

**The Resilience of  
Transit-dependent Communities During COVID-19  
in the Boston Metropolitan Area**

A thesis submitted by

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## **Abstract**

Public transportation has experienced severe disruption during the COVID19 pandemic - from partial closures and service reductions to complete network shutdowns. It resulted in less reliable transportation systems, limiting individual access to destinations. While some studies have examined the spatial equity of individual accessibility, few have examined the resilience of communities and transit services in COVID19 or how the pandemic has influenced transit accessibility. To bridge these gaps in the literature, we focus on the vitality of transit stations in the Boston metropolitan area pre- and during- the pandemic. The resilience of transit stations is measured by aggregating the types of facilities people visit within a 15-minute walk of a transit station and analyzing the number of visits and the time of day they visit.

Moreover, we measure resilience based on changes in social demographic indicators. We also compare the built environment of different transit stations, such as road density and 15-minute walkable area, to quantify their support for resilience in the pandemic. With the POI pattern data and data mining framework for clustering analysis of POI access within the 15-minute walkable area in the Boston metropolitan area, we first explore the differences in times of day when people visit different classifications of POI and found changes in daily activities around traffic stations. We then calculate the share of time-based clustering results in each station. We introduce clustering again to observe the differences between stations and the same station pre- and during the pandemic, combined with the built environment and social demographics. We find that transit ridership and the number of POI visits within the 15-minute walk of transit stations in the Boston metropolitan area

decreased significantly. The built environment and social demographic factors played a role in the vitality around transit stations. Different combinations of POI types played a different role in transit station vitality. Finally, we provide policy recommendations and call for cities to take planning actions to mitigate the pandemic's erosion of people's accessibility, design and expand shared transit systems more equitably, and prioritize accessibility improvements.

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# Chapter 1. Introduction

## 1.1. Background

Transit creates a network of connected communities in which the transit stations anchor denser, walkable, mixed-use communities and connect those communities not only to each other but also to employment locations and other destinations throughout the transit-served region. However, the COVID-19 dilemma has brought additional challenges to urban transportation networks, particularly in metropolitan areas where people are densely concentrated in the same location simultaneously.

The pandemic and increased social distancing have declined opportunities for people to use public transportation to access activities comfortably and safely.

Guidelines ranging from partial closures and capacity reductions to continuous network closures have resulted in insufficient street networks and a lack of reliable transportation systems, restricting people's access to various locations, services, and facilities. Besides, to ensure adequate social distancing, cities anticipate an imminent need to provide full-capacity transit services while confronted with unprecedented budget shortfalls - in the billions of dollars for large metropolitan areas due to declining ridership (Gelinias, 2020).

The United States Federal Transit Administration (FTA) defines 'transit

dependent' people simply as 'all persons who live in a household with no private vehicle available' (2013). Thus, public transportation might be the principal means of getting to school or work, doing family maintenance activities, and managing and maintaining social and familial relationships for people without access to private automobiles.

Exploring the vitality around transit stations gives a more comprehensive view of whether and how the pandemic has changed visit patterns around transit stations.

Services and segregation are essential, especially for those with lower socio-economic backgrounds (Grengs, 2005; Moulding, 2005; Ranchordas, 2020). Reduced transport capacity may raise the risk of virus exposure for disadvantaged populations who already have fewer transportation alternatives and are more likely to work in service sectors that need them to go in person rather than telecommute (Lubitow et al., 2017).

Moreover, Points of Interest (POIs) provide valuable information about specific geographical locations and can be considered spatio-temporal labels for some areas (Han et al., 2021). As a micro-indicator of individual activity, POI visits collected from cell phone records during the pandemic reflected people's response to severe infectious diseases. Therefore, an analysis of the accessibility to facilities within a 15-minute walking distance from transit stations demonstrates how changes in individual behaviors before and during the pandemic are related to local environmental

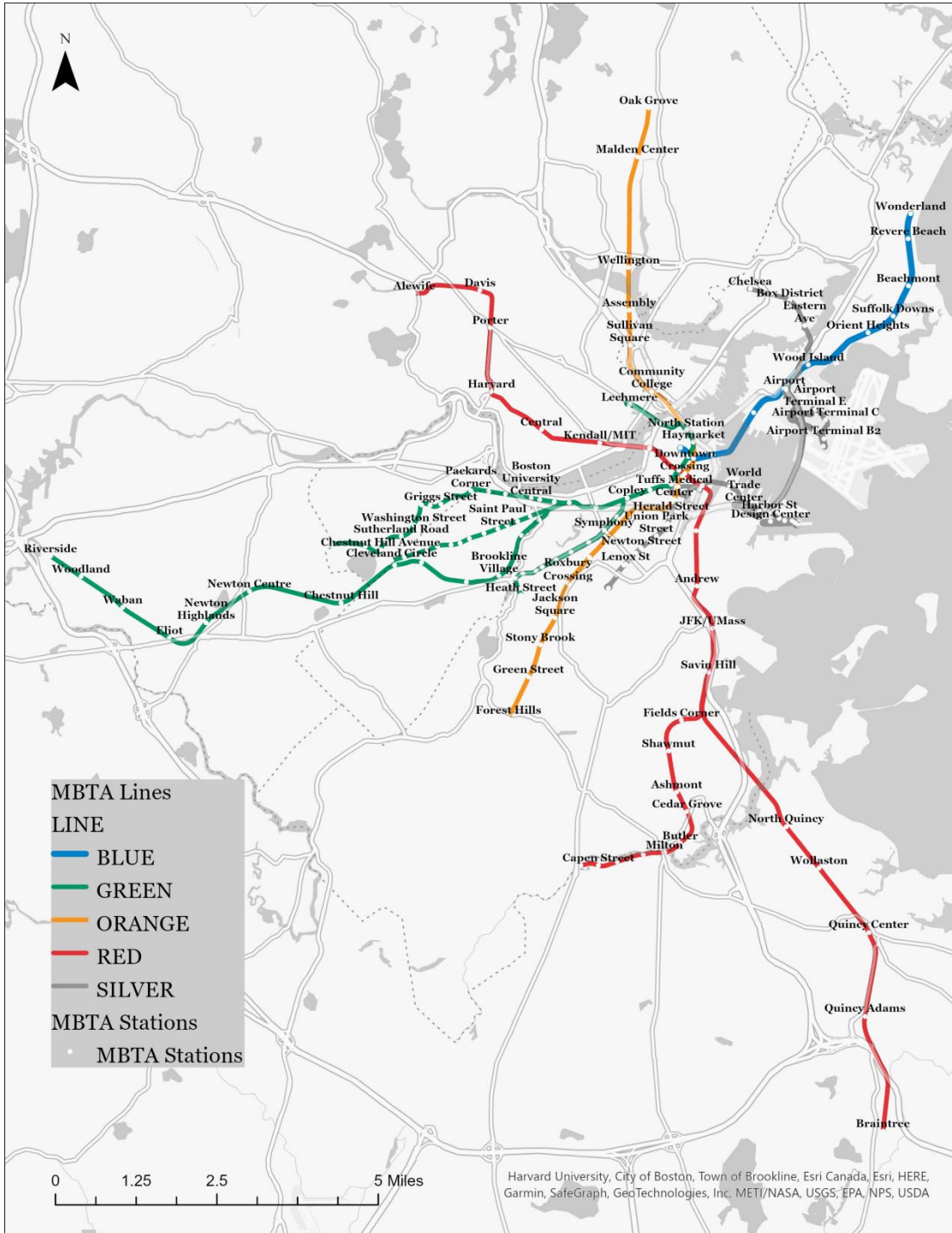
circumstances. The spatial analysis results of access to these widely utilized services and resources illustrate the accessibility disparities between transit stations.

