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Non-linear effects of children's daily travel distance on their travel mode choice considering different destinations

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ABSTRACT

The scientific layout of child-friendly facilities in the community is of great significance to children's daily activities and healthy growth, which is also a vital concern of the United Nations. However, there is little evidence to prove the intrinsic mechanism of children's daily travel behavior and daily travel destinations. Therefore, this study takes 118 communities in Shuangliu District, Chengdu, as an example and uses a eXtreme Gradient Boosting (XGBoost) model to explore the non-linear effects and threshold effects of children's daily travel distance on their travel mode choices by considering different destinations of children's daily travel in the communities. We found that children's daily travel distances and destinations are vital for their travel mode choice, especially the most significant effect of travel distance. For different children's daily travel destinations, travel distance has a more substantial threshold effect on children's non-walking travel mode choice. Therefore, to scientifically and rationally distribute child-friendly facilities in the community, which may help children's healthy development, a child-friendly city should be planned, constructed, or renewed through the internal logical relationship between children's daily travel destinations, travel distances, and travel mode choices should be considered comprehensively.

1. Introduction

Children are the future of cities, and building a child-friendly city is crucial to their growth and development (Naftali, 2009), and understanding children's daily travel mode choices is of great value in building a more friendly and inclusive human habitat, as well as helping to promote the construction of child-friendly cities (Wang et al., 2023). Children's daily travel modes not only impact their quality of life but also affect their health and development (Falconer et al., 2015). Understanding the mechanisms influencing children's daily travel mode choices is an essential insight for urban planning and policy decision-makers, which may help improve the quality of child-friendly urban planning.

Children's travel mode choice is closely related to travel distance (Singh and Vasudevan, 2018). Research on the relationship between travel distance and travel mode choice for children's daily activities has received much attention from scholars and yielded valuable findings. For example, some studies have found a statistically significant relationship between children's travel distance and travel mode (Sidharthan et al., 2011; Faulkner et al., 2013), while others have delved deeper into the mechanisms of travel distance's influence on the choice of travel mode selection to reveal how travel distance affects children's travel mode choice (Chillón et al., 2015). Other studies have focused on the effect of different destinations on children's travel mode choice (Nevelsteen et al., 2012; Villanueva et al., 2013), finding that for various travel destinations, children may travel differently and that this choice may be influenced by travel distance (Mitra and Manaugh, 2020). Therefore, considering the influence of different purposes of daily travel of children in the community and exploring the effect of travel distance of travel mode choice of children in the community can not only help us understand the behavioral patterns of children's travel mode choice more profoundly but also is an essential part of building a child-friendly city.

In fact, the relationship between travel distance and travel mode choice usually exhibits non-linear characteristics with certain threshold effects(Kim et al., 2021; Yang et al., 2022b; He et al., 2022; Tao and Cao, 2023). Sometimes, even if the same travel distance is traveled, the travel modes adopted by children may be different due to different

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destinations, and thus, travel mode choice is influenced by a variety of factors (e.g., distance, nature of destination) (Curtis et al., 2015; Kaplan et al., 2016; Zhu and Fan, 2018). Studying such non-linear effects requires us to take into account more complex factors and scenarios, as well as a more refined and in-depth analysis.

Therefore, this study explores the non-linear effects of children's daily travel distance on their travel mode choice by considering different daily travel destinations using a XGBoost model with 118 neighborhoods in Shuangliu District, Chengdu City, Sichuan Province, China. The main objectives are as follows: (1) the importance ranking of the factors influencing children's travel mode choice for neighborhood activities is clarified; (2) the mechanism of the influence of different destinations on children's travel mode choice is explored; and (3) the non-linear relationship between travel distance and children's daily travel mode and the threshold effect is confirmed. (4) explore the non-linear influence and threshold effect of travel distance on travel mode choice of different destinations.

This paper is organized into five sections. In addition to this section, Section 2 provides a literature review that identifies research gaps and directions for development. Section 3 describes the research content, data sources, and research methods. Section 4 presents the modeling results in detail. Section 5 summarizes the key findings and discusses the implications for relevant planning practices.

2. Literature review

2.1. Travel distance and travel mode choice

The process behind children's selection of travel modes is crucial for guiding the development of child-friendly urban spaces. While existing research consistently highlights travel distance as a key determinant of children's travel mode choices (Nelson et al., 2008; Yarlagadda and Srinivasan, 2008; Mitra and Buliung, 2012; Nordbø et al., 2020), there's a growing recognition of the need to delve deeper into the nuances of this relationship, exploring potential non-linear dynamics and threshold effects that could further inform urban planning strategies. *Chacha and Bwire* found that travel distance had the most significant impact on children's choice of walking or cycling (Chacha and Bwire, 2013); the shorter the travel distance, the greater the likelihood that children would choose to walk (McDonald, 2007), and conversely, the further the travel distance, the greater the possibility of selecting a motorized travel mode (Li et al., 2022). Furthermore, there exists an acceptable range of distances for children to choose a proactive mode of travel (Kontou et al., 2020), and when the distance exceeds a certain threshold, children are likely to choose a motorized mode of travel, such as public transit or car (Kelly and Fu, 2014). Specifically, *Duncan* found that children mostly choose to walk or ride when the distance traveled is <2 km (Duncan et al., 2016). Similarly, *Easton and Ferrari* using a sample of children from the United Kingdom, confirmed that for distances <1 mile, 82% of children would choose to walk to school (Easton and Ferrari, 2015). Most of these findings measure acceptable travel distances for children walking or cycling through statistical analysis methods and mainly focus on a single mode of travel, with behavioral explanations for multiple travel mode choices unclear.

2.2. Travel destinations and travel mode choice

Research exploring how various travel destinations influence children's mode of travel choice has started to shed light on the complexity of these decisions (Loebach and Gilliland, 2016; Moran et al., 2018). Investigations into the differing travel modes between school and non-school-related trips reveal a nuanced picture (Stark et al., 2018); for instance, families residing in the suburbs are more likely to use cars to get to medical facilities (Du et al., 2020). This body of work underscores the importance of considering destination-specific factors in the context of child-friendly urban planning. *Beck* et al have also identified that children traveling for shopping or leisure activities (e.g., to business districts or parks) were more likely to choose walking or biking as their mode of travel (Beck et al., 2023), which may be related to factors such as the trip's purpose and the distance traveled, and in general, different trip characteristics for different trip destinations can lead to differences in children's choice of travel mode.

2.3. Travel distance and travel mode choice for different travel destinations

Although studies have been conducted to analyze the effects on children's travel mode choice from the dimensions of travel distance and destination, few scholars have considered different travel destinations to deeply explore the specific intrinsic relationship between travel distance and travel mode choice. Applying non-linear models such as machine learning may help to better reveal the complex non-linear relationship among the three (Ryo and Rillig, 2017; Sabouri et al., 2020), for example, for different travel destinations (e.g., schools, hospitals, parks). Therefore, XGBoost model are established to predict children's choices of various modes of travel based on different travel distance possibilities, which provides a specific reference for this study. However, systematically considering the heterogeneity of travel destinations and revealing the relationship between children's daily travel distances and their travel mode choices require more attention from scholars to enrich the research theory of children's daily behavior and provide a reference for the practice of building child-friendly cities.

