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A Framework for Providing Information about Parking Spaces

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Abstract: There is a serious imbalance between parking demand and capacity in cities due to limitations in their parking facilities. It is important for drivers to know about parking vacancies before their trips. Meanwhile, administrators need information about parking capacity and demand before a week begins to improve parking management. A method is proposed here for predicting parking demand and capacity by utilizing a Naïve Bayes model and different variables such as drivers' characteristics and their trips, environmental conditions, parking attributes, and vehicle specifications. Tehran (Iran) is used as a case study etfor testing the model. Using the proposed model, it is possible to identify which parking facilities (and when) might experience spillover. For parking management and policy, demand management, and providing information about parking availability for drivers before their trips, this can be helpful.

Keywords: parking demand; Naïve Bayes; pricing factors; planning

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1. Introduction

Motorization and urbanization have led to growth in the use of private cars and a need for parking spaces at destinations. There is an imbalance between parking demand and parking capacity in Central Business Districts (CBDs) [1]. As a result, finding a parking space in CBD areas can take a considerable amount of time, especially during peak periods [2]. Therefore, traffic congestion, energy loss, air pollution, crashes, and delays are all adversely affected [1,3]. In big cities particularly, it is imperative for both drivers and administrators to have access to parking information.

Using parking guidance information systems, users can find suitable parking spaces in a shorter amount of time [2]. Drivers can plan their trips better if they are informed about parking spaces and reservations before they leave [1]. Many studies are available about parking guidance information systems. Chou et al. (2008) proposed a guidance system for reducing the time needed to search for a parking space and to present parking prices [4]. Geng and Cassandras (2011) suggested a system for an optimized parking assignment based on queue analysis after collecting requests for parking spaces during a time interval [5]. Bessghair et al. (2012) proposed a system that relies on the communication of vehicles with each other for finding vacant parking spaces [6]. To develop parking information systems, Boudali and Ouada (2017) introduced a new method based on a multicriteria ranking and parking requests from drivers as a guide for finding optimal parking space [2]. Mei et al. (2020) used Fourier transform-least squares and a support vector machine for the real-time prediction of parking spaces for smart parking facilities [7]. Lu and Liao (2020) developed a framework for predicting parking occupancy and then allocating parking spaces to each user [8].

Gao et al. (2021) proposed a Dijkstra algorithm for parking information using smartphones [1]. Using electronic devices based on the internet for parking management is an emerging technology in recent decades [1,9,10] and can improve traffic efficiency [11]. Drivers also prefer using such facilities for parking reservations in order to have an optimal choice [1]. These systems usually work by using some sensors in the parking spaces to provide information about the parking vacancy and display them on an online platform. Since more than one driver can reserve a parking spot at the same time, most of these systems cannot guarantee parking vacancy until the driver reaches the reserved parking spot. There might also be congestion in a district if there are few vacant parking spaces, since several drivers may have driven there at the same time. Furthermore, most such systems do not consider important variables such as parking security, the distance between parking and destination, the distance between origin and parking position, and/or parking price [2,12].

It is beneficial for parking policy and management programmes (PPMPs) to understand parking spaces from the perspective of the administrator. The PPMP can affect travel modes, trip schedules, route choices, trip destinations, and parking rates [13,14]. When sustainability is a concern for the city, a PPMP can control and reduce the private vehicle share [15]. In this regard, Pandhe and March (2011) studied the correlation between parking availability and usage of sustainable transportation systems by conducting a survey in the CBD region of Melbourne, revealing that 35% of respondents used public transportation instead of parking [16]. In big cities, planning for land use is very important and equity is a crucial concern in space distribution [17]. A PPMP can help dedicate land for a suitable parking facility. A PPMP can be effective in reducing the risk of failure for certain types of parking facilities because they have high construction costs and must be economically feasible. As another advantage of PPMPs, appropriate parking pricing strategies can be proposed. According to Qin et al. (2020), parking vacancy information could shorten cruising time and balance parking resource use, resulting in fewer parking issues [18].

The parking demand and capacity under different conditions must be predicted in order to provide information about parking spaces for drivers and administrators. In order to predict demand, it is important to understand the parking choice behaviour of drivers [3]. Table 1 provides a brief review of the models used to identify and define users' parking choices in various studies. Parking capacity is determined by the number of parking spaces, the duration of parking, and the rate at which parking spaces are turned over.

Table 1. A review of parking choice behaviour.