Furthermore, a comparative study of the visit patterns of POI around transit stations pre-and during the pandemic allows us to evaluate the resilience of communities with transit stations and how this shift varies in space and time.

## **1.2. Transit in the Boston Metropolitan Area**

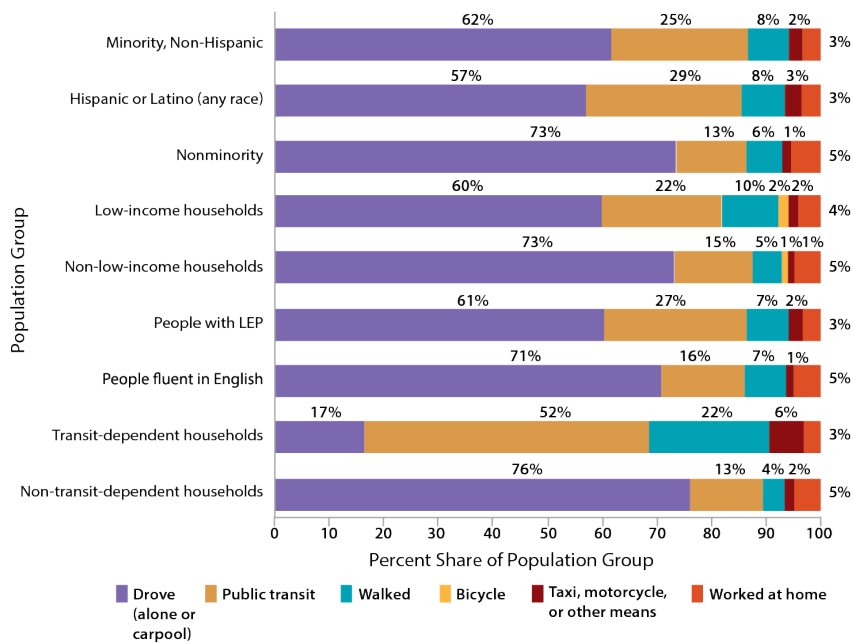
Since the earliest horse-drawn railways, transit-oriented development has been vital to Boston's growth. Currently, the Massachusetts Bay Transportation Authority (MBTA) is one of only five transit systems in the United States, with more than 200 transit stations and more than a century of service. It contains three heavy-rail lines (Red, Orange, and Blue), two light-rail lines (Green, Ashmont-Mattapan), and one bus rapid transit route underneath (Silver). Thus, the Boston metropolitan area is a good location to study the effects of a comprehensive transit system on regional land use and travel behavior, as there is sufficient station area for potential region-wide effects.

While the resilience of such a mature, extensive system to support the surrounding region during a pandemic may not be typical of newer or smaller transit systems, it provides a crucial snapshot of the potential for transit stations to impact the accessibility of individual activities during a pandemic.



**Figure 1. MBTA transit lines and stations**

According to census data, transit-dependent families have the largest public transport mode share, with 52 percent using this mode, and the lowest driving mode share, with 16 percent.



**Figure 2. Travel modes percent share of a population group**

Nonetheless, when the outbreak formally made landfall in Massachusetts, the abrupt cessation of all forms of transportation by road, rail, and air resonated throughout the nation. Travel was severely limited as people stayed home in compliance with state and CDC regulations and public health guidelines.

The MBTA lost the greatest number of passenger trips in the first year of the pandemic, about 340 million. In the first four months of the pandemic, the MBTA saw a 73 percent decline in ridership relative to March 2019 through June 2019. More recently, MBTA passenger traffic moderated slightly from March 2021 to June 2021, declining 64 percent from March 2019 to June 2019.

## Chapter 2. Literature Review

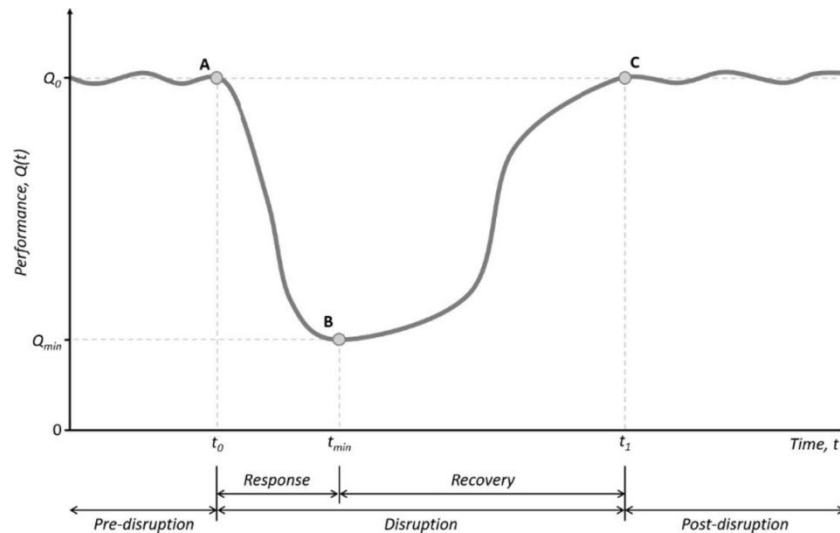
### 2.1. Resilience

The concept of resilience has been the subject of several controversial definitions (Aldunce et al., 2014), resulting in differing perspectives on what it should encompass and how to measure it (Winderl, 2014). Holling (1973) described resilience as a measure of system durability and the ability to absorb changes and disturbances. According to the US President's Policy Directive (PPD-21, 2013), resilience refers to the ability to prepare for and adapt to changing conditions and quickly recover from interruptions.

