

Predicting active travel durations in Tehran: A multilayer perceptron approach

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ABSTRACT

This study investigates the impact of built environment factors (BEFs) on active travel (walking and cycling) habits in Tehran, Iran, aiming to reduce car dependency and promote sustainable urban transportation. Utilizing data from the Transport, Health, and Environment Survey (THES), the study employs Multilayer Perceptron (MLP) models to analyze how walkability, cyclability, destination accessibility, and land use density influence the duration and frequency of walking and cycling trips across different purposes: shopping, recreational, cultural, and work-related travel. Key findings reveal that walkability and destination accessibility significantly influence walking trip durations, while cyclability and land use density strongly impact cycling trip durations, particularly for retail and leisure activities. Sensitivity analysis demonstrates that even minor improvements (5–20 %) in perceived BEFs can lead to substantial increases in active travel durations. These findings underscore the critical role of urban planning in promoting sustainable transportation, emphasizing the need for policies that enhance walkability, cycling infrastructure, and accessible land use planning to encourage active travel and reduce car dependency in urban areas.

1. Introduction

Recently, modernization and car dependency have resulted in physical inactivity and sedentary behaviors in many societies, leading to numerous health problems, including obesity, high blood pressure and cholesterol levels, and diabetes (Thivel et al., 2018). Regarding the importance of being sufficiently physically active, Researchers found that people who engaged in moderate to vigorous physical activity faced a lower risk of health problems and non-communicable diseases compared to those reporting no adequate activity (Ding et al., 2016). Among people's daily habits, walking and cycling, also known as active and independent modes of transportation, are the most practical and common ways to fulfill sufficient physical activity levels (Mitra, 2013). Previous studies have also depicted that people who travel on foot or by bicycle experience healthier lifestyles and more life satisfaction than those traveling by private cars or public transportation (De Vos et al., 2016; Shaer et al., 2021). In addition, cycling increases the range of mobility and access to opportunities and services over long distances, compared to walking (Shaer et al., 2021), and provides quicker and cheaper trips than transit in congested areas (Lee et al., 2018).

Furthermore, walking and cycling have recently gained worldwide popularity among urban planners as environmentally friendly substitutes for private cars to promote urban mobility and achieve sustainable transportation goals (Böcker et al., 2020). The modal shift toward active modes not only reduces road congestion and incidents, increasing parking space demand, noise and air pollution, greenhouse gas emissions, and fossil fuel consumption (Li et al., 2021; Dehghani & Soltani, 2024; Nguyen et al., 2018) but also mitigates the first and last mile problem of public transportation (Chen et al., 2022). To this end, in addition to incentive and disincentive policies to decrease the usage of private cars, urban planners and authorities should aim to make residential neighborhood environments more cycling- and walking-friendly. Numerous studies have demonstrated a significant association between the built environment and people's travel behavior, especially the choice of active travel modes.

To promote sustainable mobility, policymakers are increasingly adopting car-reduction strategies, but their effectiveness depends on factors such as political commitment, urban planning integration, and evidence-based policies (van der Lee & Veeneman, 2025). Models like the 15-minute city emphasize walkability and local accessibility by

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using structured, modular street networks to enhance pedestrian movement (Alawadi et al., 2025). Research on Abu Dhabi's modular NPU and Dubai's non-modular NPU shows that structured layouts improve pedestrian route directness, while irregular patterns hinder walkability (Alawadi et al., 2025). Similarly, Barcelona's Superblocks model prioritizes pedestrian zones by restricting vehicle traffic while maintaining accessibility. These planning models align with this study's objective to examine how built environment factors (BEFs)—including walkability, cyclability, land use density, and destination accessibility—influence active travel behaviors in Tehran.

Generally, the built environment refers to the human-made surroundings where people live, work, and meet their daily needs (Roof & Oleru, 2008). Key built environment factors (BEFs) include land use density and diversity, street design and patterns, destination accessibility, distance to transit, walkability, cyclability, bike-sharing infrastructure, aesthetics, safety, security, and population density (Shaer et al., 2021; Soltani et al., 2022b). Despite growing interest, most scholars have applied traditional statistical models to analyze the relationships between BEFs and mobility behavior. However, a major limitation of these models is their inability to capture complex nonlinear relationships (Tao et al., 2020).

Statistical models (e.g., Poisson regression, Negative Binomial regression, Multivariate regression, Random Effect Negative Binomial, and Multinomial Logit) primarily rely on strong assumptions (e.g., normal distribution for the error term, linearity, and equality of variance) and rigid model structures assuming a predefined relationship between the dependent and independent variables (Ma et al., 2022). Results could be biased if the data is inconsistent with those assumptions or if the proper relationship between dependent and independent variables does not follow the predefined structure. Therefore, there is a need for methods addressing the critical limitations of statistical methods. Artificial Intelligence (AI) modeling, especially Artificial Neural Network (ANN) models, has gained growing attention as an alternative approach that is capable of accounting for nonlinear and complex relationships and predicting multiple target variables (Y. Y. Yang et al., 2022). An Artificial Neural Network (ANN) is a computational model inspired by the human brain, consisting of interconnected neurons organized in layers. A Multilayer Perceptron (MLP) is a type of ANN with at least three layers: an input layer, one or more hidden layers, and an output layer, where each neuron applies an activation function to process data. MLPs are fully connected feedforward networks that learn through backpropagation, adjusting weights to minimize errors. They are widely used for classification and regression tasks, forming the foundation of many deep learning models (Pham et al., 2019; Sharma et al., 2023).

MLP is uniquely suited for modeling active travel duration as it captures complex interactions between socioeconomic, environmental, and behavioral factors without relying on predefined assumptions (Betkier., 2025). Unlike traditional models, MLP learns patterns from high-dimensional, nonlinear data, improving predictive accuracy and generalization. This study advances the field by demonstrating MLP's effectiveness in uncovering nuanced travel patterns often missed by conventional approaches.

In addition to applying cutting-edge methods to analyze BEF on walking and cycling and addressing limitations of statistical models, previous studies highlighted the importance of distinguishing between different active travel purposes because of the different roles of BEF on walking and cycling behavior (Vale et al., 2016). For instance, Gao et al. (2020), and Shaer and Haghsheenas (2021) have shown that BEF has different effects on active travel for different purposes, such as shopping, access to public transportation stations and destinations, and recreational. Moreover, Cerin et al. (2009) illustrated a different association between active travel and health indicators. Hence, the relationships between active travel for different purposes and BEF should be analyzed separately rather than evaluating them without considering trip purposes.

Despite the growing body of literature on BEFs and active travel, most studies rely on econometric or statistical models, with only limited research employing AI techniques. Therefore, the present study aims to apply MLP to analyze the relationship between perceived BEFs and walking/cycling durations for different trip purposes in Tehran, Iran. As a rapidly developing metropolis, Tehran presents a unique case study due to its challenges with population growth, air pollution, traffic congestion, and urban sprawl (Abdi & Soltani, 2022). Additionally, the city's diverse socio-cultural dynamics significantly influence travel behavior (Dingil et al., 2019; Panahi et al., 2022; Qadikolaie et al., 2024). Examining active travel behavior in Tehran can provide valuable insights for cities facing similar mobility challenges.