2.4. Non-linear effects using machine learning methods

The advent of big data and advancements in machine learning (ML) have opened new avenues for examining the non-linear relationships between travel distance and mode choice among urban residents, including children. This technological progression enables a more sophisticated analysis of travel behaviors, offering novel insights that challenge traditional understandings and promising more targeted approaches to fostering child-friendly urban environments. Early studies have utilized machine learning models to examine residents' travel behaviors (Chang et al., 2019; Guo et al., 2023), such as commuting behaviors (Ding et al., 2022), physical activities of older adults (Yang et al., 2022a), and walking behaviors (Zang et al., 2022). Regarding the children's group's specific needs and behavior patterns, *Huang* validated the non-linear and threshold effects between the built environment and children's physical activity using the Gradient-boosting decision tree (GBDT) model (Huang et al., 2021). However, the non-linear relationship and threshold effects between travel distance and mode of travel choice under different destination categories are still unclear. Most studies on children focus on the travel roads and behaviors between school and home environments (Mitra et al., 2010; Wang et al., 2022; Zhang et al., 2017), with few researching the distance effects of children's other daily travel destinations, especially in the context of building child-friendly cities (Riggio, 2002).

Machine learning provides a powerful tool for analyzing and predicting children's behavior patterns when discussing children's mode of travel choices. *Koushik* reviewed the application of machine learning in activity-travel behavior research, highlighting the potential of ML technology in parsing complex behavior patterns (Koushik et al., 2020). In a thorough examination of the literature through Web of Science using the keywords ‘travel mode choice’ and ‘non-linear’, we identified 151 articles. Remarkably, only one article directly addressed the non-linear relationship in children's travel mode choices, employing Structural Equation Modeling (SEM) for analysis. Additionally (Stark et al., 2018), the research by *Arentze and Timmermans* extended the understanding of children's activity-travel behavior models, finding significant differences in travel patterns between children and heads of households, emphasizing the importance of considering children's unique behavior patterns in the models (Arentze and Timmermans, 2008).

In summary, exploring the non-linear and threshold effects of travel distance on children's travel mode choice, considering the influence of children's daily travel destinations, is a complex and multifactorial issue. Although there have been some studies exploring the mechanism of the effect of distance on children's travel mode choice (Faulkner et al., 2013; McGrath et al., 2016), there are still deficiencies and improvements to be made in terms of the research methodology, analysis of the mechanism, and travel destination scenarios. Therefore, this study systematically combs through the community children's daily travel activity destinations, analyzes the relationship between travel distance and children's daily travel mode choice for different daily travel destinations, understands children's daily travel demand more deeply, and provides theoretical references for the planning and construction of child-friendly cities and communities.

3. Data and methodology

3.1. Data

Shuangliu District is located in the southwest of the downtown area of Chengdu City, Sichuan Province, and is known as the “south gate of Chengdu City”, which is an important peri-urban area of Chengdu, but its economic development has not fully met the expectations. As of 2022, the total area under the jurisdiction of Shuangliu District is 466 square km, and the population of children aged 0–14 years old is about 200,000, accounting for 13.65% of the total population. It is worth noting that Shuangliu District is one of the earliest districts (municipalities) and counties in Chengdu to carry out the construction of a child-friendly community, so taking children in Shuangliu District as the research object, we can examine the choice of transportation mode in the context of child-friendliness, and the conclusions of the study are

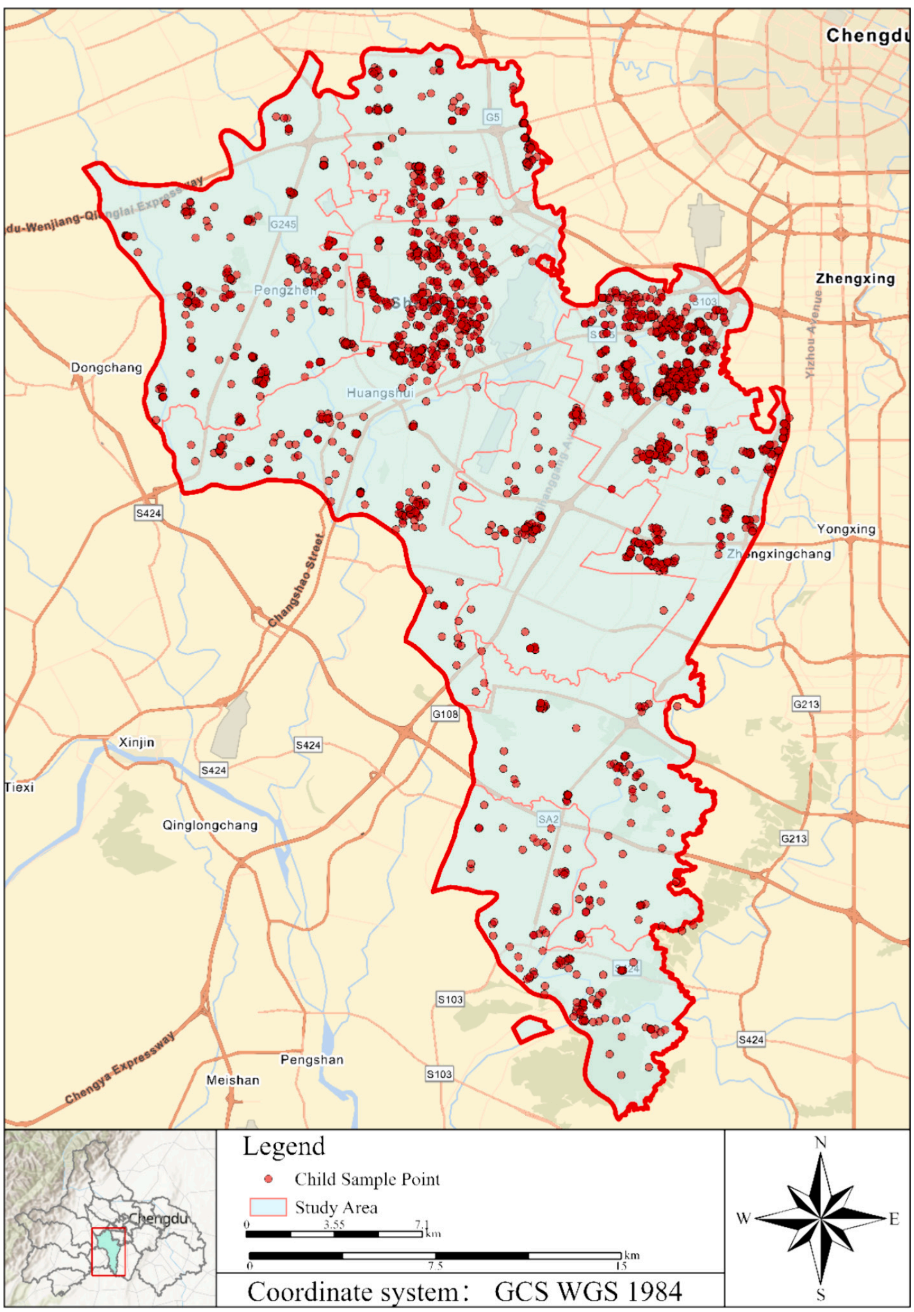

Fig. 1. Spatial distribution of household locations of children interviewed.

