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UTC PARKING DYNAMICS ANALYSIS (PARKING ANALYTICS)

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Abstract

Having adequate parking and parking services on university campuses is vital for improving the student experience, reducing traffic congestion, enhancing safety, generating revenue, and increasing accessibility. This capstone project attempts to provide the University campuses with an experimental predictive modeling tool, which is significantly driven by the huge vastrded historical data obtained from the target case area of the University of Tennessee at Chattanooga.

The project analysis is primarily focused on four research questions listed in the paper's objective section. Most parking utilization studies are often based on many variables, including lot type, day, year, time, and events. However, few models have been developed based on the building's proximity and lack of occupants. This project aims to analyze parking data with these two new variables and include the rest to observe their impact on Lot utilization.To do so , the analysis is conducted using machine learning algorithms, and all the algorithms are compared to check for the best model with better prediction accuracies.

The findings of the paper revealed that the primary factors affecting utilization were the permit price followed by lot type spaces and the building proximity (blocks within 0.11 miles of a parking lot). In addition, it can be observed that out of all the machine learning algorithms, the Forest tree model reportedly gave us the above-stated accuracy. Therefore, this machine learning algorithm can be recommended to the UTC parking authority to test the parking data further with more test variables that are missing in this particular model to improve accuracy and further be deployed on their live data as a future recommendation.

Keywords

Parking lot utilization, predictive modeling, machine learning.

Introduction

Parking is undoubtedly one of the most pervasive and annoying issues affecting American colleges and institutions. Many college students, faculty, and staff would agree with Clark Kerr's words. The former president of the University of California once wrote, "I have sometimes thought of the modern university as a series of individual entrepreneurs held together by a common grievance over parking" (Kerr, 1966, p. 20) [3]. The lack of suitable parking facilities within university campuses can create stress and become a significant issue for students, faculty, and staff daily due to difficulty finding parking. This, in turn, can affect their academic and work performance.

Maintaining parking supply and meeting demand within university campuses, especially in urban areas, can be challenging. Parking management at universities plays a crucial role in shaping the campus environment and overall experience for students, faculty, staff, and visitors (International Parking & Mobility Institute, n.d.). Effective parking management ensures convenient access to campus facilities and contributes to safety, sustainability, and the efficient use of limited resources. However, university administrations face numerous challenges in managing parking resources, ranging from fluctuating demand to budget constraints and environmental concerns.

To address these challenges, university administrations must adopt comprehensive parking management strategies and practices prioritizing sustainability, accessibility, and efficiency (University of California, Berkeley, n.d.). This may involve implementing policies to incentivize alternative transportation options, optimizing parking facility design and layout, leveraging technology to improve parking efficiency, and efficient decision-making processes.

In conclusion, university Parking Management is critical in shaping the campus environment and experience for students, faculty, staff, and visitors. These practices need to be leveraged efficiently, and to this effect, universities should shift from their traditional methods of managing parking that rely on manual observations and subjective assessments to new methods like parking analytics that can revolutionize how parking facilities are managed and optimized.

UTC Campus & Parking Outlook

The University of Tennessee at Chattanooga is a metropolitan university spread across 145 acres of land with over 90 buildings, including administrative, academic, residential, and athletic facilities on campus. It has an enrollment of approximately 12000 students and 1075 faculty members. Due to its prime location in the downtown area of Chattanooga, the campus often needs to adjust and update its parking services to meet the parking needs and demands of the university community.

The University's Parking and Transportation Services Department manages the UTC parking services. The campus has a total of 6117 parking spaces. These spaces are further classified as General, Reserved, Visitor, and Accessible parking lots. The total number of lots and parking spaces for each category of parking lots are summarized in Exhibit 1. In Exhibit. 2 and 3, the aerial view of the UTC campus and its parking lots clearly represents the departments located on the campus and their corresponding parking lots. Additionally, in Exhibit 3 , the general parking lots are indicated in yellow, and the reserved parking lots are marked in blue for reference.

Parking management at UTC, like at many institutions, has historically relied on traditional methods characterized by manual observations and subjective assessments. However, the limitations of these conventional approaches in understanding their parking behavior have become increasingly evident, leading to inefficiencies, frustration, and challenges in effective parking utilization.

Recognizing the need for efficiency, the University of Tennessee at Chattanooga has been chosen as the target case area for studying the on-campus parking performance. With the implementation of parking analytics, the aim is to delve deeper into the projected on-campus parking behavior and derive actionable insights and recommendations to inform and guide the existing parking management practices adopted at UTC.

Exhibit 1. UTC Parking Information

SL.NO	PARKING TYPE	TOTAL SPACES
1.	Reserved	3167
2.	General	2569
3.	Visitor	211
4.	Accessible	170

Exhibit 2. Aerial View of UTC Campus

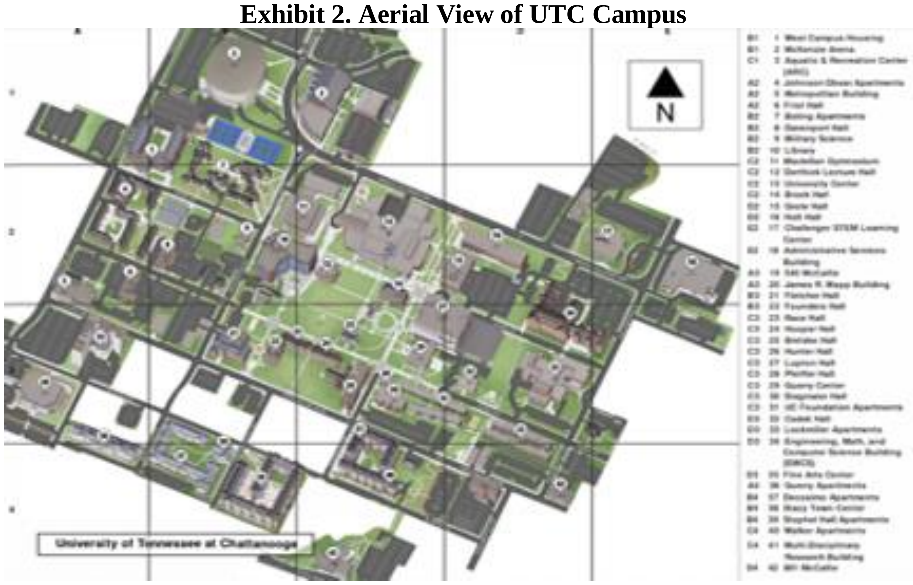


Exhibit 3. Aerial View of Parking Lots

Due to the unique ways in which land is used and how people move around the campus, especially with the target case area that is located in the Downtown area of the city of Chattanooga, the most significant need and challenge that this campus parking presents is the complexity in determining the key factors that affect parking lots utilization.
Past research has studied the effect of factors like peak hours, days, and campus events on lot utility; however, no model has been developed that tested lot utilization-based on-campus buildings' proximity to the lots and their occupants. By accurately modeling the relationship between the stated factors and their effect on Lot Utilization, we can derive substantial insights by integrating Parking analytics and insights through data-driven modeling that allows parking management to efficiently handle their recorded data and make data-driven decisions for optimizing their parking management practices. This reasoning is what led to the objective of this project.