In the field of transportation, resilience is defined as the ability of the system to maintain its demonstrated level of service or to restore itself to that level of service in a specified timeframe (Freckleton et al., 2012). Even if only a limited number of roads are affected, it will cause disruption and delays to the transportation system, resulting in inconvenience (Koetse and Rietveld, 2009). The pandemic lowers the accessibility of services such as mail and park use and mobility within communities and other locations, especially in less developed areas where the pandemic severely restricts families' access to jobs, food, and basic public services.

As shown in Figure 1, the existing resilience framework is time-dependent and is

intended to describe system performance throughout the pre-disruption, disruption, and post-disruption phases. This study focuses on pre- and during the pandemic. It is important to note that even though a return to pre-pandemic levels is a signal of recovery, the equilibrium may shift permanently in reaction to the pandemic, and a new equilibrium may be established. Besides, the lessons learned from this pandemic will help to prepare for the new emerging pandemic.



**Figure 3. The generalized conception of system performance (Martello et al., 2018)**

Research on traffic network analysis often uses network centrality measures and connectivity methods. Omer et al. (2011) proposed a networked infrastructure resilience framework (NIRA) based on the road network of New York. Resilience is measured as the ratio of travel time before a network interruption to travel time after the network interruption. Similarly, Kim et al. (2015) investigated how the potential failure of a node interruption affects the transportation system, considered the impact of the

interruption on ridership and travel time, and examined the changes in the reliability of the transportation system using a case study in the metropolitan area of Washington, DC. These measurements overcome the problem of ignoring the inherent differences in travel modes and capture the impact of travel behavior on resilience.

Another indication of resilience is based on socioeconomic variables (e.g., employment, income). The Resilience Capacity Index (RCI) (Foster, 2007) is a highly complicated metric comprised of 12 equally weighted components grouped into three categories: economic capacity, socio-demographic capacity, and community connectivity capacity.

Unfortunately, this metric does not adequately account for spatial mobility mitigation and shock recovery potential (Östh et al., 2018) — proxied through geographic connectivity and spatial openness based on accessibility. Due to the power of geographic resilience, a highly accessible system may expedite productivity gains and efficiency improvements in the region and contribute to a quicker recovery. Therefore, in addition to RCI and the Resilience Employment Index (REI), Östh et al. (2018) also implemented an empirical survey of spatial interaction data based on local accessibility. Research indicates that the equity of availability to accessibility is essential in transport planning and communication with policymakers.

This research adopt the methodology of Östh et al. (2018) for spatial resilience analysis and include accessibility based on traditional social and economic metrics. Social geographic interaction and building environment elements are explicitly treated as spatial accessibility metrics in the context of community resilience. Consequently, this study defines resilience as the capacity of a transit station to absorb the changes and disruptions caused by the pandemic and maintain the same surrounding vitality as before the pandemic, which means that people still have free access during the pandemic to surrounding facilities.

## **2.2. Accessibility**

Accessibility, as an indirect measure of transport mobility, has been utilized to demonstrate connections between land use, regional activities, and transportation enhancements. Burns (1979) defines accessibility as individuals' freedom to decide whether to engage in different activities. Liu and Zhu (2004) believe that accessibility is an activity through specific travel patterns from one place to another. Geurs and Wee (2004) define accessibility as the extent to which land-use and transport systems enable individuals to reach activities or destinations using a (combination of) transport modes. Although there is no consistent definition or measure of accessibility (Páez et al., 2012), measuring the accessibility of each transit station and its surrounding area is essential

for this study.

Previous research has demonstrated that transportation, land-use, temporal and individual components are the four most crucial things to consider when assessing accessibility (Geurs and van Wee, 2004). Each component has its reflections and perspectives. Land use components reflect the quantity, quality, spatial distribution of the opportunities, and demand at the origin locations. Land use design can significantly impact travel patterns (Rodrigue, 2020), and planners have been active in creating high-quality local communities and concentrated development around locations accessible to public transport (Banister, 2011). In all cases, the goal is to reduce the need to drive, encourage greater use of public transportation (as well as walking and cycling), and minimize travel distances. Hence, the key is to supply quality and convenient local services and facilities so that people do not need to travel long distances.

The second is the transportation components, which likewise represent the inefficiency of employing a particular mode of transport to cover the distance between the origin and destination. Use a variety of measures to analyze the performance or service level of transport infrastructures, such as the locations of transit stations and connections between different transit lines, operation cost, congestion, and operation

speed on the road network.

Furthermore, People's ability to take advantage of the accessibility and attractiveness of a given physical environment will differ based on their financial, cognitive, and physical skills (Miller, 2018). In other words, individual components decide people's travel needs, abilities, and opportunities, including income, education, age, and ethnic differences. These characteristics affect a person's degree of access to transportation and spatial distribution opportunities and may considerably affect overall accessibility results. Nevertheless, individual accessibility measures are rarely fully implemented (Kwan and Weber, 2003, Miller, 2007) since collecting many person-level data samples is time-consuming and expensive. Moreover, such a study based on historical data is always subject to a time lag (Neutens, 2015).

Recent improvements in information and communication technology have enabled the collection of large spatio-temporal data, such as mobile phone and social media data (Bertone and Burghardt, 2017). These large datasets provide an unparalleled opportunity to move beyond location-based aggregate accessibility research to individual accessibility investigations (Kwan and Weber, 2003, Miller, 2007). Chen et al. (2016) examined the spatial fairness of accessibility by summarizing accessibility through the collection of smartphone data from users in cell towers, as opposed to

specific activity diary survey data. They found that mobility can lessen spatial inequities between people living in various geographical areas.