representative. The research team conducted this study in cooperation with the Sichuan Research Center for Child Protection and Development. The study was approved by the College of Environment and Civil Engineering, Chengdu University of Technology, and used questionnaires to collect data in two steps: in the first step, questionnaires were distributed to 118 communities in Shuangliu District to collect basic information about the configuration of child-friendly facilities and community population to gain a comprehensive understanding of the construction of a child-friendly environment in Shuangliu District. In the second step, a random sampling method was employed, selecting 25 households from each community for an electronic survey, with children completing the questionnaire with their parents' assistance. The questionnaire included information on family demographics, daily travel data, and subjective travel perceptions. Each questionnaire corresponds to a single child, who may have multiple trips during different daily activities; thus, a single questionnaire may contain multiple pieces of travel data. The entire survey was conducted from August to November 2022, lasting nearly four months, with a total of 3332 questionnaires collected. After filtering by age (retaining those aged 6 to 18) and removing outliers, 1127 valid questionnaires were finally recovered, containing 3227 usable travel record data. It is essential to note that although questionnaires completed by children aged 0–6 were initially included under parental supervision, this age group was subsequently excluded due to concerns over their capacity for autonomous decision-making regarding their travel behaviors. The sample covers most of the 118 communities in Shuangliu District, which is very representative and provides reliable data support for an in-depth examination of the mechanism of the influence of a child-friendly environment on travel mode choice. Fig. 1 shows the spatial location distribution of the interviewed children's households.

Based on the construction requirements for children's public service facilities in the Guidelines for the Construction of Child-Friendly Spaces in Cities (for Trial Implementation) issued jointly by the National Development and Reform Commission, the Ministry of Housing and Urban-Rural Development, and the Office of the State Council's Working Committee for Women and Children in 2022 and the Handbook for Constructing Child-Friendly Cities and Communities issued by the United Nations Children's Fund (UNICEF) in 2019, as well as the examination of the local situation in the course of the research, the research team summarizes the following 24 categories of child-friendly facilities, which are divided into five categories of children's public service facilities according to their functions: children's comprehensive services, children's public culture, children's medical and health care, children's education, and children's leisure and shopping. Table 1 shows the categorized directory of child-friendly facilities. Through community research, data on child-friendly facilities in 118 communities in Shuangliu District were obtained, and the density heat map of child-friendly facilities is shown in Fig. 2.

Children's travel involves walking (49.12%), bicycles (4.64%), buses (2.84%), private cars (21.53%), and e-bikes (21.37%), while motorcycles (0.50%) account for a very low percentage. 4.66%), public transportation (share reaches 2.85%), private cars (share is 21.64%), and electric bicycles (share rises to 21.48%), which are the five most commonly used modes of travel.

For the acquisition of children's travel distance data, using the “path planning” API of the Gaode open platform, we input the latitude and longitude coordinates of children's travel origins and destinations, as well as the travel modes into the written program and output the information of different paths, and use the distance of the preferred paths as an approximation of the travel distance from the origins to the destinations. We estimate the distance of the preferred path as an approximation of the travel distance from the origin to the destination so that the travel distance considers the actual travel path and road conditions, which ensures the accuracy of the children's travel distance data. Specifically, the ‘travel distance’ is determined by the distance of the route associated with the child's chosen mode of travel. For example, if a child selects walking as their mode of travel, the ‘travel distance’ exclusively represents the walking distance, not considering any other modes. This detailed approach ensures that our analysis accurately associates each travel mode choice with its corresponding distance, clearly elucidating the impact of distance on mode selection. Table 2 lists the sample variables for selecting children's travel modes, including socioeconomic and travel characteristics.

Table 1
Child-friendly facilities directory.

Classes	Child-friendly facilities
Children's comprehensive services	Party and Mass Service Center Children and Women Community Centre Cultural Activity Center Children's Home
Children's public culture	Library Museum Children's palace Theater Odeum Farm experience Park
Children's medical and health	Public Health Service Center Intra-community hospitals (including public general hospitals, maternal and child health hospitals, and private hospitals) Child Mental Health Room (Clinic) Infant care (nursery) institutions Care facilities for children with special needs (welfare homes, uninsured centers/shelters)
Children's education	Kindergarten Primary school Junior high school High school
Children's leisure shopping	Indoor sports hall Open outdoor children's play/exercise/rest and leisure areas (such as squares, sports centers, parks, greenways, and corridors.) Child-friendly community supermarket Child-friendly community mall Other child-friendly places in the community

3.2. Methodology

This study utilizes Extreme Gradient Boosting (XGBoost) technology to analyze the non-linear relationship between children's daily travel distance and mode of transportation choice under different destination backgrounds. XGBoost, originally proposed by *Chen* et al. (Chen and Guestrin, 2016), is an optimization based on GBDT and represents an efficient gradient-boosting algorithm framework. It builds and iterates step by step using decision trees as the base learner, generating new decision trees in each round of iteration to fit the residuals between the previous model predictions and the actual results (Mienye and Sun, 2022). In its objective function, XGBoost employs a second-order Taylor expansion to optimize the first-order derivative calculation in traditional gradient boosting methods, thereby improving prediction accuracy (Ogunleye and Wang, 2020). This article builds the model using the “xgboost” library in Python 3.11.4.

Assuming the dataset contains n samples, each with m dimensional features x_i, the output of each tree is y_i, as seen in Eq. (1):

$$y_i = \sum_{k=1}^{K} f_k(x_i) \tag{1}$$

Where x represents the features of the i-th sample, y is the predicted value for that sample. k is the number of base models, and f_k is the k-th base model. The objective optimization function of XGBoost is:

$$Obj = \sum_{i=1}^{n} l(Y_i, y_i) + \sum_{t=1}^{T} \Omega(f_t(x)) \tag{2}$$

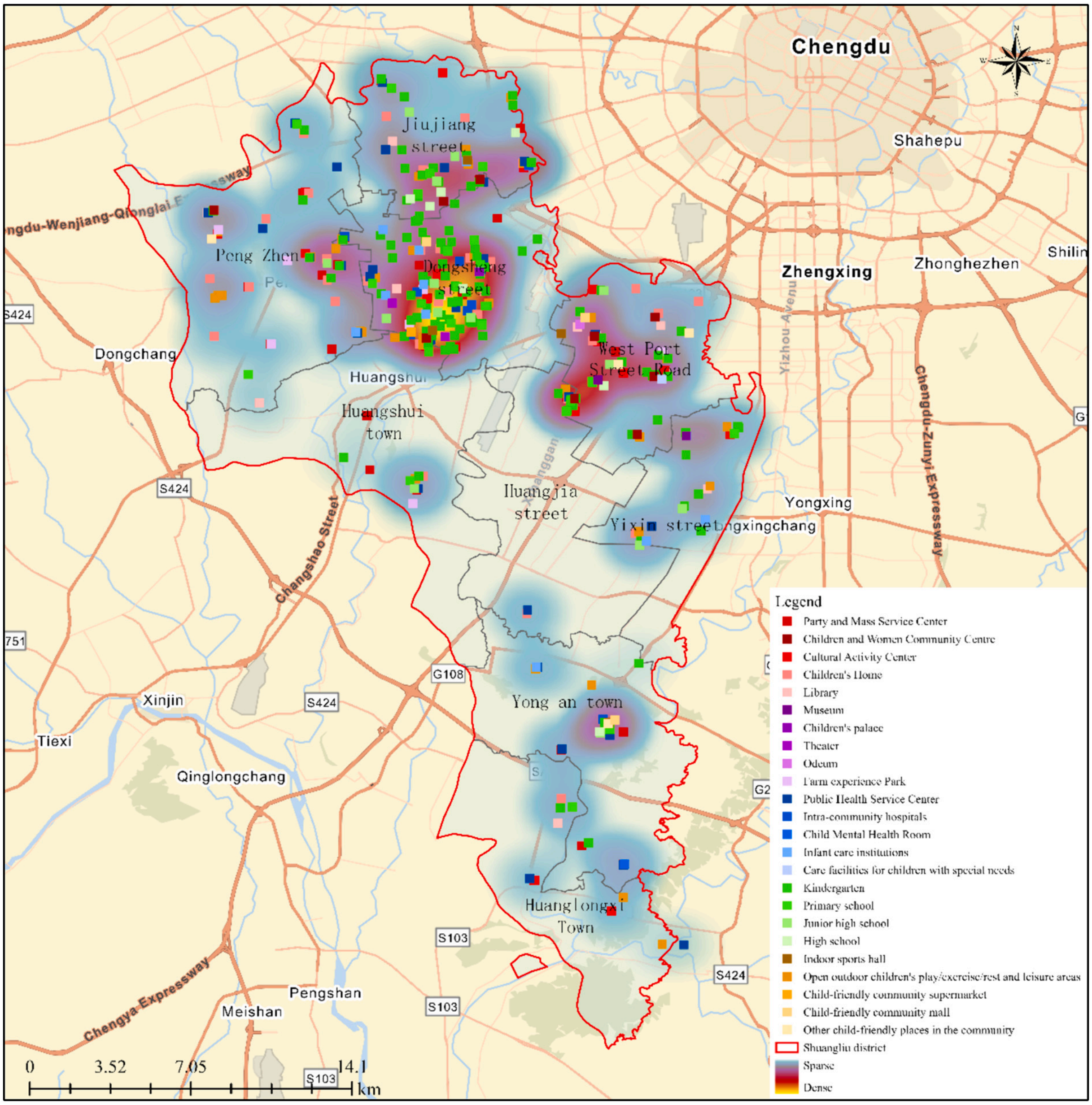

Fig. 2. Distribution and heat map of child-friendly facilities.

where Y_i and y_i represent the actual and predicted values of the i-th sample, respectively. $\Omega(f_t(x))$ represents the added regularization term, controlled by the parameter γ to regulate the complexity of the tree, T represents the number of leaves in the tree, w represents the number of output leaf nodes, and λ is used for weight penalty to affect the overall optimization of the model.

$$\Omega(f_t(x)) = \gamma T + \frac{1}{2}\lambda\|w\|^2 \tag{3}$$

A key feature of the XGBoost model is its ability to reveal the relative importance of predictive variables and the relationship between dependent and independent variables. This metric is embedded within the "xgboost" library, measuring the proportion of variance reduction caused by an independent variable to the total variance reduction caused by all independent variables. This method not only quantifies the contribution of each independent variable to the dependent variable but also facilitates the comparison of the importance of different independent variables due to its standardized form. The study also uses the "PyALE" library to visualize the specific relationship between independent and dependent variables through Accumulated Local Effects (ALE) plots (Apley and Zhu, 2020).

4. Result

In order to improve the performance of the model and to tune three key parameters of the XGBoost: max_depth, learning_rate, and n_estimators (Wang and Zhou, 2024). we used the grid search technique (Claesen and De Moor, 2015). The steps were: the range of parameters was preset, the max_depth was set from 1 to 20, the learning_rate was selected from 0.1 to 1, and the n_estimators was formed from 10 to 1000 (in steps of 10). Then, we evaluated 20,000 (20 × 10 × 100) combinations and tested the model performance by out-of-bag error (Cheng et al., 2019). After testing, we found the model to perform optimally when the max_depth was 9, the learning_rate was 0.1, and the n_estimators was 200. We then carried out the subsequent analysis based on this optimal model.

Table 2
Descriptive statistics of independent variables.

Variable	Definition/Description	Mean (standard deviation)/ percentage
Socio-demographics		
Age	Child age (years)	9.14(2.95)
Male	Male =1; Female =2	1 = 49.6%; 2 = 50.4%
Household size	Household size (persons)	4.67(1.24)
Household income	Annual household income level (CNY) (1 = Under ¥1 W; 2 = 1–3¥W; 3 = 3–5¥W; 4 = 5–15 ¥W; 5 = Over¥15 W)	1 = 3.37%;2 = 7.01%;3 = 35.05%;4 = 31.50%;5 = 23.07%;
Father occupation	1 = unemployed/unemployed; 2 = farming; 3 = Professionals (including but not limited to teachers/doctors/lawyers.); 4 = Civil servants/public institutions/government personnel; 5 = employees of state-owned enterprises; 6 = private sector employees; 7 = odd jobs; 8 = self-employed; 9 = other	1 = 5.06%;2 = 9.49%;3 = 3.28%;4 = 6.65%;5 = 6.21%;6 = 25.02%;7 = 15.08%;8 = 20.67%;9 = 8.52%
Father education	1 = Middle school and below; 2 = High school to junior college; 3 = Undergraduate and above	1 = 27.42%;2 = 38.86%;3 = 33.72%
Mother occupation	1 = unemployed/unemployed; 2 = farming; 3 = Professionals (including but not limited to teachers/doctors/lawyers.); 4 = Civil servants/public institutions/government personnel; 5 = employees of state-owned enterprises; 6 = private sector employees; 7 = odd jobs; 8 = self-employed; 9 = other	1 = 15.62%;2 = 9.32%;3 = 4.70%;4 = 7.81%;5 = 3.99%;6 = 24.13%;7 = 13.93%;8 = 12.87%;9 = 7.63%
Mother education	1 = Middle school and below; 2 = High school to junior college; 3 = Undergraduate and above	1 = 22.45%;2 = 45.43%;3 = 35.12%
Bike ownership	The number of bikes owned by households	0.30(0.65)
E-bike ownership	The number of electric bikes owned by households	0.83(0.83)
Car ownership	The number of cars owned by households	1.02(0.64)
Travel information		
Travel destination	The 24 categories of child-friendly facilities are shown in Table 1	
Travel frequency	0 = Never been there; 1 = Go every day; 2 = once a week; 3 = once every two weeks; 4 = once a month; 5 = once every two months; 6 = once every six months; 7 = Once a year	0 = 0%;1 = 17.60%;2 = 25.50%;3 = 9.05%;4 = 19.49%;5 = 7.65%;6 = 11.25%;7 = 9.45%
Travel companion mode	1 = alone; 2 = Parental companionship; 3 = Grandparents companionship; 4 = Friends companionship; 5 = other	1 = 16.39%;2 = 65.26%;3 = 7.53%;4 = 9.82%;5 = 0.99%
Travel distance	Distance by mode of travel (km)	2.02(2.29)

