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Predictive Analytics for Car Dependence: A Machine Learning Approach to Influence Travel Behavior

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Abstract

Travel behavior is vital for producing effective interventions because car dependence is one of the main barriers to achieving sustainable urban mobility, which highlights the importance of a deeper understanding of the contributing factors. Understanding and altering driving behavior: analysis with ML Predictive analytics enable to forecast behavioral trends and help to change driving behaviors. We applied various machine learning methods including random forests, gradient boosting, and neural networks, to predict individual travel Behaviors and to find key determinants of car dependence. These designs resulted from using a comprehensive data set that revealed travel survey results, GPS data, and demographic information. This dataset included factors such as travel time, costs, availability of public transport, and city density. To determine the effectiveness of the models, we measured accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC) for each of the models. The models accurately predicted car dependence with 85% accuracy (AUC-ROC 0.89), confirming that they were able to maintain predictive power. Ensuring access information on public transport and urban density were the key factors that were indicative in our analysis of feature importance. Moreover, we designed a personalized travel planning intervention informed by our predictive models, which ultimately reduced car usage by 15% and increased ridership of public transport by 18%. These findings highlight the capacity of machine learning and predictive analytics to provide deeper insights into car dependence, and to guide targeted interventions that promote sustainable travel in urban environments. Future studies will be directed towards investigating the long-term effects of such interventions and integrate other factors for example, social norms that may impact travel behavior.

Keywords: *Car dependence, Predictive analytics, Machine learning, Travel behavior, Random forests, Gradient boosting, Neural networks.*

1. Introduction

Urban mobility has long been a challenge plagued with car dependence causing congestion, pollution, and public health problems [1]. Knowing what drives car dependence is important to designing effective interventions to promote sustainable travel behaviors. Traditional methods are based on travel surveys and extensive policy applications; in contrast, recent developments in machine learning (ML) present novel opportunities to improve predictive power and customize the behavioral processes [2]. This study utilizes predictive analytics to develop a model for car dependence based on a variety of data sources, which consist of travel surveys, GPS mobility data, demographic properties, and characterization of the

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built environment. We leverage machine learning methods (Random Forests, Gradient Boosting and Neural Networks) to better understand the factors driving car dependence and the relative strength of their predictive capacity. Convincingly, our results show that public transport accessibility, urban density, and travel cost significantly affect travel modes, which is coherent with earlier findings [3]. This manner of predictive intelligence to help model the potential for targeted interventions: that is, travel plans and mobility management could be informed by these predictive insights to help avoid car dependency. Early insights indicate that tailoring ML recommendations reduce car usage by up to 15%, correspondingly increasing public transport fare [4]. This research adds to the burgeoning field of data-driven transportation planning by showing the potential for predictive analytics to inform decreased cost policy design and behavior change initiatives. any movement of time, it can be tracked and provide sudden help by getting the information regarding GPS coordinates. Demand for safety and security continues to increase in all sectors. The next part of this article proposes a low-cost, portable online and offline tracking and accident alert system based on Node MCU by implementing a sophisticated algorithm that has lightning speed and low power backup. The sleep wake-up algorithm reduces the consumption of power. We are using IoT in the cloud to store the data and access the data using cloud and MEMS accelerometer in case of accident detection and ultrasonic sensor to avoid accident. It also works as an antitheft device for vehicles, sending an SMS alert to relevant persons. Further testing and implementing these ideas into real-time data by collecting speed and location; data will be stored in thing speak. This can also provide the information into RTO if any number inserted into this system [5]. A small business website design is an integral part of your target audience making a remarkable first impression. AWS provides a free tier for new users to test lightweight services, and the essential backbone for interlinked companies. While versatile web hosting can be convoluted and expensive, traditional web architectures must compromise between reliability and static expectations regarding traffic. During peak traffic periods, the network is underutilized while the associated operational costs remain high [6].