However, accessibility fairness is not investigated on an individual level ,and journey time unpredictability is completely disregarded. In reality, travel times fluctuate irregularly owing to traffic accidents, road construction, and inclement weather. As a result, action-based models (Hagerstrand, 1970) are growing in popularity and prevalence. Through the aggregation of statistical learning methods and data mining, Jiang et al. (2012) suggested a new modeling framework for clustering the daily patterns of individual activities. Several machine learning approaches, such as the K-means clustering algorithm and principal component analysis (PCA), were employed to investigate daily activities' internal structure and connect the temporal and spatial dimensions.

While these four components are theoretically relevant for measuring accessibility, Teklemariam et al. (2020) emphasize that each part concentrates on a single aspect of accessibility while disregarding the others. The relationship between different infrastructures is crucial; these interdependencies can have a domino effect. The failure of one infrastructure can directly or indirectly affect other infrastructures, thus affecting large geographical areas. It also ignores the potential impact of transportation strategies

on land use, such as increased driving speed in urban expansion (Rodrigue, 2020).

Bravo et al. (2010) analyzed the combined land-use and transportation system (LU&T) and found that land-use changes directly affect traffic demand patterns, thereby changing accessibility and location decisions. Nevertheless, their model only considers private transportation in the transportation system and does not include public transport. Therefore, the interaction between land use and transportation system on public transit needs further research. Hence, in addition to the provision of transit station infrastructure and services and the surrounding land use system will independently impact people's accessibility, it is crucial to strengthen their integration. Sung et al. (2014) conducted a spatial regression analysis to empirically demonstrate the impact of transit service coverage and station accessibility on ridership in Seoul and surrounding metropolitan areas. They discovered that the density of development near transit stations and accessibility measures at the station level was the most important and consistent factors influencing ridership.

This study will adopt the accessibility concept presented by Liu and Zhu (2004) and utilize the accessibility measurements of Geurs and Wee (2004) and travel-based modeling by Jiang et al. (2012). It has developed a land use and transport model to evaluate the spatial accessibility of transport networks, taking into account changes in

land use and transportation and their accompanying social implications. I attempt to connect the development of transport networks and land use and how persons with unique characteristics perceive and utilize them.

## Chapter 3. Data and Methodology

### 3.1. Data

#### 3.1.1. *POI Patterns and Places*

SafeGraph's POI patterns and places data serve as this thesis's major source of information. The study's geographic framework consisted of 149 transit stations in the Boston metropolitan area, with a focus on the 15-minute walking area around these transit stations. The study focused on two timespans, before and during the pandemic. We used data from 16<sup>th</sup> September to 22<sup>nd</sup> September 2019 for the pre-pandemic period and 14<sup>th</sup> September to 20<sup>th</sup> September 2020 for the pandemic period. Both are one-week periods, comprising 76,483 visitation records in total. These POI record information regarding the activities, including their unique id, location, North American Industry Classification System (NAICS) code (which classifies these POI by the type of economic activity), number of visitors, number of visits, and time of visits. Since a single user may visit a POI numerous times, we utilize the number of visits to determine the visit volume for each POI. The POI pattern data is distributed seven days per week (from Monday to Sunday) during the data collection and divided 24 hours into 1-hour intervals.

In addition to the POI patterns and places the data, in this thesis, we focus on

information about road density, walkability, node degree, and density patterns (e.g., population density, employment rate, job density). These data can help us find interesting and illuminating station-level cluster features.