MLP was selected as the modeling approach due to its ability to approximate nonlinear relationships between variables, making it one of the most effective ANN models for complex mobility studies (Pham et al., 2019). This paper is the first to utilize MLP to explore the nonlinear relationships between BEF and active mobility for different trip purposes. We use the most common perceived BEF in the literature, such as land use density and diversity, design and street pattern, destination accessibility and distance to transit, walkability, cyclability and bike-sharing infrastructures, aesthetics, and security. Prior research indicates that in Iran, the most common purposes for active travel include cultural activities, shopping, recreation, and work-related trips (Shaer et al., 2022; Soltani et al., 2022a, 2019a). Therefore, these four trip purposes are analyzed in the present study. The objectives of this paper seek to investigate the connections between BEF and active travel behavior for various trip goals. Additionally, the study aims to evaluate the efficacy of MLP modeling in revealing these intricate linkages. The research questions are listed below:

- What is the impact of perceived BEF, such as walkability, cyclability, destination accessibility, and land use density, on the length of walking and cycling for various trip reasons in urban locations, namely Tehran, Iran?
- What are the distinctive effects of BEF on active travel behavior for different trip purposes such as shopping, recreational, cultural, and work-related travels, emphasizing the relevant aspects unique to each purpose?
- Using data from the THES conducted in Tehran, Iran, can MLP modeling accurately uncover the complex connections between perceived BEF and the duration of walking and cycling trips for various objectives?

This research examines the influence of multiple environmental factors, such as walkability, cyclability, destination accessibility, and land use density, on transportation choices for shopping, recreation, cultural outings, and work-related travel. By dissecting the impact of these elements, the study provides a detailed understanding of how they affect people's decisions regarding mobility. A unique addition is MLP modeling, a methodology that outperforms conventional statistical methods. The study employs MLP to examine the complicated and nonlinear relationships between perceived BEF and active travel behaviors. This analysis offers a more comprehensive understanding of the complex interplay between environmental elements and travel choices, particularly in metropolitan settings like Tehran, Iran.

2. Literature

In this section, we review the literature on the associations between Built Environment Factors (BEF) and active travel using statistical and AI models, highlighting how the present paper contributes to the literature. Cervero et al. (2009) investigated various BEFs, including land use density and diversity, transit accessibility, street density and connectivity, and proximity to cycling routes. While dense and diverse land uses do not significantly affect active travel, other factors, such as transit accessibility and street connectivity, have remarkable impacts. Using a

logit regression model, [Troped et al. \(2011\)](#) demonstrated that accessibility to recreation centers and retail availability is positively associated with women's physical activity in the USA. Similarly, [Beenackers et al. \(2012\)](#) explored the influence of BEF on cycling choices in Perth, Australia, using binomial logistic regression modeling. They revealed that residential density and accessibility to parks and recreation centers positively relate to cycling activities.

To analyze the relationships between Built Environment Factors (BEF) and active travel in Curitiba, Brazil, [Hino et al. \(2014\)](#) demonstrated that the density of Bus Rapid Transit (BRT) stations and the proportion of residential and commercial regions positively affect the likelihood of walking. Conversely, diverse land uses and traffic lights adversely affected bicycle travel. In Hangzhou, China, [Su et al. \(2014\)](#) examined the effects of BEF on destinations' accessibility, street patterns and connectivity, quality of cycling and walking routes, and traffic safety on physical activity. Using multi-level regression modeling, they found that perceived accessibility to physical activity destinations significantly affects men's physical activity, while aesthetics significantly impacts women's walking. [Heesch et al. \(2015\)](#) investigated various BEF influencing cycling for transport and recreation in Brisbane, Australia. They found that distance to transit, destination accessibility, traffic safety, and vegetation were strongly associated with cycling. [Christiansen et al. \(2016\)](#) analyzed the relationships between land use mix, street pattern and connectivity, residential density, park density, and active travel. They concluded that all these variables positively affect walking, though park density does not positively influence cycling.

To explore the effects of Built Environment Factors (BEF) on active travel in Beijing, China, [Zhao et al. \(2018\)](#) showed that the density of population and jobs and accessibility to public services were positively associated with walking and cycling. [Gao et al. \(2018\)](#) examined the impacts of residential and street density, land use mix, and distance to transit stations on cycling duration in The Netherlands. Using multi-level Tobit regression methods, they found that cycling duration was positively affected by residential density, the number of bus stops, and available transit stations. [Lu et al. \(2019\)](#) investigated the relationship between young people's walking and BEF, such as the density of population, bus stops, facilities, and mixed land use. They demonstrated that shop retail and population density had positive effects, while bus stop density negatively influenced the total walking time. [Cheng et al. \(2019\)](#) used similar variables and the zero-inflated ordered probit model to analyze the influence of BEF on older adults' active travel in China. Their results highlighted that accessible retail shops and recreational facilities significantly affected older adults' active travel. [Stefansdottir et al. \(2019\)](#) assessed the effects of population density, distance to the city center and services, and park accessibility on physical activity and active travel. They found that improving cycling and walking routes to access facilities and parks increased activity.

Using the International Physical Activity Questionnaire-Long Form, [Ferrari et al. \(2020\)](#) revealed that land use mix and traffic safety positively influenced the likelihood of walking, while walkable and cyclable routes and aesthetics promoted cycling. [Neves et al. \(2021\)](#) utilized binomial logistic regression to analyze the associations between land use density and diversity, distance to transit, destination accessibility, and street density and connectivity on walking choices. Their findings indicated that land use diversity was the most influential factor in walking in São Paulo, Brazil. [Ahmadipour et al. \(2021\)](#) examined the effective BEF on walking choices in Tehran, Iran, using regression and binomial probit models. They found that land use density, diversity, and residential density positively affected walking likelihood. Additionally, they highlighted that gym availability was positively associated with walking duration. [Frank et al. \(2022\)](#) analyzed self-reported data from British Columbia, Canada, using general linear multivariable methods to explore the relationships between BEF, health factors (BMI and diabetes), and physical activity (moderate to vigorous physical activity and walking). Their study found that accessibility to green areas and

neighborhood walkability significantly impacted physical activity and walking and were associated with lower rates of diabetes and obesity. They emphasized that walkable neighborhoods with mixed and accessible land uses and transit systems are crucial in enhancing health and promoting active travel.

Focusing on the applications of machine learning methods, [Cheng et al. \(2020\)](#) employed a random forest model to examine nonlinear relationships between various Built Environment Factors (BEF) such as population density, bus stops, shared bicycle stations, street pattern and connectivity, recreation service availability, and mixed land uses, and the walking habits of older adults in China. Their findings indicated that population density and mixed land uses influence older adults' walking only up to a certain threshold, beyond which an increase in these variables leads to a decrease in walking duration. [Liu et al. \(2021\)](#) utilized a gradient-boosting decision tree (GBDT) to study the impacts of BEF, including bus stop density, occupational density, intersection density, land use diversity, and distance to the city center, on active travel in Xiamen, China. Their results highlighted that BEF had a more significant impact on active travel than socio-economic factors, with stronger relationships observed for shopping trips than work-related travel. Similarly, [Huang et al. \(2021\)](#) applied GBDT to explore the relationships between BEF, including population density, land use mix, the number of public transportation stops, aesthetics, and students' physical activity in Xian, China. The study revealed that land use mix and proximity to schools and parks were the most influential factors on physical activity levels.