4.1. The relative importance of independent variables

Fig. 3 displays the relative importance of explanatory variables on the choice of transportation modes for children, prioritizing these variables. Notably, the distance of travel plays a crucial role in determining the choice among the five modes of transport for children, especially in encouraging walking, an eco-friendly and healthy option, where its influence is as high as 20.79%. This finding underscores the central position of travel distance in promoting children's health and environmentally friendly transportation choices, particularly regarding walking (Fyhri and Hjorthol, 2009; Nevelsteen et al., 2012). Besides travel distance, the role of the destination's purpose is also significant. Notably, the ownership of different modes of transportation, such as the possession of an electric bike (*E*-bike), accounts for 26.56% of the decision-making in children's use of that mode of transport, highlighting the importance of vehicle ownership in driving specific transportation choices. Additionally, socio-demographic factors, such as household income, parents' occupation and education, and the age of the children, significantly affect their choice of transportation. Remarkably, the child's age has the most substantial impact on the choice of bike (8.45%), with their transportation mode choices being significantly influenced by parents' attitudes and lifestyles as the children grow older (Johansson, 2005). In summary, travel distance is the primary factor affecting children's choice of travel modes, while the ownership of vehicles, the family's socio-demographic status, and the children's age also play important roles in the decision-making process. Nevertheless, the specific relationships among these factors, the impact of distance to different destinations, and potential threshold effects require further detailed analysis and discussion.

4.2. The influence of different destinations on travel mode choice

Fig. 4 visualizes the share of various modes of travel in different destination types in the form of bar charts. Overall, walking dominates most destination trips with the highest percentage. Specifically, walking has the highest proportion of use in children's leisure and shopping, children's education, and children's comprehensive services destinations, all above 50%, especially in the children's leisure and shopping destinations, where the proportion reaches 58%. In contrast, in the medical and healthcare destinations, the proportion of private cars is the highest (40%), followed by walking and electric bicycles. Children's public culture destinations are also dominated by walking, but the share of e-bikes and private cars has increased relative to travel to children's medical and health destinations. Additionally, e-bikes and private vehicles are used in the second highest percentage of all types of destination trips compared to walking, with lower portions of bicycling and public transit use. This finding suggests that the type of destination a child travels to affects the distribution of their mode choice, and different destinations have varying impacts on children's mode choice, which needs to be taken into account in children's travel research and related policymaking.

4.3. Non-linear effects of travel distance on travel mode choice

This study investigates the relationship between travel distance and mode choice through Accumulated Local Effects (ALE) plots. In Fig. 5, the horizontal axis represents travel distance, and the vertical axis shows the impact of travel distance on mode choice. Walking is quite popular for short distances, but its attractiveness gradually decreases with increasing distance until reaching a threshold (around 3.128 km), beyond which the decline in walking's preference levels off. This finding aligns with the research by *Rodríguez and Joo*, who noted that people tend to prefer walking for short trips, but the preference for walking decreases as distance increases (Rodriguez and Joo, 2004). The preference for cycling initially increases with distance but significantly drops after reaching 2.331 km. Cycling is an effective mode of transport within a certain range, but beyond this range, its appeal diminishes due to increased physical exertion and time costs. *Heinen* also found that cycling is highly attractive for medium distances, but its appeal decreases with increasing distance (Heinen et al., 2010). The choice of buses and electric bikes increases with distance until reaching specific thresholds (approximately 4.626 km and 3.8 km, respectively), after which the rate of increase slows or begins to decline, which could be attributed to the enhanced accessibility of bus services and the convenience of using electric bikes within certain distances. However, beyond these thresholds, factors such as time costs and physical fatigue may

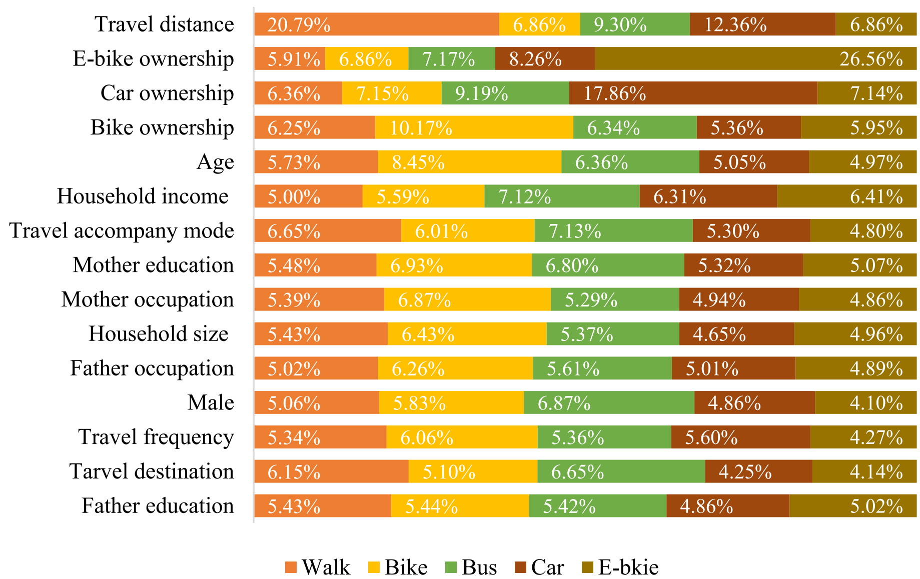

Fig. 3. The relative importance of independent variables in predicting children's travel mode choice.

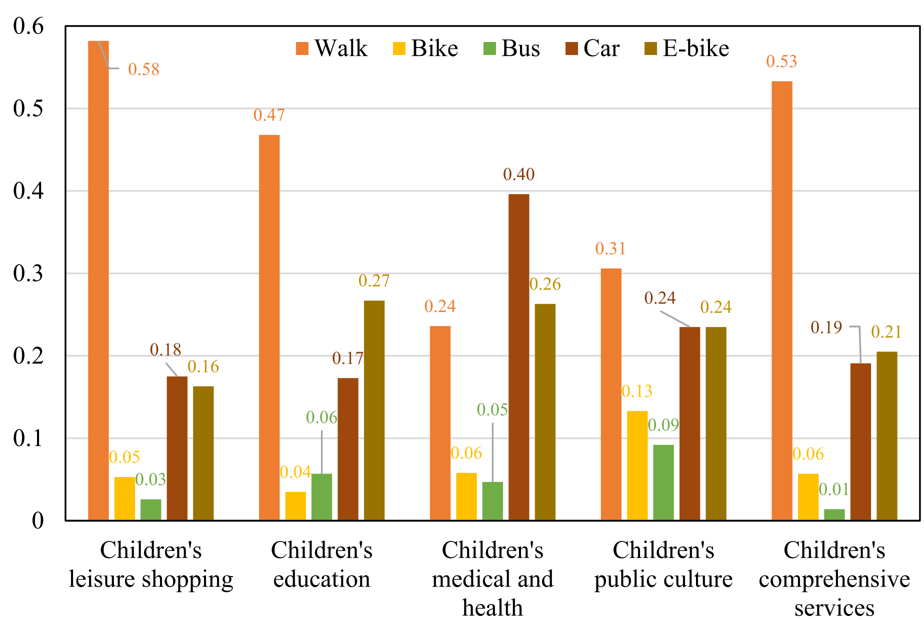

Fig. 4. The effects of different destinations on children's travel mode choice (Bar chart).

reduce the attractiveness of these modes of transport. *Pucher and Buehler* discussed how improving public transport services and encouraging bicycle-friendly policies can enhance the appeal of these modes of transport in urban settings (Pucher and Buehler, 2008). The attractiveness of private cars fluctuates with increasing distance but overall shows a positive correlation. Beyond 6.322 km, the trend of increase becomes more gradual, indicating that private cars have become a more popular choice for longer distances.