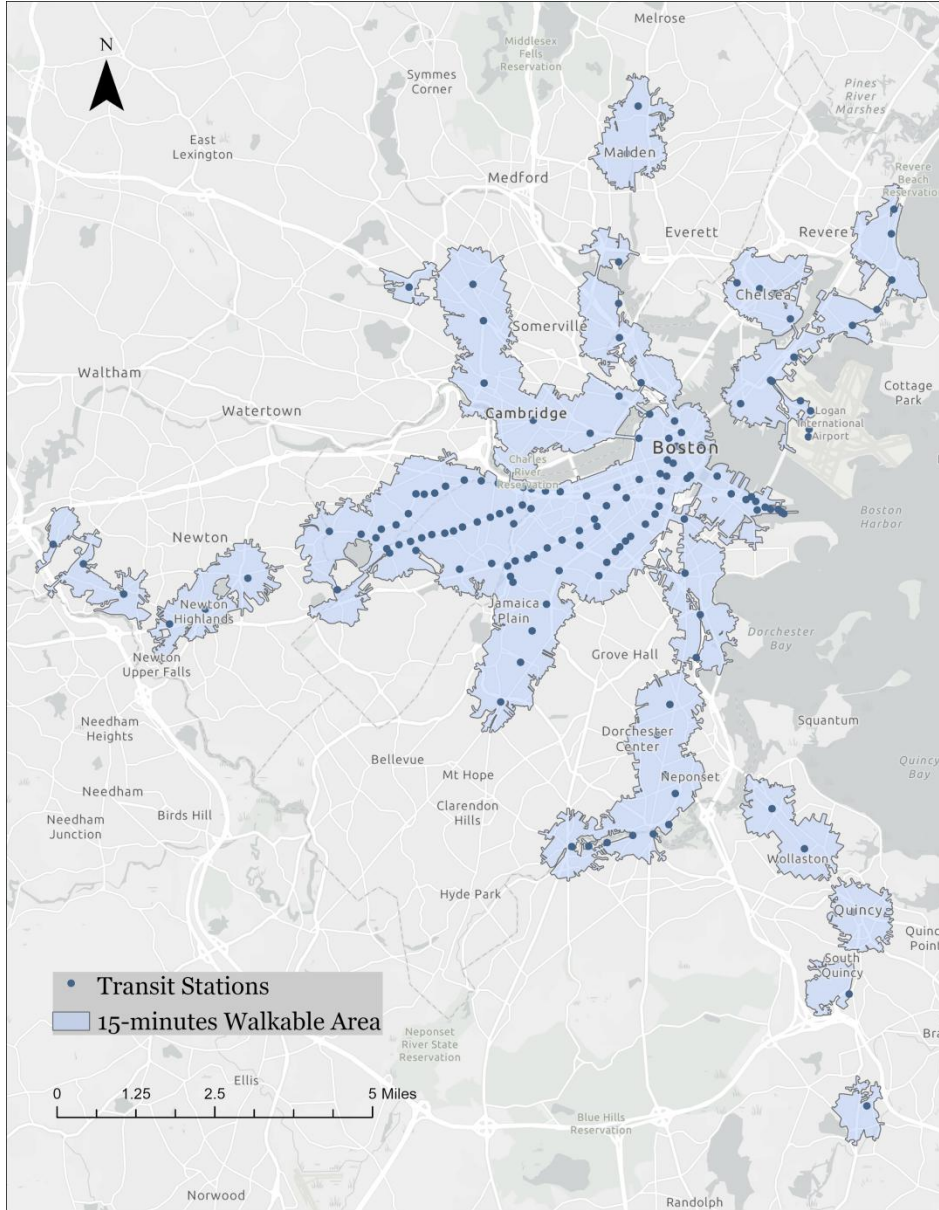
### ***3.1.2. Road Density***

In this study, road density is determined by dividing the total length (in meters) of roads inside a one-kilometer buffer around the station by the buffer's size. The Open Street Map is the source of the road network data, which includes driveways, cyclable roads, and walking roads. We extracted them using the Python OSMnX package (Boeing, 2017) based on a one-kilometer transit station buffer area. Next, we used ArcGIS to calculate the length of each road segment within each buffer and summed them together. To determine the density of roads surrounding each transit station, we applied the formula "road density = total length/1 kilometer buffer area." This calculation measures the accessibility of the transit station and its environs for various travel modes.

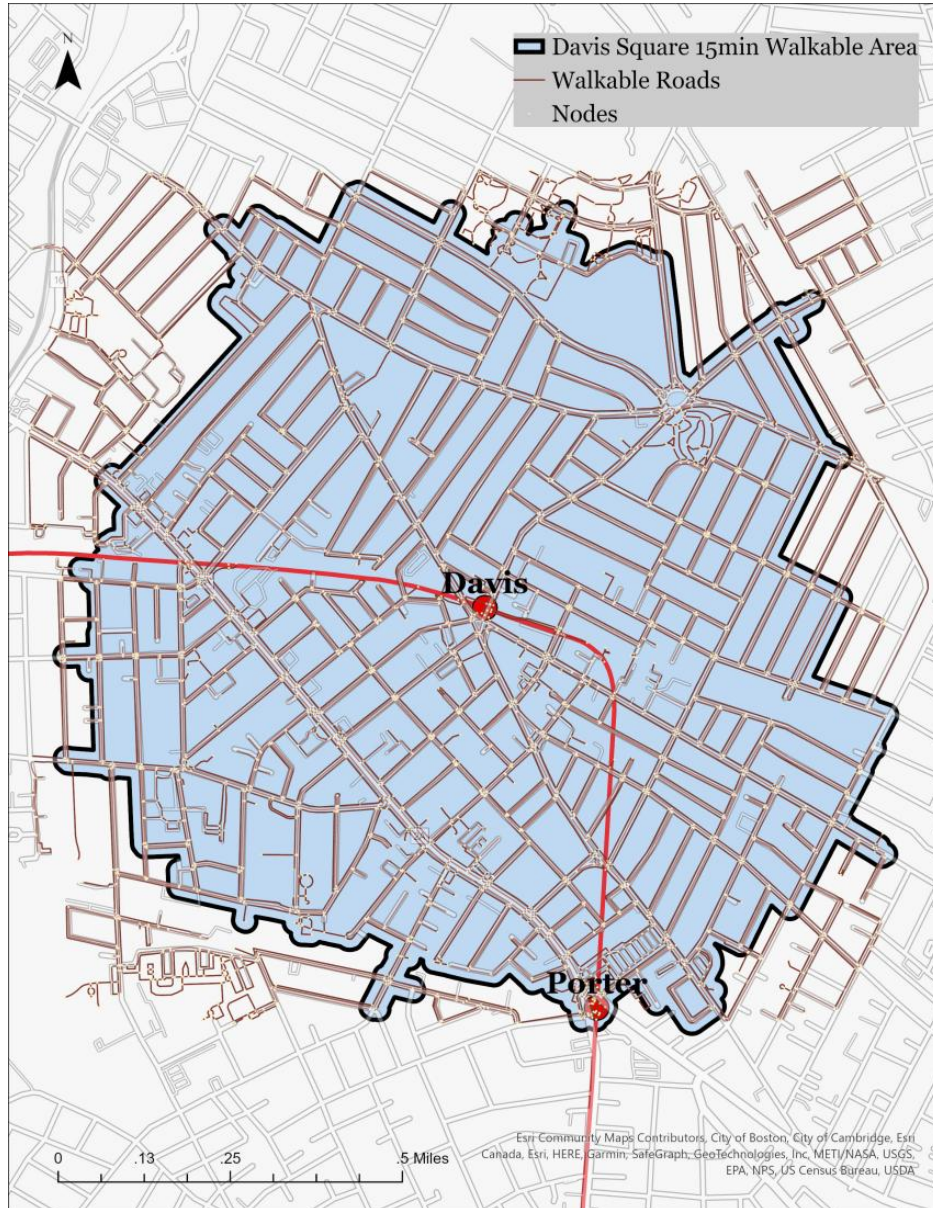
### ***3.1.3. Walkability***

In contrast to computations that employ a fixed diameter buffer, we first establish a network of walkable roads depending on the longitude and latitude of the transit

station using the OSMnX package for calculating the walkable area. Then, we use the network to generate an isochrone map representing the region accessible from the transit stations within 15 minutes of travel time and an approximate walking speed of 4.5 kilometers per hour. Lastly, the walkable area is computed using the isochrone map. The more the area is covered, the more walkable and accessible the region surrounding the transit stations is for individuals to reach facilities. Figure 4 depicts the dissolved 15-minute walkable areas surrounding the 149 subway stations in the Boston metropolitan area. Figure 5 provides Davis Square Station as an example of the road network in the station's 1km buffer and walkable areas.



**Figure 4. Walkable area of 149 transit stations**



**Figure 5. Example of a walkable area**

### ***3.1.4. Node Degree***

This study analyzes the connectivity between transit stations using the metric of node degree, which indicates the number of transit lines connected to each station. The node degree for the transit station is directional. The higher the node degree, the better

the connectivity between stations and the greater the interchangeability. Consequently, these stations are likely to have a greater ridership than those with a lower node degree.

### ***3.1.5. Density Patterns***

As more than half of all public transportation travels are for work-related purposes, connecting these locations is a method to enhance transit station ridership and create more attractive areas. When analyzing clustering data at the station level, it is necessary to consider the population density, employment rate, and job density in the vicinity of transit stations. I obtained these data from the American Community Survey Single-Year Estimates for 2019 and 2020, which the US Census Bureau published. I tallied the population of census tracts that spanned the 15-minute walkable area and then divided it by the 15-minute walkable area. The same methodology was applied to the employment rate and job density.