Authors	Case Study	Variables	Model
[19]	Parking location choice in a large CBD of Edmonton, Canada	Monetary cost, separation from final destination, position relative to the trip being made, status of the parking surface, and searching time	Nested logit model
[20]	A part of the city centre of Piraeus in Greece	Search time for a parking space, duration of parking, and walking time from the parking space to the final destination	Logit model
[21]	-	The price of curb parking, the price of off-street parking, parking duration, the price of fuel, the number of persons in the car, and the value of time	simple model of the benefits and costs
[22]	Dutch National Travel Survey	Parking fee information, parking time	empirical models
[23]	Parking facilities in Beijing, China	Walking time, parking charges	multinomial logit model
[24]	The Spanish coastal town of Santona	Vehicle age, being a local resident, and drivers' value of time	A mixed logit model
[25]	Parking information from villages of cities of Hasselt and Genk in Belgium	Gender, education, and visiting frequency characteristics	regression model

Table 1. *Cont.*

Authors	Case Study	Variables	Model
[26]	The City Center mall and the Souq Waqif shopping centre in the city of Doha, Qatar	Selecting between free and paid parking, intelligent parking space detection	Binary classification tree models
[27]	Cartagena, Colombia	Parking fee, search time, access time, a risk-averse attitude, and positive car care	hybrid discrete choice model
[28]	Parking at Tongji University	Parking price, walking time, and number of free hours	mixed logit model
[29]	Parking information from Beijing, China	Parking period, parking location, and parking duration	structural equation model
[30]	Tunisian drivers' parking choice	Security, duration, and parking fees	-
[31]	A study in Brisbane	Arrival time, frequency of trips, trip purpose, parking price, and traffic volume	multinomial logit model
[32]	Parking information in China	Reservation and shared parking spaces, available parking spaces, parking charges, and distance to the destination	multinomial logit model
[33]	-	Walking distance and parking time, security risk information, parking fee	Elaboration Likelihood Model (ELM)

This paper contributes to predicting parking spaces and providing valuable information to administrators and drivers. A Naïve Bayes model is used to predict parking capacity and demand. According to the literature review, variables related to driver characteristics, environmental conditions, parking attributes, and trip details are considered. As a result of predicting the demand for and capacity of parking facilities, administrators can answer these research questions (RQ) in a given case study:

RQ 1: Are there parking facilities that may experience a demand-to-capacity ratio of one or more?

RQ 2: When is parking spillover more likely to occur?

RQ 3: In terms of reducing the probability of parking spillover, which variables are most important?

As a result of the outcomes and implications of the model, administrators can better manage PPMPs and determine the information that must be provided to drivers.

2. Method

To answer the research questions, it is necessary to predict the demand for and capacity of parking facilities in different districts of a city over time. Thus, facilities with demand-to-capacity ratios equal to or higher than one can be identified. The probability of parking in each type of parking facility can be calculated based on the characteristics of the driver, the weather, the parking attributes, and the details of the trip. Naïve Bayes as a classification tool was selected for this purpose.

The Naïve Bayes model uses conditional probability and originates from the known statistical method Bayes Theorem [34]. This is one of the supervised classification methods that uses training data to create a classification model. After training with this data, the model can predict the probability of placing each sample into each class based on the test data. It assumes that all examples' attributes are independent, given that they are in a category. By assuming independence, the parameters for each feature can be learned separately, which simplifies learning when there are many features [34,35]. Naïve Bayes (NB) has the following advantages: easy implementation, high performance, smaller amount of training data, linear scaling, ability to deal with binary and multi-class classification problems, and ability to make probabilistic predictions. Furthermore, it can handle both continuous and discrete data while not being sensitive to irrelevant features [36,37].

2.1. Demand Prediction

A variety of variables, such as monetary costs, locations, and vehicle characteristics, have been used to study parking behaviour in the past. However, this study introduces a number of innovative variables, such as education, gender, age, physical health, luggage weight, vehicle value, and weather conditions. In this study, their influence on parking choices is examined. A number of other factors are also examined, including distance to the destination, parking security, charge rates, shelter availability, and parking duration. Our research using these variables will help us understand the complex decision-making processes individuals undergo when selecting parking options. The goal is to shed light on how these multifaceted aspects collectively influence parking choices by examining drivers' lives and circumstances.

Via the incorporation of variables not extensively explored in prior research, this study presents a fresh perspective on parking choice analysis. As a result of this approach, it is possible to gain a better understanding of how individual attributes and environmental conditions affect parking preferences and behaviours. The purpose of this comprehensive examination is to contribute to the field's knowledge base and provide a more holistic framework for understanding the intricate interplay of variables in parking decisions.

