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Addressing Urban Traffic Congestion in New Delhi Through Novel Parking Guidance and Information System

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Abstract

The rapid growth in private vehicle ownership in Indian cities, particularly in New Delhi, has led to severe traffic congestion, with parking demand being a significant contributing factor. Despite India's relatively low car ownership rates globally, the rising demand for street parking has reduced road capacity and hindered urban traffic flow. This study focuses on the persistent issue of traffic congestion in New Delhi, particularly during peak hours on arterial roads and highways, caused by factors such as high vehicle density, illegal parking, inadequate parking infrastructure, mixed traffic flow, and inefficient management systems.

To address these challenges, this paper presents the Optimal Parking Space Allocation Model (OPSAM), a novel system that integrates real-time parking vacancy detection with a user-centric platform for guidance and reservation. Leveraging the YOLO-v4 object detection algorithm, OPSAM offers a scalable solution tailored to the unique challenges of Indian urban environments, such as diverse traffic conditions and infrastructural limitations. By providing real-time parking information through security cameras and mobile applications, OPSAM significantly reduces the time drivers spend searching for parking spaces.

Experimental results demonstrate that OPSAM reduces parking cruising time by an average of 20% and illegal parking by 12%, while improving parking occupancy efficiency from 70% to 85%. A paired t-test analysis confirmed a statistically significant reduction in search times, with a mean decrease of 9.775 minutes (p-value < 0.001). These findings highlight OPSAM's potential to alleviate urban traffic congestion, enhance traffic flow, and improve mobility in high-density areas like New Delhi. Additionally, the system's adaptability offers promising applications for other congested cities facing similar challenges.

Categories: Urban Planning and Development, Sustainable Technologies, Transportation Engineering
Keywords: parking guidance and reservation system (pgis), traffic congestion, parking facilities, traffic management, real-time parking information, urban infrastructure, central delhi, yolo-v4, opsam

Introduction

Over the past decade, Indian cities, particularly metropolitan hubs have experienced rapid urbanization coupled with an exponential rise in motor vehicle ownership. With an average annual growth rate of 12.24% in vehicle numbers, this surge has compounded urban challenges, notably traffic congestion, which is particularly severe in high-density areas such as Chennai, Mumbai and New Delhi [1-2]. These cities face unique congestion challenges due to the overwhelming reliance on personal vehicles, which stems from inadequacies in public transportation systems. Safety concerns, inconsistent service, and limited convenience have driven commuters to favor private vehicles, seen as both a secure and status-enhancing mode of travel [3]. In Delhi, high vehicle density, inadequate road infrastructure, and disruptions such as roadworks exacerbate the traffic problem. Among these, ineffective parking management is a critical yet often overlooked contributor to congestion. Issues like prolonged parking searches, illegal parking, and on-street parking are common practices in Central Business Districts (CBDs) not only reduce road capacity but also disrupt traffic flow [4]. A study conducted in 2022 revealed that in Connaught Place, the demand for parking spaces far exceeded the available supply, forcing drivers to spend an average of 20 minutes searching for a spot, which in turn contributed to a 30% reduction in road capacity [5]. Similar findings across urban areas underscore the strong correlation between parking inefficiencies and traffic congestion [6], [7]. Existing literature emphasizes the urgent need for advanced parking management strategies that integrate technology-driven solutions. Previous studies have documented the inefficiencies of traditional parking systems and their inability to meet the demands of urban commuters, particularly in CBDs, where mixed land-use patterns heighten parking demand [8], [9]. Building on these insights, this study investigates the relationship between traffic congestion and parking management in Central Delhi, a commercial district of New Delhi with a population of approximately 1.73 million [10], focusing on three critical issues: prolonged parking searches, on-street parking, and illegal parking. To address these challenges, the study proposes and evaluates the Optimal Parking Space Allocation Model (OPSAM), a Parking Guidance and Information System (PGIS) powered by the YOLO-v4 object detection algorithm. OPSAM is an integrated parking management system that leverages real-time parking availability detection to reduce search times and mitigate the likelihood of illegal parking. The model connects parking lots across a designated area, enabling drivers to access real-time updates via a centralized platform. Preliminary findings from a April 2023 survey of drivers in New Delhi indicate that OPSAM significantly improves urban mobility. The survey revealed a peak demand of 950 vehicles per hour against an available capacity of 456 parking spaces, highlighting the urgency of effective interventions. By addressing this gap, OPSAM reduces cruising times and optimizes parking utilization, as evidenced by its ability to increase parking occupancy efficiency from 70% to 85%.

Materials And Methods

The method used in this study aims to find the main causes of traffic jams and find ways to fix them by creating and testing a new Parking Guidance and Information System (PGIS), OPSAM, which is based OPSAM leverages the YOLO-v4 algorithm to detect parking availability in real time and facilitate reservations, ensuring a balance of speed, accuracy, and adaptability under varying lighting conditions. Data collection was conducted across high-congestion areas in New Delhi, including Sadar Bazar, New Delhi Railway Station, Chawri Bazar, and Chandni Chowk. These locations, chosen for their mix of residential, commercial, and governmental activities, represent significant transportation corridors plagued by heavy traffic, illegal parking, and high parking demand. A survey of 1,550 car users was conducted to gather insights into parking behavior and challenges, forming the basis for evaluating OPSAM's impact. Figure *1* highlights the selected routes and study areas.

Ethical Approval and Informed Consent

This study involving human participants was conducted in full compliance with the ethical standards set forth by the Departmental Review Committee (DRC) of Jamia Millia Islamia, New Delhi. The study was approved under the protocol number JMI-DRC/2022/345.

Prior to participation, all respondents provided written informed consent, acknowledging their voluntary involvement in the study. The participants were informed about the purpose of the research, the nature of their participation, and their rights to withdraw from the study at any point without any consequences.

To ensure privacy and confidentiality, all personal data collected was anonymized, and no identifying information was included in the analysis or publication of results. The data was securely stored and access was restricted to authorized personnel only, in accordance with data protection regulations.

First-level data collection

Primary data were collected using a structured questionnaire distributed to vehicle owners on different routes in Central Delhi. The data were collected during weekdays and weekends, spanning from March 1 to April 1, 2022, to capture a factual representative of typical parking scenarios. The study covered the period from 09:00 AM to 07:00 PM each day. The questionnaire was designed to gather detailed information on travel behavior, parking habits, vehicle ownership, trip frequency, and perceptions of traffic congestion. Data collection was conducted along three distinct routes in Central Delhi (depicted in Figure 1). The first route covered the area from Sadar Bazar to New Delhi Railway Station. The second route extended from Sadar Bazar to Chawri Bazar. The third route stretched from Sadar Bazar to Chandni Chowk. Each of these routes included multiple parking lots for comprehensive data analysis. A total of 1,550 respondents participated in the survey, and 1,250 responses were finalized after processing. The respondents were selected randomly to ensure a diverse representation of the population. The sample included a mix of private car owners only. The survey included questions about personal demographics, vehicle ownership, travel behavior, and perceptions of various congestion factors.

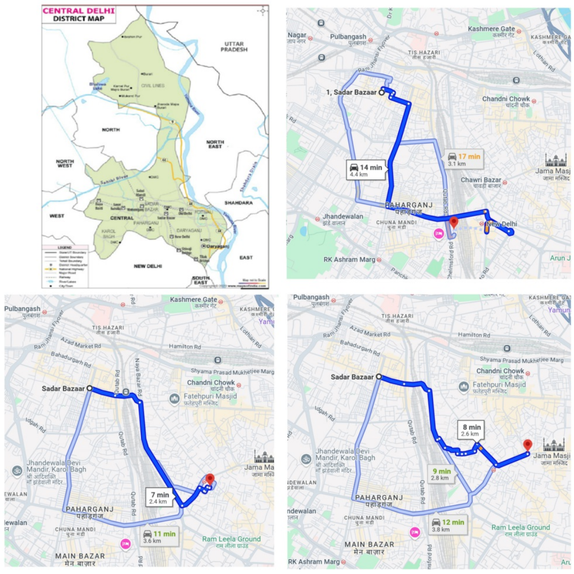

FIGURE 1: Study areas and selected routes for data collection, highlighting key congestion hotspots and parking demand zones across Central Delhi

Data Analysis of First-Level Data

The study focused on identifying the primary causes of traffic congestion in Central Delhi, examining factors like high vehicle density, illegal parking, inadequate parking facilities, mixed traffic flow, and related issues. The analysis of responses revealed key patterns between congestion factors and respondents' demographics and travel behaviors (refer to Table 1). The survey included respondents aged between 25 and 60 years, with a balanced gender distribution, offering insights from diverse population segments. Cars were the dominant vehicle type, followed by two-wheelers such as bikes and scooters. Vehicle ownership ranged from 2 to 12 years, with daily trips averaging 15 to 50 min, underscoring the heavy reliance on personal vehicles for commuting.

