Geospatial Health 2025; volume 20:1363

Spatio-temporal analysis of foot traffic dynamics in Charleston County, South Carolina: before, during, and after COVID-19

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Abstract

While the COVID-19 pandemic significantly disrupted urban mobility in general, its effects on spatio-temporal foot traffic patterns remain insufficiently explored. This study addresses this issue by analysing foot traffic dynamics across various regions of Charleston County, South Carolina, before, during and after the pandemic. We examined changes across nine distinct stages of the pandemic from 2018 to 2022 at the sub-county level, utilizing point of interest data and public health records. Various machine learning models, including Random Forest, were employed to predict foot traffic trends, achieving high predictive accuracy with an R^2 value of 0.88. Our findings reveal varying foot traffic patterns across the county. Prior to the pandemic, foot traffic was generally consistent across county subdivisions, maintaining steady levels in each area. The onset of the pandemic led to significant decreases in foot traffic across most subdivisions, followed by gradual recovery, with some areas surpassing pre-pandemic levels. These results underscore the need for tailored crisis management and urban planning, particularly in midsized counties with similar structures to inform more effective resource allocation and improve risk management in public safety during public health crises.

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Key words: foot traffic, COVID-19, public health, spatio-temporal analysis, median dwell time, USA.

Conflict of interest: the authors declare no potential conflict of interest, and all authors confirm accuracy.

Availability of data and materials: all data generated or analyzed during this study are included in this published article and in the referenced texts.

Acknowledgements and funding: we would like to thank anonymous reviewers for taking the time and effort to review the manuscript. The study has been partially supported by the National Science Foundation EPSCoR Program under NSF Award #OIA-2242812, and the School of Engineering, Computing, and Mathematics at the College of Charleston.

Received: 8 November 2024.
Accepted: 29 April 2025.

Geospatial Health 2025; 20:1363
doi:10.4081/gh.2025.1363

Introduction

Foot traffic data provides insight into public responses to health advisories, perceived risks, and the broader impact of the pandemic on daily routines (Bonaccorsi *et al.*, 2020; Gursoy & Chi, 2020). The COVID-19 pandemic significantly disrupted communities around the world, affecting social interactions and mobility patterns (World Health Organization, 2023). Urban areas, once vibrant, became desolate as governments enforced stay-at-home orders, halting normal traffic and leaving public spaces empty (Google LLC, 2020). The shift to work at distance drastically reduced commuter traffic (DeFilippis *et al.*, 2020), while healthcare facilities experienced increased activity due to the surge in patients (Bartsch *et al.*, 2020). These disruptions were most visibly reflected in altered foot traffic patterns. As the pandemic progressed, distinct stages emerged, each associated with specific health advisories and restrictions, which appeared to influence mobility patterns (Google LLC, 2020). Governments implemented various measures—mask wearing mandates, social distancing and vaccination campaigns—that factored in shaping societal behaviour and mobility dynamics, though the relationship between these measures and changes in foot traffic is complex and multifaceted.

Previous studies have explored the impact of COVID-19 on mobility, providing valuable insights across various contexts and scales. Warren & Skillman (2020) examined global and national reductions in mobility using anonymized mobile device data, highlighting the broad effects of behavioural changes and governmental restrictions. Similarly, Gao *et al.* (2020) mapped county-level mobility pattern changes in the United States (U.S.) revealing consistent patterns across many states. However, these studies primarily focus on macro-level perspectives, whereas our research diverges by concentrating on the sub-county level for a more localized analysis of foot traffic patterns.

A recent study by Arambepola *et al.* (2023) analysed fine-scale mobility changes in 26 U.S. cities revealing how local demographic and policy factors influence mobility patterns. While their findings highlight urban mobility dynamics, they do not capture the sub-county intricacies that can significantly affect foot traffic patterns. Our study addresses this gap by emphasizing localized mobility patterns within Charleston County's distinct subdivisions. Moreover, Elarde *et al.* (2021) utilized dwell-home-time (the duration of time an individual spends at home) as a measure to reflect mobility changes during COVID-19 across various counties in the US. Although their analysis offers valuable insights, it adopts a broad approach that primarily identifies correlations among counties. In contrast, our research not only focuses on visit counts but also incorporates individual dwell time data at different locations, providing a multi-dimensional perspective on how the duration of visits changed during the pandemic (Allard *et al.*, 2023).