The project's objectives, mainly would be to answer the following research hypothesis questions in the paper.
RQ 1: Investigating the general projected parking dynamics at the UTC campus.
RQ 2: Identifying the factors affecting the Lot utilization rate at UTC.
RQ 3: Testing which machine learning algorithm fits best to accurately predict the parking utilization class.

The answer to (RQ 1) will provide the UTC parking planning bodies with insights into observed parking trends and patterns occurring in UTC based on historical data and allow them to focus on the significant ones while considering changes in their future parking planning proposals. The answers to (RQ 2) identify substantial factors affecting lot utilization, and (RQ 3) will indicate if the usage of advanced parking analytical models like Machine learning models can more accurately help to classify the Parking Lots on a university campus and to understand which Machine Learning can be best relied upon to conduct parking analytics or lot utilization studies for their on-campus parking data.

Literature Review

The review includes Prior studies on UTC parking, Lot Utilization studies, and Machine learning algorithms. To begin with, the Chattanooga Parking Authority (CPA) and River City Company (River City) commissioned a comprehensive survey in 2018 of parking in central Chattanooga that also evaluates the parking characteristics at the UTC campus due to its location in the central Chattanooga area. The study is intended to understand the challenges and opportunities related to parking as the city continues to grow [13].

UTC's parking plan is developed with the goal of efficiently utilizing all available parking spaces [13, p.103]. The study's primary analysis compared information on supply (parking inventory), levels of use, and expected demand to understand true gaps in parking potential. While "Fig. 3" illustrates the parking use and demand profile, "Fig. 4", demonstrates the estimated future parking demand within the UTC campus area.

Exhibit 4. UTC Campus area Parking Utilization and Demand, (*2018*) [13].

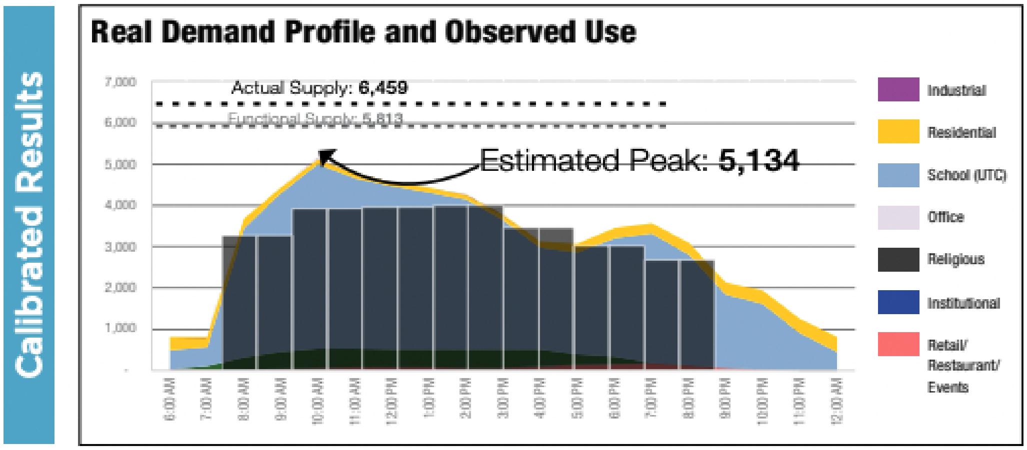
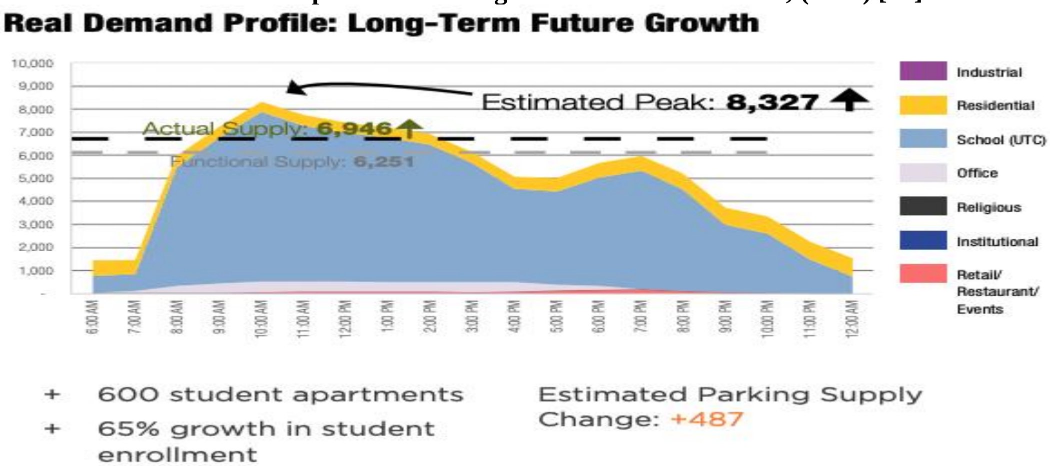


Exhibit 5. UTC Campus area Parking Utilization and Demand, (*2018*) [13].



The University's master plan includes growth to 15,000 students (from its current) in 10 to 15 years. However, the study reports that certain parts of the study area, especially UTC, are expected to grow to levels that will exhaust the current parking supply if the current parking usage increases at the same rate [13]. Additionally, based on "Exhibit 4&5, the demand for parking is projected to exceed its current capacity, resulting in limited parking availability in the area. However, to cope with this demand, the study recommends a hike in parking pricing to match demand and ensure maximum utilization of the available parking spaces.

Overall, the previous study has demonstrated the expected peak in parking demand and utilization within the campus, considering the University's scheduled student growth rate for the next 10 to 15 years. Moreover, the study also stated the need for UTC to reconstruct its parking management practices, ensuring maximum parking utilization with the available spaces instead of spending on building new parking facilities.

Traditionally, campus parking management relied on historical data and anecdotal evidence to make decisions. However, advancements in data analytics and machine learning offer promising solutions. This literature review explores the factors affecting parking lot utilization on university campuses, with a particular focus on the potential impact of building proximity and occupant count.

Numerous studies have investigated the factors influencing parking lot utilization on university campuses. These factors can be broadly categorized into:

Temporal factors: Peak hours, days of the week, semesters (fall vs. spring), and special events significantly impact parking demand. Studies by [Park et al., 2015] [1] and [Li et al., 2017] [2] demonstrate that models incorporating time can accurately predict parking occupancy rates.

Spatial factors: Location plays a crucial role. Central campus lots experience higher utilization compared to peripheral ones [Cao et al., 2019] [3]. The type of parking (surface lot vs. garage) can also influence demand.

User factors: The university population (students, faculty, staff, visitors) and their commuting habits significantly impact parking demand. Studies by [Chen et al., 2018] [4] highlight the need for differentiated user access based on needs.