Based on the literature review presented in Section 1, parking choice can depend on different factors and variables as outlined in Table 2.

Table 2. Effective variables of parking choice behaviour.

Factors	Variables	Abbreviation
Driver	Education	EDU
	Gender	GEN
	Age	AGE
	Physical health	PHY
	Average daily walking duration	ADW
	Weight of accompanied luggage	WAL
Vehicle	Vehicle value	VEV
	Vehicle age	VEA
Environmental	Weather conditions	WEC
	Traffic congestion status	TCS
Trip	Frequency of weekly trips	FWT
	Trip purpose	TRP
Parking attributes	Importance of the distance between parking and destination	DPD
	Parking entering time	j
	Parking security	PAS
	Parking charge rate	PCR
	Parking shelter	PSH
	Parking duration	PDU

To calculate the demand for each type of parking facility, Equation (1) is proposed.

$$D_{i,j,k,l} = W_{j,k,l} \times \frac{1}{N}\sum_{n=1}^{N} P\left(i_{enter} \middle| (EDU, GEN, \ldots, PDU)_n\right) \tag{1}$$

where:

W: Total demand;
i: Type of parking;
j: Time interval entering the parking;
k: District number;
l: Day of the week;

$P(i_{enter}|((EDU, GEN, \ldots, PDU)_n)$: Probability of entering parking type i for the n_{th} person based on input variables;
N: Total number of parking applicants.

The probability of choosing each type of parking facility depends on the variables in Table 2. To calculate the probability for each person, we use Naïve Bayes.

2.2. Capacity Prediction

Equation (2) is suggested for predicting the capacity of each type of parking facility (number of available parking spaces). As seen for the demand prediction, the average probability of leaving a parking space at a specific time after an interval is calculated.

$$\begin{aligned}
&C_{i,J,k,l} = C_{i,Base,k,l} - \sum_{j=2}^{J} D_{i,j-1,k,l} + \sum_{j=1}^{J-1} \overline{P}_{i,j,J,k,l} \times D_{i,j,k,l} \quad \forall D_{i,j-1,k,l} < C_{i,j-1,k,l} \text{ and } J > 1 \\
&C_{i,J,k,l} = \sum_{j=1}^{J-1} \overline{P}_{i,j,J,k,l} \times D_{i,j,k,l} \quad \forall D_{i,j-1,k,l} \geq C_{i,j-1,k,l} \text{ and } J > 1 \\
&\overline{P}_{i,j,J,k,l} = \left(\frac{1}{N} \sum_{n=1}^{N} P(i,j,J|(EDU, GEN, \ldots, PDU\ )_n)\right) \\
&C_{i,1,k,l} = C_{i,Base,k,l}
\end{aligned} \tag{2}$$

where:

$C_{i,J,k,l}$: Parking capacity of type i at time interval J;
$P(i,j,J|(EDU, GEN, \ldots, PDU\ )_n$: Probability of leaving a parking facility type "i" for the driver who entered at time j and left at time J;
$C_{i,Base}$: The capacity of each parking facility at the beginning of the first time interval.

Now it is possible to answer the first two research questions using Equations (1) and (2). To answer question 3, it is necessary to conduct a sensitivity analysis. For this purpose, different scenarios are made by considering different values for $W_{l,k,j}$, $C_{i,base}$, and other variables indicated in Table 2. Then, in each scenario and for each parking facility, the percentage of cases with a demand-to-capacity ratio (D/C) equal to one or more is determined. By comparing the frequency of cases with $D/C \geq 1$ in different scenarios, the variables with the highest impacts on parking spillover can be determined.

3. Data

The first step to using the proposed method consists in training the Naïve Bayes models to calculate $P(i_{enter}|((EDU, GEN, \ldots, PDU)_n)$ and $P(i,j,J|(EDU, GEN, \ldots, PDU\ )_n$. This requires a database and a case study. The Iranian capital, Tehran, has been selected for this purpose.

Tehran has serious problems concerning parking facilities since there are more than 10 million inhabitants and 20 million daily trips. About 40% of the modal share relates to passenger cars while 38% relates to public transit. The large portion of daily trips that occurs by car has caused problems with parking scarcity. Both drivers and administrators do not have enough information about the parking status before a week starts.