Pan Y *et al.* (2020) focused on short-term daily mobility across the U.S. from March to May 2020 to examine the immediate effects of COVID-19 on mobility patterns. Similarly, Angel *et al.* (2023) analysed pedestrian traffic and walking patterns in Israel during the pandemic from January to July 2020. While these studies offer valuable perspectives on mobility changes, our research spans a broader time frame from January 2018 to September 2022, allowing us to capture both immediate and sustained shifts in mobility patterns. In terms of pandemic staging, Tegally *et al.* (2022) conducted a global mobility study indicating that the waves of the pandemic suggest the need for fine-staging. Stasi *et al.* (2020) divided the pandemic into four stages from a pharmacological perspective. In contrast, we introduced a more granular nine-stage model based on local COVID-19 cases, deaths and government responses. This approach captures subtle variations in foot traffic across different phases of the pandemic, allowing for a more nuanced understanding of mobility dynamics.

This study addresses the gaps in understanding both short-term and long-term impacts of the COVID-19 pandemic on foot traffic by providing a fine resolution and stage-by-stage analysis over a five-year period and offering a detailed, extended analysis of mobility patterns at the sub-county level. To the best of our knowledge, this is the first study to analyse the spatial and temporal variations in foot traffic with high spatial resolution for distinct stages of the pandemic, including before and after. Our research aimed to understand how foot traffic patterns evolved across regions during the various stages of the pandemic, while also evaluating the performance of predictive models. These models can be leveraged in future studies to evaluate predictive power and relationships among features, ultimately informing more effective public health and urban planning strategies during similar crises. The insights gained from this study also offer valuable guidance for optimizing resource allocation in cities and enhancing risk management in public safety, helping policymakers better respond to mobility changes in future public health emergencies.

Materials and Methods

Charleston County, South Carolina (SC), USA offers a representative case for studying pandemic-induced changes in foot traffic thanks to its diverse mix of residential, commercial, and tourist zones (Charleston County Development, 2023). We used county-level COVID-19 data obtained from USAFacts.org. that provides detailed weekly reports of both COVID19 cases and death numbers in Charleston County. This dataset allowed us to correlate changes in foot traffic patterns with shifts in the local severity of the pandemic, providing meaningful context to our mobility data.

Spatial and temporal scope

Study area

Charleston County, located in south-eastern SC, covers approximately 1,358 mile^2 (3,517 km^2) with a population exceeding 400,000 individuals (U.S. Census Bureau, 2022). The county's geographical coordinates range from 79.267946 to 80.453629 in longitude and from 32.493328 to 33.215136 in latitude. For this study, we divided the county into 10 district regions based on delineations provided by the U.S. Census Bureau, as detailed in Table 1.

Time periods

To better analyse the impact of COVID-19 on foot traffic in Charleston County, we divided the study period into nine distinct stages, as detailed in Table 2. These stages were defined based on the trends in COVID-19 cases and deaths, as shown in Figure 1,

Table 1. Key traits of regions in Charleston County.

Region	Description
Mount Pleasant	Predominantly residential, characterized by a scenic suburban lifestyle with a growing community.
Charleston Downtown	The most densely populated area, with bustling tourism and a wide range of commercial establishments.
Kiawah Island-Seabrook Island	Exclusive residential communities dominated by natural beauty with limited commercial development, with sparse population due to seasonal residents.
West Ashley	Diverse suburban residential area, with commercial centres and shopping districts.
Johns Island	Rural residential community with limited commercial presence characterized by spacious properties and natural landscapes.
North Charleston	Primarily suburban residential area balancing between residential sparsity and industrial zones, with military bases and some commercial areas.
Wadmalaw Island	Sparsely populated residential area with limited commercial development.
Ravenel-Hollywood	Quiet, residential region with limited commercial establishments and a mix of housing types with emphasis on residential sparsity and rural living.
James Island	Suburban community offering a blend of residential neighbourhoods featuring some commercial areas and easy access to outdoor amenities.
McClellanville	Small coastal town with limited commercial activity and residential focus including historic homes surrounded by nature.

with data sourced from the South Carolina Department of Health and Environmental Control (DHEC) and Charleston County COVID-19 updates (South Carolina Department of Health and Environmental Control, 2023a). The segmentation into stages was based on key events in the pandemic, including the initial outbreak, peaks in infection rates, the introduction of restrictions, vaccination efforts and the emergence of new variants. This approach is consistent with established epidemiological studies and public health reports, which similarly segment the pandemic timeline to reflect its major phases (Centers for Disease Control and Prevention, 2021; Huang, 2021; WHO, 2021).