These existing studies provide a strong foundation for understanding the dynamics of parking lot utilization. However, limited research has explored the specific impact of building proximity and occupant count on parking lot utilization.The current understanding of parking lot utilization focuses more on general spatial factors like central vs. peripheral location. This review proposes a deeper dive into the specific impact of building proximity and occupant count. The underlying rationale is as follows:

i. Buildings with a high number of occupants (e.g., large lecture halls, dormitories) likely generate higher parking demand in nearby lots.
ii. The closer a parking lot is to a building, the more likely it is to be used by occupants of that building, especially for short-term parking needs.

This hypothesis aligns with the concept of "frictionless parking" proposed by [Schaller, 2018] [5], which suggests that users are more likely to choose parking options that are closer and more convenient.Investigating the relationship between building proximity, occupancy, and parking lot utilization can offer valuable insights into the following:

i. Optimizing parking allocation: University parking authorities can prioritize parking spaces for specific buildings based on occupant needs.
ii. Developing data-driven models: Integrating building proximity and occupancy data into existing machine learning models could improve prediction accuracy for parking utilization.
iii. Encouraging alternative transportation: Understanding parking demand patterns around specific buildings can inform strategies to promote carpooling, cycling, or walking, especially for short trips.

Machine learning algorithms have emerged as powerful tools for analyzing complex data and predicting parking lot utilization. Studies by [Li et al., 2017] [2] and [Chen et al., 2020] [6] demonstrate the effectiveness of machine learning models in predicting parking occupancy rates. These models typically use historical parking data, including sensor information and timestamps, to identify patterns and predict future utilization.Several machine learning algorithms are well-suited for parking management applications. Here are some prominent examples:

Supervised Learning Algorithms:

i. Support Vector Machines (SVMs): Powerful for classification and regression tasks.In parking management, they can classify parking lots as occupied or vacant based on historical data and real-time sensor readings.
ii. Decision Trees: Tree-like structures that make predictions based on a series of sequential questions. They are useful for understanding relationships between factors like building proximity, time of day, and parking occupancy.
iii. Random Forests: Ensembles of decision trees trained on slightly different data subsets.Averaging their predictions improves overall accuracy, making them well-suited for handling complex and non-linear relationships between variables in parking management.

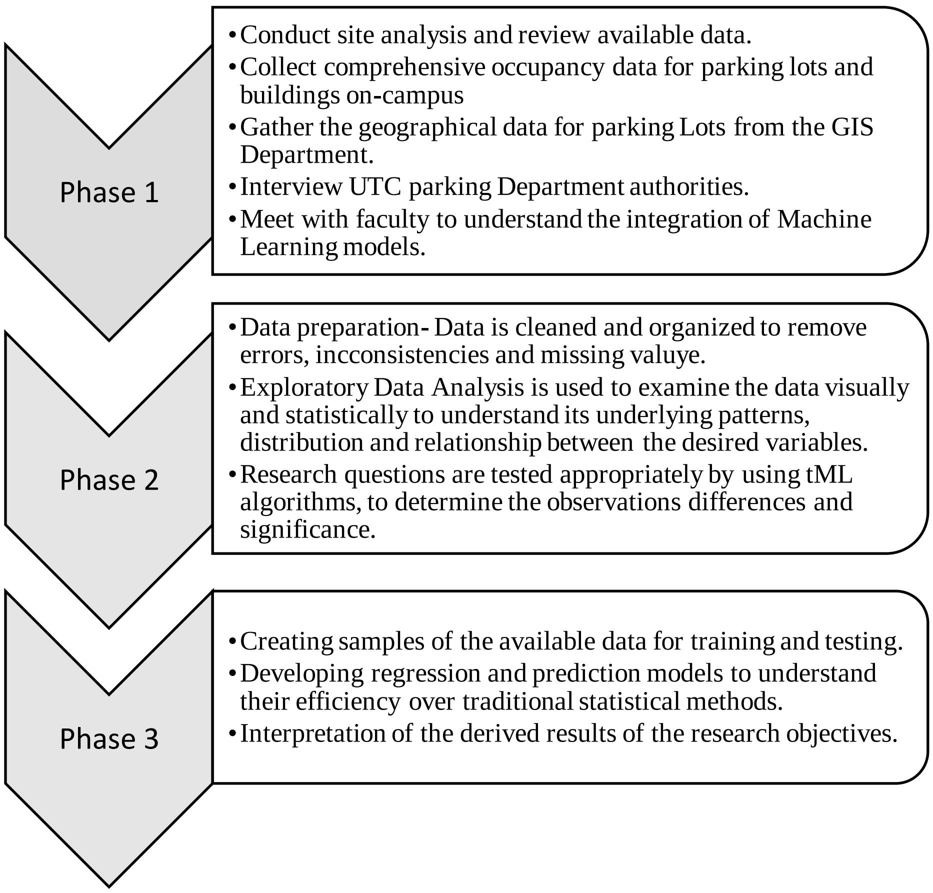
This review highlights the potential benefits of incorporating this data into parking management strategies.By leveraging machine learning and data analytics, universities can develop data-driven models that predict parking demand with greater accuracy. This information can be used to optimize parking allocation, provide real-time parking information to users, and develop dynamic pricing models to incentivize alternative transportation. However, challenges related to data availability, integration, and model complexity need to be addressed. Future research should focus on case studies, data collection strategies, advanced machine learning algorithms, and user behavior modeling to further refine our understanding of parking utilization patterns and develop effective management solutions.

Overall, this review highlights a gap in existing research regarding the quantitative analysis of the relationship between building proximity, occupant count, and university parking lot utilization. By incorporating this data into machine learning models for parking utilization prediction, universities can potentially improve parking management strategies. Future research should focus on developing and evaluating such models, considering user categories and parking type alongside building proximity and occupancy data. Addressing these gaps can lead to data-driven parking management solutions that optimize resource allocation, provide real-time parking information to users, and encourage alternative transportation options.

Methodology

As a primary higher education institution with its key location and increasing student rate, the campus presents an opportunity to analyze the different factors that affect parking utilization- allowing us to derive critical insights into the UTC parking utilization to improve the parking management systems on the campus.

Exhibit 6. Methodology



The data used for this project was gathered from several different departments- the UTC Parking Department, The Geographic Information System (GIS) Department, and the Planning, evaluation, and Institutional Research Department. The datasets utilized include the parking Type, lots, university buildings, dorm's physical location (latitude and longitude), and also their occupancies recorded within a week for the Fall Semester for three years (2018,2019, 2022). It also has a record of parking utilization within a particular time frame during the weekdays. Table 2 lists the data attributes and description of each attribute used for the regression.

This research investigates how building proximity and occupant count affect parking lot use on campus. We'll clean and combine this data, ensuring consistency. For example, time stamps and unique IDs (building/parking lot IDs) are used to merge data sets. We may also change the data format for machine learning analysis.

Machine learning models will be developed to predict the Lot utilization category. These models will consider factors like time of day, day of week, semester, building proximity, and occupant count. Support Vector Machines, Random Forests, or Decision Trees are potential algorithms.
Model performance will be assessed using metrics like mean squared error (MSE) to measure how well predictions match actual utilization class. Visualizations will also be used to understand model predictions and input variable relationships.