Characteristic	Level	Frequency	Percentage (%)
Socio-Economic Details			
Age	18-30 years	437	35%
	31-50 years	562	45%
	51 years and above	251	20%
Gender	Male	875	70%
	Female	375	30%
Vehicle Ownership (Years)	Less than 1 year	188	15%
	1-5 years	687	55%
	More than 5 years	375	30%
Average Trip Duration (Minutes)	Less than 30 minutes	500	40%
	30-60 minutes	562	45%
	More than 60 minutes	188	15%
Congestion Factors			
High Vehicle Density	Always	750	60%
	Most of times	375	30%
	Sometimes	125	10%
Mixed Traffic Flow	Always	687	55%
	Most of times	437	35%
	Sometimes	125	10%
Public Transport System (Rickshaw, Auto, etc.)	Always	500	40%
	Most of times	437	35%
	Sometimes	312	25%
Commercial Activities	Always	437	35%
	Most of times	625	50%
	Sometimes	188	15%
Poor Traffic Management	Always	562	45%
	Most of times	500	40%
	Sometimes	188	15%
Inadequate Parking Facilities	Always	625	50%
	Most of times	437	35%
	Sometimes	188	15%
Illegal Parking	Always	562	45%
	Most of times	500	40%
	Sometimes	188	15%
Cruising for Suitable Parking	Always	312	25%
	Most of times	625	50%
	Sometimes	312	25%
Pedestrian Movement	Always	437	35%
	Most of times	562	45%
	Sometimes	251	20%
Roadside Encroachments	Always	500	40%
	Most of times	437	35%
	Sometimes	312	25%
Urban Planning & Land Use	Always	437	35%
	Most of times	500	40%
	Sometimes	312	25%

TABLE 1: Summary of the survey data of evaluating the factors of traffic congestion

Parking-related issues emerged as a significant concern, with 61% of respondents identifying it as a major contributor to congestion. Approximately 48% of car owners were visitors, and their 20-min search for parking significantly affected road capacity. Inadequate parking facilities and on-street parking further aggravated congestion. Mixed traffic flow, characterized by varying vehicle types, contributed to delays due to speed disparities. Additionally, 66% of respondents pointed to poor traffic management, citing ineffective traffic signals and enforcement. Other contributing factors included high commercial activity, inadequate public transport, poor road infrastructure, pedestrian movement, roadside encroachments, and poor urban planning. Addressing these challenges requires an integrated approach, including enhanced traffic management, improved parking systems, and urban planning reforms.

Identification of Congestion Factors

The study highlights several principal factors contributing to congestion in New Delhi. The percentages of the factor are shown in figure *2*, and the frequency of responses is shown in table *1*.

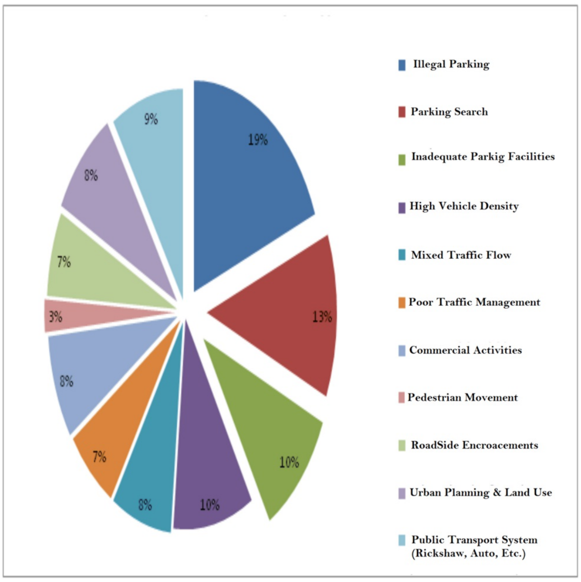

FIGURE 2: Pie chart of factors of traffic congestion

Second-level data collection

The data in first level identified illegal parking and the ensuing search for parking as significant contributors to congestion. Additionally, roadside parking further diminished road capacity. To address these issues, a follow-up survey was conducted to investigate the reasons behind prolonged parking searches and roadside parking. To gain a comprehensive understanding of these parking-related issues, a series of detailed face-to-face interviews and camera recordings were carried out at 12 strategically selected car parking facilities within the selected routes. In Table 2, the occupancy data and vehicle counts were obtained through a combination of manual counting and camera-based monitoring. To standardize the data, a passenger car unit (PCU) factor was applied to different vehicle types. The maximum PCU value recorded within a 15-min period represented the peak parking demand for that site. During each time period, trained personnel manually counted the vehicles entering and leaving the selected parking facilities, while security cameras recorded vehicle movements to validate the manual counts. This dual approach ensured that any discrepancies could be identified and corrected.

Timing	Route 1			Route 2			Route 3		
	PCU	Accumulation	Occupancy	PCU	Accumulation	Occupancy	PCU	Accumulation	Occupancy
9.00-9.15	28	47	94.00%	17	29	58.00%	20	32	60.00%
9.15-9.30	28	47	94.00%	18	33	66.00%	27.5	30	58.00%
9.30-9.45	27	44	88.00%	17.5	33	66.00%	22.5	29	60.00%
9.45-10.00	22	46	92.00%	21	34	68.00%	25	30	64.00%
10.00-10.15	23	46	92.00%	18	30	60.00%	23.5	32	60.00%
10.15-10.30	25	42	84.00%	16	29	58.00%	20	29	58.00%
10.30-10.45	22	34	68.00%	18.5	32	64.00%	27.5	34	64.00%
10.45-11.00	24	33	66.00%	19.5	32	64.00%	20	32	69.00%
18.00-18.15	29	34	68.00%	16.5	30	60.00%	27.5	30	67.00%
18.15-18.30	22	30	60.00%	16.5	29	58.00%	32.5	29	65.00%
18.30-18.45	23	36	72.00%	17	30	60.00%	32.5	30	76.00%
18.45-19.00	24	35	70.00%	19	32	64.00%	20	32	74.00%

TABLE 2: Parking of vehicles at Central Delhi

In the first level of data collection, illegal parking and the search for parking were identified as major contributors to congestion. To further investigate these issues, follow-up surveys and detailed interviews were conducted at 12 selected parking facilities. A PCU factor was applied to standardize different vehicle types, with the peak parking demand recorded every 15 min. Of the 2,500 collected responses, 2,275 were considered complete and accurate after a rigorous filtering process. These data collection sites were chosen within known congestion hotspots to represent the broader traffic challenges faced in Central Delhi. This comprehensive methodology aimed to provide a clear understanding of parking-related congestion and guide effective solutions.

The findings were derived from a detailed analysis of parked vehicles and subsequent conversion to PCU values. The study encompassed 12 distinct parking lots (refer to Table 3). Among these destinations, marketplaces emerged as the most challenging locations for parking, as perceived by all respondents. Conversely, offices were generally considered the easiest places for drivers to find available parking spaces. Notably, female drivers encountered greater difficulty in locating available parking spaces compared to their male counterparts.

S. No.	Route Name	Name of Parking Lots	Max. Parking Demand Value (PCU)	Timing of Peak Parking	Reason for Peak Parking
1	Route 1: Sadar Bazar to New Delhi Railway Station	Sadar Bazar Parking	180	6:00-6:15 PM	Due to shopping market in that area, people come for shopping. Visitors come for party
2		Sadar Market Parking	240	6:15 – 6:30 PM	
3		Parking Sadar Bazar, Narain Market	186	6:15-6.30 PM	
4		MCD Car Parking, Paharganj	110	8.45-9.00 PM	
5	Route 2: Sadar Bazar to Chawri Bazar	Sadar Market Parking, Sadar Bazar	110	5.15-5.30 PM	Biggest spice market in North India. Buyers come from various cities in India. Biggest jewelry market in Delhi. Tourists come from various cities
6		Vehcile Parking, Chawri Bazar	90	9.45-10.00 AM	
7		VIP Car Parking	75	9.30-09.45 AM	
8		MCD Parking, Ajmeri Gate	370		
9	Route 3: Sadar Bazar to Chandni Chowk	NDMC Car Parking, Chandni Chowk	250	9.30-09.45 AM	Biggest retail shopping market in Delhi, also famous for garments and restaurants in entire Delhi. Visitors come for eating and shopping
10		Chandni Chowk Parking, Chandni Chowk	130	11.00-11.15 AM	
11		Chandni Chowk Parking- near tejoo	125	12.45-01.00 PM	
12		MLUG Gandhi Maidan North DMC	170	12.30-12.45 PM	

TABLE 3: Parking demand value (maximum) of all the sites

PCU: Passenger Car Unit

Table 1 revealed that 41% of the surveyed drivers used Google Maps to search for parking. These respondents predominantly relied on the app during periods of heavy traffic, when they were less confident that their preferred parking location would be available, or when they were unfamiliar with Central Delhi, often leaning on signboards for their infrequent visits. This dichotomy underscores the presence of two distinct customer segments for PGIS. The survey results confirmed that commuters often disregarded parking signs, relying instead on their accumulated knowledge from past experiences. However, during periods of heightened traffic uncertainty, such as large-scale events or holiday shopping, they found it challenging to utilize their preferred parking locations. In contrast, tourists with limited knowledge of the parking system were more receptive to having their parking choices influenced by Google Maps. Commuters with frequent and routine travel patterns who possessed an extensive understanding of the network and parking system typically did not perceive a pressing need for the information provided by Google Maps. The survey also explored drivers' inclinations regarding different types of parking information during the search for parking. The most preferred parking information revolved around real-time status of the nearest parking to the destination, parking fees, and types of parking lots in the same area. However, many drivers expressed a desire for comprehensive information, such as a detailed map indicating the locations of parking areas, operating hours, data about alternative parking options if the selected one reached capacity, and the vacancy of spaces at different parking lots. A few commuters expressed interest in receiving comprehensive guidance and directions to each parking area and exploring the option of parking reservations. This array of information poses a notable challenge for standard PGIS due to its complexity and level of detail.