2. Background

Banister (2019) stated that growing car dependence for urban mobility contributes to traffic congestion, environmental problems, and ineffectual public transport solutions. Urban design, socioeconomic factors, and psychological preferences played a pivotal role in dependency on personal vehicles. Vehicle usage is influenced heavily by urban design, especially through the walkability of an area and access to public transit. Moreover, transportation access is influenced by socioeconomic conditions, in that wealthier individuals tend to have more vehicles, while public transit is more used among people of lower socioeconomic status and is not as effective. Cao et al. As noted by Yang & Wang (2020) and Schwanen & Mokhtarian (2020), low-density suburbs have limited access to public transportation and people also tend to use cars for mobility since they value the convenience of automobile usage. Car-oriented living makes it harder to use sustainable transport methods like biking, walking, or public transit, which compounds traffic congestion, air pollution and urban sprawl. Solving these issues will involve better public transportation infrastructure and promoting a wider, more accessible set of transport options in suburban areas. According to Gössling (2021), the reliance on cars leads to higher carbon footprints, urban spread, and harmful health consequences. This dependency creates unhealthy devotions and lengthened commutes. These problems can be solved by leveraging innovative techniques in predictive analytics and machine learning (ML). This technology can even analyze travel data in a manner that can predict behaviors and we can use that information to encourage the use of sustainable forms of transport and build healthier living spaces [7]. Guo et al. (2020) emphasized that predictive analytics is crucial in transportation research, helping planners to study the past travel behaviors and predict future behaviors. It produces powerful insights for decision-making Designed in conjunction with huge data sets. Researchers traditionally relied

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on statistical models such as the multinomial logit and regression techniques that included demographic and spatial variables to improve their accuracy [25]. In contrast, the traditional volume-based approach to transportation planning often cannot adjust quickly enough to reflect shifts in travel patterns during a period of rapid change and evolution in urban commuting the use of predictive analytics enables transportation planners or any other stakeholders to both visualize trends and model them, forecast changes in travel behavior, and optimize systems to better allocate resources and make the transportation system more adaptable to changing travel demand. These advancements enable novel applications, such as the use of big data analytics and machine learning for predicting how individuals will act (Predictive analytics | Forrester), where Zhang 2021, state new solutions can improve the accuracy of travel behavior forecasting [24]. Predictive analytics, drawing on real-time data from GPS, smart cards, and IoT sensors, identify the factors driving car dependency. Data-driven methods not only help to understand travel trends, but provide helpful information for transportation policy makers as well. As a result, these techniques help tailor public transit approaches, regulate episodic loads [which strain the transportation system], and support alternative mobility methods, leading to more effective responses of public transit incentives use over more personal transport. Aledjew et al. (2021) show how machine-learning techniques have enhanced modeling of travel behavior and the prediction of car dependence. These approaches use supervised learning algorithms such as decision trees and support vector machines to classify consumers into transportation choices based on demographic, economic, and travel preference data. Such an analysis helps urban planners and policymakers understand how people travel from point A to point B, and devise plans for more sustainable transit systems, a long-term goal in reducing dependency on cars in urban areas. Recent studies have demonstrated that deep learning methods such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are able to accurately forecast traffic patterns in real-time and analyze complex mobility behaviors in urban spaces (Xiao et al., 2021; Liu et al., 2022). These models excel at efficiently processing and analyzing massive datasets, and their combination with reinforcement learning would allow them to continuously optimize and update these incentives, taking into account real-time changes in consumer preferences. This trend allows urban planners and transportation authorities to better predict car dependence, and to make timely interventions to promote alternatives (e.g., public transit, carpooling) that support mobility sustainability and lead to less urban congestion [19]. What predictive analytics can do for behavioral interventions addressing the problem of car dependency I already know what you might be thinking, `Research suggests that targeted and data-driven travel recommendations can compellingly incentivize commuters to switch to other modes of transportation. Real-time prompts and gamified features in mobile applications can enable the use of public transit as well as active transportation (e.g., walking or cycling). Optimizing everything from congestion pricing to public transport schedules, machine learning improves transportation systems, making sustainable travel choices more attractive and efficient. Custom recommendations are tailored to individual commuting habits, adding a greater level of engagement to the experience. Gamification techniques provide rewards and progress tracking to motivate users to discover alternative solutions for their transportation [8]. These methods encourage greener commuting while also improving the consistency and convenience of transportation. Liu et al., 2022 multiple research initiatives in recent years have indicated that the integration of machine learning (ML)-based travel demand responds to urban planning strategies for transportation management, in order to promote the improvement of different aspects, among them, to minimize reworks and maximize the entire planning response. They can also assist the establishment of dynamic pricing model, carbon credit model, and incentivize multiple transport types [9]. While such innovations are promising, a number of major challenges must be addressed to successfully scale them up. Overcoming these issues is a matter of paramount importance to enable organizations to reap the fruits of these ML-anchored paradigms without compromising et. Machine learning based approaches for efficient routing in WSNs with a focus on network lifetime optimization were explored by Nawkhare and Singh (2022) [22]. Techniques such as energy-efficient routing, load balancing, clustering, and data aggregation could be useful in this regard. They discussed limitations of traditional routing corresponding to low adaptivity, dependence on mathematical models, and single-factor optimization [10]. ML can also optimize resource use and facilitate efficient and adaptable routing strategies to improve WSN utility, as shown by the research.

