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Evaluating the influence of cyclists' route choices incorporation into travel demand modelling: A case study in greater Helsinki

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ABSTRACT

Cycling is a sustainable transport mode that endorses an active lifestyle. While cycling shows great potential, it is essential for urban planning to consider attributes influencing the choices that cyclists act upon. Cyclists' route choices have been studied since the Eighties with knowledge being applied in cycling network planning. Yet, the role of cycling as a sustainable transportation mode has been largely absent from travel demand modelling. This paper researches cyclists' route choice preferences and evaluates the opportunity of incorporating route choice modelling into travel demand modelling to improve the accuracy of cycling route choice. To this end, a route choice framework is developed in which a stated preference survey for data collection is conducted, a multinomial Logit model is applied to the data to identify the factors that significantly influence cyclists' route choice behaviour. The generated route choice utility models are further integrated into an existing regional travel demand model to evaluate the performance of cyclists' route choice modelling in the presence of additional factors. Then, the route choice model outputs are validated against two sets of external data. The results show that bike facilities, traffic volume, and trip length are the key factors influencing cyclists' route choice preferences, and the generated route choice models can be an applicable improvement in incorporating the influences of cyclists' preferences into travel demand modelling.

1. Introduction

1.1. Motivation

Promoting active transportation modes, such as walking, wheeling, and cycling, is gaining popularity, due to the numerous advantages including improved health (Raustorp and Koglin, 2019; Shaker et al., 2021), alleviated congestion (Wang and Zhou, 2017), and decreased air pollution (Keall et al., 2018). In particular, the World Health Organization (WHO) recommends adults aged 18–64 years to have 150–300 min of moderate-intensity aerobic physical activity per week (World Health Organization, 2020) and an increase in usage of active transportation modes can help the population to meet the WHO's global health recommendations. Besides, using active modes contributes to emission reduction. For instance, if 41% of the short car trips are replaced with walking or cycling, CO_{2e} emissions will be reduced by around 5% (Neves and Brand, 2019). The European Cyclists' Federation has defined strategic cycling development as a key measure in EU policy-making for achieving climate targets (European Cyclists Federation, 2017) while delivering cost savings and improving the well-being of people.

Cyclist choices are exposed to numerous factors related to the physical environment, with personal preferences influencing the choice outcome. This has brought forward the need to study attributes influencing the choice outcome of trips as well as the extent of their impacts. Utility theory has been successfully used to measure cyclists' choices, particularly their mode choice (Maat et al., 2005; Pinjari et al., 2007; Oakil et al., 2016) and route choice (Casello and Usyukov, 2014; Sobhani et al., 2019) behaviours, by assuming individuals follow utility-maximization behaviour (Train, 2009). This theory has accumulated knowledge on individual travel behaviour and to what extent policy changes affect modal share.

Travel Demand Modelling (TDM) has been applied to foresee the effects of transport plans. In the last few years, while cycling has begun to gain more attraction in planning processes, a mismatch often exists between cyclists' route choice preferences and implementing cycling in TDM. Route choice models commonly follow trip length minimization or classification of preferential bike facilities (Broach and Dill, 2016), which do not factorize in all the attributes influencing route choice preferences. This raises the question of whether the addition of new factors could improve forecasting cycling route choice behaviour.

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1.2. Background on cycling route choice

One of the earliest cycling route choice studies is presented by Bovy and Bradley (1985), arguing in favour of understanding cyclists' choices for predicting their habits and making trade-offs along with behavioural changes that may occur after network modifications. Since then, many studies (Stinson and Bhat, 2003; Sener et al., 2009) discussed researching route choice to be an act of enabling a better understanding of cyclists' preferences and pinpointing influential design attributes to facilitate better designing of cycling networks and their facilities.

Aultman-Hall et al. (1997) used a GIS database to compare routes taken by commuter cyclists with the shortest routes and provided insight into factors affecting route choices such as willingness to avoid grades and high-activity areas. Casello and Usyukov (2014) investigated the impacts of trip length, traffic speed and volume, gradient, and the presence of bike lanes as the main factors in cyclists' route choice. The impacts of other factors such as the number of trees and public transport stops along the path, as well as the presence of attractions also have been investigated in cyclist route choice (Sobhani et al., 2019). Influential factors on cyclists' behaviour can be classified into appropriate groups based on their characteristics to perform comparisons within and among groups (Stinson and Bhat, 2003; Sener et al., 2009). Grond (2016), for instance, defined four groups of factors: (i) physical road characteristics, (ii) trip characteristics, (iii) user characteristics, and (iv) features of the built environment. A more detailed review of factors affecting cyclists' route choice is presented in Section 2.2.

1.3. Background on cycling in travel demand modelling

To estimate the current traffic situation and forecast future travel behaviour, studying the transport system with TDM was conducted (Ben-Akiva et al., 1985; de Dios Ortúzar and Willumsen, 2011). Porter et al. (1999) explained that TDM, which is commonly referred to as a four-step model, was originally designed for only cars and public transport trips. The extent of modelling can range from a city scale to a national scale. As the scope of the case study in our research extends to a regional level, the abbreviation RTDM referring to regional travel demand modelling is further used, without loss of generality. The advantages of RTDM are its ability to analyse travel choices such as mode and route choices on aggregated and disaggregated levels, consideration of land use and transportation systems as part of influencing trip-making, and capability to examine the effect of alternative policies and operations in travel patterns (Schwartz et al., 1999; Porter et al., 1999).

Incorporating cycling and walking into RTDM has faced challenges due to their short trip scale that varies significantly from motorized trips (Eash, 1999). Broach and Dill (2016) described cycling incorporation into RTDM as sluggish, and models have rarely fully incorporated cycling. Cycling is often combined with walking as a non-motorized mode (Singleton and Clifton, 2013; Bradley et al., 2019). Recently, some RTDM approaches that account for cycling route choice behaviour have been developed. Bradley et al. (2019) presented examples of RTDM that have incorporated a cycling trip assignment step into the application of cycling route choice theory, namely tour-based SF-CHAMP of San Francisco, trip-based Portland Metro of Portland, and activity-based SANDAG of San Diego. In Finland, the latest version of the RTDM called Helmet 4[1] currently accounts for simplistic cyclists' route choice decisions through preferential bike facilities (West et al., 2020).

However, there is a lack of studies on incorporating a comprehensive behavioural route choice model into RTDM to investigate its contribution to forecasting the accuracy of cycling route choice decisions. It should be noted that the documentation of developed modelling of cyclists and pedestrians in RTDM is often lacking or not readily available in English. This issue also applies to Helmet 4. Thus, this paper provides updated information, insights, and advancements in the field, especially for the Finnish RTDM.

1.4. Research objectives

Following what is discussed above, we identify the following gaps in the field of cycling route choice behaviour.