4.4. Non-linear effects of travel distance on travel mode choice for different destinations

Fig. 6 reveals the non-linear relationships between travel distance and mode choice across different destination categories, where the X-axis represents travel distance, and the Y-axis shows the impact of travel distance on mode choice. In the "Children's comprehensive services" category, within a 0.6 km range, the impact value of walking is relatively high, while the impact values of other modes of travel show varying degrees of negative effects. Beyond 3.323 km, the impact of travel distance on walking gradually stabilizes, and when the travel distance exceeds the average of 1.938 km, the influence of private cars and buses starts to increase significantly. This finding aligns with the research by *Handy and Niemeier*, who emphasize that walking not only benefits health but also reduces environmental pollution in short trips, suggesting urban planning should promote walking and cycling, especially around comprehensive service facilities frequently visited by children (Handy and Niemeier, 1997). The research by *Böcker* et al. further confirms that enhancing the safety and convenience of walking and cycling can significantly increase their attractiveness (Böcker et al., 2013). Moreover, a combination of bus travel with walking and cycling becomes particularly important for medium distances, requiring good bus connections and convenient bicycle parking facilities. Private cars and e-bikes, as distance increases, become more attractive options, with time efficiency and comfort becoming more critical considerations.

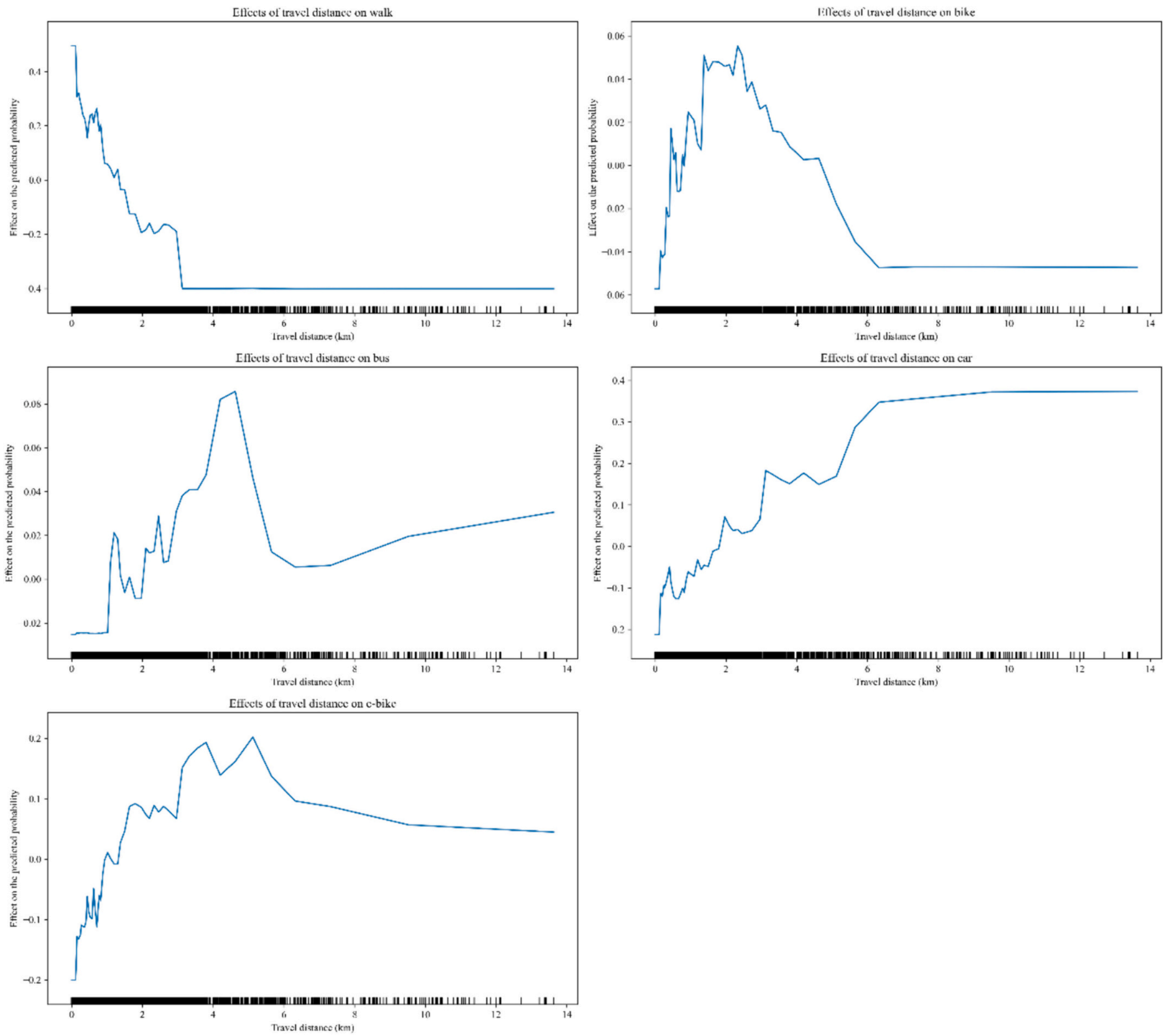

Fig. 5. Non-linear effects of travel distance on children's travel mode choice.

Schwanen et al. argue that despite the convenience of private cars, their negative environmental impact and high operational costs should also be considered in urban transportation planning and policy (Schwanen et al., 2001).

In the "Children's public culture" category, a preference for modes of travel when children visit public cultural facilities is revealed, with walking and cycling being the preferred choices for short distances (within an average of 3.738 km), while the choices of buses, private cars, and e-bikes are relatively limited. The positive impact of buses becomes more significant as distance increases (significantly beyond 2.537 km for medium distances). This finding emphasizes the need for urban planning to enhance walking and cycling infrastructure near public cultural facilities and improve public transport services to ensure that children and their families can conveniently and safely reach these facilities. Research by *Mackett and Brown* shows that children prefer walking or cycling to visit public cultural facilities related to their love for exploration and outdoor activities (Mackett and Brown, 2011). This preference supports the importance of increasing green spaces and safe walking/cycling paths in urban planning to promote positive travel mode choices among children. *Pucher and Dijkstra* discuss enhancing the attractiveness of buses as a mode of travel by improving their accessibility and convenience, especially services connecting major cultural and entertainment facilities (Pucher and Dijkstra, 2003).