## **3.2. Methodology**

I utilized clustering techniques to accomplish the research goals. The initial clustering was performed at the POI level to classify the visit time of POIs. The second clustering was performed at the level of commercial type to compare the visit timings and patterns of various commercial types. Then, a cluster analysis was conducted at the

transit station level based on the results of the two preceding clustering. According to the composition of the different types of temporal cluster results and commercial type cluster results, the differences in the resilience of transit stations derived through cluster analysis at various levels are examined.

### ***3.2.1. Pre-Processing***

The POI patterns data gives location information for individual POI, which I clip according to the 15-minute walking areas of transit stations to obtain their POI records. The raw data also includes the number of visits per hour over a week, totaling 168 hours, which I divided and assigned to a 24-hour range with 1-hour intervals. Since I will simultaneously perform cluster analysis on 2019 and 2020 data, I appended the years to each POI id for identification purposes, resulting in a total of 16,735 items. The cluster analysis for commercial type level and station level yielded 34 and 298 items, respectively, using the same approach.

### ***3.2.2. K-means Clustering***

This study used clustering, an unsupervised learning technique, to examine the resiliency of transit stations in the face of changes in access to POI before and after the pandemic. *K*-means clustering algorithm divides  $n$  observation into  $k$  ( $k \leq n$ ) sets of

clusters  $S = \{S_1, S_2, \dots, S_k\}$  such that each observation is assigned to the set of clusters whose cluster center has the least Euclidean distance from it. In brief, this method splits data points into groups based on features that are more similar to those of the same group than those of other groups. Cluster analysis was chosen as the method for this study since it does not require any prior human knowledge, and the findings are produced only from the input data.

To observe the daily structural changes in POI visiting patterns before and during the pandemic, the POI-based cluster analysis will divide the dissimilarity of POI access times around transit stations into multiple clusters. The commercial type based cluster analysis assisted in comparing the temporal and dynamic variation of different commercial types and provided an opportunity to evaluate the role of various commercial type combinations in transit station vitality. The anticipated outcome of the two cluster analyses at the station level was a typology of transit stations. Then, we review the built environment and social demographic characteristics of transit stations from various clusters to investigate the factors that may influence their resilience.

In addition, I employed two measures, the Davies-Bouldin index (DBI) and the Silhouette Coefficient (SC), which represent the compactness and separation of clusters,

to assist us in estimating the optimal number of clusters that best fit the inherent partition of the data set. A smaller number suggests superior and more distinct clustering for the DBI. While the SC is the inverse of the DBI, a higher SC value indicates a better clustering outcome.

### ***3.2.3. Visualization***

First, I monitor the daily visits to each POI using heat maps and compare the 2019 and 2020 statistics. After identifying the optimal number of clusters, the mean values for each parameter in each cluster were computed, and the results of the temporal cluster mean value were shown as line charts so that the fluctuation in visit patterns during the day could be observed. I also choose a line chart to compare the vitality difference for presenting the station-level cluster mean value. Then, I select radar charts to represent the built environment and density patterns, as they facilitate the examination of individual parameters that vary across multiple dimensions. In addition, I geocoded these two data sets with clustered labels and displayed them in ArcGIS to find the geographical differences across clusters. By comparing the distribution and variation of POI visit patterns around transfer stations, I discuss the differences in the resilience of transfer stations studied in this paper.

## Chapter 4. Result and Analysis

### 4.1. POI Temporal Visitation Patterns

We assess the visitation of POIs over time using heat maps. By displaying the change in visitation for each sample POI along the time axis, we can maintain valuable information about the activity around transit stations at different times of the day.

Before and during the pandemic, Figures 6 and 7 demonstrate 24-hour visit patterns of POI in the Boston metropolitan area. The x-axis represents time (beginning at midnight and ending at 11:59 p.m.). In contrast, the y-axis represents all samples (i.e., each line parallel to the x-axis represents an individual POI record). The diagram depicts fewer visits with darker lines and more visits with lighter lines. We've set the maximum number of visits to 300 for ease of observation, as the number of visits varies widely among POI.

Figure 6 demonstrates that there are three peak visit periods for POI during the day: 7:00 a.m. to 9:00 a.m., noon to 2:00 p.m., and around 8:00 p.m. Moreover, only a handful of POI maintains an unusually high volume of visits throughout the day. On the other hand, Figure 7 demonstrates that the total number of visits to the recorded POI was low, with the only rise occurring around 8:00 p.m., showing that individual visits to the POI declined dramatically throughout the pandemic. Furthermore, the

initial visit time characteristics shifted, indicating that the pandemic restricted the utilization of facilities near transit stations.