1. The factors that influence cyclists' route choice preferences have not been studied widely, especially in Finland, as cyclists' preferences may be location-dependent, due to, e.g., cultural legacy or weather conditions.
2. The role of cycling as a transport mode has been largely absent from RTDM.

Therefore, the focus of this paper is two-fold. The first objective is to generate more knowledge on factors influencing cyclists' route choice behaviour. The second objective is to integrate a route choice model into RTDM, investigating whether the presence of additional factors can improve the performance of cyclists' route choice modelling in terms of forecasting accuracy.

The remainder of this paper is organized as follows. Section 2 provides the methodological framework of the route choice; it introduces Greater Helsinki as the case study; and explains how the estimated results are integrated into a regional travel demand model. Section 3 describes the sample characteristics, model outputs, and validation of the proposed route choice model incorporated in existing TDM efforts. Finally, Section 4 draws the concluding remarks of our paper.

2. Method and data

2.1. Methodological framework

The methodological framework of the study, as presented in Fig. 1, is split into four stages: (1) identification of factors, (2) data collection, (3) model estimation, and (4) model integration and validation. Stages 1 through 3 are part of the route choice framework, while stage 4 is related to the application of the route choice model in RTDM. In the following subsection, the study area is briefly introduced, followed by detailed explanations of various stages.

2.2. Study area

Greater Helsinki, Finland, is a collaborative region of 14 municipalities encircling the capital Helsinki, which consists of three distinct areas: the inner capital area, the outer region, and other areas. A map of the study area is shown in Fig. 2. The area's population is around 1.53 million inhabitants with 1.20 million inhabitants living in the inner capital area (Tilastokeskus, 2021).

The latest region-wide travel behaviour survey in 2018 (Brandt et al., 2019) estimated around 4.7 million daily trips across the region on a normal weekday. The share of walking, cycling, and public transportation is found to be 60%. The share of cycling as a primary mode is also found to be 9% in 2018, which accounts for approximately 420,000 daily trips.

2.3. Defining study factors and levels

Factors of interest must be considered as those frequently emerging in cycling route choice studies, while also being preferable to cyclists. Since the study aims at incorporating the route choice model into RTDM, compatibility with the regional travel demand model implementations and suitability for the context of the study area are also necessary.

[1] The open-source materials to install and run Helmet 4 can be found in https://github.com/HSLdevcom/helmet-model-system.

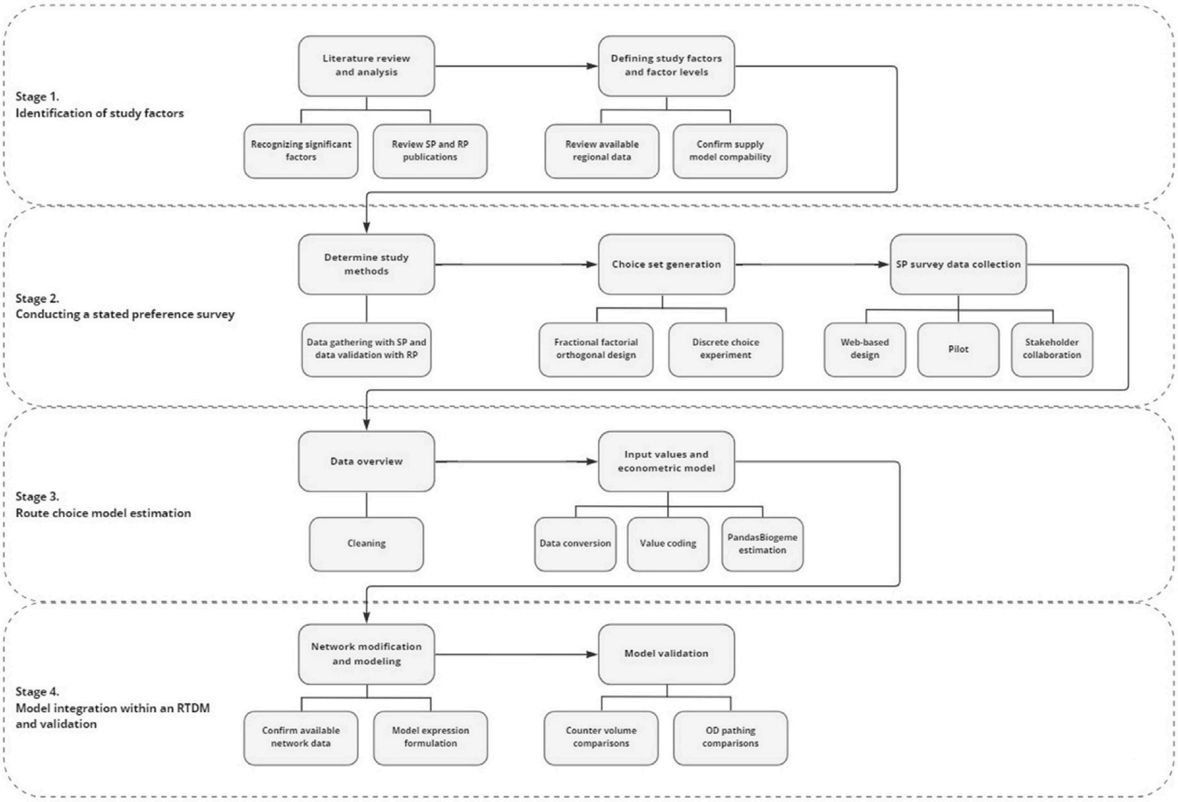

Fig. 1. Overview of the employed methodological framework.

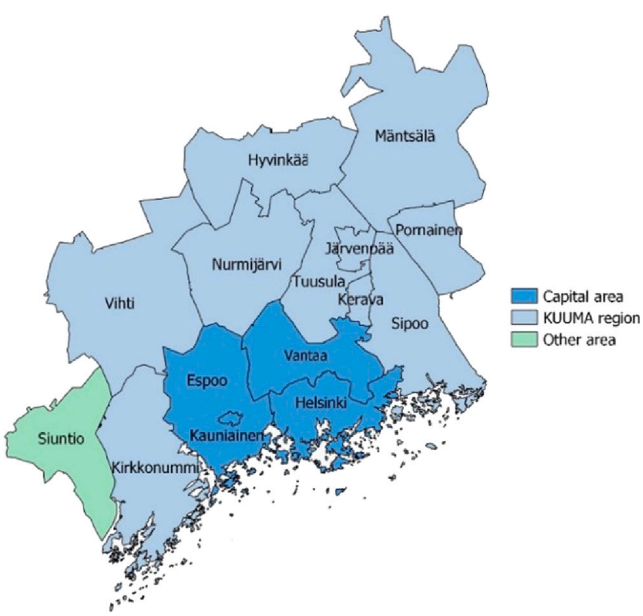

Fig. 2. The study area, including 14 municipalities of Greater Helsinki and Siuntio.