Data collection

Point of interest (POI) data

Our study utilized POI data, sourced from SafeGraph (https://www.safegraph.com/), a leading data company known for its rich anonymized location data repository, and Dewey Data Platform, a provider of U.S. consumer foot traffic data (https://www.deweydata.io/). Our data spans from January 2018 to May 2022. SafeGraph accounted for the records prior to February 2022, while data from the period from February to September 2022 were sourced from Dewey, which primarily aggregates SafeGraph data for academic use. The transition was due to changes in data access budget and availability. The POI data include location-specific information such as latitude, longitude, raw visit counts, and median dwell times. These data were collected through mobile and web-based sources, utilizing principles of participatory sensing (SafeGraph; Tonekaboni *et al.*, 2019; Figure 2).

Administrative boundaries data

The delineation of subdivision boundaries within Charleston County, such as North Charleston, Charleston Downtown, Mount Pleasant, among others, was attained from the US Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER) line database (U.S. Census Bureau, 2022).

Public news and policy updates

News articles and official announcements serve as indispensable resources for understanding the progress and response to the

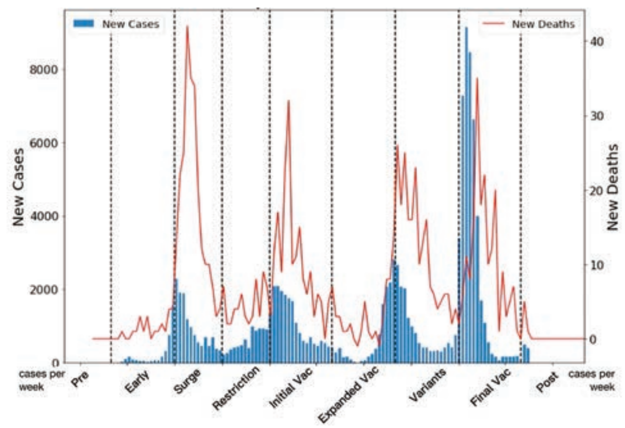

Figure 1. Weekly New COVID-19 cases and death counts from January 2018 to June 2022.

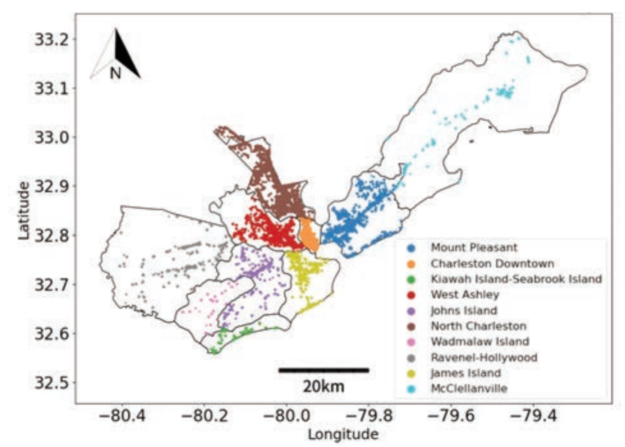

Figure 2. Distribution of walkable points of interest in Charleston County, SC, USA.

Table 2. Summary of pandemic stages and their descriptions.

Stage	Start Date	Descriptions according to DHEC [18] [19] [23]
Pre-pandemic [A]	01-01-2018	Period providing a normalcy baseline for comparison.
Early pandemic [B]	03-06-2020	Initial COVID-19 cases in South Carolina and Charleston's inaugural COVID-19 updates.
Surge [C]	07-01-2020	Sudden increase in COVID-19 cases, with the emergency ordinance requiring face coverings in public areas.
Restriction [D]	10-01-2020	South Carolina's COVID-19 vaccination plan's release signifying proactive measures, including mask wearing mandates, curfew and capacity limits on businesses.
Initial vaccination [E]	01-06-2021	Phase 1 of vaccination stated in South Carolina; all frontline health workers urged to schedule vaccine appointments.
Expanded vaccination [F]	05-03-2021	Phase 2 of vaccination started in SC; appointments available to all instate residents age 16 and above.
Virus variants [G]	08-27-2021	Pervasive *Delta* and *Omicron* variants in Charleston; above 6,000 daily COVID-19 cases for the first time since Jan.15.2021
Final vaccination [H]	01-01-2022	Second and third vaccine doses encouraged.
Post-pandemic [I]	05-01-2022	Cases numbers decline and public announcements gradually cease: gradual closure of DHEC-managed vendor testing sites.

DHEC, Department of Health and Environmental Control;.