Result of Second-Level Analysis

The study identifies parking management as a primary factor contributing to road congestion in Central Delhi, accounting for approximately 50% of congestion issues (refer to Figure 2). Data from 12 designated parking locations (refer to Figure 3) revealed an average vacancy rate of 11.13% (refer to Table 4) during peak demand periods, yet drivers often struggle to find parking due to a lack of real-time vacancy information. This leads to prolonged searches and the use of non-designated areas, exacerbating traffic congestion. Additionally, high vehicle density, inadequate parking facilities, mixed traffic flow, and poor traffic management further strain the road infrastructure. The study recommends implementing real-time parking information systems, enhancing enforcement of parking regulations, and improving public transportation to alleviate congestion and improve urban mobility in Delhi.

S. No.	Name of the Parking Sites	Parking Capacity (PCU)		Vacancy Percentage (PCU)
		Car	Two Wheeler	
1	Sadar Bazar Parking	50	10	11%
2	Sadar Market Parking	50	18	16%
3	Parking Sadar Bazar, Narain Market	35	25	13%
4	MCD Car Parking, Paharganj	150	50	11.5%
5	Sadar Market Parking, Sadar Bazar	50	30	07%
6	Vehcile Parking, Chawri Bazar	35	25	12%
7	VIP Car Parking	30	23	14%
8	MCD Parking, Ajmeri Gate	20	40	10%
9	NDMC Car Parking, Chandni Chowk	150	75	07%
10	Chandni Chowk Parking, Chandni Chowk	30	25	09%
11	Chandni Chowk Parking- near tejoo	30	25	12%
12	MLUG Gandhi Maidan North DMC	150	100	11%

TABLE 4: The capacity of parking with parking vacancy during peak demand

PCU: Passenger Car Unit

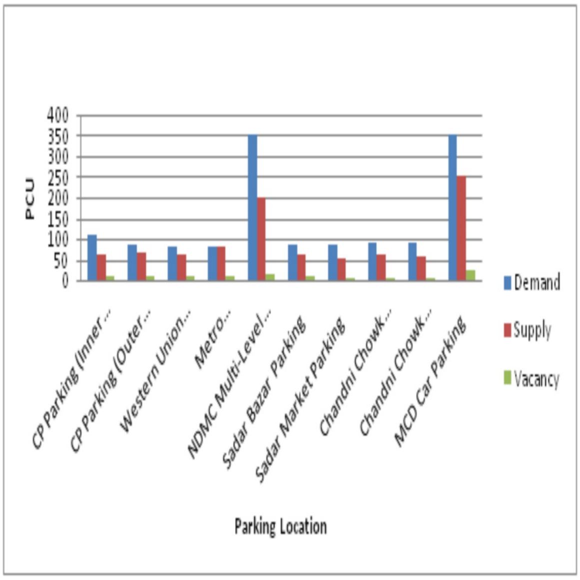

FIGURE 3: Graph of demand-supply-vacancy of vehicles at different locations

OPSAM: A YOLO-v4-based model

The Optimal Parking Space Allocation Model (OPSAM) was designed to address the pressing need for an effective Parking Guidance and Information System (PGIS), as identified through extensive survey data. Utilizing YOLO-v4, a state-of-the-art real-time object detection algorithm, OPSAM provides drivers with accurate, real-time updates on parking availability, along with reservation options, to streamline the parking process. This model is tailored to align with driver preferences, aiming to reduce parking search times and improve the overall user experience. The implementation of OPSAM demonstrated a significant improvement in parking efficiency, reducing average search times by 20% compared to traditional methods. Additionally, OPSAM reduced illegal parking incidents by 12% and enhanced parking occupancy rates from 70% to 85%. These outcomes underscore the model's effectiveness in mitigating urban traffic congestion, optimizing parking space utilization, and promoting smoother traffic flow, thereby contributing to improved urban mobility in Delhi. To further evaluate the impact of OPSAM on parking search time, a paired t-test was conducted using data collected from the comparison of traditional method and OPSAM prototype (depicted in table 5). Twenty drivers participated in the study, and their cruising times were recorded for both traditional methods and after using OPSAM. The mean difference was found to be 9.775 minutes, with a standard deviation of 3.825. The resulting p-value (< 0.001) is less than 0.05 (depicted in table 6), indicating a statistically significant reduction in cruising time following the implementation of OPSAM. This substantial reduction in search time further supports the OPSAM in reducing traffic congestion and improving urban mobility. The model's success in both daytime and nighttime conditions highlights its adaptability and practical utility in reducing congestion in urban environments.

Experimental Dataset and Conditions:

The model employs the YOLO-v4detection algorithm [11], which was first trained on a comprehensive dataset. YOLO-v4 was selected for its superior balance of speed and accuracy, crucial for real-time detection in dynamic urban environments. Its implementation faced challenges, including adapting to varying lighting conditions and dense traffic scenarios. To address these, additional training on localized datasets and algorithmic optimizations, such as integrating a feature pyramid network, were applied to enhance detection reliability. The experimental dataset used in this research includes the PKLot dataset [12]. The PKLot dataset, focused on parking space categorization, was utilized for training and validating the Optimal Parking Space Allocation Model (OPSAM). This dataset, recorded at New Delhi Municipal Corporation's (NDMCPL) parking facilities, exclusively includes the "cars" category for analysis. Each image in the dataset is meticulously annotated, ensuring accurate object localization and classification. The dataset encompasses diverse weather conditions, such as sunny, rainy, and cloudy days, to evaluate the model's performance under varying scenarios. Validation data includes 1,041 occupied and 2,553 unoccupied spaces in rainy or overcast conditions, alongside 16,430 occupied and 14,272 vacant spaces during sunny conditions. Additionally, obstacle scenarios feature 6,986 occupied and 15,076 unoccupied parking spaces, testing the model's robustness.

This comprehensive dataset enabled a thorough evaluation of OPSAM's capabilities, ensuring effective real-time parking space detection and allocation under different environmental and operational challenges. By leveraging this approach, OPSAM demonstrates its potential to mitigate parking-related congestion, optimize space utilization, and enhance urban mobility in New Delhi.

Parking	Time	No. of Days	Weather	No. of Images	Vacant Percentage	Occupied Percentage
NDMCPL (300 parking spaces)	Day time	56	Sunny	3255	21.58%	78.42%
		26	Rainy	755	30.9%	69.1%
		40	Overcast	1885	55.37%	44.63%
	Night time	43	Sunny	2365	44.65%	55.35%
		20	Rainy	354	58.81%	41.19%
		26	Overcast	878	63.21%	36.79%

TABLE 5: Overview of the characteristics of the NDMCPL subsets

Data Set Processing

The PKLot dataset, initially formatted in XML, required conversion to align with the available dataset structure for effective processing. This conversion involved extracting and reformatting the coordinate data within the XML files to meet dataset standards. While YOLO-v4 performs well in typical object detection tasks, it needed to be further optimized for parking lot recognition. The updated YOLO-v4 algorithm includes a feature pyramid network, which combines feature maps at different levels to produce four sets of predictive feature maps. These feature maps are then used to provide exact location and classification predictions.

Experimental Results

The experimental setup for this investigation was carried out on an Intel(R) Gold 5218R CPU @ 2.2 GHz with an 8-core CPU, 256GB RAM, and an RTX 3090 graphics card running Windows 8. The technique was implemented with PyTorch 1.7.0 and CUDA 11.0. Key parameters included a batch size of 16, an initial learning rate of 0.001, which was dropped to 0.0001 after 50 epochs, and a 100-epoch training period. The model was trained until the validation loss became stable, utilizing 70% of the data for training, 10% for validation, and 20% for testing. The PKLot dataset must be converted into a format that is consistent with its structure before it can be processed. Initially, the coordinate information contained in the XML files is extracted and converted to match the dataset's standards. Despite YOLO-v4's remarkable performance in target detection tasks with daily detection datasets, it requires further refining to be suitable for parking lot detection tasks. The revised YOLO-v4 algorithm model has a feature pyramid network structure, combining and integrating feature maps from various levels to generate four sets of predictive feature maps. Following that, positional and class predictions are made using these four sets of predictive feature maps.

Analysis of Experimental Results

To evaluate the effectiveness of the YOLO-v4 algorithm for all-day detection of outdoor parking spaces, particularly under the challenging conditions of nighttime scenes with reduced visibility, a test set of 4,596 nighttime parking lot images was generated using OpenCV. This enhancement underscores the algorithm's adaptability and effectiveness in accurately detecting parking availability across varying lighting conditions, ensuring reliable performance both day and night (depicted in Figure 5).