After the identification of study factors, factor levels, which indicate how a factor may change in different situations, must be determined to measure the change in each factor's influence. Determining enough levels for each factor is essential, as too few levels may not describe the factor's impact accurately while identifying too many levels produces unnecessary complexity.

Among the extensive literature on factors affecting cyclists' routing behaviour, 15 publications are selected. Choosing publications that vary culturally, spatially, and temporally is determined to be important to minimize choosing factors that might indicate strong preference at a specific setting during a certain temporal period. Additionally, selecting popular publications that are cross-referenced frequently is also found relevant aspect for comparing findings between papers. Our study uses a classification style, for factors affecting cyclists' route choice behaviour, similar to Grond (2016). Table 1 presents factors emerging in the literature concerning the four predefined classes, and a coding scheme for them. Then, Table 2 uses the encoded letters to summarize the findings from publications and determine factors that have been collectively found most influential. Besides influential factors, Table 1 provides information on the study area and the type of data, e.g., stated preference (SP) and/or revealed preference (RP), used to investigate cyclists' behaviour.

Factors such as gradient, bike facility, and trip length seem to have a strong presence and influence in numerous studies. Many factors are not found significant in the selected studies. This does not imply that those factors have no effect; on the contrary, it may refer to the fact that some factors do not influence a particular cultural or spatial setting or such influence exists but its effect is deemed weaker than the effect from several other factors.

The process of choosing factors for this study consists of 2 steps. First, the number of factors presented in Table 2 was reduced as many of them were not found to have accessible data (e.g., street green), were not seen as significant in the context of our case study (e.g., bridge facilities are not frequent in Greater Helsinki), or were not suitable for the current form of the TDM implementation (e.g., turns). Cutting off those factors, the conclusive six chosen factors for this study are listed as (1) bike facility, (2) road class, (3) traffic volume, (4) controlled intersection, (5) gradient, and (6) trip length. Besides, limiting the number of study factors (i.e., 6 in this study) prevents the SP from becoming too exhausting and difficult to complete. In the second step, factor levels are determined based on existing model parameters and levels that are found to be suitable among the examined set of studies.

Table 1
Types of emerging factors in route choice studies.

Road characteristics		Trip characteristics		User characteristics		Built environment features	
A	Gradient	L	Trip length	R	Age	CC	Scenery
B	Signalized intersection	M	Average speed	S	Gender	DD	Street green
C	Bike facility	N	Travel time	T	Cycling purpose	EE	Crowdedness
D	Traffic volume	O	Wrong-way travel	U	Cycling experience	FF	Residential unit density
E	Road quality	P	Left and right turns	V	Income	GG	Street lighting coverage
F	On-street parking	Q	Road continuity	W	Cycling frequency	HH	City features
G	Speed limit			X	Cycling with children	II	Land use mixture
H	Number and width of lanes			Y	Car ownership	JJ	Public transport service level
I	Road class			Z	Level of education		
J	Bridge facility			AA	Weather influence		
K	Tram tracks			BB	Bike operation cost		

Table 2
Most significant identified factors in each study.

Publication	A	B	C	D	E	G	I	J	L	N	O	P	Q	S	T	CC	DD	FF	GG	JJ	Study area	Data
Stinson and Bhat (2003)		✓	✓		✓		✓	✓		✓											US	SP
Sener et al. (2009)		✓		✓		✓				✓			✓								Texas, US	SP
Menghini et al. (2010)	✓		✓						✓												Zurich, Switzerland	RP
Hood et al. (2011)	✓		✓						✓		✓			✓	✓						San Francisco, US	RP
Winters et al. (2011)	✓		✓	✓	✓											✓					Vancouver, Canada	SP
Broach et al. (2012)	✓	✓	✓	✓					✓			✓									Portland, US	RP
González et al. (2016)			✓						✓								✓			✓	Providencia, Chile	SP, RP
Grond (2016)	✓		✓	✓					✓			✓									Toronto, Canada	SP, RP
Vedel et al. (2017)		✓	✓				✓										✓				Copenhagen, Denmark	SP
Zimmermann et al. (2017)	✓		✓	✓				✓	✓												Eugene, US	RP
Chen et al. (2018)	✓		✓			✓			✓										✓		Seattle, US	RP
Majumdar and Mitra (2018)			✓	✓															✓		Kharagpur & Asansol, India	SP
Bernardi et al. (2018)									✓					✓	✓						The Netherlands	RP
Ghanayim and Bekhor (2018)			✓				✓		✓							✓		✓			Tel Aviv, Israel	RP
Hardinghaus and Papantoniou (2020)			✓		✓					✓											Munich, Germany & Athens, Greece	SP

Table 3 contains a list of six examined variables, their levels, and their definitions.

2.4. Stated preference survey design

After the identification of study factors, data reflecting the preferences of the cyclists must be acquired. SP data is used in this context since it allows the researchers to define several scenarios and to have full control over the variables with a lower operational effort and cost, compared with RP data (Hensher et al., 2005).

The first step of designing an SP survey is to describe the alternatives that are available to the individual. This collection of relevant alternatives is called a discrete choice set from which individuals choose their preferred outcome. Choice set size and composition influence the results of model estimation and prediction (Ton et al., 2018). A full factorial design containing every possible combination of factor levels can be performed to make the choice set, however, the extent of a choice set can end up being too large. For instance, in this research, with the predefined factors and their levels, excluding the trip length, there are 432 ($4^2 \times 3^3$) alternatives according to a full factorial design, and it has to be reduced to a manageable size (Hensher et al., 2005) by using a fractional factorial design.

In the end, a fractional factorial design is applied to generate reasonable-sized choice sets in the statistical analysis software SPSS. The generated 32 choice alternatives are split into four blocks with each block having eight unlabelled choice questions between two alternatives for each participant to select. The number is in line with the existing literature (Sener et al., 2009; Vedel et al., 2017; Hardinghaus and Papantoniou, 2020).

A survey is designed with an online questionnaire in the Webropol software (Webropol, 2021) and active cyclists over 15 years old are targeted. A pilot survey was conducted in August 2021 to gain an overview of how the survey's contents were perceived. After the final review, the contents were translated alongside Finnish into Swedish and English. Data were collected during September 2021. Information about the survey was shared via online platforms and social media channels. Brochures were also designed and distributed locally to make sure that cyclists who may not follow online media could participate.

The structure of the questionnaire consists of two main sections. The first section of the questionnaire requests respondents to imagine themselves in a hypothetical situation where participants are given randomly one choice set, containing 8 scenarios with two alternatives. In each scenario, respondents are asked to choose the alternative that is more suitable to their preferences. To assist respondents in imagining possible outlooks for each alternative, grey-scaled photographs, which resemble each choice alternative to a degree, are included in the questionnaire. An exemplary choice pair that is presented to some

Table 3
Identified factors and determined levels with definitions.