COVID-19 pandemic at a local level. We gathered pertinent information from DHEC (2023b) and the Charleston County website (City of Charleston, 2023).

Data preprocessing

Our dataset, encompassing nearly 70 attributes, includes data from commercial establishments (c), walkable places (wp), and general points of interest (g). Given our focus on wp data, which consists primarily of geometry data points like enclosed areas (both outdoor and indoor), we aimed to track mobility volume in locations likely to incorporate walking behaviour. While it is acknowledged that some of these locations may involve driving, our primary interest lies in understanding foot traffic volume rather than strictly tracing physical patterns. A rigorous cleaning process was necessary to address inconsistencies arising from the dataset's dual origin from the SafeGraph and Dewey platforms. We employed systematic harmonization techniques to ensure uniform data density across the timeline, providing a solid foundation for analysing foot traffic patterns specifically within wp places. During the data refinement process, features irrelevant to our research focus were excluded. Specifically, columns with minimal variances, such as device type and non-North American origin, were removed. Additionally, columns unique to data providers, like 'place key,' were omitted due to challenges in accessing original Application Programming Interfaces (APIs). High-granularity metrics, such as hourly foot traffic and polygon representations, were also bypassed to maintain the focus on overarching trends. We used geocoding techniques, including the Point-in-Polygon method (Longley *et al.*, 2015), to address spatial data inconsistencies by verifying and correcting geographic labels against the TIGER/Line shapefile. This process ensured that all data points were accurately aligned with Charleston County's official boundaries.

Feature engineering

In preparing the data for analysis, we focused on enhancing geographic accuracy and standardizing labels. The 'city' column, which initially contained discrepancies and colloquial names, was refined by cross-referencing longitude and latitude coordinates with the TIGER/Line shapefile. This ensured that each data point's location was correctly aligned with official designations, enhancing the dataset's reliability.

Outlier detection was another important aspect of feature engineering. While the Interquartile Range method flagged locations like Charleston International Airport as outliers due to high foot traffic, these were retained and contextualized as genuine reflections of urban dynamics. We also established 'Stage 0' as a pre-COVID baseline, which was essential for standardizing foot traffic counts across different stages of the pandemic. Categorical features such as city, street name, and location name were label-encoded. Missing values for street names and region names were filled in based on longitude, latitude and place names, ensuring completeness and accuracy in the dataset.

Model construction

For the model construction, the dataset was split into training and testing sets, with 70% of the data used for training and 30% for testing. This split allowed for sufficient data to train the models while reserving a portion to evaluate their generalization performance. To ensure robust model evaluation, we performed a 5-fold cross-validation, where the dataset was divided into five parts, with each part used for testing, while the others were used for training. This method helped to reduce potential bias and provided a more accurate assessment of model performance. The primary objective was to predict the visit counts of a location within a week, using independent variables such as longitude, latitude, region name, street name, date and location. Multiple models were considered in this analysis, including Random Forest, Decision Tree, K-Nearest Neighbour (KNN), Gradient Boosting, Lasso and Linear Regression. Each model's performance was evaluated based on its ability to accurately predict weekly visit counts, with a particular focus on minimizing prediction errors and maximizing R^2 values.

Results

Foot traffic dynamics

Our study revealed that the COVID-19 pandemic significantly impacted the foot traffic dynamics within Charleston County as indicated by the colour legend in Figures 3 and 4. Prior to the pandemic, foot traffic was generally consistent across various subdivisions, maintaining steady levels in each area. However, the onset of the pandemic marked a notable decrease in foot traffic across all subdivisions. Despite this initial decrease, foot traffic gradually began to show signs of recovery, eventually returning to pre-COVID levels, and in some instances, surpassing them.