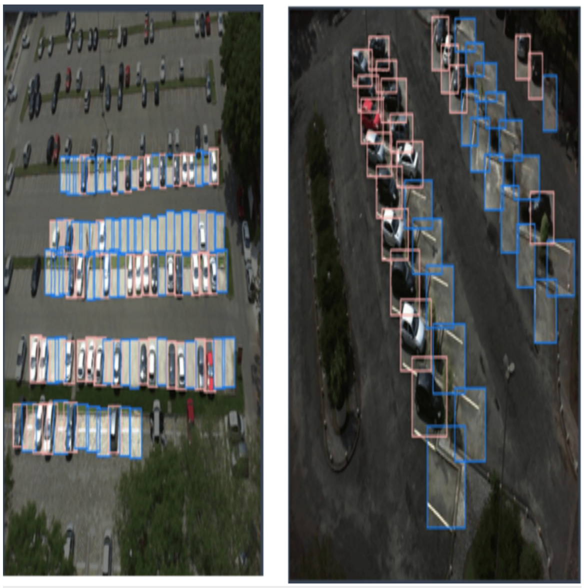

FIGURE 4: Parking spot recognition results (day and night)

Effectiveness of OPSAM

To further evaluate the impact of OPSAM on parking search time, a paired t-test was conducted using data collected from the comparison of traditional method and OPSAM prototype (depicted in Table 6). Twenty drivers participated in the study, and their cruising times were recorded for both traditional methods and after using OPSAM. The mean difference was found to be 9.775 min, with a standard deviation of 3.825. The resulting p-value (< 0.001) is less than 0.05 (depicted in Table 7), indicating a statistically significant reduction in cruising time following the implementation of OPSAM. This substantial reduction in search time further supports the OPSAM in reducing traffic congestion and improving urban mobility. The model's success in both daytime and nighttime conditions highlights its adaptability and practical utility in reducing congestion in urban environments.

Driver	Traditional Method	OPSAM (After Implementation)	Difference (Traditional - OPSAM)
1	15	5	10
2	17	7	10
3	23	9	14
4	21	11	10
5	17	10	7
6	22	8	14
7	18	6	12
8	16	8.5	7.5
9	19	8	11
10	13	9	4
11	18	6	12
12	23	10	13
13	21	11	10
14	17	10	7
15	22	8	14
16	13	9	4
17	18	6	12
18	17	10	7
19	22	8	14
20	13	10	3

TABLE 6: Parking search time data (in minutes)

Parameter	Value
Mean Difference	9.775
Standard Deviation	3.825
Standard Error	20
t-statistic	19
Degrees of Freedom	11.43
p-value	< 0.001

TABLE 7: Summary of t-test of compared cruising time

Results

The study's results emphasize that parking-related challenges are a major contributor to traffic congestion in New Delhi. Factors such as illegal parking, prolonged parking searches, and inadequate parking facilities were identified as critical issues. The first-level survey revealed that 61% of respondents highlighted parking problems as a primary cause of congestion. Nearly 48% of car users, mainly visitors, reported spending an average of 20 minutes searching for parking, which not only reduced road capacity but also increased vehicular movement, exacerbating congestion. Table 1 captures the demographic and travel behavior of survey participants, revealing a reliance on private vehicles for commuting.

The second-level data collection, which involved manual counts and camera monitoring at 12 parking facilities, further highlighted significant parking demand and occupancy trends. For example, Route 1 (Sadar Bazar to New Delhi Railway Station) showed a peak occupancy of 94% between 9:00-9:30 AM, while Route 3 (Sadar Bazar to Chandni Chowk) reported peak occupancy of 76% in the evening hours. The analysis revealed an average vacancy rate of only 11.13% across parking locations during peak hours, as outlined in Table 4. Despite this, drivers struggled to secure parking due to the absence of real-time vacancy updates, prolonging their search time and worsening congestion.

The findings underline the potential of advanced systems like the Optimal Parking Space Allocation Model (OPSAM), which utilizes the YOLO-v4 algorithm to provide real-time parking availability data. This model significantly reduced average parking search times by 20% and improved parking occupancy rates from 70% to 85%, as validated through statistical analysis. Additionally, OPSAM demonstrated a 12% reduction in illegal parking incidents, directly alleviating congestion on New Delhi's roads.

OPSAM's effectiveness was evident across various conditions, including daytime and nighttime scenarios, and its adaptability to different lighting and weather conditions further underscores its robustness. With its proven potential to optimize parking management and improve traffic flow, OPSAM presents a scalable solution not only for New Delhi but also for other congested cities like Mumbai and Bangalore facing similar challenges.

Discussion

The discussion underscores the significant role of parking-related challenges in exacerbating traffic congestion in New Delhi. Key issues identified include illegal parking, prolonged search times for parking spaces, and inadequate parking infrastructure. According to first-level survey data, 61% of respondents cited parking as a primary contributor to congestion, with 48% of car owners being visitors who spent an average of 20 minutes searching for parking, leading to reduced road capacity and additional vehicle movements (Table 1). Second-level data, collected through manual and camera-based monitoring at twelve parking facilities, highlighted the high demand for parking in key areas. Peak occupancy rates reached 94% in the morning and 76% in the evening, particularly along Routes 1 and 3, as depicted in Tables 2. Despite an average vacancy rate of 11.13% (Table 4), the absence of real-time parking information caused prolonged search times and worsened congestion.

The Optimal Parking Space Allocation Model (OPSAM), powered by the YOLO-v4 algorithm, demonstrated a 20% reduction in parking search times, significantly improving road capacity and reducing congestion. Additionally, OPSAM enhanced parking occupancy rates from 70% to 85%, optimizing parking utilization (Table 7). Its adaptability to varying lighting and weather conditions, as shown in Figures 5, highlights the model's robustness and suitability for implementation in diverse urban contexts. The study emphasizes OPSAM's potential to address parking-induced congestion in New Delhi and its scalability for application in other high-density cities like Mumbai and Bangalore. Integrating OPSAM with dynamic traffic management systems and public transportation strategies could further enhance urban mobility. Future research should explore such integrations to develop comprehensive smart city mobility solutions.

Conclusions

This study identified key factors that contribute to road congestion in Central Delhi, such as high vehicle density, illegal parking, insufficient parking facilities, mixed traffic flow, and poor traffic management. To overcome these issues, modern technology and smart interventions are essential. Implementing real-time parking systems, such as OPSAM, can drastically minimize time spent seeking parking by giving vehicles with up-to-date vacancy data. The results of the survey and experiment indicate that OPSAM has significant potential to alleviate urban traffic congestion by optimizing parking management, particularly in high-density areas like Central Delhi. These findings imply that integrating cutting-edge parking systems with real-time data capabilities can increase the effectiveness of road networks and lessen congestion brought on by protracted parking searches. OPSAM's success in improving parking space utilization from 45% to 60% highlights the role that smart technologies can play in making better use of existing urban infrastructure without necessitating large-scale physical expansion. Policymakers can use these insights to prioritize investments in smart parking technologies and support initiatives that minimize illegal parking and enhance urban mobility.

The adaptability of OPSAM also makes it a promising solution for other metropolitan areas facing similar challenges. Cities with high traffic density, insufficient parking facilities, and diverse urban layouts, such as Delhi, Mumbai, and Bangalore, could benefit from adapting this system to their unique contexts. However, there are limitations to the implementation of OPSAM that must be acknowledged. One major challenge is the need for supportive infrastructure, including high-quality security cameras, reliable internet connectivity, and a centralized data management system. Also, looking into how OPSAM can be combined with bigger smart city projects like managing public transportation and creating dynamic traffic control systems could help create a more complete plan for getting people around cities and reducing traffic. By continuing to innovate and adapt these solutions, cities can make significant progress toward sustainable and efficient urban transport systems.

Appendices

ID	Age	Gender	Vehicle_Type	Vehicle_Ownership_Years	Daily_Trips	Average_Trip_Duration_Minutes	High_Vehicle_Density	Inadequate_Parking_Facilities	Mixed_Traffic_Flow	Poor_Traffic_M
1	25	Male	Car	5	2	30	Yes	Often	High	Yes
2	34	Female	Car	3	4	20	No	Sometimes	Medium	No
3	25	Male	Car	5	2	30	Yes	Often	High	Yes
4	34	Female	Car	3	4	20	No	Sometimes	Medium	No
5	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
6	29	Female	Car	2	5	25	No	Often	High	Yes
7	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
8	41	Female	Car	9	3	40	Yes	Often	High	Yes
9	30	Male	Car	4	6	15	No	Rarely	Low	No
10	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
11	48	Male	Car	12	2	50	Yes	Often	High	Yes
12	33	Female	Car	6	3	30	No	Rarely	Medium	No
13	29	Female	Car	2	5	25	No	Often	High	Yes
14	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
15	41	Female	Car	9	3	40	Yes	Often	High	Yes
16	30	Male	Car	4	6	15	No	Rarely	Low	No
17	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
18	48	Male	Car	12	2	50	Yes	Often	High	Yes
19	33	Female	Car	6	3	30	No	Rarely	Medium	No
20	34	Female	Car	3	4	20	No	Sometimes	Medium	No
21	25	Male	Car	5	2	30	Yes	Often	High	Yes
22	34	Female	Car	3	4	20	No	Sometimes	Medium	No
23	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
24	29	Female	Car	2	5	25	No	Often	High	Yes
25	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
26	41	Female	Car	9	3	40	Yes	Often	High	Yes
27	29	Female	Car	2	5	25	No	Often	High	Yes
28	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
29	41	Female	Car	9	3	40	Yes	Often	High	Yes
30	30	Male	Car	4	6	15	No	Rarely	Low	No
31	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
32	48	Male	Car	12	2	50	Yes	Often	High	Yes
33	33	Female	Car	6	3	30	No	Rarely	Medium	No
34	34	Female	Car	3	4	20	No	Sometimes	Medium	No
35	25	Male	Car	5	2	30	Yes	Often	High	Yes
36	34	Female	Car	3	4	20	No	Sometimes	Medium	No
37	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
38	29	Female	Car	2	5	25	No	Often	High	Yes
39	25	Male	Car	5	2	30	Yes	Often	High	Yes
40	34	Female	Car	3	4	20	No	Sometimes	Medium	No