[H. Yang et al. \(2022\)](#) also employed the random forest approach to examine the effects of population density, land use mix, street pattern, and accessibility to transit and services on active travel duration for men and women. Their findings indicated that service accessibility significantly increased active travel time for men, whereas population density was the most influential factor for women's active travel duration. Additionally, [H. Yang et al. \(2022\)](#) applied Gradient Boosting Decision Tree (GBDT) methods to assess the nonlinear relationships between BEF and the walking behavior of approximately one thousand employees in Shanghai, China. The results highlighted that aesthetics, mixed land uses, and accessibility to city centers and destinations, particularly workplaces, significantly influenced walking behavior.

An aspect of the studies that is noteworthy is their geographical diversity, which includes numerous countries and urban landscapes ([Cheng et al., 2020](#); [Liu et al., 2021](#); [Huang et al., 2021](#); [H. Yang et al., 2022](#); [Neves et al., 2021](#); [Ahmadipour et al., 2021](#); [Soltani et al., 2019](#)). This is evident from [Table 1](#). A global perspective on the effects of BEFs on active travel is afforded by this diversity, which considers the subtleties of various infrastructure and cultural contexts. Furthermore, the research encompasses a diverse range of BEF variables, such as transit connectivity ([Neves et al., 2021](#); [H. Yang et al., 2022](#)), density ([Cheng et al., 2020](#); [Liu et al., 2021](#); [Ahmadipour et al., 2021](#)), accessibility ([Ferrari et al., 2020](#); [Cheng et al., 2020](#); [Liu et al., 2021](#); [H. Yang et al., 2022](#)), and safety ([Ferrari et al., 2020](#); [Cheng et al., 2020](#); [Stefansdottir et al., 2019](#)), thereby providing a comprehensive comprehension of the influence of urban environments on active mobility. The literature review offers extensive research papers that employ statistical models, including logistic, binomial, and multi-level regression analyses, and sophisticated artificial intelligence techniques like random forest and gradient-boosting decision trees (GBDT). These methodologies facilitate the investigation of intricate correlations between BEF and active travel. By incorporating a variety of methodologies, a comprehensive comprehension of the elements that impact active mobility in urban environments is achieved.

Although the literature agrees regarding identifying critical BEF factors that impact active travel, including density, accessibility, and safety, there are conflicting results. For example, the influence of population density on active travel may differ among research studies, as some propose positive correlations ([Evans et al., 2022](#)), whereas others indicate conflicting findings ([Gim, 2012](#)). The variations underscore the

Table 1
Summary of previous studies.

Study (Authors, Year)	Context	Specific BEF Focused On	ANN or ML Techniques Employed
Cheng et al. (2020)	Older adults' walking in China	Population density, mixed land uses, street pattern, transit accessibility	Random Forest
Liu et al. (2021)	Active travel in Xiamen, China	Bus stop density, occupational density, intersection density, land use diversity, distance to the city center	Gradient Boosting Decision Tree (GBDT)
Huang et al. (2021)	Students' physical activity in Xian, China	Population density, land use mix, public transportation stops, aesthetics	Gradient Boosting Decision Tree (GBDT)
H. Yang et al. (2022)	Active travel duration for men and women in Shanghai, China	Population density, land use mix, street pattern, transit and services accessibility	Random Forest, Gradient Boosting Decision Tree (GBDT)
Neves et al. (2021)	Walking in São Paulo, Brazil	Land use diversity, distance to transit, street density, and connectivity	Binomial Logistic Regression
Ahmadipour et al. (2021)	Walking in Tehran, Iran	Land use density and diversity, residential density, gym availability	Regression, Binomial Probit Model
Korbmacher and Tordeux (2021)	Pedestrian Trajectory Prediction in Paris, France	Scene topology, pedestrian interactions	Deep Learning, Knowledge-based Models
Martín-Baos et al. (2023)	Travel mode choice prediction in Madrid, Spain	Various travel mode factors	Machine Learning Approaches

intricacy of urban settings and the necessity for nuanced analyses. Furthermore, the generalizability of the findings needs to be improved, but several limitations exist. Self-reported data may introduce potential biases and inaccuracies in certain studies (Flint et al., 2014). Additionally, the applicability of the findings from these studies is constrained by contextual differences among various urban environments and cultural contexts (Evans et al., 2022). The difficulty in extrapolating results to broader contexts highlights the criticality of exercising prudence in interpreting and conducting analyses specific to each situation.

While artificial intelligence-based approaches such as decision trees (Cheng et al., 2020) and gradient boosting (Huang et al., 2021) have been increasingly utilized to model active travel, the application of Multilayer Perceptron (MLP) in this domain remains relatively limited. Betkier (2025) demonstrated the efficacy of MLP in combination with a Graph Convolutional Neural Network (GCN) for travel time prediction in Poland's Mazovia region. This study highlighted the importance of incorporating spatial and temporal dependencies, revealing that key factors such as weather conditions, time of day, and road infrastructure significantly influenced predictive accuracy. Notably, the optimized GCN-MLP model outperformed traditional MLP approaches, achieving a Mean Absolute Percentage Error (MAPE) of approximately 8 % and demonstrating superior performance in minimizing Mean Squared Error (MSE). Zhang et al. (2023) used MLP to analyze active travel behaviors but lacked differentiation across trip purposes, limiting its interpretability. Compared to tree-based models like random forests, MLP excels in capturing complex, nonlinear relationships among behavioral and environmental factors (BEFs), particularly when properly regularized to mitigate overfitting (Goodfellow et al., 2016). This study builds on prior work by leveraging MLP to analyze active travel duration across distinct trip purposes, offering a more granular perspective on how BEFs

influence walking and cycling behaviors. By incorporating regularization techniques such as dropout and L2 regularization, this approach ensures robust model performance while maintaining interpretability (Srivastava et al., 2014). These findings underscore the potential of MLP in capturing complex feature interactions within transport modeling.

The literature review identifies several research gaps this study aims to address and significantly contribute to. Using statistical models, current research extensively examines the connection between built environment factors (BEF) and active travel. However, more studies need to employ advanced AI methods, specifically multilayer perceptron (MLP) modeling, to fully comprehend the intricate relationships between BEF and the durations of walking and cycling for different trip purposes. Prior research has not utilized MLP applications, which hinders a thorough investigation of the complex and nonlinear connections between perceived BEF and active travel behaviors. Additionally, previous studies often need to categorize the purposes of the trip before exploring the effects of BEF on active transportation. As a result, there is limited understanding of how these factors influence walking and cycling behaviors for various activities, such as shopping, recreational outings, cultural activities, and work-related trips.

3. Methodology

3.1. ANN and MLP models

Artificial Neural Network (ANN) models, inspired by biological neural structures, serve as robust tools for data processing. They have been extensively applied in various domains, including classification, clustering, pattern recognition, function approximation, estimation, and optimization. A fundamental strength of ANNs lies in their architecture, which comprises multiple interconnected processing units, or neurons, that collaboratively address complex computational challenges (Pham et al., 2019). Among the diverse ANN models, the Multilayer Perceptron (MLP) is particularly distinguished for its simplicity and computational efficiency. As a feedforward ANN, MLP consists of a minimum of three layers: an input layer, one or more hidden layers, and an output layer. Each node, except for those in the input layer, functions as a neuron employing a nonlinear activation function. This structural design enables MLPs to effectively model complex, nonlinear relationships between input and output variables. The backpropagation algorithm, utilized in MLP, applies gradient descent to optimize the loss function, facilitating effective network training and performance enhancement (Nelles, 2020).