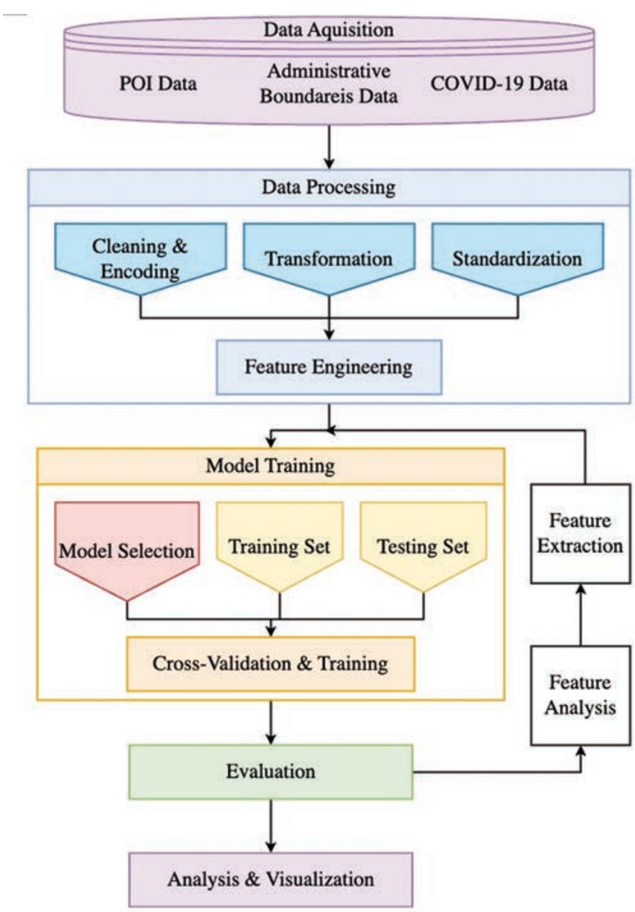

Figure 3. Data flowchart.

Pre- and early pandemic stages

During the pre-pandemic stage, foot traffic across all regions remained stable, with standardized average weekly visit counts centered around zero, reflecting deviations from a normalized baseline rather than actual visit numbers. As we transitioned into the early pandemic stage, there was a decline in movement due to public health precautions. At 40% below pre-pandemic levels, downtown Charleston experienced the largest drop in foot traffic, while Mount Pleasant, North Charleston, West Ashley and James Island experienced about a 20% decline. However, other areas, such as McClellanville, Ravenel-Hollywood, and Kiawah Island-Seabrook Island had minimal changes.

Surge and restriction stages

During the surge phase, foot traffic patterns varied by location. Downtown Charleston and West Ashley experienced substantial reductions, falling to 40.2% and 30.7% below pre-pandemic levels, respectively. In contrast, areas such as Kiawah Island-Seabrook Island maintained relatively stable traffic, with changes ranging from a 9.1% increase to a 21.1% increase compared to pre-pandemic levels. The restriction phase brought an additional decline in foot traffic across all cities relative to the surge phase, although vaccination efforts began to show signs of recovery in foot traffic volume.

Vaccination and virus variants stages

Foot traffic increased consistently across cities during this period. North Charleston experienced an increase of approximately 4.9% than restriction stage during the initial vaccination stage, followed by a 5.3% rise from initial vaccination stage to expanded vaccination stage. Downtown Charleston experienced a significant rise, approaching pre-pandemic levels. Despite this recovery, the variants stage introduced a minor decline in foot traffic in various regions.

Post pandemic stage

Many regions, particularly Downtown Charleston and West Ashley, experienced notable increases in foot traffic in the post-pandemic stage. Downtown Charleston and West Ashley reached levels 70.0% and 39.6% above pre-pandemic levels, respectively. Conversely, McClellanville showed a more modest recovery, with traffic around 9.0% above pre-pandemic levels. North Charleston and James Island faced difficulties, with traffic reaching only 14% and 10% below pre-pandemic levels.

Dwell time alterations

The COVID-19 pandemic significantly altered the median dwell time in various subdivisions of Charleston County, as shown in Figure 5. For this analysis, data from Wadmalaw Island - a rural, sparsely populated area dominated by agricultural land use and limited commercial development - was excluded due to identified irregularities and consistently low foot traffic volume.