This methodology will investigate the impact of building proximity and occupant count on parking lot utilization. By combining machine learning and data from various sources, this study aims to develop a clearer understanding of parking dynamics on university campuses.

Analysis- To answer RQ1

The UTC parking lots are divided and grouped as general, reserved, ADA Accessibility, and visitor parking. However, this project only focuses on the information about general and reserved lots due to the limited availability of the other groups. The general and reserved lots are further attached to the building types on campus and are segregated based on them. The description of the segregation is in Exhibit 7.

Exhibit 7. UTC Building Type Description

BUILDING TYPE	DESCRIPTION
AA	Administration and academics
RH	Residence Halls
SR	Sports and Recreation
OB	Other Buildings

Exhibit 8. Variable Description

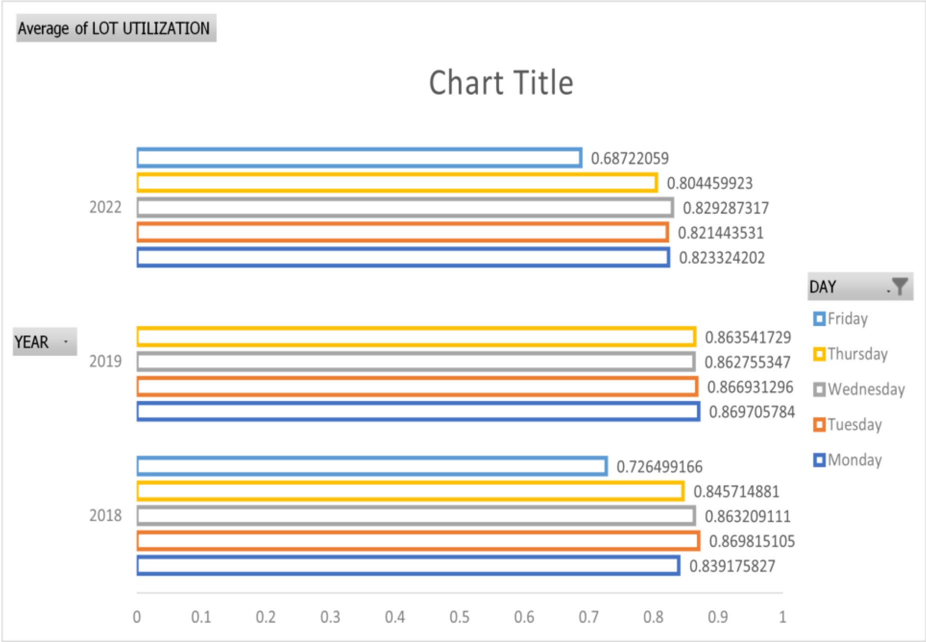
SL.NO	VARIABLES	DESCRIPTION
1	Year	Describes the data recorded for 2018,2019 and 2022.
2.	Weekdays	Describes the parking data collected from Monday- Friday.
3.	Lot Type	Provides information about two types of lots: Reserved and General parking lots.
4.	Time	Provides information on the time of recorded parking occupancies for each day. (9:30,12:30.13:30,15:30)
5.	Loc Type	Provides information about the type of buildings within the campus.
6.	Total occupants	Provides data on the total no of occupants within the campus buildings.
7.	Max-find nearest	Provides data on all the blocks that are within 0.11 miles of each parking lot.
8.	Lot utilization category	Provides information on all the parking lots' utilization and their categorization as High, Low, Moderate, and Full.

Exploratory Data Analysis (EDA) of the UTC parking utilization and historical data involves a comprehensive examination to unveil intrinsic patterns, distributions, and relationships within the dataset. This process begins by meticulously inspecting the data for anomalies, missing values, and outliers, ensuring data quality and integrity. Subsequently, statistical summaries, such as measures of central tendency and dispersion, are computed to provide initial insights into the data's characteristics.

Visualization techniques, including histograms and scatter plots, are employed to graphically represent the data's distributions and identify potential trends or clusters. Correlation analysis is conducted to elucidate relationships between variables, shedding light on factors influencing parking utilization.

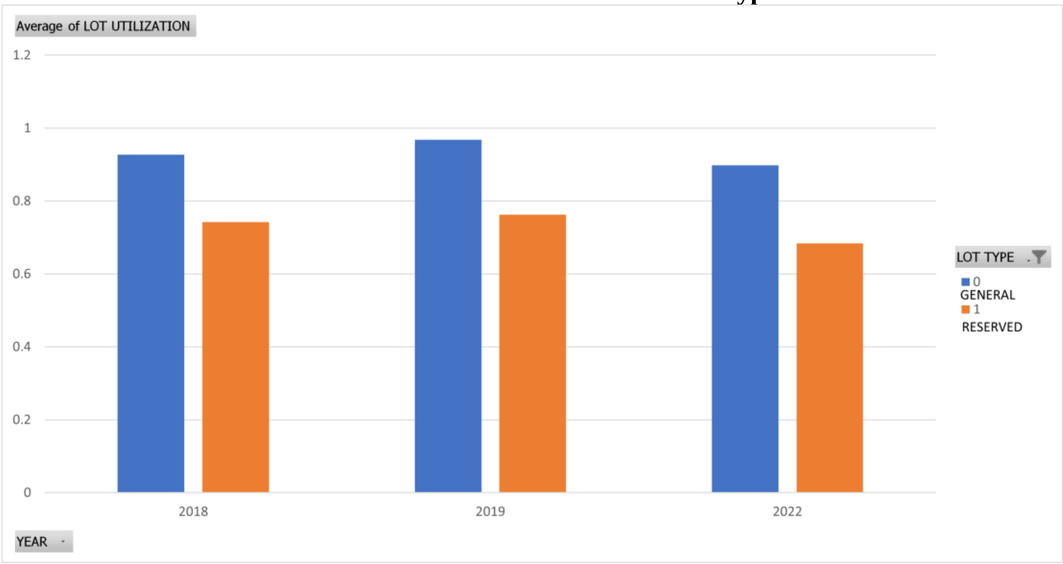
By systematically exploring the dataset, EDA aims to uncover actionable insights that can inform decision-making processes and guide the formulation of effective parking management strategies at UTC. Through this process, researchers gain a deeper understanding of the dynamics shaping parking utilization, paving the way for informed interventions and improvements to enhance the overall campus parking experience. The current scenario based on the historical data is presented below to illustrate the Lot Utilization based on variables' Time, Year, Day, Lot Type' for the fall semester of 2018, 2019, and 2022.