	Factor	Level	Level definition
1	Bike facility	Mixed traffic	Cyclists ride among motorized vehicles
		Bike lane	On road painted bike lane
		Adjacent cycle path	Designated cycle path for cyclists next to a road
		Separated cycle path	Cycle path that is completely separated from the road
2	Road class	Local street	The route follows small residential and collector streets
		Main street	The route follows the main streets
		Arterial road	The route follows arterial roads
3	Traffic volume	Light	Roads along the route have hardly any cars (0–500 veh/h)
		Moderate	Roads along the route have some cars (500–1000 veh/h)
		Substantial	Roads along the route have a noticeable amount of cars (1000–2000 veh/h)
		Heavy	Roads along the route are full of cars (>2000 veh/h)
4	Signalized intersection	No traffic signal	There are no signalized intersections
		Few traffic signals	There are one to two signalized intersections
		Many traffic signals	There are at least three signalized intersections
5	Gradient	No hills	There are no noticeable hills along the route (0–2.5%)
		Moderate hills	There are moderate hills along the route (2.5%–5%)
		Steep hills	There are steep hills along the route (>5%)
6	Trip length[a]	–	–

[a] Trip length is treated as a continuous variable.

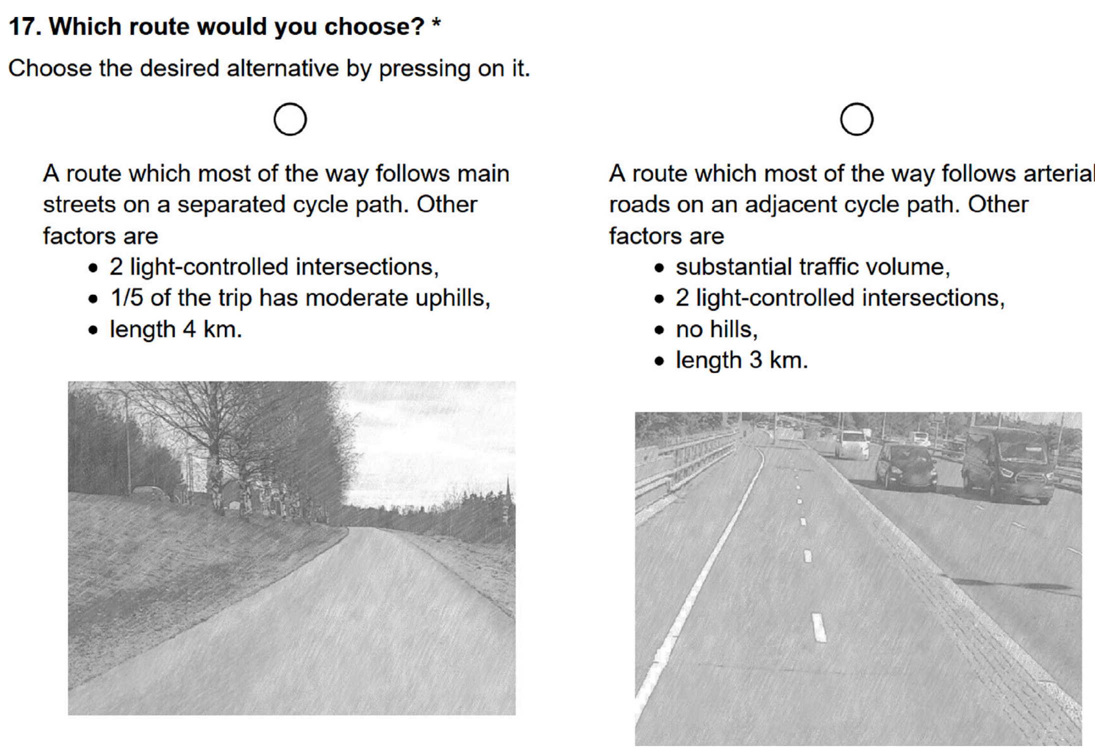

Fig. 3. An example of choice pair presented to respondents in the SP survey.

respondents is shown in Fig. 3. The second section of the survey asked for information concerning respondents' residential municipality, age group, gender, and cycling experience. Respondents are also asked about their purpose for cycling, when they generally cycle, the average trip length, and frequency, and whether they use e-bikes that can affect the cyclists' route choice by removing the burden of cycling.

2.5. Route choice model estimation

Modelling the choice of discrete decisions with uncertainty is performed with models of random utility. The deterministic component of the utility of alternative i for the decision maker (i.e., a person) n, V_{ni}, is a sum function that consists of a factor value with its assigned weighting (coefficient) describing a factor's share in the whole utility. This is defined by

$$V_{ni} = \sum_{k} \beta_{ki} f(X_{kni}), \tag{1}$$

where k represents the number of factors, $k = 1, \ldots, K$, and is included with every element specific to the ith alternative, β_{ki} assigns a weighting to a factor k for alternative i and $f(\cdot)$ denotes the form of function in which factor values, X_{kni}, may be entered in different forms for different individuals (Ben-Akiva and Bierlaire, 1999; Hensher et al., 2005). Then, the utility of alternative i for person n is calculated as $U_{ni} = U_{ni} + \epsilon_{ni}$, where ϵ_{ni} is an error term.

Following the utility-maximization principle, an individual n chooses the best alternative i over alternative j from the discrete choice set C_n if the utility of i is greater or equal to the utility of j as shown in probabilistic terms as

$$P(i|C_n) = P[U_{ni} \geq U_{nj} \forall j \in C_n] = P[U_{ni} = \max_{j \in C_n} U_{nj}]. \tag{2}$$

If the random part of the utility, ϵ_{nj}, follows a Gumbel distribution, Eq. (2) turns into a multinomial Logit model. Then, the probability of an individual n choosing a route i when $[U_{ni} \geq U_{nj}]$ is given by

$$P_i = \frac{e^{V_{ni}}}{\sum_{j=1}^{J} e^{V_{nj}}}, i \neq j \tag{3}$$

In this model, ϵ_{nj}, is assumed to be independent and identically distributed (iid) (McFadden, 1974; Ben-Akiva and Bierlaire, 1999). This is widely used in discrete choice studies, and it is suitable for modelling cyclists' route choice behaviour, where survey participants are assumed to follow utility-maximizing behaviour and iid assumption.[2] Applying a maximum likelihood method allows determining coefficients, β, which can be used to estimate the effects of factors under research.

To describe a parameter's influence on utility, U, Marginal Rates of Substitution (MRS), computed as $-(dU/dx)/(dU/dy)$, is considered (Hood et al., 2011; Broach et al., 2012). MRS measures the change in the quantity of variable x divided by the change in the quantity of variable y, while keeping the utility constant. In other words, MRS describes the change in a variable's units when traded with another variable and the negative sign indicates the inverse relationship between the variables, as some quantity of one variable is substituted by more of the other variable. Thus, given that the utility function is linear with respect to all variables, the equivalent y value of a unit change in the parameter x is defined as

$$MRS = \left((\frac{\beta_x}{\beta_y}) - 1 \right) \times 100, \tag{4}$$

where β_x and β_y are the estimated coefficients of parameter x and y, respectively.