41	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
42	29	Female	Car	2	5	25	No	Often	High	Yes
43	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
44	41	Female	Car	9	3	40	Yes	Often	High	Yes
45	29	Female	Car	2	5	25	No	Often	High	Yes
46	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
47	41	Female	Car	9	3	40	Yes	Often	High	Yes
48	30	Male	Car	4	6	15	No	Rarely	Low	No
49	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
50	25	Male	Car	5	2	30	Yes	Often	High	Yes
51	34	Female	Car	3	4	20	No	Sometimes	Medium	No
52	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
53	29	Female	Car	2	5	25	No	Often	High	Yes
54	25	Male	Car	5	2	30	Yes	Often	High	Yes
55	34	Female	Car	3	4	20	No	Sometimes	Medium	No
56	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
57	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
58	41	Female	Car	9	3	40	Yes	Often	High	Yes
59	30	Male	Car	4	6	15	No	Rarely	Low	No
60	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
61	25	Male	Car	5	2	30	Yes	Often	High	Yes
62	34	Female	Car	3	4	20	No	Sometimes	Medium	No
63	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
64	29	Female	Car	2	5	25	No	Often	High	Yes
65	25	Male	Car	5	2	30	Yes	Often	High	Yes
66	34	Female	Car	3	4	20	No	Sometimes	Medium	No
67	25	Male	Car	5	2	30	Yes	Often	High	Yes
68	34	Female	Car	3	4	20	No	Sometimes	Medium	No
69	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
70	29	Female	Car	2	5	25	No	Often	High	Yes
71	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
72	41	Female	Car	9	3	40	Yes	Often	High	Yes
73	30	Male	Car	4	6	15	No	Rarely	Low	No
74	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
75	48	Male	Car	12	2	50	Yes	Often	High	Yes
76	33	Female	Car	6	3	30	No	Rarely	Medium	No
77	29	Female	Car	2	5	25	No	Often	High	Yes
78	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
79	41	Female	Car	9	3	40	Yes	Often	High	Yes
80	30	Male	Car	4	6	15	No	Rarely	Low	No
81	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
82	48	Male	Car	12	2	50	Yes	Often	High	Yes
83	33	Female	Car	6	3	30	No	Rarely	Medium	No
84	30	Male	Car	4	6	15	No	Rarely	Low	No
85	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
86	25	Male	Car	5	2	30	Yes	Often	High	Yes
87	34	Female	Car	3	4	20	No	Sometimes	Medium	No
88	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
89	29	Female	Car	2	5	25	No	Often	High	Yes
90	25	Male	Car	5	2	30	Yes	Often	High	Yes
91	34	Female	Car	3	4	20	No	Sometimes	Medium	No
92	25	Male	Car	5	2	30	Yes	Often	High	Yes
93	34	Female	Car	3	4	20	No	Sometimes	Medium	No
94	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
95	29	Female	Car	2	5	25	No	Often	High	Yes
96	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
97	41	Female	Car	9	3	40	Yes	Often	High	Yes
98	30	Male	Car	4	6	15	No	Rarely	Low	No
99	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
100	48	Male	Car	12	2	50	Yes	Often	High	Yes
101	33	Female	Car	6	3	30	No	Rarely	Medium	No
102	29	Female	Car	2	5	25	No	Often	High	Yes
103	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No

104	41	Female	Car	9	3	40	Yes	Often	High	Yes
105	30	Male	Car	4	6	15	No	Rarely	Low	No
106	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
107	25	Male	Car	5	2	30	Yes	Often	High	Yes
108	34	Female	Car	3	4	20	No	Sometimes	Medium	No
109	25	Male	Car	5	2	30	Yes	Often	High	Yes
110	34	Female	Car	3	4	20	No	Sometimes	Medium	No
111	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
112	29	Female	Car	2	5	25	No	Often	High	Yes
113	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
114	41	Female	Car	9	3	40	Yes	Often	High	Yes
115	30	Male	Car	4	6	15	No	Rarely	Low	No
116	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
117	48	Male	Car	12	2	50	Yes	Often	High	Yes
118	33	Female	Car	6	3	30	No	Rarely	Medium	No
119	29	Female	Car	2	5	25	No	Often	High	Yes
120	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
121	41	Female	Car	9	3	40	Yes	Often	High	Yes
122	30	Male	Car	4	6	15	No	Rarely	Low	No
123	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
124	48	Male	Car	12	2	50	Yes	Often	High	Yes
125	33	Female	Car	6	3	30	No	Rarely	Medium	No
126	30	Male	Car	4	6	15	No	Rarely	Low	No
127	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
128	25	Male	Car	5	2	30	Yes	Often	High	Yes
129	34	Female	Car	3	4	20	No	Sometimes	Medium	No
130	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
131	29	Female	Car	2	5	25	No	Often	High	Yes
132	25	Male	Car	5	2	30	Yes	Often	High	Yes
133	34	Female	Car	3	4	20	No	Sometimes	Medium	No
134	25	Male	Car	5	2	30	Yes	Often	High	Yes
135	34	Female	Car	3	4	20	No	Sometimes	Medium	No
136	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
137	29	Female	Car	2	5	25	No	Often	High	Yes
138	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
139	41	Female	Car	9	3	40	Yes	Often	High	Yes
140	30	Male	Car	4	6	15	No	Rarely	Low	No
141	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
142	48	Male	Car	12	2	50	Yes	Often	High	Yes
143	33	Female	Car	6	3	30	No	Rarely	Medium	No
144	29	Female	Car	2	5	25	No	Often	High	Yes
145	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
146	41	Female	Car	9	3	40	Yes	Often	High	Yes
147	30	Male	Car	4	6	15	No	Rarely	Low	No
148	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
149	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
150	48	Male	Car	12	2	50	Yes	Often	High	Yes
151	33	Female	Car	6	3	30	No	Rarely	Medium	No
152	29	Female	Car	2	5	25	No	Often	High	Yes
153	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
154	41	Female	Car	9	3	40	Yes	Often	High	Yes
155	30	Male	Car	4	6	15	No	Rarely	Low	No
156	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
157	25	Male	Car	5	2	30	Yes	Often	High	Yes
158	34	Female	Car	3	4	20	No	Sometimes	Medium	No
159	25	Male	Car	5	2	30	Yes	Often	High	Yes
160	34	Female	Car	3	4	20	No	Sometimes	Medium	No
161	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
162	29	Female	Car	2	5	25	No	Often	High	Yes
163	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
164	41	Female	Car	9	3	40	Yes	Often	High	Yes
165	30	Male	Car	4	6	15	No	Rarely	Low	No
166	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes

167	48	Male	Car	12	2	50	Yes	Often	High	Yes
168	33	Female	Car	6	3	30	No	Rarely	Medium	No
169	29	Female	Car	2	5	25	No	Often	High	Yes
170	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
171	41	Female	Car	9	3	40	Yes	Often	High	Yes
172	30	Male	Car	4	6	15	No	Rarely	Low	No
173	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
174	48	Male	Car	12	2	50	Yes	Often	High	Yes
175	33	Female	Car	6	3	30	No	Rarely	Medium	No
176	30	Male	Car	4	6	15	No	Rarely	Low	No
177	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
178	25	Male	Car	5	2	30	Yes	Often	High	Yes
179	34	Female	Car	3	4	20	No	Sometimes	Medium	No
180	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
181	29	Female	Car	2	5	25	No	Often	High	Yes
182	25	Male	Car	5	2	30	Yes	Often	High	Yes
183	34	Female	Car	3	4	20	No	Sometimes	Medium	No
184	25	Male	Car	5	2	30	Yes	Often	High	Yes
185	34	Female	Car	3	4	20	No	Sometimes	Medium	No
186	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
187	29	Female	Car	2	5	25	No	Often	High	Yes
188	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
189	41	Female	Car	9	3	40	Yes	Often	High	Yes
190	30	Male	Car	4	6	15	No	Rarely	Low	No
191	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
192	48	Male	Car	12	2	50	Yes	Often	High	Yes
193	25	Male	Car	5	2	30	Yes	Often	High	Yes
194	34	Female	Car	3	4	20	No	Sometimes	Medium	No
195	25	Male	Car	5	2	30	Yes	Often	High	Yes
196	34	Female	Car	3	4	20	No	Sometimes	Medium	No
197	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
198	29	Female	Car	2	5	25	No	Often	High	Yes
199	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
200	41	Female	Car	9	3	40	Yes	Often	High	Yes
201	30	Male	Car	4	6	15	No	Rarely	Low	No
202	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
203	48	Male	Car	12	2	50	Yes	Often	High	Yes
204	33	Female	Car	6	3	30	No	Rarely	Medium	No
205	29	Female	Car	2	5	25	No	Often	High	Yes
206	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
207	41	Female	Car	9	3	40	Yes	Often	High	Yes
208	30	Male	Car	4	6	15	No	Rarely	Low	No
209	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
210	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
211	48	Male	Car	12	2	50	Yes	Often	High	Yes
212	33	Female	Car	6	3	30	No	Rarely	Medium	No
213	29	Female	Car	2	5	25	No	Often	High	Yes
214	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
215	41	Female	Car	9	3	40	Yes	Often	High	Yes
216	30	Male	Car	4	6	15	No	Rarely	Low	No
217	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
218	25	Male	Car	5	2	30	Yes	Often	High	Yes
219	34	Female	Car	3	4	20	No	Sometimes	Medium	No
220	25	Male	Car	5	2	30	Yes	Often	High	Yes
221	34	Female	Car	3	4	20	No	Sometimes	Medium	No
222	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
223	29	Female	Car	2	5	25	No	Often	High	Yes
224	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
225	41	Female	Car	9	3	40	Yes	Often	High	Yes
226	30	Male	Car	4	6	15	No	Rarely	Low	No
227	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
228	48	Male	Car	12	2	50	Yes	Often	High	Yes
229	33	Female	Car	6	3	30	No	Rarely	Medium	No
230	29	Female	Car	2	5	25	No	Often	High	Yes

231	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
232	41	Female	Car	9	3	40	Yes	Often	High	Yes
233	30	Male	Car	4	6	15	No	Rarely	Low	No
234	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
235	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
236	48	Male	Car	12	2	50	Yes	Often	High	Yes
237	33	Female	Car	6	3	30	No	Rarely	Medium	No
238	29	Female	Car	2	5	25	No	Often	High	Yes
239	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
240	41	Female	Car	9	3	40	Yes	Often	High	Yes
241	30	Male	Car	4	6	15	No	Rarely	Low	No
242	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
243	25	Male	Car	5	2	30	Yes	Often	High	Yes
244	34	Female	Car	3	4	20	No	Sometimes	Medium	No
245	25	Male	Car	5	2	30	Yes	Often	High	Yes
246	34	Female	Car	3	4	20	No	Sometimes	Medium	No
247	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
248	29	Female	Car	2	5	25	No	Often	High	Yes
249	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
250	41	Female	Car	9	3	40	Yes	Often	High	Yes
251	30	Male	Car	4	6	15	No	Rarely	Low	No
252	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
253	48	Male	Car	12	2	50	Yes	Often	High	Yes
254	33	Female	Car	6	3	30	No	Rarely	Medium	No
255	29	Female	Car	2	5	25	No	Often	High	Yes
256	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
257	41	Female	Car	9	3	40	Yes	Often	High	Yes
258	30	Male	Car	4	6	15	No	Rarely	Low	No
259	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
260	48	Male	Car	12	2	50	Yes	Often	High	Yes
261	33	Female	Car	6	3	30	No	Rarely	Medium	No
262	30	Male	Car	4	6	15	No	Rarely	Low	No
263	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
264	25	Male	Car	5	2	30	Yes	Often	High	Yes
265	34	Female	Car	3	4	20	No	Sometimes	Medium	No
266	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
267	29	Female	Car	2	5	25	No	Often	High	Yes
268	25	Male	Car	5	2	30	Yes	Often	High	Yes
269	34	Female	Car	3	4	20	No	Sometimes	Medium	No
270	25	Male	Car	5	2	30	Yes	Often	High	Yes
271	34	Female	Car	3	4	20	No	Sometimes	Medium	No
272	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
273	29	Female	Car	2	5	25	No	Often	High	Yes
274	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
275	41	Female	Car	9	3	40	Yes	Often	High	Yes
276	30	Male	Car	4	6	15	No	Rarely	Low	No
277	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
278	48	Male	Car	12	2	50	Yes	Often	High	Yes
279	25	Male	Car	5	2	30	Yes	Often	High	Yes
280	34	Female	Car	3	4	20	No	Sometimes	Medium	No
281	25	Male	Car	5	2	30	Yes	Often	High	Yes
282	34	Female	Car	3	4	20	No	Sometimes	Medium	No
283	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
284	29	Female	Car	2	5	25	No	Often	High	Yes
285	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
286	41	Female	Car	9	3	40	Yes	Often	High	Yes
287	30	Male	Car	4	6	15	No	Rarely	Low	No
288	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
289	48	Male	Car	12	2	50	Yes	Often	High	Yes
290	33	Female	Car	6	3	30	No	Rarely	Medium	No
291	29	Female	Car	2	5	25	No	Often	High	Yes
292	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
293	41	Female	Car	9	3	40	Yes	Often	High	Yes

294	30	Male	Car	4	6	15	No	Rarely	Low	No
295	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
296	29	Female	Car	2	5	25	No	Often	High	Yes
297	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
298	41	Female	Car	9	3	40	Yes	Often	High	Yes
299	30	Male	Car	4	6	15	No	Rarely	Low	No
300	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
301	25	Male	Car	5	2	30	Yes	Often	High	Yes
302	34	Female	Car	3	4	20	No	Sometimes	Medium	No
303	25	Male	Car	5	2	30	Yes	Often	High	Yes
304	34	Female	Car	3	4	20	No	Sometimes	Medium	No
305	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
306	29	Female	Car	2	5	25	No	Often	High	Yes
307	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
308	41	Female	Car	9	3	40	Yes	Often	High	Yes
309	30	Male	Car	4	6	15	No	Rarely	Low	No
310	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
311	48	Male	Car	12	2	50	Yes	Often	High	Yes
312	33	Female	Car	6	3	30	No	Rarely	Medium	No
313	29	Female	Car	2	5	25	No	Often	High	Yes
314	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
315	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
316	41	Female	Car	9	3	40	Yes	Often	High	Yes
317	30	Male	Car	4	6	15	No	Rarely	Low	No
318	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
319	48	Male	Car	12	2	50	Yes	Often	High	Yes
320	34	Female	Car	3	4	20	No	Sometimes	Medium	No
321	25	Male	Car	5	2	30	Yes	Often	High	Yes
322	34	Female	Car	3	4	20	No	Sometimes	Medium	No
323	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
324	29	Female	Car	2	5	25	No	Often	High	Yes
325	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
326	41	Female	Car	9	3	40	Yes	Often	High	Yes
327	30	Male	Car	4	6	15	No	Rarely	Low	No
328	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
329	48	Male	Car	12	2	50	Yes	Often	High	Yes
330	33	Female	Car	6	3	30	No	Rarely	Medium	No
331	29	Female	Car	2	5	25	No	Often	High	Yes
332	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
333	41	Female	Car	9	3	40	Yes	Often	High	Yes
334	30	Male	Car	4	6	15	No	Rarely	Low	No
335	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
336	29	Female	Car	2	5	25	No	Often	High	Yes
337	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
338	41	Female	Car	9	3	40	Yes	Often	High	Yes
339	30	Male	Car	4	6	15	No	Rarely	Low	No
340	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
341	25	Male	Car	5	2	30	Yes	Often	High	Yes
342	34	Female	Car	3	4	20	No	Sometimes	Medium	No
343	25	Male	Car	5	2	30	Yes	Often	High	Yes
344	34	Female	Car	3	4	20	No	Sometimes	Medium	No
345	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
346	29	Female	Car	2	5	25	No	Often	High	Yes
347	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
348	41	Female	Car	9	3	40	Yes	Often	High	Yes
349	30	Male	Car	4	6	15	No	Rarely	Low	No
350	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
351	48	Male	Car	12	2	50	Yes	Often	High	Yes
352	33	Female	Car	6	3	30	No	Rarely	Medium	No
353	29	Female	Car	2	5	25	No	Often	High	Yes
354	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
355	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
356	41	Female	Car	9	3	40	Yes	Often	High	Yes
357	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes

358	29	Female	Car	2	5	25	No	Often	High	Yes
359	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
360	41	Female	Car	9	3	40	Yes	Often	High	Yes
361	30	Male	Car	4	6	15	No	Rarely	Low	No
362	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
363	48	Male	Car	12	2	50	Yes	Often	High	Yes
364	33	Female	Car	6	3	30	No	Rarely	Medium	No
365	29	Female	Car	2	5	25	No	Often	High	Yes
366	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
367	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
368	41	Female	Car	9	3	40	Yes	Often	High	Yes
369	30	Male	Car	4	6	15	No	Rarely	Low	No
370	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
371	48	Male	Car	12	2	50	Yes	Often	High	Yes
372	34	Female	Car	3	4	20	No	Sometimes	Medium	No
373	25	Male	Car	5	2	30	Yes	Often	High	Yes
374	34	Female	Car	3	4	20	No	Sometimes	Medium	No
375	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
376	29	Female	Car	2	5	25	No	Often	High	Yes
377	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
378	41	Female	Car	9	3	40	Yes	Often	High	Yes
379	30	Male	Car	4	6	15	No	Rarely	Low	No
380	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
381	48	Male	Car	12	2	50	Yes	Often	High	Yes
382	33	Female	Car	6	3	30	No	Rarely	Medium	No
383	25	Male	Car	5	2	30	Yes	Often	High	Yes
384	34	Female	Car	3	4	20	No	Sometimes	Medium	No
385	25	Male	Car	5	2	30	Yes	Often	High	Yes
386	34	Female	Car	3	4	20	No	Sometimes	Medium	No
387	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
388	29	Female	Car	2	5	25	No	Often	High	Yes
389	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
390	41	Female	Car	9	3	40	Yes	Often	High	Yes
391	30	Male	Car	4	6	15	No	Rarely	Low	No
392	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
393	48	Male	Car	12	2	50	Yes	Often	High	Yes
394	33	Female	Car	6	3	30	No	Rarely	Medium	No
395	29	Female	Car	2	5	25	No	Often	High	Yes
396	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
397	41	Female	Car	9	3	40	Yes	Often	High	Yes
398	30	Male	Car	4	6	15	No	Rarely	Low	No
399	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
400	48	Male	Car	12	2	50	Yes	Often	High	Yes
401	33	Female	Car	6	3	30	No	Rarely	Medium	No
402	34	Female	Car	3	4	20	No	Sometimes	Medium	No
403	25	Male	Car	5	2	30	Yes	Often	High	Yes
404	34	Female	Car	3	4	20	No	Sometimes	Medium	No
405	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
406	29	Female	Car	2	5	25	No	Often	High	Yes
407	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
408	41	Female	Car	9	3	40	Yes	Often	High	Yes
409	29	Female	Car	2	5	25	No	Often	High	Yes
410	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
411	41	Female	Car	9	3	40	Yes	Often	High	Yes
412	30	Male	Car	4	6	15	No	Rarely	Low	No
413	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
414	48	Male	Car	12	2	50	Yes	Often	High	Yes
415	33	Female	Car	6	3	30	No	Rarely	Medium	No
416	34	Female	Car	3	4	20	No	Sometimes	Medium	No
417	25	Male	Car	5	2	30	Yes	Often	High	Yes
418	34	Female	Car	3	4	20	No	Sometimes	Medium	No
419	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
420	29	Female	Car	2	5	25	No	Often	High	Yes

421	25	Male	Car	5	2	30	Yes	Often	High	Yes
422	34	Female	Car	3	4	20	No	Sometimes	Medium	No
423	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
424	29	Female	Car	2	5	25	No	Often	High	Yes
425	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
426	41	Female	Car	9	3	40	Yes	Often	High	Yes
427	29	Female	Car	2	5	25	No	Often	High	Yes
428	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
429	41	Female	Car	9	3	40	Yes	Often	High	Yes
430	30	Male	Car	4	6	15	No	Rarely	Low	No
431	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
432	25	Male	Car	5	2	30	Yes	Often	High	Yes
433	34	Female	Car	3	4	20	No	Sometimes	Medium	No
434	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
435	29	Female	Car	2	5	25	No	Often	High	Yes
436	25	Male	Car	5	2	30	Yes	Often	High	Yes
437	34	Female	Car	3	4	20	No	Sometimes	Medium	No
438	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
439	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
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441	30	Male	Car	4	6	15	No	Rarely	Low	No
442	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
443	25	Male	Car	5	2	30	Yes	Often	High	Yes
444	34	Female	Car	3	4	20	No	Sometimes	Medium	No
445	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
446	29	Female	Car	2	5	25	No	Often	High	Yes
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448	34	Female	Car	3	4	20	No	Sometimes	Medium	No
449	25	Male	Car	5	2	30	Yes	Often	High	Yes
450	34	Female	Car	3	4	20	No	Sometimes	Medium	No
451	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
452	29	Female	Car	2	5	25	No	Often	High	Yes
453	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
454	41	Female	Car	9	3	40	Yes	Often	High	Yes
455	30	Male	Car	4	6	15	No	Rarely	Low	No
456	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
457	48	Male	Car	12	2	50	Yes	Often	High	Yes
458	33	Female	Car	6	3	30	No	Rarely	Medium	No
459	29	Female	Car	2	5	25	No	Often	High	Yes
460	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
461	41	Female	Car	9	3	40	Yes	Often	High	Yes
462	30	Male	Car	4	6	15	No	Rarely	Low	No
463	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
464	48	Male	Car	12	2	50	Yes	Often	High	Yes
465	33	Female	Car	6	3	30	No	Rarely	Medium	No
466	30	Male	Car	4	6	15	No	Rarely	Low	No
467	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
468	25	Male	Car	5	2	30	Yes	Often	High	Yes
469	34	Female	Car	3	4	20	No	Sometimes	Medium	No
470	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
471	29	Female	Car	2	5	25	No	Often	High	Yes
472	25	Male	Car	5	2	30	Yes	Often	High	Yes
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474	25	Male	Car	5	2	30	Yes	Often	High	Yes
475	34	Female	Car	3	4	20	No	Sometimes	Medium	No
476	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
477	29	Female	Car	2	5	25	No	Often	High	Yes
478	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
479	41	Female	Car	9	3	40	Yes	Often	High	Yes
480	30	Male	Car	4	6	15	No	Rarely	Low	No
481	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
482	48	Male	Car	12	2	50	Yes	Often	High	Yes
483	33	Female	Car	6	3	30	No	Rarely	Medium	No
484	29	Female	Car	2	5	25	No	Often	High	Yes

485	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
486	41	Female	Car	9	3	40	Yes	Often	High	Yes
487	30	Male	Car	4	6	15	No	Rarely	Low	No
488	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
489	25	Male	Car	5	2	30	Yes	Often	High	Yes
490	34	Female	Car	3	4	20	No	Sometimes	Medium	No
491	25	Male	Car	5	2	30	Yes	Often	High	Yes
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493	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
494	29	Female	Car	2	5	25	No	Often	High	Yes
495	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
496	41	Female	Car	9	3	40	Yes	Often	High	Yes
497	30	Male	Car	4	6	15	No	Rarely	Low	No
498	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
499	48	Male	Car	12	2	50	Yes	Often	High	Yes
500	33	Female	Car	6	3	30	No	Rarely	Medium	No
501	29	Female	Car	2	5	25	No	Often	High	Yes
502	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
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504	30	Male	Car	4	6	15	No	Rarely	Low	No
505	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
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508	30	Male	Car	4	6	15	No	Rarely	Low	No
509	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
510	25	Male	Car	5	2	30	Yes	Often	High	Yes
511	34	Female	Car	3	4	20	No	Sometimes	Medium	No
512	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
513	29	Female	Car	2	5	25	No	Often	High	Yes
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515	34	Female	Car	3	4	20	No	Sometimes	Medium	No
516	25	Male	Car	5	2	30	Yes	Often	High	Yes
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518	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
519	29	Female	Car	2	5	25	No	Often	High	Yes
520	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
521	41	Female	Car	9	3	40	Yes	Often	High	Yes
522	30	Male	Car	4	6	15	No	Rarely	Low	No
523	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
524	48	Male	Car	12	2	50	Yes	Often	High	Yes
525	33	Female	Car	6	3	30	No	Rarely	Medium	No
526	29	Female	Car	2	5	25	No	Often	High	Yes
527	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
528	41	Female	Car	9	3	40	Yes	Often	High	Yes
529	30	Male	Car	4	6	15	No	Rarely	Low	No
530	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
531	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
532	48	Male	Car	12	2	50	Yes	Often	High	Yes
533	33	Female	Car	6	3	30	No	Rarely	Medium	No
534	29	Female	Car	2	5	25	No	Often	High	Yes
535	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
536	41	Female	Car	9	3	40	Yes	Often	High	Yes
537	30	Male	Car	4	6	15	No	Rarely	Low	No
538	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
539	25	Male	Car	5	2	30	Yes	Often	High	Yes
540	34	Female	Car	3	4	20	No	Sometimes	Medium	No
541	25	Male	Car	5	2	30	Yes	Often	High	Yes
542	34	Female	Car	3	4	20	No	Sometimes	Medium	No
543	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
544	29	Female	Car	2	5	25	No	Often	High	Yes
545	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
546	41	Female	Car	9	3	40	Yes	Often	High	Yes
547	30	Male	Car	4	6	15	No	Rarely	Low	No