Table 1 Key Studies on Car Dependence and ML Applications

Source	Key Points
Banister (2019)	over the resulting car dependence will come congestion, pollution, and inadequate public transit. Urban design (walkability, transit access), socioeconomic conditions, preferences, and factors.
Cao et al. (2020) & Schwanen & Mokhtarian (2020)	Low density suburban development forces residents to rely on their cars as transit service is both sparse and inconvenient, exacerbating congestion and pollution. Solutions: better transit and access.
Gössling (2021)	Car dependence is driving up carbon emissions, urban sprawl and adverse health impacts. Predictive analytics and ML can be used to analyze behaviors and facilitate sustainable transportation.
Guo et al. (2020)	Through examining past behaviors, predictive analytics focuses on providing future trends, which not only enhances the planning process but also helps allocate resources effectively.
Zhang et al. (2021)	With the real-time travel behavior examining through big data.The ML increases the accuracy of forecasting in FS using GPS, smart card, and IoT sensors. Insights also assist policymakers in managing congestion and encouraging public transit.
Aledjew et al. (2021)	Machine learning techniques (like decision trees and SVMs) also enhance the modeling of travel behavior—these models assist planners to create sustainable transit strategies that would reduce reliance on cars for commuting.
Liu et al. (2022), Xiao et al. (2021)	Machine learning techniques (like decision trees and SVMs) also enhance the modeling of travel behavior—these models assist planners to create sustainable transit strategies that would reduce reliance on cars for commuting.
Behavioral Interventions	Personalized travel recommendations, gamification, and real-time incentives can help facilitate behavioral changes through predictive analytics.
Shen et al. (2020), Liu et al. (2022)	Data privacy, AI bias and the ethical deployment of machine learning (ML)-based travel demand models (a key application that empowers urban planners, allows for dynamic pricing systems like congestion charging and carbon credit schemes) remain challenges to be addressed.
Nawkhare & Singh (2022)	WSNs-based ML routing for network lifetime improvement. Techniques: energy-efficient routing, load balancing, clustering, data aggregation. There is a progressive increase of their relevance, that contrasts with the limitations of traditional methods.ML enables better resource utilization and adaptive power-efficient routing.

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3. Methods and Material

The purpose of the study is to exploit machine learning models to highlight the reasons behind car reliance in cities through analyzing the access to public transit and urban spread. More specifically it seeks to assess the potential of predictive analytics to lower the use of a car by providing personalized travel behavior interventions centered around sustainable travel choices [11]. Table 1 shows Key Studies on Car Dependence and ML Applications.

3.1 Conceptual Model

Inputs used for the analysis include mobility data (travel frequency, travel routes), socio-demographic data (age, income level and household type), geographic data (e.g., urban density, transport hub proximity), environmental data (e.g., weather, traffic congestion, air quality) and infrastructure data (public transit quality, cycling networks, road and parking availability). Initial steps of data preprocessing consist of cleaning for removal of any erroneous data points, feature engineering to find relevant variables, normalization for scaling of models, and categorization based on user-based grouping as per travel behaviors [26]. The development of machine learning models is centered on supervised learning for predicting car use, unsupervised learning for profiling users' behavioral patterns, and reinforcement learning for evaluating interventions. Car dependence the predictions explain when and why people choose to drive and the behavioral insights shed light on things like convenience, cost, etc. Model-based approaches that encompass tailored interventions can facilitate targeted policies and interventions where they are likely to be most effective (e.g., public transit improvement, congestion management identification) with implications for how policies at local and regional levels can be informed using the model to understand travel behaviors at the on-set (i.e., infrastructure planning) [23]. The prediction chain: Based on data from the past to the present, models are created and then tracked in the future with real-time updates to the data: All models are fine-tuned so that predictions stick and policies are tuned iteratively as results come in and event-based driving can also impact travel patterns [20].

3.2 Sample Characteristics

The Sample characteristics segment outlines the demographic of the individuals for which data will be collected for the purpose of generating predictive models and understanding car dependence and travel behavior [21]. Firms use these characteristics, which reflect different dimensions of the population, to derive insights on how factors affect travel choice. Key variables like age, income, education, employment, and household size/composition greatly influence travel behavior and car-dependence. Geographic traits shape individuals' propensity to use a car as well do they live in urban, suburban or rural regions? are they close to public transit? How far do they need to go to get to the things they want to access? In addition, transportation and mobility behavior - including car use frequency, public transit usage, non-motorized transport preferences, carpooling behavior, travel time, and distance - reflects individual mobility patterns. Socioeconomic and behavioral factors such as alternative transportation access, technology affinity, environmental awareness, and car ownership are important in understanding car dependence. Moreover, temporal factors including time of day, seasonality, and event-based driving can also impact travel patterns, as humans may adjust their travel preferences according to particular situations or conditions. Together, these attributes serve as a robust framework for understanding travel behavior and car dependence among diverse populations [12].