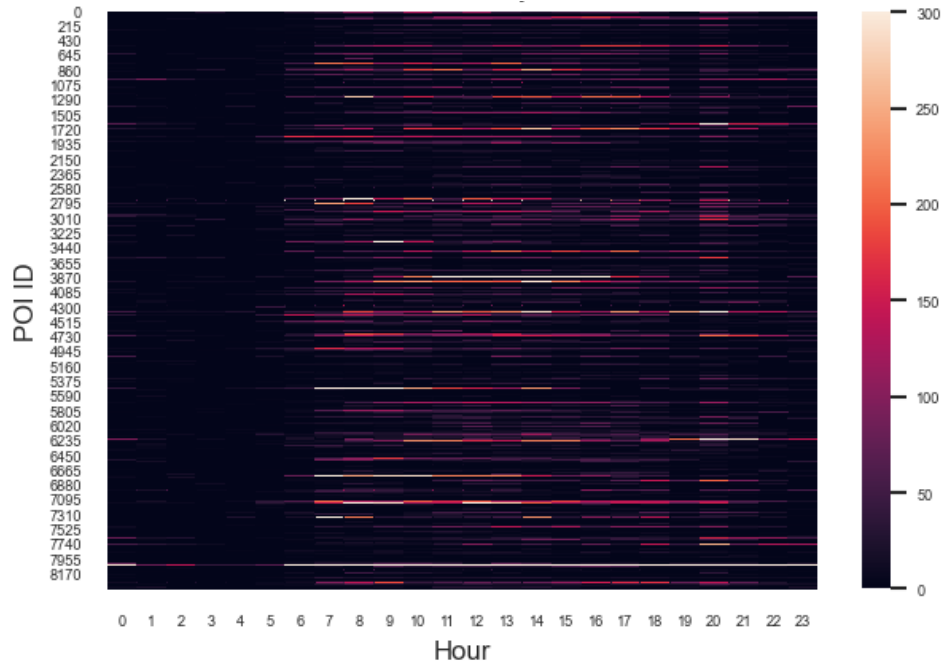


Figure 6. 2019 POI visits by hour

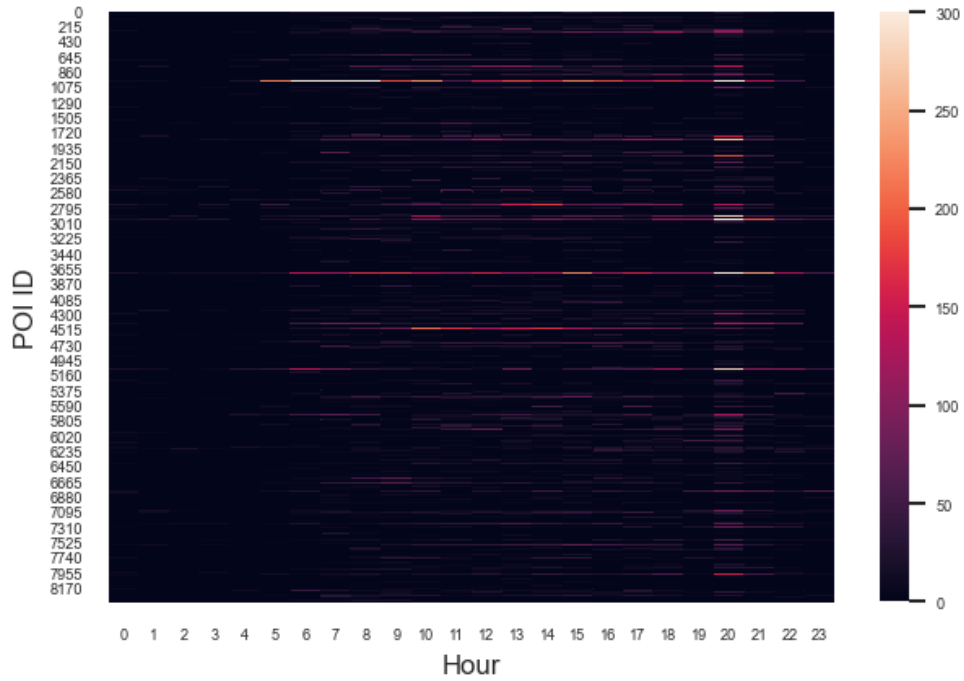


Figure 7. 2020 POI visits by hour

## 4.2. POI Based Clustering

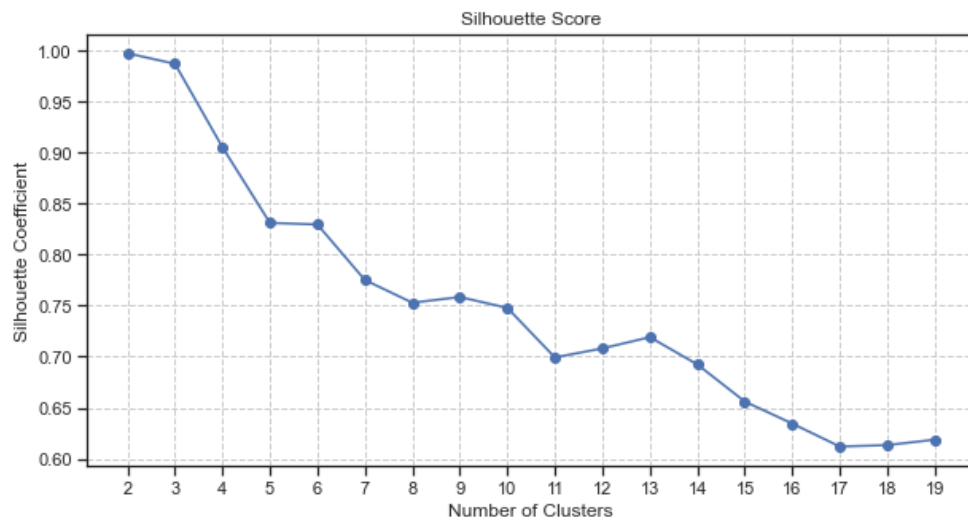
### 4.2.1. Cluster Validity of POI Temporal Cluster

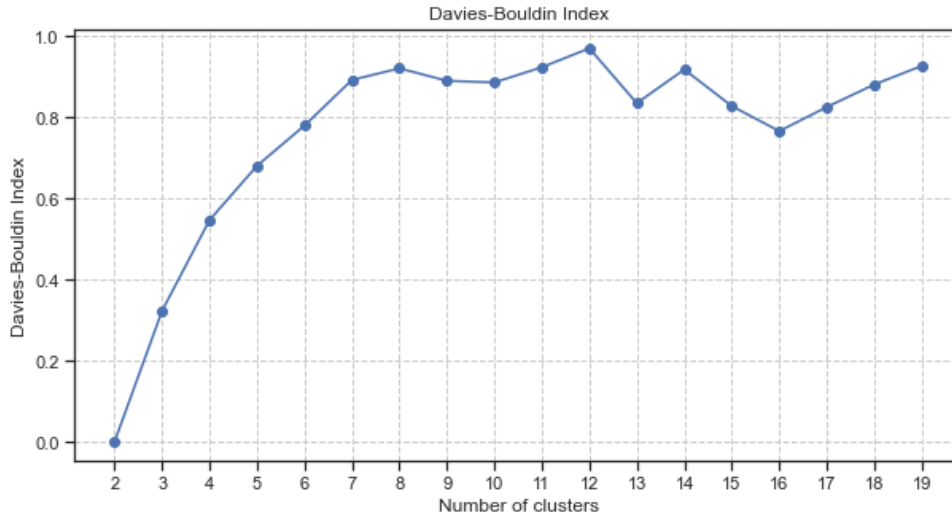
The results of the SC (left) and DBI (right) calculations are displayed in Figure 8.

When  $k = 2$ , the clustering result is distinctive but less meaningful and interesting.