Also, the contribution of utility (Stinson and Bhat, 2003) is used to compute the average impact of each parameter to be assessed. This is not possible with the estimated parameters themselves due to the coding of the values having different scaling. Thus, the contribution of utility by a parameter, $\bar{U}_x$, is formulated as

$$\bar{U}_x = \mu \times \beta_x, \tag{5}$$

where μ is the average coded value.

2.6. Model integration with RTDM

The last stage of the study aims at observing whether applying the results from the route choice model could potentially improve route choice forecasting accuracy in RTDM. This needs the integration of the route choice model with RTDM that requires network modification, developing an expression formulation, and results validation.

Helmet, the RTDM of the Greater Helsinki area, is designed as a four-step model of trip generation, distribution, mode choice, and trip assignment. In Helmet 4, after considering cycling as an explicit mode, cycling demand models were formulated for mode choice, and a simple description of the cycling network was built, which has been gradually further detailed during the last few years. Demand models of Helmet 4 are run solely with Python macros while supply models utilize a combination of Python and the transport modelling software Emme (INRO, 2021) for network traffic assignment.

To incorporate the cyclists' route choice model into Helmet, first, network attributes should be inspected to reveal the existing and suitable data to be available for the study factors. After network modifications, utilities have to be assigned to links through an expression formulation that describes relative utility U for link l, concerning the study factors. The utilities will be used as a generalized cost in the traffic assignment model of RTDM, meaning that the proposed models are only implemented in the route choice stage.

After the link utilities are computed, the standard traffic assignment of Emme, i.e., based on a linear approximation method, can be performed.[3] Various link expression permutations are tested during the traffic assignment with new coefficients being estimated for each permutation. Models that are considered to reflect the best cyclists' behaviour are further used. The cycling assignment results are, then, validated against two sets of external data. The first set of validation data uses quantitative cyclists' counterpoints for comparison with current cyclists' demand of Helmet. The second set of data makes comparisons between route choices. In the second case, the functionality of route choice modelling as a part of TDM is validated by observing whether the modelled route is realistic, and how much the modelled results overlap with actual cyclists' choices and the outputs of the existing RTDM, which is already applied in regional forecasts for transport and land use impact assessments.

3. Results

3.1. Sample description

1069 participants partook in the survey and after data cleaning, the final sample consists of 1029 participants. Most responses are, by far, received from Helsinki cyclists as it is the largest municipality in the region. Although numerous cycling route choice studies have shown males as the clear dominant gender group (Hood et al., 2011; González et al., 2016; Chen et al., 2018; Ghanayim and Bekhor, 2018; Hardinghaus and Papantoniou, 2020), the gender distribution of our sample shows a very good balance between male (47.2%) and female (49.3%) respondents. The shape of the results, as shown in Fig. 4, presents how the sample contains a relatively equal amount of both women and men among all age groups. This figure resembles normal distribution with the working class in the middle and teen and elderly groups being at the tail ends.

Based on a simple qualitative self-judgment, the overall cycling experience distribution is evaluated. Half of the respondents considered themselves very experienced cyclists and 43% of participants are at least somewhat experienced, which is in line with the study's goal to reduce inconsistent results that are more likely to emerge among those who are inexperienced or cycle infrequently. On average, survey participants cycle 4 to 5 days a week between 5 to 10 km. Regarding the purposes of cycling, respondents are allowed to choose up to three choices that best describe their cycling purpose. Leisure is found to be the most popular cycling activity as, on average, four out of five people claimed to often ride for leisure purposes. Commuting to work and exercising are found to be other frequent answers among respondents.

3.2. Route choice estimation results

In this study, two models defined as M1 and M2 are formulated in a way to cover all the study factors and their levels. The expressions for the deterministic part of the utility of a link in M1 and M2 follow the linear function in Eq. (1). Both models integrate trip length into road class and bike facility to make link attributes addable over links

[2] Using the same data, Khavarian et al. (2024) compare the outputs of multinomial Logit models and random parameter Logit models for regular and electric bike users' route choices. Their findings imply that the SP data captures the preferences of the individuals, so the IID assumption is held. This suggests that using multinomial Logit can lead to similar outputs with random parameter Logit, without increasing the complexity of the estimation process.

[3] Note that we also tested a stochastic assignment method for this task, without observing any significant difference compared to the (simpler) standard traffic assignment model.

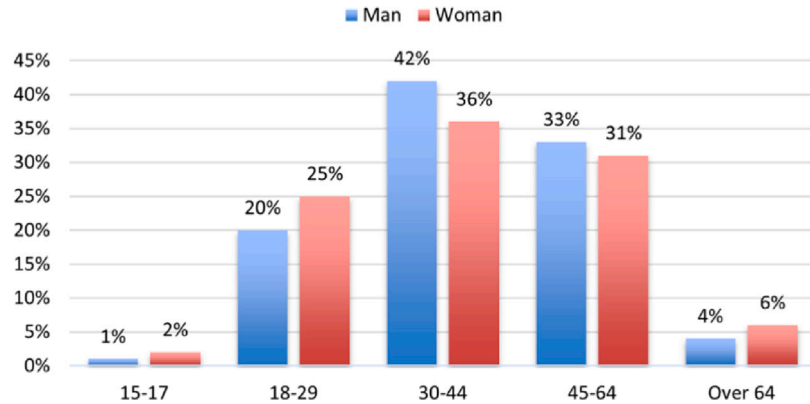

Fig. 4. The distribution between gender and age of participants (n = 1029).

with different characteristics. The difference between the two models is that M2 includes an interaction effect between trip length and gradient while M1 excludes it.

The estimated coefficients of the two models, M1 and M2, are shown in Table 4. Although coefficient values vary between M1 and M2, their signs, the relative difference between values, and statistical significance are similar. Estimation of the two models is performed in Python with PandasBiogeme (Bierlaire, 2020). As mentioned earlier, each participant responded to eight choice questions producing 8232 (1029 × 8) observations for estimation. Table 5 also presents MRS and contribution of utility for M1, computed using Eqs. (4) and (5), respectively. MRS, for route choice, is often denoted as an exchange between two parameters with the dependent parameters being denoted in length due to it being easier to interpret. In this study, as trip length is integrated into road class and bike facility, *separated bicycle facility* × *length* is served as the y parameter in MRS formulation. Lastly, M2 is used to estimate the interaction between main effects and sociodemographics to observe whether particular factors influence certain cycling demographics in Greater Helsinki. All interaction effects are first estimated in M2 and then narrowed to only statistically significant ones, as shown in Table 6.