Exhibit 9. Lot Utilization Trend



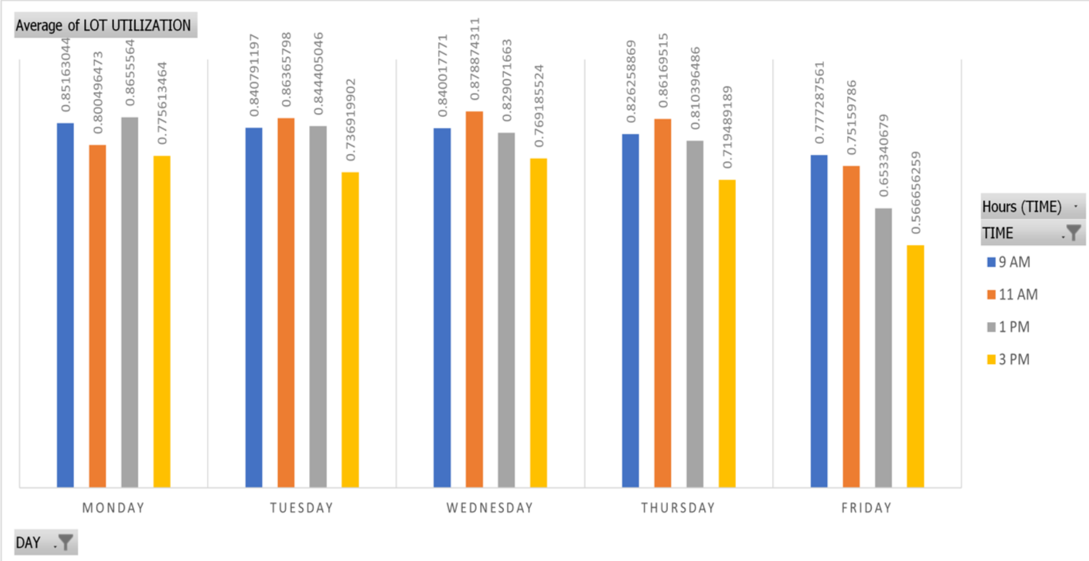
The Bar chart above illustrates the Average Lot Utilization based on the Year and Day of that week in a fall semester. It can be observed that lot utilization ranges from 0.68 to 0.86 from the chart, varying with the days of the week. Overall, the parking lots are highly occupied on Tuesdays, Wednesdays, and least on Fridays.

Exhibit 10. Lot Utilization vs Lot Type



The Bar chart above illustrates the Average Lot Utilization based on 'Lot Type'.It can be observed that the general lots capture significant lot utilization when compared to reserved lots, with a range from 0.86 to 0.95. On the other hand, the reserved lots illustrate a range between 0.68- 0.75. Therefore, it can be stated that the General Lots at UTC are utilized more efficiently than reserved lots.

Exhibit 11. Trends in lot utilization at UTC based on time



The bar chart above illustrates Average Lot Utilization based on 'Time .' It can be observed that the peak hours of maximum lot utility during any day in the week are between 9 AM and 11 AM. However, based on the overall pattern, 11 AM can be stated as the peak hours of lot occupancy, while 3 PM seems to be the time when parking Lots are least utilized.

Overall, the exploratory data analysis shows us the underlying patterns and trends for parking lot utilization and allows us to understand parking behavior at the UTC, specifically related to general and reserved lots. The derived insights can further help us to test our objectives, especially with RQ 2, where we are looking to identify variables that impact the general and reserved lots and further develop predictive modeling analysis.

Regression and Affecting Factor Analysis (experiment1):

To determine the factors affecting the utilization rate, the analysis considers the variables related to parking lot conditions and their relationship with surrounding buildings and their occupancies. The logistic regression was chosen due to the type of variables the model is analyzing. It will allow us to analyze and model the relationship between the independent variables and a binary dependent variable. Here, the parking Utilization Rate (90% vs. 80%) was chosen as the dependent variable in this model as most of the parking lots have a utilization rate between 80-90 percent. However, different utilization rates can be used to expand this study. For this model, the dependent variable is a binary variable (0 or 1). For the 90% utilization rate model, 1 indicates a utilization rate over 90%, and 0 indicates less than 90%. For the 80% utilization rate model, 1 indicates a utilization rate over 80%, and 0 indicates less than 80%.

The project involves spatial analysis to locate the parking lots and all the buildings within 0.11 miles with the help of latitude and longitude attributes to understand the parking utilization rate at a particular location. According to Mary S. Smith, P.E., and Thomas A. Butcher, P.E., 0.11 miles is considered the maximum walking distance a person feels comfortable reaching their respective parking lot [8]. Additionally, it is important to conduct a regression analysis to analyze the overall effects of all the variables presented in the dataset.

Exhibit 12. **Logistic regression model (parking utilization rate at 90%)**

	Estimate	**Std. Error**	**Z Value**	**Pr(>|z)**
Intercept	1.325	6.815	1.943	0.05196
Year	-0.065	3.374	-1.934	0.05305
Monday	2.100	2.110	9.949	< 2.2e-16
Thursday	1.803	2.085	8.647	< 2.2e-16
Tuesday	1.972	2.100	9.389	< 2.2e-16
Wednesday	2.079	2.107	9.868	< 2.2e-16
TYPE Reserved	-5.387	2.131	-25.281	< 2.2e-16

11:30:00	0.140	1.631	0.861	0.38902
13:30:00	-0.4467	1.630	-2.740	0.00613
15:30:00	-1.832	1.737	-10.545	< 2.2e-16
X1112	-0.3628	3.893	-9.318	< 2.2e-16
X1113	-0.1024	5.811	-1.762	0.07796
X1114	-0.6237	6.568	-9.495	< 2.2e-16
X1115	-0.1526	1.251	-1.220	0.22245
X1116	1.109	1.143	9.702	< 2.2e-16
X1127	0.8035	8.079	9.944	< 2.2e-16
X1142	-0.3631	2.685	-1.352	0.17625
X1144	1.373	3.395	4.042	5e-05
X1151	-0.9942	5.724	-1.737	0.08239
X1190	-0.3892	2.152	-1.808	0.07053
Dorm Capacity	-0.0007	4.123	-1.877	0.06044
Sum Student Campus	0.0009	1.895	4.977	6.45e-07

The regression model revealed important findings regarding the factors that affect the parking utilization rate at 90 percent vs 80 percent. From Exhibit 12, It can be determined that the variables that have a p-value less than the significance level of 0.05 are considered statistically significant in predicting the 90% parking utilization Rate. Further, the individual assessment of the significant attributes association and effect on parking Utilization rate can be stated as:

- Year-The coefficient estimate for the variable 'YEAR" is -0.065. This means that for every unit increase in the year, the log odds of achieving a 90% parking Utilization rate decrease by 0.065, holding everything else constant.
- Weekday- The coefficient estimates for the weekday variables (Monday, Tuesday, Wednesday, and Thursday) are positive, indicating that these variables are positively associated with a 90% parking utilization rate. For example, the coefficient estimate for Monday is 2.100, which means that holding all other variables constant, the log odds of having a 90% parking utilization rate on Monday are 2.100 higher than on Friday (the reference category).
- Lot Type: The coefficient estimate for the Lot Type variable (Reserved) is -5.387, indicating that holding all other variables constant, the log odds of having a 90% parking utilization rate in a reserved parking lot are 5.387 lower than in a non-reserved lot.
- Time: The coefficient estimates for the Time variables (13:30 and 15:30) are negative, indicating that parking utilization rates are lower at these times compared to 9:30 AM. For example, the coefficient estimate for 15:30 is -1.832, which means that holding all other variables constant, the log odds of having a 90% parking utilization rate at 15:30:00 are 1.832 lower than at 09:30 AM.
- Loc Type: The coefficient estimates for the Loc Type variables (1116, 1127, 1144) are positive, indicating that parking utilization rates are higher in these locations compared to the reference location. For example, the coefficient estimate for 1116 is 1.109, which means that holding all other variables constant, the log odds of having a 90% parking utilization rate in location 1116 are 1.109 higher than in the reference location.
- Also, the coefficient estimates for the Loc Type variables (1112, 1114) are negative, indicating that parking utilization rates are lower in these locations compared to the reference location.
- Total campus occupants: The coefficient estimate for the Total Campus Occupants variable is 0.0009, indicating that holding all other variables constant, for every unit increase in total campus occupants, the log odds of achieving a 90% parking Utilization rate increase by 0.0009, holding everything else constant.

Overall, comparing the coefficient estimates of all the predictor variables, it can be stated that 'Weekdays' are the primary influencing factor for the parking utilization rate at 90 percent, followed by 'Loc Type' within the campus. However, we did a utilization analysis for the 80 percent model to see how they differ.

Exhibit 13: **Logistic regression model (parking utilization rate at 80%)**

	Estimate	Std.Error	zValue	Pr(>|z|)
Intercept	1.268	6.409e+01	1.9786	0.04786
Year	-6.248	3.172e-02	-1.9696	0.04888
Monday	1.773	1.935e-01	9.1666	< 2.2e-16
Thursday	1.434	1.911e-01	7.5070	6.04e-14
Tuesday	1.762	1.944e-01	9.0627	< 2.2e-16
Wednesday	1.823	1.939e-01	9.4040	< 2.2e-16
TYPE Reserved	-4.278	1.774e-01	-24.1163	< 2.2e-16
11:30:00	5.663	1.560e-01	3.6291	0.00028
13:30:00	1.841	1.539e-01	1.1960	0.23169
15:30:00	-1.030	1.550e-01	-6.6406	3.12e-11
X1112	-1.818	3.464e-02	-5.2495	1.52e-07
X1113	-2.386	5.292e-02	-4.5089	1e-05
X1114	-5.775	5.925e-02	-9.7465	< 2.2e-16
X1115	2.972	1.337e-01	2.2230	0.02622
X1116	9.789	1.025e-01	9.5503	< 2.2e-16
X1127	5.600	7.301e-02	7.6702	1.71e-14
X1142	-5.744	2.336e-01	-0.2458	0.80582
X1144	4.287	3.499e-01	0.1225	0.90249
X1151	-7.938	5.274e-01	-1.5052	0.13226
X1190	-1.406	1.944e-01	-0.7234	0.46944
Dorm Capacity	-4.308	3.684e-04	-1.1693	0.24229
Sum Student Campus	9.224	1.675e-04	5.5069	3.65e-08

The regression model revealed important findings regarding the factors that affect the Parking Utilization Rate at 80 percent. From the above Exhibit 13, It can be determined that the variables that have a p-value less than the significance level of 0.05 are considered statistically significant in predicting the 80% parking Utilization Rate. Further, the individual assessment of the significant attributes association and effect on parking Utilization rate can be stated as:

- Year-The coefficient estimate for the variable 'YEAR" is -6.248. This means that for every unit increase in the year, the log odds of achieving an 80% parking Utilization rate decrease by 6.248, holding everything else constant.

- Weekday-The coefficient estimate for the weekday variables (Monday, Tuesday, Wednesday, Thursday) is positive indicating that these variables are positively associated with the 80% parking utilization rate. For example, the coefficient estimate for Wednesday is 1.823, which means that holding all other variables constant, the log odds of having an 80% parking utilization rate on Wednesday are 1.823 higher than on Friday (the reference category).
- Lot Type: The coefficient estimate for the Lot Type variable (Reserved) is -4.278, indicating that holding all other variables constant, the log odds of having an 80% parking utilization rate in a reserved parking lot are 4.278 lower than in a non-reserved lot.
- Time: The coefficient estimates for the Time variables 15:30:00 is negative, indicating that parking utilization rates are lower at these times compared to the reference time (9:30 am). For example, the coefficient estimate at 15:30 is -1.030, which means that holding all other variables constant, the log odds of having an 80% parking utilization rate at 15:30 are 1.035 lower than at 09:30 a.m.
- Loc Type: The coefficient estimates for the Loc Type variables (1116, 1127, 1115) are positive, indicating that parking utilization rates are higher in these locations compared to the reference location.For example, the coefficient estimate for 1116 is 0.97, which means that holding all other variables constant, the log odds of having a 90% parking utilization rate in location 1116 are 0.978 higher than in the reference location.
- Total campus occupants: The coefficient estimate for the Total Campus Occupants variable is 0.0009, indicating that holding all other variables constant, for every unit increase in total campus occupants, the log odds of achieving a 90% parking Utilization rate increase by 0.0009, holding everything else constant.

Overall, by comparing the coefficient estimates of all the predictor variables it can be stated 'Weekdays' are the primary influencing factor for the parking utilization rate at 80 percent, followed by 'Loc type'.

Results:

Based on both regression models, the dominant influencing factors for parking utilization are listed below.

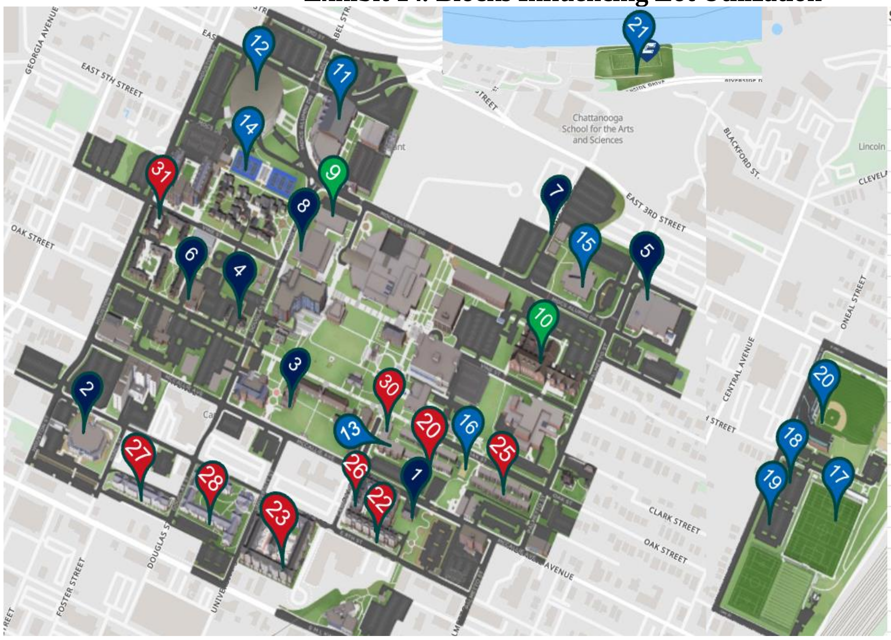
- Weekdays (Wednesday) -From the above analysis, it can be observed that out of all the weekdays, the utilization of parking is notably high on Wednesdays followed by 'Mondays' and is also the primary influencing factor at 90 percent and 80 percent parking utilization at UTC.
- Loc Type- Here, the Loc Types denote the categorization of buildings in UTC (Recreation, Residence Halls, and Administration Facilities). The analysis from Table 2 indicated that Loc Type 1144 (Visitor Information Center) block is the main driver of the 90% parking utilization rate, followed by Loc Type 1116, which includes most of the residence halls. However, in contrast to the 90 percent model, the Loc Type 1144 remained an insignificant factor for the parking utilization rate at 80 percent. Both models clearly demonstrated that Loc Type 1114 has the least impact on the utilization rate. "Fig. 8" provides information on all the block names that influence the parking utilization rates at 90% and 80%.
- Time- The analysis indicates that the utilization rate greatly impacted at 1:30 PM for the 90% model and at 11:30 AM for the 80% model. These times correspond with the expected duration of the highest utilization rate.