The selection of the Multilayer Perceptron (MLP) for this research is based on its ability to address the limitations associated with traditional statistical methods. While logistic and linear regression techniques are effective for analyzing linear relationships, they often fall short in capturing the complex, nonlinear interactions inherent in real-world data. In contrast, MLPs, with their deep learning capabilities, can model these intricate relationships more accurately, leading to more reliable predictions and insights. Additionally, MLP's supervised learning approach, which involves training the model on labeled data, aligns well with the objectives of this study. This method enables precise model tuning to accurately represent underlying data patterns, making MLP a powerful tool for analyzing the complex relationships between Built Environment Factors (BEF) and active travel behaviors. By leveraging MLP, this research seeks to overcome the challenges posed by conventional methods and develop a more comprehensive understanding of the influence of urban environments on active mobility. The architecture of a feedforward MLP neural network is illustrated in Fig. 1.

Mathematically, an MLP model can be written as the following equation:

$$y_t = w_0 + \sum_{k=1}^l w_{kf} \left(\sum_{j=1}^n \beta_{j,k} y_{t-1} + \beta_{0,k} \right) + \varepsilon_t$$

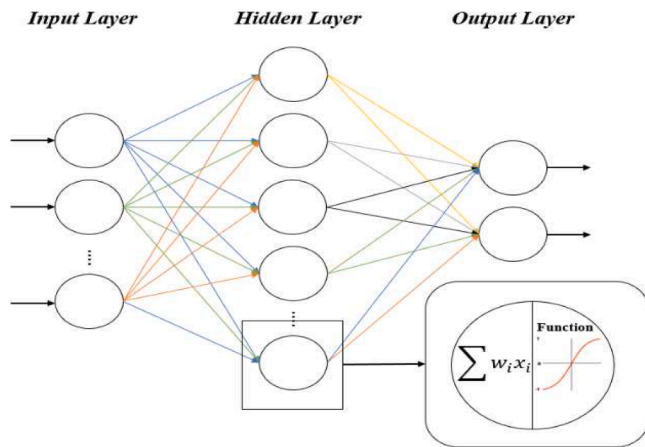


Fig. 1. The architecture of a feedforward MLP model.

Where y_i is a target variable in the output layers; y_{i-1} the explanatory or dependent variable in the input layer; n the number of neurons in the input layer; l the number of neurons in the hidden layers; f activation functions; w_k the weight vector for connection from hidden to output neurons; $\beta_{j,k}$ weight vector for connections from input to hidden neurons; and w_0 and β_0 bias terms. Transfer or activation functions in the hidden layers link the input layers to the output (Arulampalam & Bouzerdoun, 2003). Hyperbolic tangent sigmoid, commonly known as Tansig, and Log-sigmoid, commonly known as Logsig, are two frequently used activation functions.

Among the various ANN architectures, the MLP is selected for analyzing the relationship between BEF and active travel due to its status as a universal approximator and its effectiveness as one of the most powerful artificial neural networks. MLP has the capability to approximate any nonlinear relationship between dependent and independent variables, making it well-suited for capturing the complexities of urban mobility patterns (Pham et al., 2019). Additionally, this study employs cross-validation and early-stopping techniques to optimize the MLP model's performance and prevent overfitting.

In determining the number of hidden layers and iterations, Mrowicki et al. (2020) and Chakraborty et al. (2019) demonstrated that a feedforward MLP neural network with a single hidden layer is capable of approximating any bounded continuous and multivariate function with a specified degree of precision. These studies further indicate that such a network can approximate any measurable function to any desired accuracy, affirming that feedforward MLP neural networks belong to the class of universal approximators. Consequently, we adopt an architecture with one hidden layer for the MLP model. Additionally, we employ the early stopping criterion to determine the optimal number of training iterations for weight matrix optimization. This criterion helps prevent overfitting by monitoring the generalization error and halting the training process if no improvement is observed or if the error increases after a certain number of iterations (Arulampalam & Bouzerdoun, 2003).

3.2. Data and case study

This study used data from the Transport, Health, and Environment Survey (THES). THES was conducted by the Municipality and the State Welfare Organization of Tehran, Iran, between October 2021 and August 2022 to get insight into how BEF affects citizens' health and active travel behavior. The largest city in the Middle East and the capital of Iran, Tehran, covers a land area of about 750 Km², splitting into 22 districts with their municipality. At the 2021 census, the city's population was about 8.7 million. In the recent decade, traffic congestion, road incidents, and air and noise pollution have become an absolute nightmare for citizens because of an unstoppable increase in car dependency

and other car-oriented policies in the city. Therefore, incentive and disincentive policies to increase cycling and walking are a solution to this predicament. In doing so, Tehran's municipality has assigned a considerable budget to develop infrastructures for travel on foot or by bike to fight against the problems mentioned above. THES targeted >50,000 individuals over 15 years old who were randomly selected in 22 districts of the metropolis. Thirty-eight thousand five hundred thirty people participated in the survey, and 31,174 interviewees completed the survey. Fig. 2 presents the administrative districts of Tehran and its major road network.

The sampling method was a multi-stage cluster. In the first stage, each of the metropolitan districts of Tehran was considered as a general cluster, the districts within them as sub-clusters, and the blocks within the districts as sub-clusters of the districts. Then, proportional to the number of samples allocated in each district, several blocks were randomly selected from each district. Within the blocks, people were interviewed using a random systematic method. The interviews were conducted in temporary stations on sidewalks, green areas, and parks, and people were randomly invited to the interview. Then, the study and its aims were explained to the participants verbally. People also visited these stations to get free information about their health. Inclusion criteria included having at least 15 years old and willingness to participate in the survey, and exclusion criteria were reluctant to participate. Each interview lasted between 25 and 40 min, and at the end of the interview, people got free check-up results.

The structured questionnaire was also designed in three parts: 1) Socio-economic characteristics at the household and individual level (age, gender, average monthly income, ownership of car, bicycle, and driving license, and the number of cars in the family), 2) Active travel information, such as purpose, duration, and frequency (per week) of walking and cycling, and 3) Perceived BEF (9-point Likert scale) including walkability, cyclability and bike-sharing infrastructures, land uses density and diversity, design and street pattern, destination accessibility and distance to transit, aesthetics, and security.

Focusing on preparing data, the data was divided into the training dataset, composed of 80 % of observations, and the test dataset, composed of 20 %. It is worth noting that we also tried other divisions, but this division gained the best performance. A normalization process (min-max) was also conducted to scale input variables in the range of 0–1, considering that the normalization process is shown to effectively increase the accuracy and performance of models (Madhilarasan & Deepa, 2017). The MLP model consisted of one hidden layer with 26 neurons, determined through a trial-and-error process. The hidden layer utilized the hyperbolic tangent sigmoid (Tansig) activation function, while a linear activation function was applied to the output layer. The learning rate was set to 0.01, and training was performed using the Levenberg-Marquardt backpropagation algorithm. To prevent overfitting, an early stopping criterion was implemented, where training ceased when the validation loss no longer improved. We used MATLAB 2021a for modeling purposes.

4. Results

Of 31,174 participants, 63 % are men, 53 % have a driving license, 36 % own a private car, 58 % are employed, and 19 % have a bicycle. The related sociodemographic information is presented in Table 2.

Table 3 shows that walking and cycling trips include shopping (walking (w) = 23.1 %, cycling (b) = 21 %), cultural (w = 19.7 %, b = 13.5 %), recreational (w = 37.1 %, b = 43.6 %), work (w = 13.9 %, b = 12.2 %), and others (before: w = 6.2 %, b = 9.7 %). The results also illustrate that the average duration and frequency of walking and cycling per week were 141.7 and 58.3 min and 24.1 and 10.7, respectively. Briefly, recreational and shopping purposes have the most significant amounts among percentages, the average duration of, and the average frequency of walking and cycling trips.