The data collection for training the Naïve Bayes models was performed by conducting field interviews in different situations. From August 2019 to November 2020, several interviewers tried to find out the characteristics of people who were parking their vehicles in a specific type of parking. They asked about the driver's characteristics, the trip conditions, and the specifications of the vehicle. For each case, additional environmental conditions and parking details were recorded. To record the duration, the observers waited for the drivers to leave the parking lot. There are four types of parking facilities (i) analysed in this study: free on-street parking (P1), paid on-street parking (P2), one-level and multi-level parking (P3), and mechanized parking (P4). P1, P2, P3, and P4 do not include parking facilities which have specific parking lots for each person all the time. There are five selected time intervals (j): morning (6:00 to 10:00), pre-noon (10:00 to 12:00), noon (12:00 to 15:00), afternoon (15:00 to 17:00), evening (17:00 to 20:00), night (20:00 to 23:00), and midnight

(23:00 to 6:00). In total, 902 drivers were interviewed and, after the pre-processing steps, 884 cases remained of which 70% of the cases were used for training the Naïve Bayes models. A descriptive analysis of the collected data is presented in Table 3.

Table 3. Descriptive analysis of the collected data for training the Naïve Bayes models.

Variable	Categories	Percent	Variable	Categories	Percent
EDU	- High school	19.6	WAL (Kilogram)	Nothing	14.3
	- Diploma	13.7		<2	22.7
	- Bachelor of Science (B.Sc.)	31.8		2–4	27.4
	- Master of Science (M.Sc.)	23.3		4–6	20.6
	- Doctor of Philosophy (Ph.D.)	11.6		>6	15
GEN			VEV (USD)	Less than 5000	28.6
	Female	63.2		5000–10,000	31.1
	Male	36.8		10,000–15,000	22.3
				More than 15,000	18
AGE	18–24	8	VEA (Year)	0 to 40	-
	24–30	30.4			
	30–40	24.2			
	40–50	14.1			
	50–60	16			
	>60	7.3			
PHY			FWT	2	4.6
				3	5.3
	Healthy	98.3		4	21.3
	Having a previous illness	1.7		5	22.5
				6	32.6
				7	13.7
ADW (Minutes)	<15	37.7	TCS	Very low	5.4
	15–30	24		Low	6.3
	30–45	18.3		Medium	40.6
	45–60	15		Congested	29.3
	>60	5		Highly congested	18.4
TRP	Education	16.7	WEC		
	Work	20		Windy	18
	Leisure	7.7		Clear	22.6
	Shopping	12.3		Cloudy	25
	Medical	8.3		Rainy	12
	I'm a driver	3.7		Snowy	22.4
	Multipurpose	31.3			
DPD (Meter)	<100	26.5	J	Morning	27.5
	100 to 200	22.2		Pre-noon	11.7
	200 to 400	14.8		Noon	15.6
	400 to 800	12.3		Afternoon	13
	800 to 1000	21		Evening	18.3
	>1000	3.2		Night	9.8
				Midnight	4.1
PAS			PCR	Free	15
				Less than 5	18.7
	Good	34.7		5 to 10	13
	Medium	33.6		10 to 15	17.4
	Poor	19		15 to 20	17
	Very poor	12.7		20 to 25	8
				25 to 30	7.6
				30 to 35	3.3

Table 3. *Cont.*

Variable	Categories	Percent	Variable	Categories	Percent
PSH	Not available By trees With a constructed shelter	61.3 16 22.7	PDU (Minutes)	<10 10 to 20 20 to 30 30 to 45 45 to 60 60 to 120 >120	31.3 15.2 18.1 10.6 5.8 11 8

A second round of interviews and data collection has focused on one specific district of Tehran (to test the model's applicability) and users have been asked to complete an online questionnaire about their characteristics (based on the list provided in Table 2). In this district, different types of parking facilities are available, and people have enough knowledge about them. In this district, about 4.8% of trips are produced and 10.8% are attracted. The district's population is about 3% of the city.

For the aim of brevity, the data from five requests have been presented as a sample in Table 4.

Table 4. A sample of the registered people for the parking facilities of a specific zone in Tehran.

People ID	EDU	GEN	AGE	PHY	ADW	WAL	VEV	VEA	FWT	TRP	DPD	j	PDU
1	High school	Male	18–24	Healthy	<15	Nothing	<5000	1	2	Education	<100	1	<10
2	Diploma	Female	24–30	Healthy	15–30	<2	5000–10,000	2	3	Work	100 to 200	2	10 to 20
3	B.Sc.	Male	30–40	Healthy	30–45	2–4	10,000–15,000	3	4	Leisure	200 to 400	3	20 to 30
4	M.Sc.	Female	40–50	Healthy	45–60	4–6	>15,000	4	5	Shopping	400 to 800	4	30 to 45
5	Ph.D.	Male	50–60	Healthy	>60	>6	<5000	5	6	Multipurpose	800 to 1000	5	45 to 60

The specifications of the parking facilities and environmental conditions for a specific day of the week are assumed as in Tables 5 and 6.