In the "Children's medical and health" category, the impact value of walking is very high in the initial phase, indicating that walking is an important mode of travel, especially for shorter distances (from 0.002 km to 2.624 km), when visiting medical and health-related facilities. As the distance increases to an average of 3.136 km, the attractiveness of other modes of travel increases, reflecting that families might choose other modes of travel for longer medical visits. Research by *Litman* emphasizes the importance of walking and cycling as healthy, low-cost modes of travel when accessing medical facilities, contributing to physical activity, reducing traffic congestion, and decreasing environmental pollution (Litman, 2013). However, as distance increases, using private cars or public transport becomes a more practical choice for families visiting medical facilities frequently. Research by *Zhang* et al, highlights the importance of urban planning in improving the accessibility of medical facilities to ensure community members can access

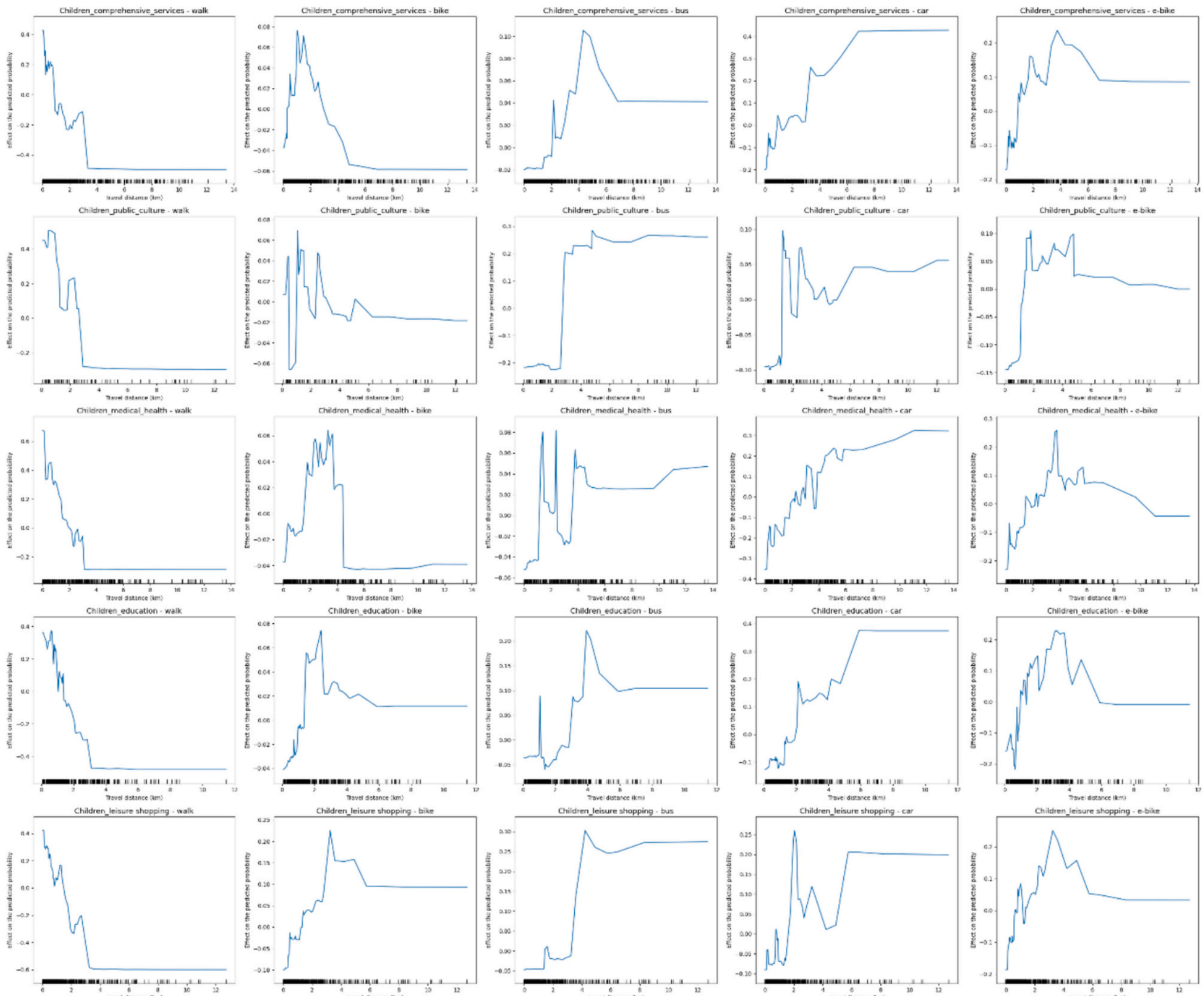

Fig. 6. Non-linear effects of travel distance on travel mode choice in different destinations.

necessary medical services (Zhang et al., 2015).

In the "Children's education" category, walking is also preferred for short-distance travel (<1.178 km), but as the distance increases beyond 5 km, families may consider alternatives such as bicycles or e-bikes. Research by *McDonald* shows that families' choices of travel modes for children's school commutes are influenced by distance, safety, time, and convenience. Walking and cycling are effective ways to promote physical activity and reduce traffic congestion for short distances, but as the distance to school increases, families are more likely to use public transport or private cars (McDonald, 2008). Research by *Ewing and Cervero* emphasizes the importance of good urban planning in promoting safe walking and cycling to school for children (Ewing and Cervero, 2010).

In the "Children's leisure shopping" category, the impact value of walking is relatively high initially, making walking a popular mode of travel for short distances (<0.942 km). However, as distance increases, its impact decreases, and bicycles, public transport, private cars, and e-bikes become more important choices, especially for medium to long distances (beyond 2.226 km), considering the convenience and safety of carrying shopping items. *Mackett* notes that encouraging families to use active modes of travel for short leisure shopping trips is essential for promoting health, reducing traffic congestion, and lowering environmental pollution (Mackett, 2003). Moreover, providing safe, reliable public transport services and optimizing private car parking facilities can offer more flexibility and choices for leisure shopping trips.

4.5. Model performance comparison

We use four evaluation metrics to compare the difference in performance between the XGBoost mode, random forest (RF) model, and the multinomial logit (MNL) model in predicting travel mode choice, namely accuracy, precision, recall, and F1 value(Powers, 2020). The metrics are formulated as follows:

$$Accuracy = \frac{\sum_{j=1}^{K}\left(TP_j + TN_j\right)}{\sum_{i=1}^{K}\left(TP_j + TN_j + FP_j + FN_j\right)} \tag{4}$$

$$Precision = \frac{\sum\limits_{j=1}^{K}\left(TP_j\right)}{\sum\limits_{j=1}^{K}\left(TP_j + FP_j\right)} \tag{5}$$

$$Recall = \frac{\sum_{j=1}^{K}\left(TP_j\right)}{\sum_{j=1}^{K}\left(TP_j + FN_j\right)} \tag{6}$$

$$F1score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{7}$$

Table 3
Evaluation index result.

	Evaluation Indicators			
	Accuracy	Precision	Recall	F1 Score
RF-Model	0.74303	0.762446	0.54437	0.58724
MNL-Model	0.67555	0.54090	0.41838	0.42156
XGBoost-Model	0.77399	0.69622	0.56964	0.87100

Where K is the number of samples in the test set, and for the *j*th travel mode, TP_j denotes the number of correctly predicted positive samples, TN_j denotes the number of correctly predicted negative samples, FP_j denotes the number of misclassified positive samples, and FN_j denotes the number of misclassified negative samples.