We used Root-Mean-Square Error (RMSE) and the R^2 to show the

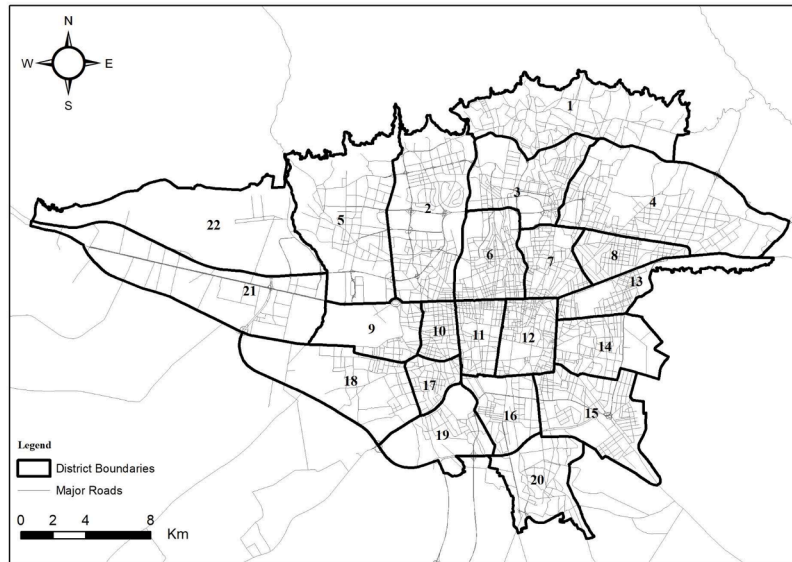


Fig. 2. Map of Tehran showing administrative district boundaries and major road network.

Table 2
Interviewees' sociodemographic characteristics.

	n	%		n	%
Gender			Driving license ownership		
Male	19,639	63	Yes	16,522	53
Female	11,535	37	No	14,652	47
Employed			Car ownership		
No	18,080	58	Yes	11,222	36
Yes	13,094	42	No	19,952	54
Monthly Income (Tomans)			Bike ownership		
≤ 10 million	23,068	74	Yes	5923	19
> 10 million	8106	26	No	25,251	81
Age category			Education		
15–39	14,963	48	>16	5611	18
40–64	9352	30	12–16	14,651	47
+65	6859	22	< 12	10,912	35

Table 3
Percentages, Ave. duration, and Ave. frequency of walking and cycling trips.

	Percent		Ave. duration (min)		Ave. frequency	
	walking	cycling	waking	cycling	waking	cycling
Shopping	31.1	29.0	33.8	12.4	5.4	2.0
Cultural	19.7	15.5	23.0	10.1	4.7	1.6
Recreational	34.1	40.6	49.7	28.1	6.6	3.4
Work	10.9	9.2	18.0	7.7	3.9	2.4
Other	4.2	5.7	17.2	6.0	3.5	1.3
Total	100	100	141.7	58.3	24.1	10.7

Table 4
Predictability of walking and cycling models for different purposes.

	Dataset	Shopping		Recreational		Cultural		Work	
		RMSE	R ²	RMSE	R ²	RMSE	R ²	RMSE	R ²
Walking	Train	8.11	0.60	9.08	0.52	14.71	0.46	23.87	0.30
	Test	10.38	0.59	10.60	0.50	16.52	0.41	23.96	0.29
Cycling	Train	13.04	0.57	14.66	0.49	19.00	0.36	25.40	0.27
	Test	13.53	0.55	15.82	0.45	20.11	0.33	26.37	0.25

predictability of models of walking and cycling for different purposes, including shopping, recreational, cultural, and work. These predictability measures are provided in Table 4. Considering these two measurements, our findings show that walking and cycling models offer the same levels of accuracy for shopping and recreation, which is better than other purposes. These variations in prediction are due to differences in the amount of data in models with various purposes. For instance, high RMSEs and low R²s in walking and cycling models for purposes of religion and work originate from this issue. Hence, further studies with the same amount of data or over/under-sampling methods for different purposes are essential to analyze the accuracy and predictability of models.

4.1. Variable importance and sensitivity analysis

We now examine how different variables contribute to crash predictability in different models. In doing so, we evaluate variable importance values and note that all variables are scaled between 0 and 1 so that we can conveniently compare their importance in various models. Policymakers can also consider different measures to make the built environment more walkable- and cyclable-friendly. In order to prioritize these measures and inform the budget allocation process, the first step is to quantify the effectiveness of each policy. In this section, we consider some changes that could increase walking and cycling for four trip purposes, including increasing perceived walkability, cyclability, destination accessibility, the density of land uses, aesthetics, bike-sharing infrastructures, and distance to transit. To assess the impacts of these measures, we trained the MLP models, and then 5, 10, 15, and 20 percent increases were made to the selected variables in the test dataset. The variable importance and sensitivity analysis results are presented in Figs 3 to 10.



Fig. 3. Variable importance in shopping trips model.
Source: Authors' analysis, based on THES 2021–2022.

4.1.1. Shopping trips model

Walkability followed by destination accessibility are the most influential factors on walking duration, and cyclability followed by land use density are the most influential variables on the duration of cycling for shopping purposes. However, aesthetics followed by design and street patterns positively impact walking and cycling in shopping trips. Other input variables, including bike-sharing infrastructures, distance to transit, and security, also have moderate effects on variables of interest in these trips (Fig. 3). Fig. 4 also depicts that by increasing the value of perceived walkability and destination accessibility from 5 % to 20 %, the predicted average of walking duration in shopping trips increases from 4.5 % to 14.1 % and from 2 % to around 7 %, respectively. Further, 5 % to 20 % changes in perceived cyclability and land use density lead to about 12 % and 5 % raises in cycling duration in this model.

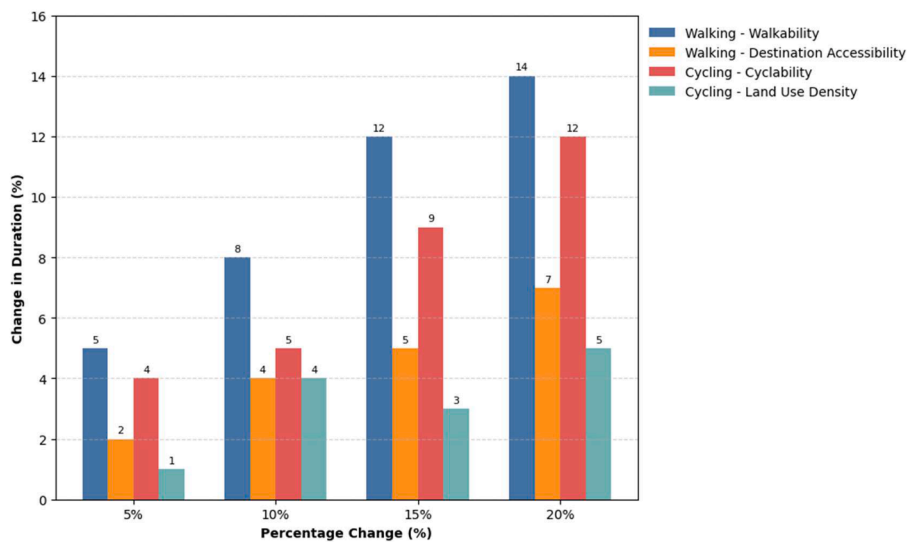


Fig. 4. Sensitivity analysis of changes in the duration of walking and cycling for shopping trips.
Source: Authors' analysis, based on THES 2021–2022.