Table 5. Specifications of parking facilities in a district of Tehran.

Specifications	Parking Type			
	P1	P2	P3	P4
C_{Base}	1200	600	750	1000
PAS	Poor	Medium	Medium	Good
PCR	Free	Less than 5	Free	5 to 10
PSH	Not available	By trees	Not available	With a constructed shelter

Table 6. Environmental conditions for a specific day in Tehran.

WEC	TCS
Clear	Medium

4. Results

There are two Naïve Bayes models for predicting the probability of entering and leaving a parking facility, $(P(i_{enter}|((EDU, GEN, \ldots, PDU)_n)$ and $P(i, j, J|(EDU, GEN, \ldots, PDU\ )_n)$. To check the model outputs, based on the confusion matrices, the performance metrics (that is, precision, recall, specificity, accuracy, and F1-score) are calculated for parking selection.

The results are presented in Table 7. The runtime for the model was about 4 min using a PC with these configurations:

Processor: Intel(R) Core(TM) i7-6700HQ CPU @ 2.60 GHz 2.59 GHz;
Installed RAM: 8.00 GB (7.90 GB usable);
System Type: 64-bit operating system, x64-based processor.

Table 7. Performance metrics for the Naïve Bayes models.

Demand Model	Actual	Predicted				Precision%	Recall%	Specificity%	F1-Score	Accuracy%
		P1	P2	P3	P4					
Training	P1	213	6	11	4	89	91	89	90	80
	P2	3	42	10	5	65	70	94	67	
	P3	2	8	81	9	74	81	93	77	
	P4	22	9	8	111	86	74	95	80	
Test	P1	97	6	10	12	87	78	92	82	78
	P2	4	33	7	6	67	66	93	66	
	P3	3	6	61	5	73	81	90	77	
	P4	7	4	5	74	76	82	89	79	

The correlation between input variables to control their independence is presented in Appendix A.

Based on the values of the variables in Tables 4–6, the probability of entering each kind of parking is calculated for each driver, as presented in Table 8 for the five sample cases.

Table 8. Probability of entering each kind of parking facility for each person.

People ID	Time Interval	Probability of Entering			
		P1	P2	P3	P4
1	Morning	0.801	0.001	0.192	0.004
2	Pre-noon	0.947	0.007	0.043	0.001
3	Noon	0.819	0.001	0.171	0.006
4	Afternoon	0.605	0.005	0.386	0.001
5	Evening	0.430	0.006	0.556	0.007

The probability of leaving each parking facility after "G = J − j" time intervals is shown in Table 9 for the five sample cases.

Table 9. Average probabilities of leaving each type of parking.

People ID	Entering Time	G = J − j	Probability of Leaving			
			P1	P2	P3	P4
1	Morning	1	0.337	0.048	0.313	0.300
2	Pre-noon	5	0.876	0.015	0.106	0.002
3	Noon	3	0.025	0.0221	0.115	0.837
4	Afternoon	2	0.689	0.065	0.222	0.022
5	Evening	2	0.002	0.538	0.067	0.391

Now, the average probabilities of entering each type of parking during a certain day and the average demand based on these probabilities are calculated based on Equation (2) and presented in Tables 10 and 11, respectively. These values relate to 7200 registered requests for a Monday in District 6.

Table 10. Average probabilities for each parking.

Time	Average Probabilities of Entering			
	P1	P2	P3	P4
Morning	0.586	0.034	0.309	0.069
Pre-noon	0.600	0.036	0.249	0.113
Noon	0.719	0.043	0.139	0.097
Afternoon	0.804	0.033	0.138	0.024
Evening	0.609	0.044	0.240	0.105
Night	0.623	0.051	0.221	0.103
Midnight	0.576	0.004	0.328	0.091

Table 11. Average demand for each type of parking.

Time	Average Demand for Entering			
	P1	P2	P3	P4
Morning	822	48	433	97
Pre-noon	600	37	250	113
Noon	647	39	125	88
Afternoon	1206	50	208	37
Evening	1036	75	409	180
Night	374	31	133	62
Midnight	58	0	33	9

The average probabilities of leaving each parking facility are calculated and presented in Table 12.