3.2.1. *Main effects*

Cyclists in Greater Helsinki tend to prefer routes that traverse main streets and arterial roads over local streets as local streets produce higher average disutility than main streets and arterial roads. Separated and adjacent cycling paths are the preferred bike facilities while mixed traffic is the most disliked facility option. MRS indicates that cyclists are willing to go around 30% out of their way in order to ride in the vicinity of main streets and arterial roads rather than on local streets. Local streets are observed to produce 19.8% and 22.5% higher average disutility than main streets and arterial roads.

Mixed traffic conditions are considered to be the most disliked facility option. MRS shows cyclists' willingness to travel 92.7% longer to avoid riding in mixed traffic conditions. Further dislike towards mixed traffic is indicated by the large 68.9% difference in produced average disutility between bike lanes and mixed traffic. Riding in adjacent facilities is, however, found to be equivalent to a 3.4% decrease in the separated bike lane length. Traffic volume is controlled for, but other elements of mixed-traffic streets, such as uneven pavement, road drainages, and unavoidable intersections can also have a negative influence. The surrounding environment may also contribute to choosing a type of facility, and the popularity of separated cycle paths might originate from route alternatives that traverse through green areas.

Moderate traffic volume conditions are slightly preferred over other alternatives. While MRS is unable to the explain exchange between parameter and length due to small coefficients, utility contribution indicates that moderate traffic conditions cause 1.3 more utility over

Table 4
Route choice model estimation results.

Factor	Parameter	M1		M2	
		Coefficient	t Stat.	Coefficient	t Stat.
Road class × length	β_{Local}	−4.96***	−33.1	−3.99***	−29.6
	β_{Main}	−4.14***	−28.7	−3.31***	−25.3
	$\beta_{Arterial}$	−4.05***	−25.4	−3.28***	−21.8
Bike facility × length	β_{Mixed}	−5.03***	−40.1	−4.47***	−37.7
	β_{Lane}	−2.98***	−26.2	−2.56***	−22.5
	$\beta_{Adjacent}$	−2.52***	−19.8	−1.85***	−15.3
	$\beta_{Separated}$	−2.61***	−16.0	−1.70***	−11.4
Traffic volume (Ref.: Light)	$\beta_{Moderate}$	−0.008***	−7.7	−0.005***	−5.9
	$\beta_{Substantial}$	−0.008***	−16.7	−0.006***	−14.2
	β_{Heavy}	−0.009***	−24.2	−0.008***	−3.0
Signalized intersections (Ref.: No signal)	$\beta_{FewSignals}$	−0.59*	−1.7	−0.99***	−3.0
	$\beta_{ManySignals}$	−2.00***	−10.8	−1.75***	−9.9
Gradient (×length in M2) (Ref.: No hills)	$\beta_{ModerateHills}$	−2.32***	−14	−17.20***	−10.3
	$\beta_{SteepHills}$	−2.50***	−18.6	−23.40***	−18.4
Model fit					
No. of estimated parameters		14		14	
Sample size		8232		8232	
Initial likelihood		−5706.0		−5706.0	
Final likelihood		−4031.4		−4076.1	
Initial likelihood ratio test		3349.1		3259.7	
Rho squared		0.293		0.286	
AIC		8090.8		8180.2	
BIC		8189.1		8278.4	

* Significant at 10% ($p \leq 0.10$).
*** Significant at 1% ($p \leq 0.01$).

heavy volume. Still, moderate, substantial, and heavy volumes make relatively similar impacts, indicating that additional levels of traffic volume do not cause significantly more disutility.

Routes with few or many signalized intersections are less favourable compared to those with no signal. Still, the impact of many signals is stronger than alternatives with a few traffic signals along the way. As disutility contribution shows, routes with many signals are found to cause almost 3 times higher disutility than routes having few signals. Average disutility results indicate signalized intersections have the smallest influence on cyclists' route choice preference among studied factors in Greater Helsinki. This is in line with the literature in Table 2 where signalized intersections are shown to be quite often insignificant.

Moderate and steep hills are found to be quite evenly disliked. MRS describes distance travelled on the separated cycle path to decrease by 11.1% and 4.2% for moderate and steep hills, respectively. Similarly, average utility contribution shows little difference between moderate and steep hills. The small differences between moderate and steep hills

Table 5
Parameter unit effects of M1.

Factor	Parameter	MRS	Disutility contribution	
		Distance value in aseparated bike lane (%)	Avg. coding value	Avg. disutility
Road class × length	β_{Local}	90.0	5.6 km	−27.8
	β_{Main}	58.6	5.6 km	−23.2
	$\beta_{Arterial}$	55.2	5.6 km	−22.7
Bike facility × length	β_{Mixed}	92.7	5.6 km	−28.2
	β_{Lane}	14.2	5.6 km	−16.7
	$\beta_{Adjacent}$	−3.4	5.6 km	−14.1
Traffic volume	$\beta_{Moderate}$	−99.7	838 veh	−6.4
	$\beta_{Substantial}$	−99.7	838 veh	−6.9
	β_{Heavy}	−99.7	838 veh	−7.7
Signalized intersections	$\beta_{FewSignals}$	−77.4	1.5 signals	−0.9
	$\beta_{ManySignals}$	−23.4	1.5 signals	−2.9
Gradient	$\beta_{ModerateHills}$	−11.1	2.8% elevation	−6.5
	$\beta_{SteepHills}$	−4.2	2.8% elevation	−7.0

Table 6
The relative utility of interaction effects between main effects and sociodemographics.

Factor	M2		
	Parameter	Coefficient	t Stat.
Road class	β_{Local}	−2.45***	−24.6
	Leisure	0.39*	1.9
	E-bike	1.04***	3.9
	β_{Main}	−1.50***	−17.2
	Leisure	0.56**	2.3
	E-bike	0.74**	2.4
	$\beta_{Arterial}$	−1.16***	−12.5
Bike facility	β_{Mixed}	−2.87***	−17.0
	Female	−1.07***	−6.3
	β_{Lane}	−1.30***	−8.7
	E-bike	0.75***	2.6
	$\beta_{Adjacent}$	−0.81***	−4.9
	$\beta_{Separated}$	−0.14	−0.4
	Female	0.87***	4.7
Traffic volume	β_{Light}	0.01	1.3
	Female	0.02***	5.5
	$\beta_{Moderate}$	−0.002	−0.5
	Female	0.006***	3.9
	$\beta_{Substantial}$	−0.006***	−3.8
	30–44	0.001**	2.2
	β_{Heavy}	−0.007***	−5.4
Signalized intersections	$\beta_{NoSignals}$	0	
	$\beta_{FewSignals}$	−1.42***	−3.4
	Leisure	1.96***	2.9
	$\beta_{ManySignals}$	−2.16***	−8.6
	30–44	−0.68**	−2.3
	Leisure	1.16***	2.8
Gradient	$\beta_{NoHills}$	1.17***	18.3
	E-bike	−3.15***	−3.1
	$\beta_{ModerateHills}$	−2.07***	−13.3
	$\beta_{SteepHills}$	−1.94***	−12.2
	Female	−0.91***	−4.2
Trip length	β_{Length}	−5.11***	−32.0
Model fit			
No. of estimated parameters		33	
Sample size		8232	
Initial likelihood		−5706.0	
Final likelihood		−3955.5	
Initial likelihood ratio test		3501.0	
Rho squared		0.307	
AIC		7977.0	
BIC		8208.5	