3.3 Measures

- Dataset Measure as a Descriptive Statistics: Before utilize ML models, calculate different measures that summarizes the dataset
- Measures of Central Tendency

Mean (Average):

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

Where, $\bar{x}$, is represents the mean (average) value of the dataset, n, is total number of observations (sample size), x_i, is the individual values (data points) in the dataset, $\sum_{i=1}^{n} x_i$, The summation of all individual values from i = 1 to n, $\frac{1}{n}$, The division by the total number of values ensures the sum is normalized to find the average. Median: The middle value in a sorted list of observations. Useful for skewed distributions. Mode: The most frequently occurring value in a dataset [18].

- Measures of Dispersion

Variance:

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2 \quad (2)$$

Standard Deviation:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (3)$$

Interquartile Range (IQR):

$$IQR = Q_3 - Q_1 \quad (4)$$

Measures variability between the first (Q1) and third (Q3) quartile. Correlation Coefficient (Pearson's r):

$$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2}\sqrt{\sum(y_i-\bar{y})^2}} \quad (5)$$

- Represents the linear relationship among two variables i.e. travel time and car dependence.

ML Models for Car Dependency Prediction. Logistic Regression (Baseline Model). Since car dependence is a binary variable (0 or 1), logistic regression can be used.

The probability of car dependence is modeled as:

$$P(Y = 1|X) = \frac{1}{1+e^{-(\gamma_0+\gamma_1 X_1+\gamma_2 X_2+\cdots \gamma_n X_n)}} \quad (6)$$

Uses Maximum Likelihood Estimation (MLE) to optimize parameters.

Random Forest (Ensemble Model): A collection of decision trees trained on random subsets of data. Prediction is made by majority voting (classification) or averaging (regression):

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(X) \quad (7)$$

Where $f_t(X)$ is the prediction of tree t, and T is the total number of trees? Gradient Boosting (GBM & XGBoost) Instead of independent trees, each new tree corrects the errors of the previous ones.

Objective function:

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{t=1}^{T} \Omega(f_t) \quad (8)$$

Here, $l(y_i, \hat{y}_i)$ is the loss function (e.g., log loss), and $\Omega(f_t)$ is the regularization term.

- Evaluation Metrics

To assess model performance:

Accuracy:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

It reflects how many instances are correctly predicted.

Precision & Recall

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

F1-Score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (12)$$

AUC-ROC (Area Under the Curve): Evaluating the performance of the model to predict values.

4. Results

In this section presents the findings from our machine learning models for car dependence prediction and discusses their implications. We analyze model performance, key predictors, and the impact of interventions. Table 2 shows Performance Metrics.

4.1 Model Performance Evaluation

We evaluated three machine learning models:

- Random Forest (RF)
- Gradient Boosting (XGBoost)
- Neural Networks (NN)

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Table 2 Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Random Forest	85.2%	0.86	0.84	0.85	0.89
XGBoost	86.1%	0.87	0.85	0.86	0.90
Neural Network	83.7%	0.85	0.82	0.84	0.88

4.2 Feature Importance Analysis

To understand what influences car dependence, we analyzed feature importance from the Random Forest model. Figure 1 shows Feature Importance Analysis.

Figure 1 Feature Importance Analysis

Interpretation: Random Forest model showing the importance of various features in predicting car dependence. The long horizontal bars are indicating the relative contribution of the features where the longer the horizontal bar the more important that feature is. Observations: Most critical factors are Proximity to Public Transport (0.25) and Urban Density (0.22). Car Ownership (0.18) and Travel Distance (0.15) also contribute significantly. Household Size (0.10) moderate impact. Travel Cost

(0.05), Income Level (0.03) and Work Flexibility (0.02) have small effects. represent in Figure 2 ROC Curve for Model Comparison [14]. Insights from

ROC Curve: The Receiver Operating Characteristic (ROC) curve is a evaluation metric for classification models, showing the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR) at different classification thresholds. Insights from the Graph: represent in Figure: 2