4.1.2. Recreational trips model

In trips for recreation, walkability and aesthetics are at the top of influential factors for walking duration. Turning to trips by bicycle, cyclability followed by bike-sharing infrastructures are the most influential variables on the duration of cycling in recreational trips. It seems that distance to transit, density and diversity of land uses, and design and street pattern have minor impacts on the duration of walking and cycling in recreational trips in Tehran, Iran (Fig. 5). The results of stativity analysis illustrate that 20 % rises in perceived walkability and aesthetics contribute to just <10 % increase in the percentages of walking duration (Fig. 6). These changes to perceived cyclability and bike-sharing infrastructures have led to 8 % and around 10 % increases, respectively, in the duration of cycling in recreational trips (Fig. 6).



Fig. 5. Variable importance in recreational trips model.
Source: Authors' analysis, based on THES 2021–2022.

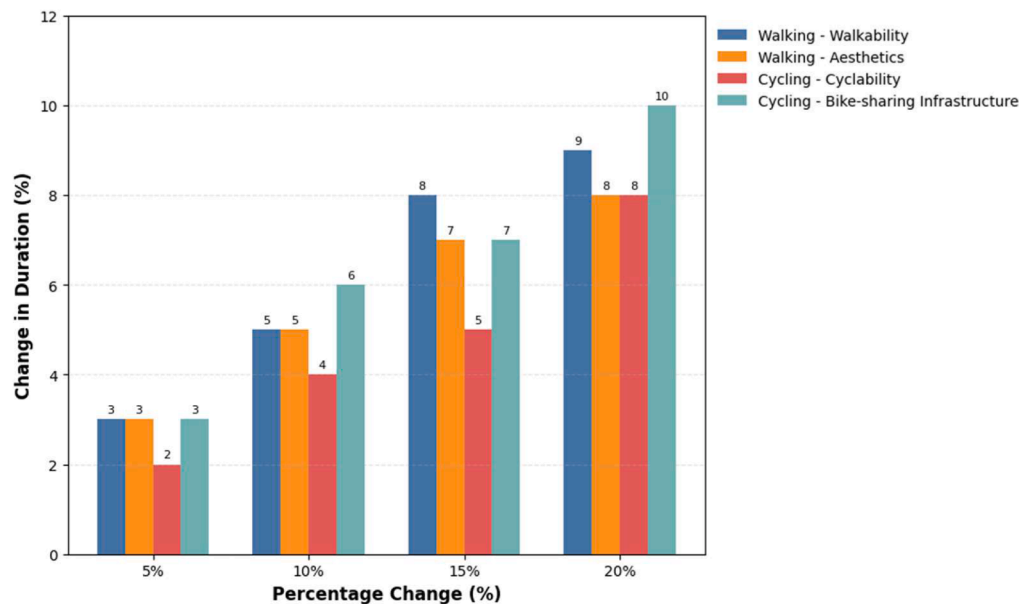


Fig. 6. Sensitivity analysis of changes in the duration of walking and cycling for recreational trips. Source: Authors' analysis, based on THES 2021–2022.

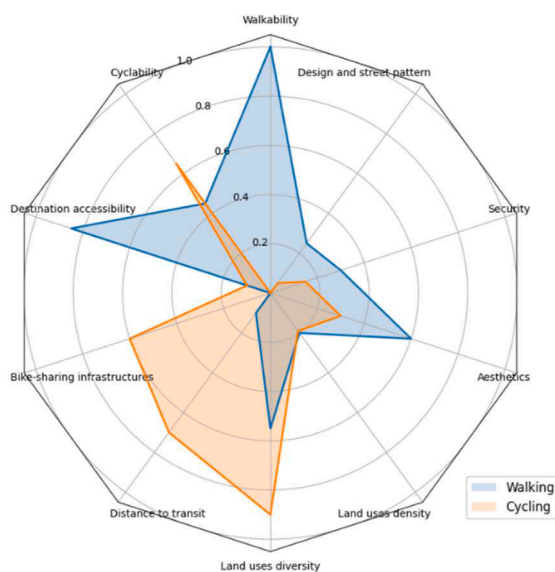


Fig. 7. Variable importance in cultural trips model. Source: Authors' analysis, based on THES 2021–2022.

4.1.3. Cultural trips model

Fig. 7 demonstrates that walkability has the most potent effect on walking duration for cultural trips in Tehran, Iran, with destination accessibility being the next most influential factor. In contrast, bike-sharing infrastructure and distance to transit exhibit the weakest influence in this model. For cycling duration, destination accessibility and land-use density are the most significant Built Environment Factors (BEF). Although we anticipated that other cycling-related factors like cyclability and bike-sharing infrastructure would play a more significant role, the model indicates only moderate effects from these variables. The substantial impact of land-use density could be attributed to people combining multiple activities within a single trip; for instance, people frequently shop or socialize in Iran after completing cultural activities. Among the less impactful factors, design, street pattern, and walkability have only a minor influence on cycling duration in cultural trips.

Furthermore, Fig. 8 shows that increasing perceived walkability and destination accessibility by 5 % to 20 % results in an approximate 7 % rise in walking duration. However, changes in destination accessibility yield less than a 4 % improvement in cycling duration for recreational trips.

4.1.4. Work trips model

Because of car dependency in Iran, people on most of their trips with the purpose of work usually take private vehicles, which is why only <10 percent of active travel is for work (Table 2). Besides, the accuracies (high RMSEs and low R^2) of work trip models are lower than other models because of differences in the amount of data in models with various purposes. However, our findings show that destination accessibility and distance to transit are the most influential variables on walking and cycling in work trips. In contrast, 5 % to 20 % changes in these variables only slightly improve the duration of walking and cycling. However, the most effective BEF in previous models (such as walkability and cyclability) have a moderate influence in these models. Also, the diversity and density of land uses, as well as security and bike-sharing infrastructures, have minor effects on the duration of walking and cycling. To learn more about variable importance and sensitivity analysis, see Figs 9 and 10.

5. Discussion

The sociodemographic features of respondents provide valuable insights into their possible impact on walking and biking activities. Employment situation, income level, age categories, gender, and possession of a driving license or private automobile are essential characteristics that can significantly influence the prevalence and regularity of walking and cycling for different purposes. For example, the data shows that car ownership stands at 36 %, which might impact the preference for using private cars for transportation instead of walking or cycling. Furthermore, one's job position might impact the limitations on time, which in turn affects how often and for how long one engages in walking and cycling activities.