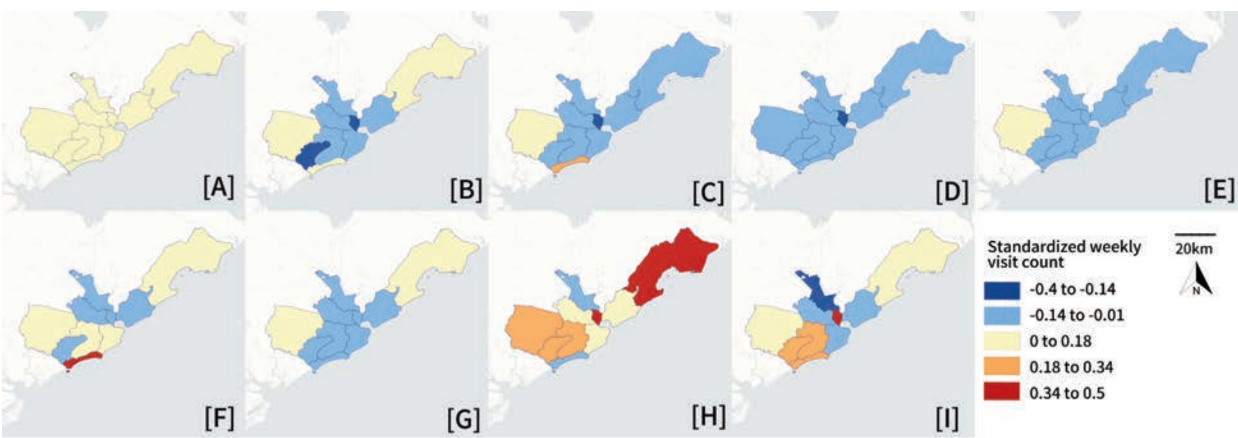

Figure 4. Standardized average weekly visit counts during the pandemic for each region within Charleston County, SC, USA.

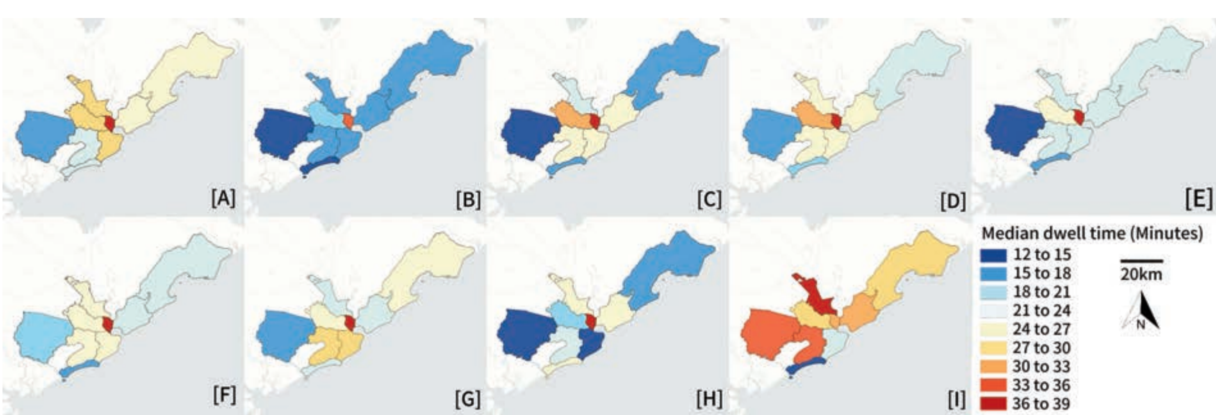

Figure 5. Median dwell time in minutes for each region during the pandemic within Charleston County SC, USA.

Pre and early pandemic stages

During the early stages, median dwell times decreased noticeably. For instance, in Mount Pleasant, the dwell time dropped from 29.0 minutes in Stage A to 23.0 minutes in Stage B, while in Charleston Downtown, it declined from 37.0 minutes to 31.3 minutes.

Surge and restriction stages

As the pandemic progressed, some areas adapted by increasing their dwell times. The dwell time in Charleston Downtown, for instance, rose to 37.0 minutes by Stage B, while West Ashley maintained relatively stable times, with minor changes around 31.0 minutes.

Vaccination and virus variants stages

With the onset of vaccinations, median dwell times generally stabilized. However, responses varied: Ravenel-Hollywood experienced fluctuations, peaking at 35.0 minutes in Stage H, while Mount Pleasant reached only 31.0 minutes by the same stage.

Post-pandemic stage

In the post-pandemic stage, the dwell time in different regions diverged. Kiawah Island-Seabrook Island saw a decline to 12.0 minutes, while Johns Island experienced a significant resurgence, increasing its median dwell time by approximately 77%, from 19.2 minutes to 34.0 minutes.

