social surroundings, the destination environment, and the physiological environment predominantly influence the last two determinants. On the other hand, the trip characteristics, the built environment, and the governmental actions can impact all four determinants.

6. Research challenges

Section 4 also identified that many factors have only been investigated for one of the travel choice levels. In some cases, a factor might arguably only influence that singular travel choice (e.g., the number of traffic lights only impacts route choice). In other cases, the author expects that a factor might also influence several other travel choices (e.g., traffic volume) but did not find studies that detail the relation between this factor and the other travel choice levels. A better understanding of the interactions between choice levels is essential to designing cities that intrinsically support pedestrian travel.

In addition, it is essential to realize that most research efforts have focused on unraveling pedestrians' mode, route, and operational choice behavior. At the same time, activity, destination, and departure time choice behavior have received limited attention. Yet, these higher choice levels are the main drivers for trip generation and significantly impact lower choice levels. Consequently, we run the risk that an imbalance in our research efforts leads to an imbalance in governmental actions to promote walking. Therefore, it is essential to understand the higher travel choice levels (i.e., activity choice, destination choice, departure time choice) better; in general for all modalities and specifically featuring pedestrian travel choices.

Moreover, Section 4 illustrates that some factors might be more or less influential for specific population segments. For example, (Borst et al., 2009) indicate that older individuals value pavement quality, and (Rodriguez et al., 2015) show that the parents of young girls value socially safe neighborhoods. We must start leveraging the more complex discrete choice models to unravel the differences in choice behavior between population segments and allow all population segments to partake in our society equally.

Lastly, this study identifies six distinct travel choices. It is essential to realize that policies that target one travel choice level can, in the end, change the choice behavior at another choice level. It is vital to better understand policies' spillover effects on other choice levels. For instance, how are changes in spatial planning policies impacting mode split and pedestrian route choices? How do dedicated walking networks in cities improve the livability of cities? To create the sustainable cities of the future where people are intrinsically motivated to walk, we can (and should) leverage the entire stack of travel choice levels.

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Ethics

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Dorine C. Duives: Conceptualization, Methodology, Formal analysis, Data curation, Writing - Original Draft, Writing - Review & Editing, Funding Acquisition, Supervision.

Appendix A.

Acronym	Full references
Aarts 2013	Aarts, M. J., Mathijssen, J. J., van Oers, J. A., & Schuit, A. J. (2013). Associations between environmental characteristics and active commuting to school among children: a cross-sectional study. International journal of behavioral medicine, 20, 538–555.
Abdulhussein 2024	Abdulhussein, A. A., & Jameel, A. K. (2024). Involving Infrastructure as a Latent Variable in Active Transportation Mode Choice: The Case Study of Baghdad City. Engineering, Technology and Applied Science Research, 14(6), 18585–18591.

Antonini 2016	Antonini, G., Bierlaire, M., & Weber, M. (2006). Discrete choice models of pedestrian walking
Aultman-Hall 2009	Aultman-Hall, L., Lane, D., & Lambert, R. (2009). Assessing impact of weather and season on pedestrian traffic volumes. Transportation Research Record, 2140, 35–43
Bafatakis 2014	Bafatakis, C., Duives, D., & Daamen, W. (2015). Determining a pedestrian route choice model through a photo survey. In The 94th annual meeting of the transportation research board (cd-compendium).
Barros 2015	Barros, A., Martinez, L., & Viegas, J. (2015). A new approach to understand modal and pedestrians route in portugal. In 18th euro working group on transportation (ewgt2015) (Vol. 10, p. 860–869).
Basu 2022	Basu, N., Haque, M. M., King, M., Kamruzzaman, M., & Oviedo-Trespalacios, O. (2022). A systematic review of the factors associated with pedestrian route choice. Transport reviews, 42(5), 672–694.
Berjisian 2019	Berjisian, E., & Habibian, M. (2019). Developing a pedestrian destination choice model using the stratified importance sampling method. Journal of transport geography, 77, 39–47.
Bernhoft 2008	Bernhoft, I. M., & Carstensen, G. (2008). Preferences and behaviour of pedestrian and cyclists by age and gender. Transportation Research Part F, 11, 83–95.
Berrigan 2002	Berrigan, D., & Troiano, R. P. (2002). The association between urban form and physical activity in US adults.American journal of preventive medicine, 23(2), 74–79.
Bode 2016	Bode, N. (2016). The effect of social groups and gender on pedestrian behaviour immediately in front of bottlenecks. In 2016 8th International conference on pedestrian and evacuation dynamics (pp. 92–99). University of Science and Technology of China Press.
Borgers 2014	Borgers, A., & Timmermans, A. (2014). Indices of pedestrian behavior in shopping areas. In 12th international conference on design and decision support systems in architecture and urban planning (DDSS2014) (Vol. 22, p. 366–379).
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