* Significant at 10% ($p \leq 0.10$).
** Significant at 5% ($p \leq 0.05$).
*** Significant at 1% ($p \leq 0.01$).

imply that cyclists are more likely to choose their route depending on whether there are hills or no over-elevation. This may have resulted from asking respondents to differentiate between qualitative moderate and steep hills. However, note that the Greater Helsinki region is flatter than many of the other locations in literature, which may be why cyclists have difficulties in comparing moderate and steep hills.

3.2.2. Interaction effects

The interaction effects between the main effects presented above and the sociodemographic characteristics are also estimated and a comparison is performed between men and women, commuters and leisure cyclists, and non-assisted bike and e-bike users. Preferences of the sample's largest respondent group between 30 and 44 years old are also estimated. Although previous studies, such as Broach et al. (2012) and Chen et al. (2018), did not find statistical significance between study factors and sociodemographics, this study demonstrates sociodemographic characteristics influence cyclists' preferences.

Women are found to dislike riding in mixed traffic conditions more than men, probably due to different safety perceptions as studied by Xie and Spinney (2018). Men, on the other hand, are found to dislike riding on separate cycle paths more than women. Women are found to also favour low-volume traffic conditions over men, which again implies the different safety perceptions between men and women while riding in the proximity of cars. Participants aged between 30–44 are found to be content with a substantial amount of traffic volume; this implies that either such cyclists have already accumulated a significant amount of cycling experience, which might have increased their understanding of how to cycle safely and efficiently in the vicinity of large traffic volumes, or they have a higher perception threshold for unsafe situations.

Women are found to dislike routes with steep hills more than men. In addition, e-bike users are found to greatly dislike routes without hills over cyclists with regular bikes. An e-bike can greatly reduce the required physical effort of climbing hills, which may also be one of the factors that has led a person to acquire an e-bike in the first place. To them, an electric-assisted bike can create whole new route options where hills are not seen as obstacles anymore.

Leisure cyclists are found to prefer routes that follow local and main streets over arterial roads with a higher preference for main streets. Leisure cyclists, traditionally, ride out for enjoyment, and routes following large and noisy arterial roads might not fulfil this aspect.

Leisure cyclists prefer routes with traffic signals over commuters. Commuter cyclists may have higher pressure to be on time, which signals can hinder, while leisure cyclists most likely do not have similar restrictions. In particular, 30-to-44-year-old cyclists are found to dislike having many signals along their routes, as signalized intersections contribute to travel time variability, hence, they influence travel time reliability (Zheng et al., 2017; Singh et al., 2019) and the users' perception of time reliability affects their route choice behaviour (Moghaddam et al., 2019). Many of these respondents are most likely active commuters to whom removal of excess stops can optimize trip-making.

Table 7
Spearman's rank correlation test results.

Pair	Correlation	Rho-square	t Stat.
Counter - Helmet 4	0.551	0.304***	3.49
Counter - M1	0.474	0.225***	2.85
Counter - M2	0.526	0.277***	3.28
Helmet 4 - M1	0.694	0.481***	5.10
Helmet 4 - M2	0.772	0.596***	6.42
M1 - M2	0.617	0.381***	4.15

*** Significant at 1% ($p \leq 0.01$).

3.3. Integration of the route choice model in Helmet 4 and validation

To integrate the route choice models, M1 and M2, into Helmet 4, preliminary configurations are first completed. A forecast based on the 2018 Greater Helsinki land use, housing, and transportation data is run in Helmet 4 to produce travel demand. It was also decided that testing would focus on morning peak hours. The assignment results are, then, validated with respect to both counter volume and OD pathing.

3.3.1. Counter volume

Models are first validated by observing cyclist volumes at different counter locations within the capital area (Eco-Counter, 2021). These counters collect and publish the daily activity of passing individuals. The observed quantities are, then, compared against the route volume results of Helmet 4 and new route choice models. Measured results of simple descriptive statistics of the 30 chosen counters around the capital area show that Helmet 4's current model, M1, and M2 have large differences compared with counter data. All three alternatives are found to assign excessive cyclists to links, with M1 showing the best accuracy by assigning, on average, only 180 extra cyclists over Helmet 4's 230 and M2's 270 cyclists.

Spearman's rank correlation test (Fieller et al., 1957) is applied to measure the correlation coefficient between observed quantities and is presented in Table 7. Null hypothesis H_0 claims that there is no correlation between observed quantities. The results show a correlation to exist among observed quantities, suggesting that the null hypothesis H_0 is rejected, meaning that there exists a correlation between the observed quantities. Still, Helmet 4 outputs have the best correlation fit with counter data. This may be attributed to the inaccuracy of the counter volume data,[4] such as undercounting or incomplete coverage of all cycling routes. As a result, we also employ OD pathing as an additional validation method to further assess the accuracy and reliability of the model results.

3.3.2. OD pathing

The second validation is performed by tracing route choices between origin–destination pairs, using aggregated RP data from Strava (2021). This data is further referred to as Strava pathing. 17 OD pairs are chosen among capital area districts that cyclists would likely travel between. An example pair is shown in Fig. 5 for both M1 and M2 models.

Results show current cyclists' route choice model of Helmet 4 to produce the longest paths among alternatives as the produced paths are found to be on average 200 m longer than Strava's pathing. On the contrary, paths that are generated with M1 and M2 are found to have similar average route lengths, which turn out to be on average 800 m shorter than the routing of Helmet 4. Strava's data revealed that cyclists actually cycle longer detours to reach their destination over modelled options as the paths are observed to detour on average by 600 m. While bias exists in Strava's results because it is especially popular among exercising cyclists, the results imply Greater Helsinki cyclists prefer routes with better cycling facilities and seamless route connectivity as they are willing to detour over the shortest option.

Evaluating the performance of route choice models M1 and M2 against the current route choice model of Helmet 4 reveals that both models outperform Helmet 4 in forecasting accuracy and have higher trip distance overlap with the actual route choice of cyclists. Examination of which route alternative has the highest overlap and, thus, is the best representation of predicting cyclists' routes, reveals that M1's shortest path overlaps 30% of the time with actual cyclists routing between all OD pairs. Similar results are found in M2, where the M2's shortest path is found to overlap 31% of the time with Strava's path. Routes generated with the current route choice model of Helmet 4 are found to overlap with Strava's results only 22% of the time. These findings suggest that both exhibit analogous levels of accuracy in predicting cycling paths, and their performance is slightly superior to that of Helmet 4.