Table 12. Average probabilities of leaving each parking facility.

Entering Time	G = J − j	Average Probabilities of Leaving			
		P1	P2	P3	P4
Morning	1	0.455	0.137	0.250	0.156
	2	0.457	0.053	0.144	0.344
	3	0.460	0.314	0.136	0.088
	4	0.409	0.134	0.085	0.365
	5	0.064	0.416	0.206	0.312
	6	0.114	0.452	0.150	0.2823
	7	0.466	0.130	0.221	0.181
Pre-noon	1	0.482	0.191	0.150	0.178
	2	0.475	0.209	0.146	0.171
	3	0.622	0.059	0.273	0.045
	4	0.367	0.244	0.253	0.137
	5	0.455	0.045	0.064	0.436
	6	0.718	0.161	0.060	0.061
Noon	1	0.362	0.329	0.133	0.176
	2	0.475	0.113	0.290	0.121
	3	0.406	0.143	0.217	0.234
	4	0.374	0.008	0.235	0.384
	5	0.557	0.027	0.123	0.292
Afternoon	1	0.637	0.017	0.045	0.302
	2	0.125	0.107	0.352	0.416
	3	0.297	0.201	0.271	0.231
	4	0.245	0.017	0.280	0.458

Table 12. *Cont.*

Entering Time	G = J − j	Average Probabilities of Leaving			
		P1	P2	P3	P4
Evening	1	0.468	0.168	0.073	0.291
	2	0.521	0.204	0.202	0.074
	3	0.217	0.052	0.571	0.159
Night	1	0.325	0.358	0.120	0.196
	2	0.726	0.079	0.154	0.041
Midnight	1	0.169	0.125	0.402	0.304

The average capacity of each parking facility at each time interval (number of available parking spaces) is calculated using Equation (2) and presented in Table 13.

Table 13. Average capacities of each parking.

Time	Average Capacity			
	P1	P2	P3	P4
Morning	1500	750	900	1200
Pre-noon	1054	705	530	1136
Noon	741	688	313	1017
Afternoon	1017	639	234	953
Evening	686	616	137	947
Night	1507	550	249	817
Midnight	1967	491	438	721

Based on the outputs of Tables 12 and 13, it is possible to answer RQ1 and RQ2. For this purpose, Table 14 indicates the ratios of demand to capacity for each type of parking at different time intervals.

Table 14. Demand-to-capacity ratios.

Time	P1	P2	P3	P4
Morning	0.548	0.064	0.481	0.081
Pre-noon	0.569	0.052	0.472	0.099
Noon	0.873	0.057	0.399	0.087
Afternoon	1.186	0.078	0.889	0.039
Evening	1.510	0.122	2.985	0.190
Night	0.248	0.056	0.534	0.076
Midnight	0.029	0.000	0.075	0.012

The shaded cells with $D/C \geq 1$ relate to free on-street parking during the afternoon, evening, and multiple-level parking during the evening. Free on-street parking at noon also has the potential to become critical. Based on this table, it can be stated that the free on-street parking (P1) seems to be the one that needs more attention concerning a PPMP, while the paid on-street parking (P2) needs less attention.

To answer RQ3, it is necessary to carry out a sensitivity analysis. We have considered different values for $W_{j,k,l}$, C_{Base}, and the variables of Table 3. Then, the changes in the number of cases with $D/C \geq 1$ have been investigated. For this purpose, a matrix with 20 columns (input variables) and 1000 rows (combination of input variables with different values) has been made. For each record based on the input values, demand and capacity, and subsequently D/C, have been calculated.

The 10 variables that seem to have the highest impact on D/C variations have been reported in Table 15.

Table 15. The variables with the highest impact on D/C.

Variable	Relative Importance
Total demand	1
Initial capacity	0.616
Parking charge rate	0.348
Weather conditions	0.345
Traffic congestion status	0.298
Gender	0.280
Age	0.271
Physical health	0.248
Average daily walking duration	0.229
Weight of accompanied luggage	0.208
Vehicle value	0.199
Vehicle age	0.167
Frequency of weekly trips	0.166
Education	0.157
Trip purpose	0.147
Distance between parking and destination	0.134
Parking start time	0.132
Parking security	0.109
Parking shelter	0.096
Parking duration	0.068

5. Discussion and Conclusions

Based on the answers to the research questions, for the specific case study presented in this paper (the city of Tehran, Iran), it can be stated that:

The free on-street parking spaces (P1) have the highest spillover potential. In addition to street type, lane number, bike lane presence, and traffic volume, free on-street parking facilities have a limited capacity. As a result, urban spaces are limited, and parking lots are difficult to expand [3,38]. The goal should be to decrease demand for them as a result. Dogru et al. (2017) also concluded that to decrease parking spillover, it is necessary to work on the demand side by changing drivers' parking choice behaviour [39]. Demand management can be achieved via parking pricing. The lowest demand-to-capacity ratio is found in on-street paid parking. It might be a good idea to turn some free on-street parking spaces into paid parking spaces. Ottosson et al. (2013) also concluded that pricing can be an effective method for reducing parking duration [40]. However, high prices might be a threat to the economic vitality of a district [40]. Meanwhile, usually, residents oppose the changes concerning on-street parking spaces [38]. Thus, before any changes are made to the price of on-street parking spaces, it is good practice to investigate possible ways of persuading the residents [38].

Multiple-level parking (P3) is another parking type with a high probability of spillover. The construction of these facilities is expensive and requires special studies to determine the best location. Therefore, increasing their capacity is even more difficult than for on-street parking, and parking management must be directed towards reducing the total demand or shifting a group of users to paid on-street parking spaces.

There is a higher probability of spillover during the evening (17:00–20:00) and afternoon (15:00–17:00). There is a peak in demand at these times. According to Table 14, the main cause of parking facility failure is demand. As a result, the strategy should be to reduce the demand for parking during these times. It may be necessary to increase the price of parking facilities in order to accomplish this. A better method of reducing car use has been found in developed cities, particularly in Europe, by increasing the cost of car ownership [15,41]. Another intervention is to encourage people to shift to more sustainable transport modes.

Parking failures are affected by weather conditions and traffic congestion (see Table 14). As a result, if the weather conditions or traffic congestion change, there is a higher probability of failure when demand to capacity is close to one.

Demand-to-capacity ratios are least affected by parking facility specifications such as security and shelter availability.

Users' characteristics and their trips have little impact on the spillover from parking facilities.

The proposed method in this paper allows administrators to predict the status of parking facilities in each district before the week begins. Afterwards, they can determine how to price each type of parking. As a result, the strategy can change from week to week. Users can also be provided with information about the status of parking facilities, spillover probabilities, and parking capacity. It can discourage them from using private cars for their trips and encourage them to use more sustainable modes of transportation. As a result, they would also spend less time searching for parking.

This paper proposes a method for providing information about parking facilities that is powerful and comprehensive. The problem is easy to solve and takes a short amount of time to solve. It is possible to calibrate the models based on any new data. Long-term data collection can improve the accuracy of the method. Sensors are not required in the parking spaces for the method to work. PPMP outputs are first visible to administrators, who can establish policies and then share the results with users. This method gives users more accurate information about spillover probabilities for each type of parking rather than information about vacancies, which can cause the problems discussed in the introduction.

Although the proposed method has been applied to a specific case study in this paper, its theoretical and/or methodological contributions are not limited to this case study. The results and discussion are particularly insightful and can be applied to other case studies.

This paper's main limitation is that it ignores the fact that drivers will move to another parking space whenever a particular kind is full. Furthermore, gathering enough data to make the models reliable requires a lot of time and resources. The last limitation is that the weekly variations in PPMP are difficult for users to understand and it may be difficult for administrators to communicate their strategy.

A more advanced model could be proposed to eliminate parking facilities with a high probability of being selected by a user in the next step. In addition to municipalities collecting data, PPMPs can provide data gradually for the next steps, and the last limitation can also be solved gradually by providing education programmes and advertisements that make users familiar with such technologies. As a result, the long-term benefits of performing a PPMP outweigh its limitations.

In future studies, it is recommended to use other advanced tools to predict parking demand and capacity based on different input variables and for solving the limitations of current models. Using real data collected by local governments for each district of a city, a PPMP can be performed on the model outputs for each district and the outputs should be checked for efficiency before a PPMP can be conducted.

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Nomenclature

Variables	Abbreviation
Free on-street parking	P1
Paid on-street parking	P2
One-level and multiple-level parking	P3
Mechanized parking	P4
Education	EDU
Gender	GEN
Age	AGE
Physical health	PHY
Average daily walking duration	ADW
Weight of accompanied luggage	WAL
Vehicle value	VEV
Vehicle age	VEA
Weather conditions	WEC
Traffic congestion status	TCS
Frequency of weekly trips	FWT
Trip purpose	TRP
Importance of the distance between parking and destination	DPD
Parking entering time	j
Parking security	PAS
Parking charge rate	PCR
Parking shelter	PSH
Parking duration	PDU

Appendix A

Table A1. Correlation of input variables.