Model evaluation

In evaluating model performance, we utilized several key evaluation metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Standardized Mean Squared Error (SMSE), and R squared (R^2). These metrics were selected to quantify prediction errors and assess how well each model captured the underlying patterns in the data. Cross-validation was also used to minimize potential biases. The results of these evaluation performances are presented in Table 3. The Random Forest model outperformed all others investigated, achieving an MAE of 8.92, indicating precise predictions with minimal error. The RMSE of 13.81 further demonstrated the model's effectiveness in reducing large prediction errors. Additionally, the SMSE score of 0.21 and R^2 value of 0.88 underscored the model's ability to explain 88% of the variance in the outcome, making it the most reliable model among others. While still reasonably accurate with an R^2 of 0.74, the Decision Tree model exhibited higher errors, with an MAE of 11.93 and an RMSE of 21.24. The KNN model demonstrated moderate performance, with an R^2 of 0.53, MAE of 17.25, and RMSE of 26.86 indicating a greater degree of error in its predictions. Gradient Boosting and the linear models (*i.e.* Lasso and Linear Regression) performed poorly, with the lowest R^2 values and the highest errors, reflecting their limited suitability for this predictive task. Feature importance analysis of the Random Forest model revealed that the encoded location name and encoded city were the most significant predictors, with a feature importance score of 0.308 and 0.175, respectively. This emphasizes the critical role that location characteristics play in determining foot traffic patterns. Geographical coordinates also emerged as important factors, with feature importance scores of 0.183 and 0.174, respectively. Temporal variables, including month (0.051), stage (0.038) and year (0.027); as well as encoded street names (0.058) and encoded sub-county name (0.22), were also influential, highlighting the combined effect of spatial and temporal elements on foot traffic dynamics.

Discussion

Our analysis based on POI data on foot traffic collected during different stages of the COVID-19 pandemic, along with spatial data for each region revealed significant variations in foot traffic volume and duration across different areas and stages of the pandemic. The predictive models, particularly the Random Forest model, demonstrated strong performance, with feature importance analysis highlighting the considerable influence of geographical features of the city indicating that foot traffic dynamic is highly region-specific. These results thus reinforce the need for policies that are tailored to the unique characteristics of each area, information that would help public health strategies and urban planning to better manage the impact of future, similar crises.

The superior performance of the Random Forest approach likely stems from our dataset's non-linear and heterogeneous nature. Its ensemble structure—that combines multiple decision trees trained on different subsets of data and features—effectively reduces variance and fits well with our data, which span a long period and reflect region-specific and continuous fluctuations in visit counts. Despite rigorous data cleaning and minimal extreme outliers, the wide value range of dataset and local variability pose modelling challenges that Random Forest was particularly effective in handling. In contrast, Gradient Boosting underperformed, which was most likely due to the sequential learning process. Given the shifting nature of foot traffic during a multi-stage pandemic, boosting may result in overfit with regard to short-term noise rather than capturing broader trends. Simpler models like Linear Regression assume linearity and independence among features, which are less suited for the interactive and region-specific patterns observed. Similarly, model like KNN scales poorly and require sensitive tuning for our large and mixed-type datasets further limiting their effectiveness.

The findings of this study offer a transferable framework for understanding mobility dynamics in other midsized urban areas during public emergencies. Cities, such as Savannah (Georgia), New Orleans (Louisiana), Nashville (Tennessee) and St. Augustine (Florida), share similarities with Charleston in terms of their reliance on foot traffic and tourism (Glaeser, 2011). Extending this methodology to other metropolitan areas could inform practical policy applications particularly during public health crises. For instance, understanding how mobility patterns fluctuate in different urban contexts can inform strategic placement and scheduling of vaccination sites, optimize emergency response services, and identify high-risk zones based on delayed mobility recovery. These insights are especially valuable when governments must allocate limited resources under tight timeframes. Understanding regional differences in foot traffic can help avoid both "resource starvation" in underserved areas and "waste" in locations with low demand,

Table 3. Model evaluation metrics.

Model	MAE	RMSE	SMSE	R^2
Random forest	8.92	13.81	0.21	0.88
Decision tree	11.93	21.24	0.31	0.74
K-Nearest neighbours	17.25	26.86	0.45	0.53
Gradient boosting	20.88	29.45	0.67	0.33
Lasso	24.71	32.00	0.75	0.18
Linear regression	24.15	32.93	0.80	0.19

enabling need-based distribution strategies Liang *et al.*, 2023). Extending this approach can help to better understand the spatial disparities and behavioural shifts triggered by public health crises in tourist-dependent urban environments.