4. Conclusions

This study aims at improving the knowledge of cyclists' route choice preferences, but most importantly it pursues to connect the results of route choice models with travel demand modelling to advance the capabilities of modelling cycling. This enables the development of more effective and inclusive transportation plans, allowing urban planners and designers to create green and user-friendly cycling infrastructure that promotes cycling and enhances safety and accessibility. To this end, a route choice framework consisting of factor identification, data collection, and parameter estimations is prepared, and then used to develop a route choice model integrated with the existing RTDM and validated.

This study, analysing SP data with over 1000 observations, finds that bike facilities, traffic volume, and trip length influence cyclists' route choice preferences considerably. Cyclists are found to favour adjacent and separated cycle paths while avoiding routes where they have to ride in mixed traffic. Signalized intersections show little influence while gradient causes moderate discomfort among cyclists. Interestingly, cyclists are observed to exhibit a similar level of detouring behaviour to avoid moderate and steep hills, probably due to the relatively gentle topological characteristics of the study area, where cyclists face challenges in distinguishing between moderate and steep hills. This study demonstrates sociodemographic characteristics influence cyclists' preferences. Women, for example, are found to detour routes with steep hills more frequently, seek out separated cycle paths, and avoid riding among mixed traffic more than men.

The results also demonstrate the successful incorporation of cycling route choice modelling into an existing RTDM (Helmet 4). The outcome of this process is validated in two stages. First, quantitative validation on cyclists' volume at different points in the network presented that modelled route choice performs slightly worse than the current cycling model of Helmet 4, while the second validation on tracing cyclists' chosen routing between specific origins and destinations demonstrated route choice modelling to perform better. The study results show route choice modelling to be an improvement over the current route choice of Helmet 4. The improvements, however, are not significantly better and additional actions are needed to further increase accuracy with suggested actions being related to input value calibration, network updates, and including costs for turn actions.

The study limitations are mostly related to how the studied factors are chosen and which factors' impacts are studied. The number of factors is limited to six to reduce the SP survey's complexity and ease the incorporation of models into the corresponding RTDM. More factors, such as the number of turns, street lighting, weather conditions especially in Nordic countries like Finland with long and intense winters, as well as bike-related costs, should be investigated. Besides, recent SP studies (Vedel et al., 2017; Majumdar and Mitra, 2018;

[4] Proulx et al. (2016), for instance, showed that the average error rate for automated pedestrian and bicycle counting technologies could be up to 17%.

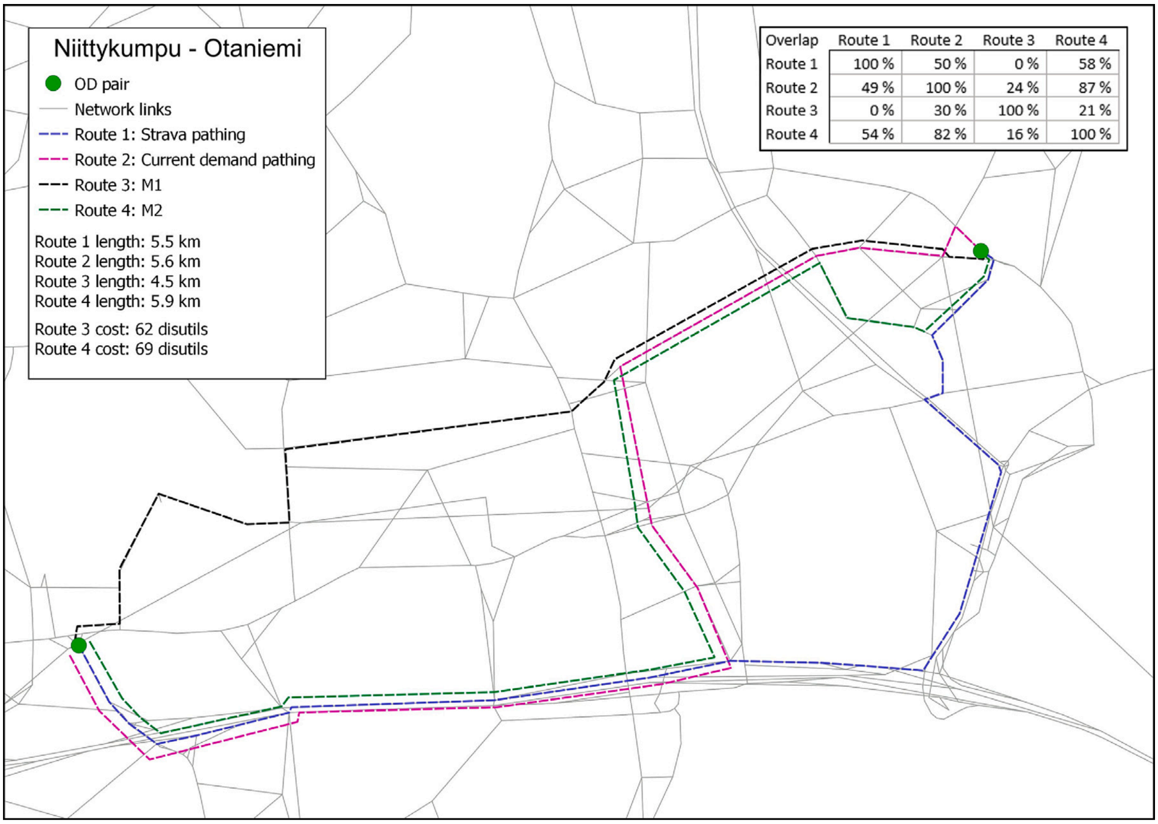

Fig. 5. Route tracing of various models between one OD pair: Niittykumpu and Otaniemi.

Hardinghaus and Papantoniou, 2020) applied mixed Logit over multinomial Logit models to allow the existence of heterogeneity among responses. Although SP has several advantages over RP, such as its ability to cover several scenarios with full control over the variables, it suffers from certain limitations including the potential for hypothetical bias and limited behavioural realism. Thus, additional data collection effort is recommended to strengthen the analysis. As walking is also being promoted in urban planning, incorporating walking into RTDM as a separate mode can be conducted through choice theory, and combined with the information presented in this study for applying a similar framework in Helmet. In addition, discussion surrounding e-bike's influence on route choice preferences is perceived to be absent.

CRediT authorship contribution statement

Konsta Tarkkala: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Shaghayegh Vosough:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Jens West:** Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Claudio Roncoli:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis.

Declaration of competing interest

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.

Data availability

The authors do not have permission to share data.

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