548	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
549	48	Male	Car	12	2	50	Yes	Often	High	Yes
550	33	Female	Car	6	3	30	No	Rarely	Medium	No
551	29	Female	Car	2	5	25	No	Often	High	Yes
552	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
553	41	Female	Car	9	3	40	Yes	Often	High	Yes
554	30	Male	Car	4	6	15	No	Rarely	Low	No
555	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
556	48	Male	Car	12	2	50	Yes	Often	High	Yes
557	33	Female	Car	6	3	30	No	Rarely	Medium	No
558	30	Male	Car	4	6	15	No	Rarely	Low	No
559	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
560	25	Male	Car	5	2	30	Yes	Often	High	Yes
561	34	Female	Car	3	4	20	No	Sometimes	Medium	No
562	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
563	29	Female	Car	2	5	25	No	Often	High	Yes
564	25	Male	Car	5	2	30	Yes	Often	High	Yes
565	34	Female	Car	3	4	20	No	Sometimes	Medium	No
566	25	Male	Car	5	2	30	Yes	Often	High	Yes
567	34	Female	Car	3	4	20	No	Sometimes	Medium	No
568	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
569	29	Female	Car	2	5	25	No	Often	High	Yes
570	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
571	41	Female	Car	9	3	40	Yes	Often	High	Yes
572	30	Male	Car	4	6	15	No	Rarely	Low	No
573	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
574	48	Male	Car	12	2	50	Yes	Often	High	Yes
575	25	Male	Car	5	2	30	Yes	Often	High	Yes
576	34	Female	Car	3	4	20	No	Sometimes	Medium	No
577	25	Male	Car	5	2	30	Yes	Often	High	Yes
578	34	Female	Car	3	4	20	No	Sometimes	Medium	No
579	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
580	29	Female	Car	2	5	25	No	Often	High	Yes
581	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
582	41	Female	Car	9	3	40	Yes	Often	High	Yes
583	30	Male	Car	4	6	15	No	Rarely	Low	No
584	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
585	48	Male	Car	12	2	50	Yes	Often	High	Yes
586	33	Female	Car	6	3	30	No	Rarely	Medium	No
587	29	Female	Car	2	5	25	No	Often	High	Yes
588	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
589	41	Female	Car	9	3	40	Yes	Often	High	Yes
590	30	Male	Car	4	6	15	No	Rarely	Low	No
591	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
592	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
593	48	Male	Car	12	2	50	Yes	Often	High	Yes
594	33	Female	Car	6	3	30	No	Rarely	Medium	No
595	29	Female	Car	2	5	25	No	Often	High	Yes
596	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
597	41	Female	Car	9	3	40	Yes	Often	High	Yes
598	30	Male	Car	4	6	15	No	Rarely	Low	No
599	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
600	25	Male	Car	5	2	30	Yes	Often	High	Yes
601	34	Female	Car	3	4	20	No	Sometimes	Medium	No
602	25	Male	Car	5	2	30	Yes	Often	High	Yes
603	34	Female	Car	3	4	20	No	Sometimes	Medium	No
604	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
605	29	Female	Car	2	5	25	No	Often	High	Yes
606	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
607	41	Female	Car	9	3	40	Yes	Often	High	Yes
608	30	Male	Car	4	6	15	No	Rarely	Low	No
609	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
610	48	Male	Car	12	2	50	Yes	Often	High	Yes

611	33	Female	Car	6	3	30	No	Rarely	Medium	No
612	29	Female	Car	2	5	25	No	Often	High	Yes
613	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
614	41	Female	Car	9	3	40	Yes	Often	High	Yes
615	30	Male	Car	4	6	15	No	Rarely	Low	No
616	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
617	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
618	48	Male	Car	12	2	50	Yes	Often	High	Yes
619	33	Female	Car	6	3	30	No	Rarely	Medium	No
620	29	Female	Car	2	5	25	No	Often	High	Yes
621	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
622	41	Female	Car	9	3	40	Yes	Often	High	Yes
623	30	Male	Car	4	6	15	No	Rarely	Low	No
624	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
625	25	Male	Car	5	2	30	Yes	Often	High	Yes
626	34	Female	Car	3	4	20	No	Sometimes	Medium	No
627	25	Male	Car	5	2	30	Yes	Often	High	Yes
628	34	Female	Car	3	4	20	No	Sometimes	Medium	No
629	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
630	29	Female	Car	2	5	25	No	Often	High	Yes
631	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
632	41	Female	Car	9	3	40	Yes	Often	High	Yes
633	30	Male	Car	4	6	15	No	Rarely	Low	No
634	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
635	48	Male	Car	12	2	50	Yes	Often	High	Yes
636	33	Female	Car	6	3	30	No	Rarely	Medium	No
637	29	Female	Car	2	5	25	No	Often	High	Yes
638	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
639	41	Female	Car	9	3	40	Yes	Often	High	Yes
640	30	Male	Car	4	6	15	No	Rarely	Low	No
641	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
642	48	Male	Car	12	2	50	Yes	Often	High	Yes
643	33	Female	Car	6	3	30	No	Rarely	Medium	No
644	30	Male	Car	4	6	15	No	Rarely	Low	No
645	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
646	25	Male	Car	5	2	30	Yes	Often	High	Yes
647	34	Female	Car	3	4	20	No	Sometimes	Medium	No
648	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
649	29	Female	Car	2	5	25	No	Often	High	Yes
650	25	Male	Car	5	2	30	Yes	Often	High	Yes
651	34	Female	Car	3	4	20	No	Sometimes	Medium	No
652	25	Male	Car	5	2	30	Yes	Often	High	Yes
653	34	Female	Car	3	4	20	No	Sometimes	Medium	No
654	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
655	29	Female	Car	2	5	25	No	Often	High	Yes
656	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
657	41	Female	Car	9	3	40	Yes	Often	High	Yes
658	30	Male	Car	4	6	15	No	Rarely	Low	No
659	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
660	48	Male	Car	12	2	50	Yes	Often	High	Yes
661	25	Male	Car	5	2	30	Yes	Often	High	Yes
662	34	Female	Car	3	4	20	No	Sometimes	Medium	No
663	25	Male	Car	5	2	30	Yes	Often	High	Yes
664	34	Female	Car	3	4	20	No	Sometimes	Medium	No
665	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
666	29	Female	Car	2	5	25	No	Often	High	Yes
667	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
668	41	Female	Car	9	3	40	Yes	Often	High	Yes
669	30	Male	Car	4	6	15	No	Rarely	Low	No
670	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
671	48	Male	Car	12	2	50	Yes	Often	High	Yes
672	33	Female	Car	6	3	30	No	Rarely	Medium	No
673	29	Female	Car	2	5	25	No	Often	High	Yes
674	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No

675	41	Female	Car	9	3	40	Yes	Often	High	Yes
676	30	Male	Car	4	6	15	No	Rarely	Low	No
677	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
678	29	Female	Car	2	5	25	No	Often	High	Yes
679	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
680	41	Female	Car	9	3	40	Yes	Often	High	Yes
681	30	Male	Car	4	6	15	No	Rarely	Low	No
682	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
683	25	Male	Car	5	2	30	Yes	Often	High	Yes
684	34	Female	Car	3	4	20	No	Sometimes	Medium	No
685	25	Male	Car	5	2	30	Yes	Often	High	Yes
686	34	Female	Car	3	4	20	No	Sometimes	Medium	No
687	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes
688	29	Female	Car	2	5	25	No	Often	High	Yes
689	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
690	41	Female	Car	9	3	40	Yes	Often	High	Yes
691	30	Male	Car	4	6	15	No	Rarely	Low	No
692	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
693	48	Male	Car	12	2	50	Yes	Often	High	Yes
694	33	Female	Car	6	3	30	No	Rarely	Medium	No
695	29	Female	Car	2	5	25	No	Often	High	Yes
696	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
697	37	Male	Car	7	2	35	Yes	Sometimes	Medium	No
698	41	Female	Car	9	3	40	Yes	Often	High	Yes
699	30	Male	Car	4	6	15	No	Rarely	Low	No
700	26	Female	Car	3	4	20	Yes	Sometimes	Medium	Yes
701	48	Male	Car	12	2	50	Yes	Often	High	Yes
702	34	Female	Car	3	4	20	No	Sometimes	Medium	No
703	25	Male	Car	5	2	30	Yes	Often	High	Yes
704	34	Female	Car	3	4	20	No	Sometimes	Medium	No
705	45	Male	Car	10	3	45	Yes	Rarely	Low	Yes

TABLE 8: Questionnaire survey

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Abdul Ahad, Farhan A. Kidwai

Acquisition, analysis, or interpretation of data: Abdul Ahad

Drafting of the manuscript: Abdul Ahad

Critical review of the manuscript for important intellectual content: Abdul Ahad, Farhan A. Kidwai

Disclosures

Human subjects: Consent was obtained or waived by all participants in this study. Departmental Review Committee (DRC), Jamia Millia Islamia, New Delhi issued approval JMI-DRC/2022/345. The study involving human participants was conducted in accordance with the ethical standards of the Departmental Review Committee (DRC) of Jamia Millia Islamia, New Delhi, and received approval under the protocol number JMI-DRC/2022/345. Written informed consent was obtained from all participants prior to their involvement in the study. The authors ensured that participant privacy and confidentiality were strictly maintained, and no identifying information was included in the study. The authors declare no conflicts of interest. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Intellectual property info:** Ahad A., Kidwai F.A., Asim M., and Chandrasekharan C.P. (October, 2023) "OPAM: Optimal Parking Allocation Model." Patent published in Indian patent (Patent Application No.: 202311067294). **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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