Table 3 presents the results of the evaluation metrics for all the models tested, with the XGBoost model performing exceptionally well across all four metrics, particularly in the F1 score. Results from the MNL model are provided in Appendices Table A1. Overall, XGBoost demonstrates the best model performance, making it well-suited for the purposes of this paper.

5. Discussion and conclusion

Child-friendly travel is crucial in constructing child-friendly cities (Gleeson and Sipe, 2006), and understanding children's travel mode choices plays a vital role in planning such urban forms. In this study, we used a XGBoost model to explore the non-linear effect of children's daily travel distance of travel mode choice under different destinations. We found that (1) the relative importance of explanatory variables on children's travel mode choice was revealed, with travel distance ranking high in importance and travel distance contributing the most; (2) there were significant differences in children's daily travel modes for different types of travel destinations; (3) a non-linear relationship between travel distance and children's travel mode choice was confirmed; (4) for different types of children's daily travel destinations, travel distance affects children's daily travel mode choice differently.

The results of the study reveal an essential influence of children's daily travel distance and travel destination on their travel mode choice, especially the most significant effect of travel distance, a result that is consistent with the studies of (Easton and Ferrari, 2015; Dėdelė et al., 2020). In addition, we also found that different modes of transportation ownership also affect children's travel mode choice, and for non-walking modes of transportation, household socioeconomic status may have a more significant impact on children's choices.

This study's outcomes shed light on the ways destination type and distance traveled shape children's travel behavior. Mirroring the observations of(Cerin et al., 2007), it was discerned that the transportation method children opted for varied according to the destination category, displaying distinct preferences across diverse destination types. For example, children seem to be more inclined to choose walking and riding to access leisure shopping and public culture destinations, while choosing public transportation is mainly children's choice to reach educational destinations. Further, an inherent relationship between travel mode choice and distance was probed more deeply within this paper. The findings here corroborate (He et al., 2022) observation that there is a non-linear relationship and threshold effect between travel distance and travel mode choice. Moreover, it was found that the threshold for walking distances to leisure-based shopping destinations was notably elevated compared to other venue types, an inference aligning with (Yang and Diez-Roux, 2012) research. Given these findings, we argue that urban and transportation policy should be tailored to the nuanced ways in which travel distance influences mode choice among children. For destinations within a 3 km radius, urban planners should prioritize the development of safe, child-friendly infrastructure for walking and biking. This includes well-lit pedestrian paths, safe crossings, and secure bike lanes that encourage active travel among children, fostering a healthy lifestyle from a young age. For travel distances beyond the walking or biking threshold, enhancing public transportation's accessibility and reliability becomes crucial, which includes providing frequent, safe, and child-friendly public transit options that can accommodate the travel needs of children, reducing dependency on private vehicles, and contributing to environmental sustainability. The findings underscore the importance of integrating transportation planning with urban development strategies to create child-friendly environments, which involves considering the location of schools, parks, and recreational facilities concerning residential areas to minimize travel distance and promote safer, more appealing travel modes for children. After recognizing the different preferences for travel modes to various destination types, tailored transportation solutions should be implemented. For instance, areas around leisure and shopping destinations should have enhanced pedestrian and biking infrastructure, whereas educational destinations may benefit from improved public transit links.

Although this study provides valuable insights into children's travel mode choices, it has certain limitations. Firstly, the limited sample size and geographic scope may not fully capture the travel behaviors of children across various urban fringe areas. Secondly, the study did not account for factors such as climate and seasonal variations that could influence travel decisions. Future research should consider incorporating children's attitudes and preferences to address potential self-selection biases, expand the sample size, include a broader range of influencing variables, and conduct comparative studies across different backgrounds.

CRediT authorship contribution statement

Yi Long: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Yibin Ao:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Haimei Li:** Visualization, Resources, Project administration, Data curation. **Homa Bahmani:** Writing – review & editing, Supervision. **Mingyang Li:** Validation, Software.

Data availability

Data will be made available on request.

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Appendix A. Appendix

Table A1
MNL model results.

Variable	Travel mode = Walk			Travel mode = Bike			Travel mode = Bus			Travel mode = Car			Travel mode = *E*-bike		
	Coef.	Std. Err.	p	Coef.	Std. Err.	p	Coef.	Std. Err.	p	Coef.	Std. Err.	p	Coef.	Std. Err.	p
Age	0.077	0.030	0.010	0.077	0.030	0.010	0.074	0.040	0.061	−0.032	0.024	0.180	−0.012	0.020	0.575
Male	−0.126	0.173	0.468	−0.126	0.173	0.468	0.045	0.228	0.843	0.015	0.130	0.911	0.048	0.115	0.675
Household size	0.055	0.073	0.450	0.055	0.073	0.450	0.222	0.095	0.019	−0.009	0.056	0.867	−0.049	0.050	0.326
Household income	−0.148	0.055	0.007	−0.148	0.055	0.007	0.079	0.068	0.248	0.202	0.040	0.000	−0.132	0.036	0.000
Father occupation	−0.095	0.042	0.023	−0.095	0.042	0.023	0.005	0.056	0.928	−0.056	0.031	0.074	0.065	0.027	0.016
Father education	0.310	0.130	0.017	0.310	0.130	0.017	0.269	0.172	0.119	−0.148	0.093	0.111	−0.130	0.081	0.111
Mother occupation	0.029	0.040	0.470	0.029	0.040	0.470	0.047	0.054	0.391	−0.039	0.028	0.172	−0.100	0.024	0.000
Mother education	−0.060	0.132	0.650	−0.060	0.132	0.650	−0.070	0.168	0.678	0.173	0.100	0.083	0.239	0.088	0.006
Bike ownership	0.834	0.102	0.000	0.834	0.102	0.000	0.155	0.181	0.392	0.021	0.100	0.837	0.083	0.082	0.312
E-bike ownership	−0.233	0.127	0.067	−0.233	0.127	0.067	−0.424	0.175	0.016	−0.336	0.094	0.000	0.898	0.078	0.000
Car ownership	−0.188	0.160	0.242	−0.188	0.160	0.242	−0.456	0.216	0.035	1.104	0.113	0.000	−0.101	0.101	0.317
Travel destination	−0.002	0.014	0.903	−0.002	0.014	0.903	0.070	0.017	0.000	0.009	0.011	0.393	0.009	0.010	0.379
Travel frequency	0.051	0.045	0.263	0.051	0.045	0.263	0.124	0.057	0.029	0.200	0.033	0.000	0.075	0.029	0.011
Travel companion mode	0.285	0.093	0.002	0.285	0.093	0.002	−0.139	0.144	0.335	−0.295	0.086	0.001	−0.168	0.070	0.017
Travel distance	1.131	0.073	0.000	1.131	0.073	0.000	1.626	0.069	0.000	1.636	0.060	0.000	1.352	0.058	0.000
Correlation parameter															
Dependent Variable	Travel mode														
Pseudo R-squared	0.3376														
Log-likelihood model	−2740.1														
LL-Null	−4136.4														
LLR *p*-value	<0.0001														

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