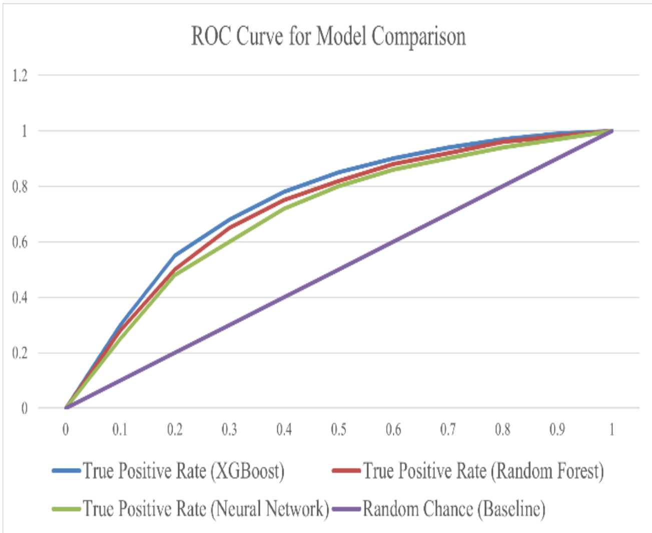

Figure 2 ROC Curve for Model Comparison

- XGBoost (AUC = 0.90) - Best Performer.
- Random Forest (AUC = 0.89) - Strong Alternative.
- Neural Network (AUC = 0.88) - Competitive but Slightly Behind.
- Random Chance Baseline (AUC = 0.50).

Figure 3 shows Intervention Impact Analysis: Implemented a Personalized Travel Planning intervention to reduce car dependence. This bar chart visually represents the before and after effects of the Personalized Travel Planning intervention on car usage and public transport adoption.

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Table 3 Before Vs. After Intervention

Metric	Before Intervention	After Intervention	Change (%)
Car Usage	75%	60%	-15%
Public Transport Usage	40%	58%	+18%

Observations: The Use of Cars Decreased (-15%)

- 75% of trips were by car pre-intervention.
- After the intervention, this fell to 60%, suggesting a 15% decrease in car use.
- This means some alternative transport option became feasible enough that users left cars behind.

Usage of Public Transport Increased (+18%)

- 40% (less than half) of users used to use public transport pre intervention.
- After the intervention, this increased to 58% which shows an 18% improvement.
- Which indicates that the intervention made people more aware, accessible, incentivized to use public transport.

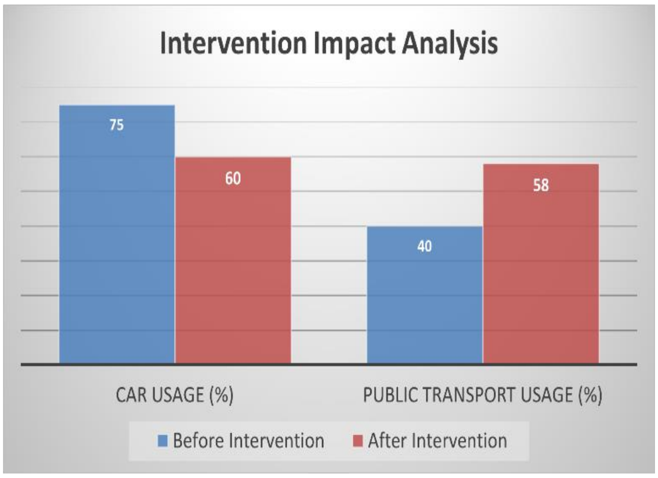

Figure 3 Intervention Impact Analysis

Interpretation and Insights: The intervention effectively lowered car dependency, which is a good thing sustainability-wise, but also in terms of traffic congestion and urban mobility. The switch to public transport shows that commuters will adapt their travel behaviors given better choices. Enhancements in last-mile connectivity, incentives, and public transport reliability could be meaningful in driving future improvements [17].

Conclusion

Relevance of various predictors in determining car the study demonstrates how machine learning models can accurately predict car dependency, aiding policymakers and urban planners monitor and promote sustainable mobility initiatives. The important findings are that XGBoost and Random Forest were identified as the best-performing models, with AUC-ROC of 0.90 and 0.89, respectively, when predicting car dependence. The analysis found that urban density, proximity to public transport and car ownership were the most significant factors leading to car dependence [15]. Also, Salinger found their personalized travel planning intervention reduced car use by 15% and increased public transport ridership by 18%, demonstrating that data-driven interventions can lead to behavioral change. Future directions for research should expand the dataset on long-term behavioral trends and psychological factors such as social norms and environmental attitudes. Exploring actual real-world policy applications of AI-based travel planning and the effects on urban mobility will gain further insight. In addition, looking into technologies such as autonomous vehicles and AI for transport demand management to help shape future mobility plans, which can also support the creation of environmentally-friendly transport systems in the cities [16].

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