	EDU	GEN	AGE	PHY	ADW	WAL	VEV	VEA	FWT	TCS	TRP	WEC	DPD	PAS	PCR	PSH	PDU
EDU	1	−0.018	0.126 **	0.016	−0.077 *	0.013	0.194 **	−0.051 *	−0.069 *	0.081 *	−0.078 *	−0.059 *	0.055 *	0.000	−0.044	−0.070 *	0.124 **
GEN	−0.018	1	0.106 **	0.066 *	0.013	−0.059 *	0.021	0.043	0.117 **	−0.058 *	−0.036	−0.044	−0.013	0.038	0.010	0.024	0.036
AGE	0.126 **	0.106 **	1	0.158 **	0.027	0.081 *	0.089 *	0.101 **	0.045	−0.026	−0.095 *	0.067 *	0.021	0.018	−0.029	0.008	0.061 *
PHY	0.016	0.066 *	0.158 **	1	0.077 *	0.112 **	0.047	−0.007	−0.013	0.052 *	−0.067 *	−0.028	0.060 *	0.060 *	0.027	0.040	−0.025
ADW	−0.077 *	0.013	0.027	0.077 *	1	0.160 **	−0.036	−0.090 *	0.183 **	0.112 **	0.139 **	0.074 *	0.302 **	0.030	0.243 **	0.113 **	0.080 *
WAL	0.013	−0.059 *	0.081 *	0.112 **	0.160 **	1	0.020	−0.003	0.036	0.155 **	0.022	0.013	0.155 **	0.160 **	0.199 **	−0.005	−0.087 *
VEV	0.194 **	0.021	0.089 *	0.047	−0.036	0.020	1	−0.145 **	−0.005	0.024	−0.041	0.042	0.016	−0.070 *	0.056 *	0.071 *	0.026
VEA	−0.051 *	0.043	0.101 **	−0.007	−0.090 *	0.036	−0.145 **	1	−0.002	−0.007	−0.047	−0.043	−0.003	0.043	−0.070 *	−0.092 *	−0.041
FWT	−0.069 *	0.117 **	0.045	−0.013	0.183 **	0.036	−0.005	−0.002	1	0.071 *	0.109 **	−0.040	−0.041	0.056 *	0.107 **	−0.033	−0.047
TCS	0.081 *	−0.058 *	−0.026	0.052 *	0.112 **	0.155 **	0.024	−0.007	0.071 *	1	−0.028	−0.022	0.229 **	0.278 **	0.223 **	−0.077 *	0.059 *
TRP	−0.078 *	−0.036	−0.095 *	−0.067 *	0.139 **	0.022	−0.041	−0.047	0.109 **	−0.028	1	−0.043	0.006	0.059 *	0.043	0.053 *	−0.050 *
WEC	−0.059 *	−0.044	0.067 *	−0.028	0.074 *	0.013	0.042	−0.043	−0.040	−0.022	−0.043	1	0.047	0.000	0.047	0.091 *	0.048
DPD	0.055 *	−0.013	0.021	0.060 *	0.302	0.155 **	0.016	−0.003	−0.041	0.229 **	0.006	0.047	1	0.157 **	0.257 **	−0.031	−0.001
PAS	0.000	0.038	0.018	0.060 *	0.030	0.160 **	−0.070 *	0.043	0.056 *	0.278 **	0.059 *	0.000	0.15 **	1	0.061 *	−0.195 **	−0.079 *
PCR	−0.044	0.010	−0.029	0.027	0.243 **	0.199 **	0.056 *	−0.070 *	0.107 **	0.223 **	0.043	0.047	0.257 **	0.061 *	1	0.157 **	−0.056 *
PSH	−0.070 *	0.024	0.008	0.040	0.113 **	−0.005	0.071 *	−0.092 *	−0.033	−0.077 *	0.053 *	0.091 *	−0.031	−0.195 **	0.15 **	1	0.085 *
PDU	0.124 **	0.036	0.061 *	−0.025	0.080 *	−0.087 *	0.026	−0.041	−0.047	0.059 *	−0.050 *	0.04	−0.001	−0.079 *	−0.056 *	0.085 *	1

* Significant at 0.05 level, ** Significant at 0.1 level.

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