Compared to existing literature, such as studies by Warren & Skillman, 2020 and Pepe *et al.*, 2020, which primarily focused on macro-level mobility trends or national contexts, our study offers a more granular, sub-county level analysis. While prior research has explored reductions in mobility during the pandemic, our study differentiates itself by examining spatial and temporal variations in foot traffic within a mid-sized county over distinct stages of the pandemic. Additionally, by incorporating both visit counts and median dwell times, our study provides a more nuanced view of how different regions responded to various stages of the pandemic. Different responses across neighbourhoods highlight the need for tailored city planning. Areas with significant foot traffic drops, such as Downtown Charleston and Wadmalaw Island, might benefit from better-located healthcare services in future crises (Pan A. *et al.*, 2020). Temporary facilities, like drive-through testing sites, could be considered in areas with decreased mobility to enhance access to essential services (Noland *et al.*, 2023). Moreover, the shifts in mobility suggest that policy measures may have varied impacts. Areas like McClellanville and Ravenel-Hollywood, with stable foot traffic, might need more localized strategies or stricter regulations (Hsiang *et al.*, 2020). A tiered approach to restrictions based on local conditions might help balance public health and economic activity more effectively. Furthermore, mobility changes may reflect different responses to public health messaging (Bavel *et al.*, 2020). Thus, some areas, like Kiawah Island-Seabrook Island, might be more responsive, suggesting effective messaging. Tailored communication to address local concerns and promoting responsible behaviour during high-mobility periods could be important for future public health efforts (Chang *et al.*, 2021).

Despite the strengths of mobility data from SafeGraph and Dewey, several equity concerns warrant careful attention since they are derived from smartphone-based application usage, which introduces selection bias. Previous studies have shown disparities in mobile device ownership and app usage across age, race and socioeconomic status (Conston *et al.*, 2021; Li *et al.*, 2023). Older adults, lower-income individuals and minority populations—groups often at greater health risk during public crises—are underrepresented in such datasets. Moreover, sampling rates have historically skewed higher in urban areas compared to rural ones (Li *et al.*, 2023). Still, at finer spatial resolutions, such as census tracts or block groups, data representativeness becomes less reliable, especially in areas with poor network coverage or limited device penetration. These gaps pose challenges in using mobility data to inform public health decisions, particularly when allocating resources like testing or vaccination sites as they may inadvertently overlook communities most in need.

Within Charleston County, mobility disparities may be especially pronounced due to stark geographic and demographic divides. Predominantly white areas like Johns Island contrast sharply with majority-Black areas, such as parts of North Charleston, where socioeconomic vulnerabilities are more concentrated. In these under-resourced neighbourhoods, low-income residents—especially essential workers—may have limited flexibility to reduce mobility during public health crises, placing them at greater risk. As race and income are strongly correlated with mobility patterns during emergencies (Roy *et al.*, 2021; Deng *et al.*, 2021), future research should integrate demographic indicators to better understand and mitigate these disparities. Moreover, resource allocation and public communication strategies should not solely rely on mobility data, which reflects only digitally connected populations. Underrepresented areas may require interpersonal outreach—such as extended in-person announcements or door-to-door communication—to ensure equitable access to critical information and services. While digital platforms dominate modern communications, intentional efforts must remain in place to support communities with limited access to technology or formal information networks (Coston *et al.*, 2021).

Limitations and future works

This study has several limitations that warrant consideration. First, the study relied on a single data source, which may limit the scope of the analysis. Incorporating additional data sources, such as mobility data from different providers or integrating real-time traffic information, could enhance the robustness of the findings. Second, while the analysis focused on Charleston County, the findings may not fully generalize to other regions with different demographic, geographic, or economic characteristics. Expanding the study to include multiple regions could provide a more comprehensive understanding of foot traffic dynamics across diverse urban areas. Additionally, handling incomplete data remains a challenge, and more advanced techniques, such as imputation methods could be applied to address missing values and improve data completeness. Future work could also explore the influence of external factors, such as local news events, public health announcements, or traffic disruptions, to provide a more nuanced understanding of public behaviour during crises. Incorporating such factors would allow for better contextualization of foot traffic patterns and improve the predictive power of the models.

Conclusions

Foot traffic is a vital indicator of urban health, economic activity and social engagement, with patterns that can shift dramatically in response to events like pandemics. Conducted in a representative midsize U.S. county, this study offered an in-depth analysis of foot traffic dynamics across diverse regions throughout various stages of the COVID-19 pandemic. Significant variations in foot traffic patterns were observed, with some areas showing marked reductions, others increases, sometimes even surpassing pre-pandemic levels. These fluctuations underscore the inherent adaptability and heterogeneity across different types of communities, extending from densely populated urban centres to more secluded rural and suburban locales. The study enhances our understanding of how individuals' time spent at various locations varies, emphasizing the need for region-specific crisis management and urban planning interventions. The Random Forest model exhibited remarkable predictive accuracy (R^2=0.88) in predicting foot traffic dynamics. Collectively, these results offer valuable contributions to city planning, policy-making, and public health suggesting a framework for targeted interventions and resilience planning for future challenges.

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