The study emphasizes the diverse effects of BEF on walking and cycling for different types of trips. Factors such as the ease of walking, the accessibility to destinations, the ability to cycle, the density of land uses, the visual appeal, the availability of bike-sharing infrastructure,

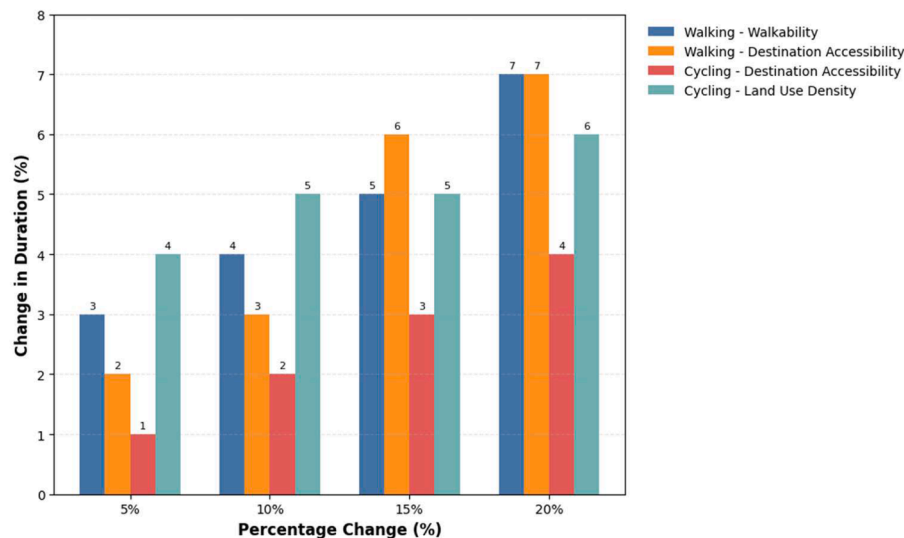


Fig. 8. Sensitivity analysis of changes in the duration of walking and cycling for cultural trips.
Source: Authors' analysis, based on THES 2021–2022.

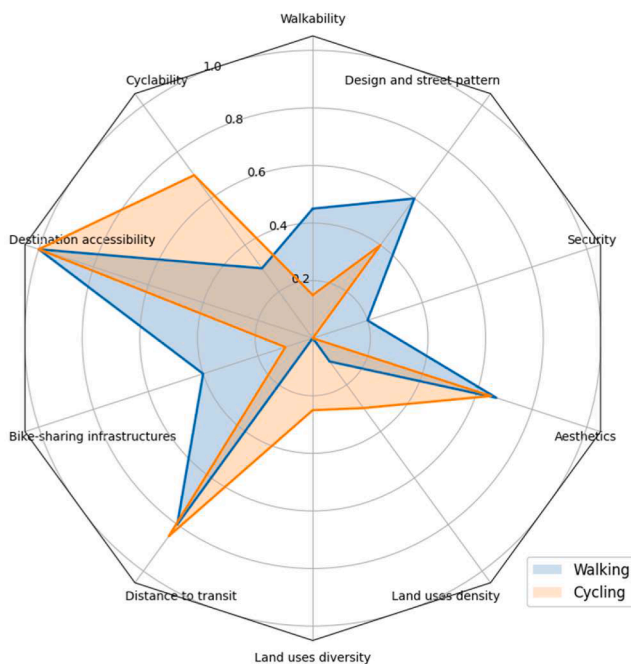


Fig. 9. Variable importance in the work trips model.
Source: Authors' analysis, based on THES 2021–2022.

and the distance to public transportation have different levels of impact on the time of walking and cycling, depending on the purpose of the journey. During shopping visits, the duration of walking is primarily influenced by walkability and destination accessibility. On the other hand, the duration of cycling is highly influenced by factors like cyclability and the density of land uses. Conversely, when it comes to leisurely outings, the ease of walking and the visual appeal of the surroundings affect the amount of time spent walking. However, the availability of cycling infrastructure and bike-sharing systems have a more significant influence on riding duration.

The research findings align with other prior studies on the influence of BEF on active travel behaviors. Consistently, several studies highlight the importance of walkability in encouraging people to walk for extended periods. This is consistent with other research studies (Cervero

et al., 2009; Beenackers et al., 2012; Frank et al., 2022) that emphasize the beneficial impact of walkability on active transportation. Previous studies by Cervero et al. (2009), Zhao et al. (2018), and Cheng et al. (2019) have highlighted the significance of accessible sites in promoting walking and cycling. This aligns with the current emphasis on destination accessibility and its significant impact on active travel (Soltani et al., 2022c, 2019b). The results of this study align with prior research by highlighting the importance of walkability and availability to destinations. However, what sets this study apart is its ability to identify the specific effects of different built environment factors on different types of trips.

In contrast to previous studies that generally emphasize the beneficial impact of BEF on active travel without identifying the aim of the trips (Su et al., 2014; Heesch et al., 2015), this research focuses on the particular effects of BEF on different types of trips. For example, it highlights that while the capacity to cycle affects leisure biking, its effect varies regarding shopping excursions. Moreover, it emphasizes that even little modifications in BEF may significantly influence active transport, offering practical information for policymakers on how incremental improvements in the built environment might promote walking and cycling behaviors.

The predictability of the models varies depending on the specific aim of the trip. Quantitative metrics such as Root-Mean-Square Error (RMSE) and R^2 indicate that models for shopping and leisure visits exhibit higher levels of accuracy in comparison to models for cultural and work-related trips. The disparity in forecast precision arises from variations in the quantity of data accessible for modeling distinct travel reasons. Factors such as the ease of walking, the accessibility of destinations, the ability to cycle, and the density of land use are essential predictors for different types of trips. However, other factors have different levels of influence depending on the purpose of the journey.

Furthermore, the MLP modeling in this paper has addressed a methodological deficiency found in prior research that frequently depends on conventional statistical approaches or particular AI models (Cheng et al., 2020; Liu et al., 2021). The application of sensitivity analysis to measure the consequences of small changes in BEF strengthens the study's methodological reliability, providing policymakers with a pragmatic comprehension of the possible influence of interventions in the constructed environment.

The research highlights the crucial significance of walkability, cyclability, destination accessibility, and land use density in shaping active travel patterns in Tehran. At the international level, urban

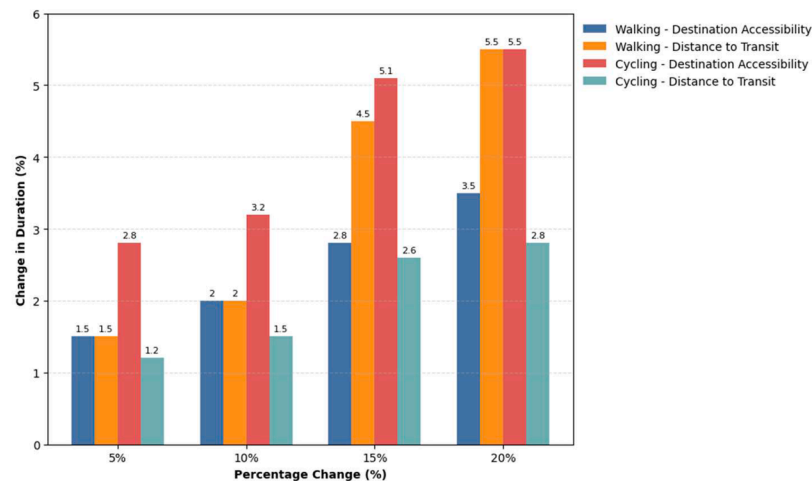


Fig. 10. Sensitivity analysis of changes in the duration of walking and cycling for work trips.
Source: Authors' analysis, based on THES 2021–2022.