Based on the findings from the spatial and logistic regression analysis, it is recommended that the UTC parking services department focus on

- The listed blocks in Exhibit 14 are primarily driving parking utilization rates on campus, and accordingly, the parking lot occupancies and future need to manage the on-campus parking services efficiently are planned.

The weekdays and time slots from the findings impact the utilization rates and use them to plan the parking space allocation accordingly. For example, from both models, Wednesday is observed to have the highest utilization rate; based on it, the UTC parking department, with further study, can consider changing the space allocations based on the supply and need whenever.

Exhibit 14. Blocks Influencing Lot Utilization



S.No	C.C	Building Name	Loc Type
1		Human Resources	1127
2		James R.Mapp Building	1127
3		Founder Hall	1127
4		Aluminni Affairs	1127
5		Administrative Service Building	1127
6		Davenport Hall	1127
7		Collins Street Office annex	1127
8		Maclellan Gym	1127
9		Visitor Information	1144
10		Emcs	1144
11		Aquatic and Recreation Center	1115
12		Mckenzie Arena	1115
13		Pfeiffer Hall	1115
14		UTC Tennis Court	1115
15		Challenger Field	1115
16		Sand Volleyball Court	1115
17		Sport Complex Clubhouse	1115
18		Upper Field	1115
19		Lower Fiels	1115
20		Engel Stadium	1115
21		Scrappy Moore Field	1115
22		Walker Apartments	1116
23		Stophel Apartments	1116
24		Town Hall	1116
25		LockMiller II	1116
26		UC Foundation Apartments	1116
27		Guerry Apartments	1116
28		Decosimo Apartments	1116
29		LockMiller I	1116

Analysis- To answer RQ 2 & 3.

The collected data is further improved by adding derived features or attributes to the stated available variables in Exhibit 15.The additional variable included is the 'Lot Utilization category,' which is formulated below by assigning certain thresholds.

Exhibit 15. Category Thresholds

LOT UTILIZATION CATEGORY	DEFINED THRESHOLDS
Full	>95%
High	Lot utilization > 0.65 but less than equal to 0.95
Moderate	Lot utilization > 0.35 but less than equal to 0.65
Low	<= 0.35

Process of conducting the analysis:

From the total dataset a, sample data is extracted using the Alteryx tool, and the percentage of the sample dataset is in the ratio 80:20. This means 80% of the sample data is used for training the machine learning algorithms, and 20% of the data is used to test the training results based on them to predict better accuracies for the classification of parking lots based on their utilization with the thresholds as stated in the table.

For this study, four separate models were used to analyze the data set, and the accuracies of each model were calculated via a cross-validation tool to determine the highest accuracy model to adapt. The validation data is then used to have each model predict the outcome and check it against the known validation data [11]. Using cross- does not necessarily require a separate test to generate a robust estimate of the understudy model [11]. The tool provides an overall accuracy, accuracy by class, and a set of confusion matrices (one for each model analyzed), with the addition of reporting the F1 score and a collection of performance diagnostics such as lift curve, gain chart, precision versus recall curves, and ROC curve [11]. The analyzed four models are the Decision Tree, Forest Model, Logistic Regression, and Naïve Bayes.

1) A Decision Tree: It is a non-parametric supervised learning method. The decision tree moves down the branches by testing an attribute and then moving down the branch that matches the value of the tested attribute [12].

2) A Random Forest: A classification model of multiple decision trees. The model is utilized in predicting data-driven events due to its ability to handle high-dimensional data [13]. The model usually produces higher-quality data than a single decision tree because it searches for the best feature within a subset of features rather than searching for the most critical feature. The model has real-world applications, such as predicting the size of matter in air based on historical data [14].

3) A logistic regression is a maximum likelihood function used to estimate the maximum chance of occurrence of unknown parameters [15].
4) *A Neural Network:* A computational model inspired by the human brain, comprising interconnected nodes called neurons organized in layers. Information flows through the network, adjusting weights between neurons during training to minimize errors. Used for tasks like classification and pattern recognition, it excels with complex, high-dimensional data in various domains.
Results:
Model Comparison- The forest Model outperformed the Decision Tree, Logistic Regression, and Neural Network model in all categories. An accuracy (ACC) score of 0.775 indicates that the model can classify 77% of the Parking Lots, whether their utilization is full, high, moderate, or low on any available day of the week.

Exhibit 16. Predictive Model Estimates

Model	ACC(%)	F1
Neural Network	0.65	0.40
Forest Model	0.81	0.80
Decision Tree	0.76	0.68

The F1 score shows the balance between the precision and the recall, see equations (1) and (2) below, ranges between 0 and 1, states that the model with the highest F1 score has the highest precision and recall and that the closer the F1-score to 1 the better the model [17]. The F1 score of (0.80), illustrated by the Forest Model, is relatively reasonable and illustrates a model with higher precision and recall.

$$Precision = \frac{TP}{TP+FP} \qquad (1)$$

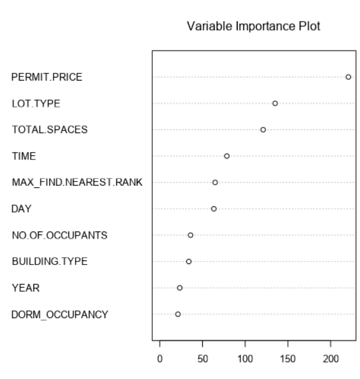
$$Recall = \frac{TP}{TP+FN} \qquad (2)$$

Where, TP = True Positive, FP = False Positive, and FN = False Negative
Variable Importance Plot:

The Forest Model generated a variable importance plot to determine which variables significantly influenced female involvement in fatality crashes.This plot provides a list of the most significant variables in descending order by a mean decrease in Gini, a coefficient measure of the dispersion within the node [13], which means that the variables are in descending order of importance. The closer the mean decrease Gini is to zero, the lower the contributing significance of the variable towards the modeled outcome. A higher mean decreases Gini, producing a higher predictive power within the model's classification of the tested condition [13].

Exhibit 17 shows the most important variables affecting the Lot Utilization Category at UTC. The essential variables affecting the parking utilization at UTC are the permit price, lot type, buildings within 0.11 miles of distance (nearest rank), and the building code (grouped parking lots). Given the nature of the plot, the data shows that the above variables are the most influencing factors when looking at the probability and likelihood of a parking lot being categorized as per the lot utilization categories.

Exhibit 17. Variable Importance Plot



Conclusion

The research project marks a significant milestone in the quest to optimize parking management practices at the University of Tennessee at Chattanooga (UTC). Through a rigorous examination of parking lot utilization patterns and the development of predictive models using advanced analytical techniques, this study has generated valuable insights that can inform strategic decision-making and improve the overall campus experience for students, faculty, staff, and visitors.

The primary goal of the research was to identify the key factors influencing parking lot utilization at UTC and offer practical recommendations for parking planning teams. Through the application of various analytical models, such as Decision Trees, Random Forests, Logistic Regression, the study achieved an average accuracy rate of 81%. Notably, the Random Forest Model emerged as the most effective, boasting an impressive accuracy rate of 81% and a higher F1-Score of 0.80.

The findings underscore the critical importance of variables such as Permit price, Lot Type, time and proximity to buildings in shaping parking lot utilization patterns. Specifically, the proximity of buildings to parking lots, within a distance of 0.11 miles, was identified as a significant determinant of lot utilization. While the number of occupants within buildings demonstrated moderate importance, it was overshadowed by the influence of building proximity.

Furthermore, the development of predictive models using machine learning algorithms, including Support Vector Machines, Neural Networks, Decision Trees, and Random Forests, showcased highly reliable accuracies in predicting parking lot utilization. The Forest Tree Model, particularly, stood out with its remarkable accuracy rate of 81%. This model's ability to handle high-dimensional data and identify complex relationships between variables makes it a valuable tool for predicting future parking demand and optimizing resource allocation.

These findings have significant implications for parking management strategies at UTC. By understanding the key drivers of parking demand and leveraging predictive modeling techniques, parking planning teams can develop proactive measures to address potential bottlenecks and optimize parking resource utilization. Additionally, the insights gained from this research can inform the design of future parking facilities, ensuring that they are strategically located and adequately sized to meet the evolving needs of the campus community.

In conclusion, this research project has provided valuable insights into parking management at UTC, offering actionable recommendations for improving parking efficiency and enhancing the overall campus experience. By harnessing the power of Parking analytics and machine learning, UTC can adopt a proactive approach to parking management, ensuring that parking resources are optimized and the needs of students, faculty, staff, and visitors are met effectively.

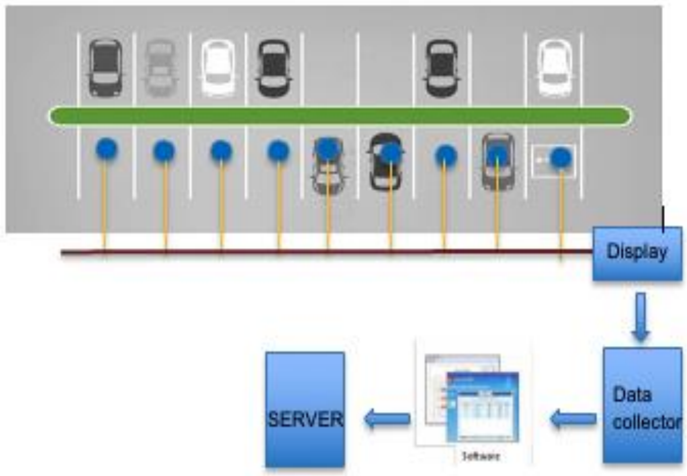
Recommendations:

Moving forward, it is imperative that UTC continues to invest in data-driven approaches to parking management and remains vigilant in monitoring parking utilization trends.In addition, the UTC parking planning team can integrate Smart parking systems by investing in the installation of sensors that can capture vehicle entries and exits and the time of stay for more precise data gathering, which can further be connected with the developed model for cross-validation and forecast lot utilization predictions.

With the gap identified above in the parking system, the project recommends the strategy of implementing Sensor Network architecture to allow the deployment of developed machine learning models to make predictions effectively with the use of real-time data.

Proposed Design:
The proposed system is a wireless sensor network with a data collector. This system is designed to gather information from sensors spread over a wide area and transmit that data to a central location for processing and analysis.

Exhibit 18. Representation of Sensor Architecture design



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The components of the proposed system include magnetic and ultrasonic sensors, a Display screen (optional), Relay nodes(optional), a Data collector, and Parking Software deployed on a cloud server. The proposed designs allow for the capture of occupancy data and also allow the user to make a decision on a parking lot based on availability. In addition, the developed machine learning model can further be deployed with the software and store the data collected via sensors for further analysis and reporting by the Parking Management department for effective monitoring and practices.

Furthermore, with this development and depending on the university parking demand, the sensor implementation can further be connected with IOT devices and UTC parking apps to provide users with more sophisticated ways to find parking lots and payment methods. This development can be left for future study depending on the parking demand and the university enrollment growth factors.

In conclusion, through collaborative efforts between parking planning teams, administrative leadership, and the wider campus community, UTC can realize its vision of a campus where parking is seamlessly integrated into the overall transportation ecosystem, supporting the University's mission of excellence in education, research, and service.

Advantages of proposed system

- Allows for capturing real time occupancy data.
- Expected life time is around 5-9 years.
- Simplified parking Management and Monitoring Practices.
- Cost efficient over building new parking facilities.

Exhibit 19. Cost Analysis between Sensor technology and Building new parking facility

S.NO	Description	Price per unit	Total cost
1	Sensor cost	$278	$139000
2	Installation cost	$30	$15000
3	Display unit	$600 x 45 no's	$27000
4	Parking Application software	$18000	$18000
8	Relay nodes	$500X10	$5000

			$204000
S.NO	**Description**	**Price per unit**	**Cost for 500 spaces**
1	Cost per space	$25000	
2	Engineering Fee	5%	$625,000
3	Soft Cost Lawyers, insurance, permits	5%	$625,000
4	Design Fee	3%	$375,000
8	Equipment cost	7%	$875,000
9	GC Fee	15%	$1,875,000
10	Labor cost	30%	$3,750,000
11	Material cost	35%	$4,375,000
			$1,250,0000

FUTURE AREA OF STUDY

- This study could be further expanded in the direction of integrating the recommended design with an IOT application that is exclusively developed for UTC parking and its users.This can allow for a simplified and efficient Parking management systems for both the parking department and the users at UTC and enhance overall campus experience.

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