agendas should promote an integrated, place-based approach that not only mitigates environmental impacts but also addresses other urban dimensions, as demonstrated by the evolution of urban regeneration in Spain [Camerin et al. \(2024\)](#). Implementing policies focusing on improving pedestrian infrastructure and investing in dedicated bike lanes and bike-sharing programs may significantly increase people's time walking and riding. Furthermore, the emphasis on the accessibility of destinations underscores the need to guarantee convenient access to diverse facilities and employment, which requires urban planning methods that prioritize the integration of various land uses and interconnected transportation networks. In parallel, there is an increasing elaboration and implementation of methodologies for ecosystem assessment oriented toward climate-change adaptation and mitigation, including ecosystem-based adaptation approaches ([Scarano, 2017](#)) and the allocation of nature-based solutions (NbS) in urban areas based on ecosystem service demand ([Longato et al., 2023](#)). It is crucial to customize treatments based on the purpose of travel, such as shopping, recreation, cultural, or work-related visits, given that subtle variations in these variables influence active travel behaviors. Moreover, these findings provide a robust foundation for the development of urban policies at national, regional, and local levels aimed at creating healthier, more inclusive, and resilient environments—an approach supported by research on urban green spaces for elderly health ([Ali et al., 2022](#)), public recreational facilities that facilitate aging in place ([Aguame et al., 2024](#)), and studies on the equitable allocation of elderly care resources ([Li et al., 2024b](#)), as well as by urban regeneration projects that focus on traffic space recovery and the creation of socially attractive public spaces ([Camerin & Longato, 2025](#)). However, it is important to note that while interventions such as traffic space recovery can enhance public space attractiveness, they may also trigger gentrification processes, underscoring the need for complementary measures to ensure social equity. These insights offer distinct guidance for policymakers to develop focused initiatives that address individual travel requirements and preferences, thereby promoting active transportation across diverse urban environments.

While the findings from this study are based on Tehran's unique socio-economic and cultural characteristics, it is important to consider how the results might vary in cities with different socio-economic or cultural dynamics. In cities with higher levels of car ownership, wealthier populations, or more car-centric transportation cultures, the impact of improvements to the built environment (such as bike lanes or sidewalks) might be less significant due to a stronger preference for private cars. On the other hand, in cities where active transportation is more culturally accepted or even incentivized, such improvements could lead to more significant increases in walking and cycling behavior.

Furthermore, while infrastructural changes like bike lanes or wider sidewalks are critical for encouraging active travel, subjective factors—such as the perception of safety or the aesthetic appeal of the environment—may have just as significant an effect. Even with the best infrastructure in place, if the public perceives a route as unsafe or unpleasant, they may still be reluctant to use it. Therefore, a combination of both objective infrastructural improvements and subjective factors like perceived safety, comfort, and visual appeal is essential for promoting active travel in urban environments.

The sensitivity analysis carried out in this study provides valuable information for making policy decisions. An analysis of the possible effects of small changes in BEF on the length of active travel, such as the significant increases expected with a 20 % improvement in BEF, is essential for making informed decisions about budget allocation and urban planning projects. The research highlights the importance of minor adjustments (ranging from 5 % to 20 %) in influential factors, emphasizing the necessity for gradual enhancements in BEF to encourage longer durations of walking and cycling. Incorporating these discoveries into policy frameworks might stimulate urban design tactics that promote physical activity during transport and coincide with broader sustainability and public health goals. Policymakers may address vehicle dependence concerns and promote physical activity, environmental sustainability, and overall well-being in urban contexts by creating communities conducive to walking and cycling. These neighborhoods should include dense and easily accessible land uses and services.

The research possesses certain limitations that warrant careful assessment. The study primarily derives its conclusions from a particular demographic in Tehran, Iran, which may restrict the broader generalizability of its results. Using data from a particular survey done by specific organizations may add biases or limitations in accurately capturing the factors influencing active travel behavior. From a methodological standpoint, although utilizing ANN models such as MLP has its benefits, it needs more transparency in explaining the exact impact of each variable on outcomes. This could impede thoroughly comprehending the connections between BEF and active travel. Additionally, the study's focus on perceived BEF may fail to include other significant elements that affect travel behavior, such as socio-cultural factors or economic concerns. These constraints indicate the necessity for a more comprehensive data representation, integration of a wide range of variables, and longitudinal research to demonstrate causal connections between BEF and active transport with greater certainty.

This study can be extended in a few directions. In this study, the accuracies of work trip models were lower than other models because of differences in the amount of data in models with various purposes.

Hence, further studies with the same amount of data or over/under-sampling methods for different purposes are essential to analyze the predictability of these models. Additionally, there were many zeros in target variables in the dataset, especially in the work trips model, so we possibly faced bias in the findings. Hence, further effort is needed to tackle the situation of zero inflation in the dataset. Coming up with the situation of zero inflation in the dataset that ANN can model is beyond the scope of this paper and, therefore, is left for future research.

6. Conclusion

Car dependency in developing countries has resulted in physical inactivity, road congestion, noise and air pollution, and greenhouse gas emissions (Soltani, 2017). Walking and cycling, however, have recently gained worldwide popularity among urban planners to tackle these problems, meet sufficient physical activity levels, and reach sustainable development goals. Because of the strong relationships between the built environment and mobility behavior, policymakers can make residential neighborhoods more cycling- and walking-friendly. However, for analyzing the relationships, researchers mostly use traditional statistical methods with the major limitation of the inability to model complex nonlinear relationships. Besides, if the data is inconsistent with solid assumptions that statistical methods rely on, they could offer erroneous or biased results.

To address these limitations, ANN modeling has gained growing attention as an alternative approach to account for nonlinear and complex relationships. Moreover, since BEF has different impacts on walking and cycling for different trip purposes, the role of BEF on active travel in each trip should be distinguished. Hence, we conducted MLP to investigate the relationships between perceived BEF and walking and cycling duration for different trips (shopping, recreational, cultural, and work) in Tehran, Iran. We also used data from the Transport, Health, and Environment Survey (THES) conducted by the Municipality and the State Welfare Organization of Tehran, Iran. THES includes 1) socio-economic characteristics at the household and individual level, 2) active travel information, 3) perceived BEF including walkability, cyclability, and bike-sharing infrastructures, land uses density and diversity, design and street pattern, destination accessibility and distance to transit, aesthetics, and security, and 4) health parameters.

Our findings show that walkability and destination accessibility are the most effective elements of walking duration, and cyclability and land use density strongly impact the duration of cycling in shopping trips. Therefore, by improving perceived walkability and cyclability, there will be >10 percent growth in the duration of walking and cycling, respectively. In recreational trips, walkability followed by aesthetics and cyclability followed by bike-sharing infrastructures have the highest influence on walking and cycling duration, respectively. The sensitivity analysis results also illustrate that if we improve these BEF by 20 %, there would be around a 10 % increase in active travel duration. In cultural trips, walkability and destination accessibility have the most substantial effect on walking duration, and destination accessibility and density of land uses are at the top of influencing BEF on cycling duration. Focusing on work trips, destination accessibility, and distance to transit are the most effective BEF for walking and cycling. 5 % to 20 % changes in influential variables in recreational and work trips make slight improvements in the duration of walking and cycling. Therefore, urban planners should consider sufficient physical activity levels, sustainable development goals, and mitigation of car dependency problems in urban areas by walking- and cycling-friendly neighborhoods with dense and accessible land uses and services.

CRediT authorship contribution statement

Meysam Rezaei: Writing – original draft, Validation, Supervision, Software, Resources. **Ali Soltani:** Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation,

Conceptualization. **Hamed Najafi Kashkooli:** Writing – review & editing, Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

We, the authors confirm that we have no financial or personal relationships with other people or organizations that could inappropriately influence or bias our work. We declare that this manuscript represents original research and has not been submitted elsewhere for publication.

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