According to the DBI and the SC, cluster number five is the second-best option.

However, we examine the number of outcomes per cluster; we find that 94.64 percent of industries fall into the same cluster. Therefore, we decided on nine as the number of clusters, which is the next-best option, as it permits a greater dispersion of the total number of observations inside each cluster and offers a relatively stable cluster.

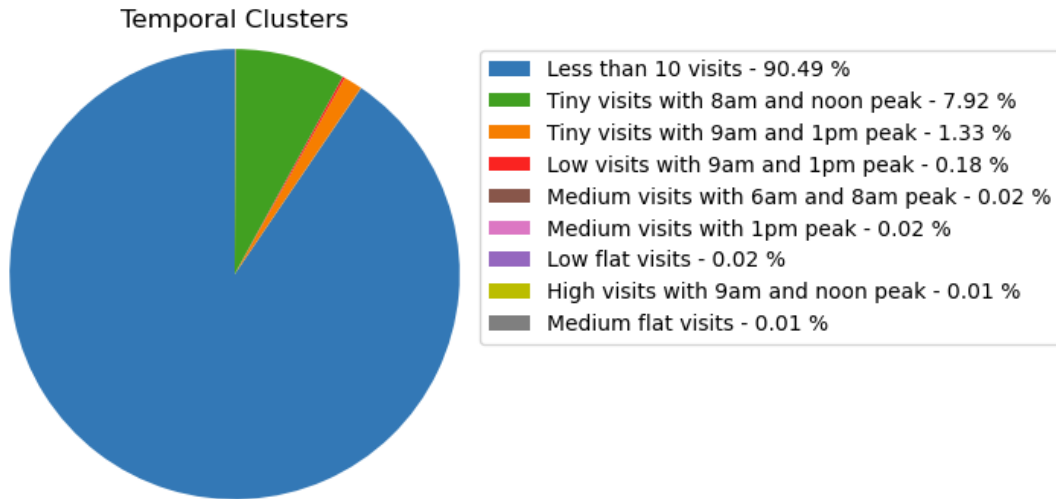




**Figure 8. Cluster validity indices for POI cluster**

#### ***4.2.2. Analysis of the POI Temporal Clustering***

The following pie chart illustrates the composition of the nine clusters. *Less than 10 visits* account for over 90 percent of all observations, constituting the greatest proportion. *Tiny visits with 8 am and noon peak* is the second-largest cluster, accounting for approximately 8 percent of the total number of all observations. *High visits with 9 am and noon peak* and *Medium flat visits* are the two smallest clusters, amounting to 0.01 percent each.



**Figure 9. Composition of temporal clusters. Note: For comparison purposes, in this pie chart and the line charts that follow, we use different colors to indicate each cluster, and the combination is fixed.**

Figure 10 depicts the *K*-means clustering (number of clusters = 9) that reveals the pattern of visits to POIs during the time series before and during the pandemic. Most of the POIs are assigned to *Less than 10 visits*, these clusters are the least visited, indicating that the majority of POIs have a low level of popularity. Conversely, a negligible proportion of POI were visited regularly, such as POIs designated as *High visits with 9 am and noon peak*. In addition, three clusters have medium visits, although the spike periods at which they are accessed vary.

In terms of time series, the first visit characteristic occurs between 6:00 a.m. and 8:00 a.m. The clusters start to see a considerable rise in visits and reach their first peak about 8:00 a.m., which means that people begin to visit the facilities around the transit

station. During this time, the likelihood of individuals using the transit station to depart or arrive at school or work is high. The second visitation characteristic happens at midday. At 8 p.m., all clusters attain their highest visit volume of the day.

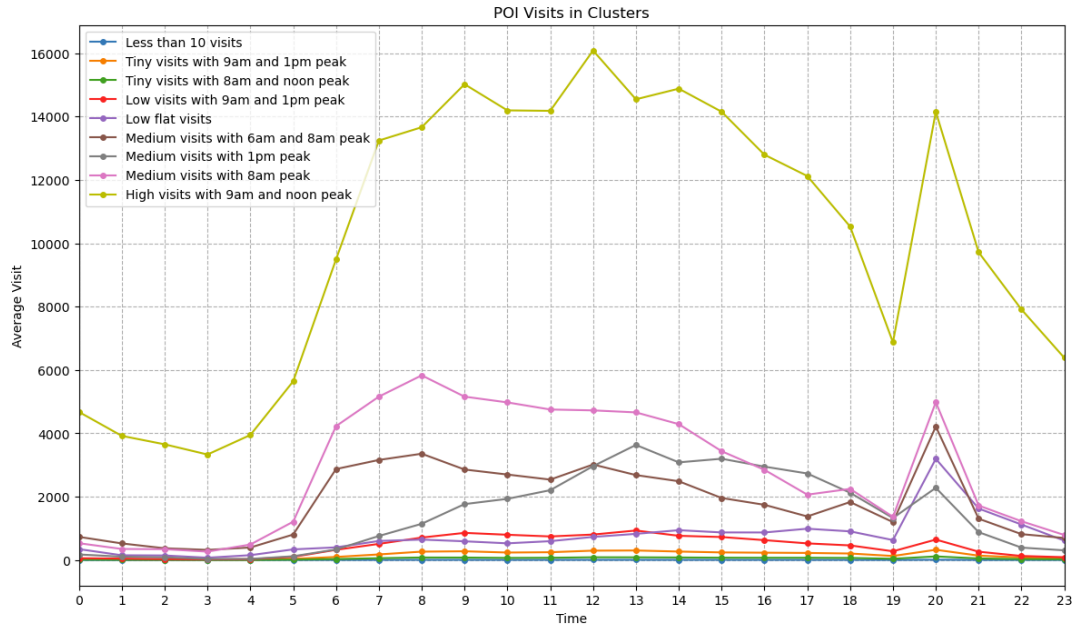


Figure 10. Plot means of temporal cluster

### 4.3. POI-Station-Level Clustering

#### 4.3.1. Cluster Component within Transit Stations

In addition to the characteristics of each POI's temporal cluster, the distribution pattern of these different clusters is also essential when comparing the vitality of transit stations. Furthermore, I applied a clustering approach for station level analysis because of the uneven distribution of POI over the 15-minute walking area of various transit stations in the Boston metropolitan area. The parameter is the number of distinct

temporal cluster results of POI. Similar to the temporal clustering technique, the 2019

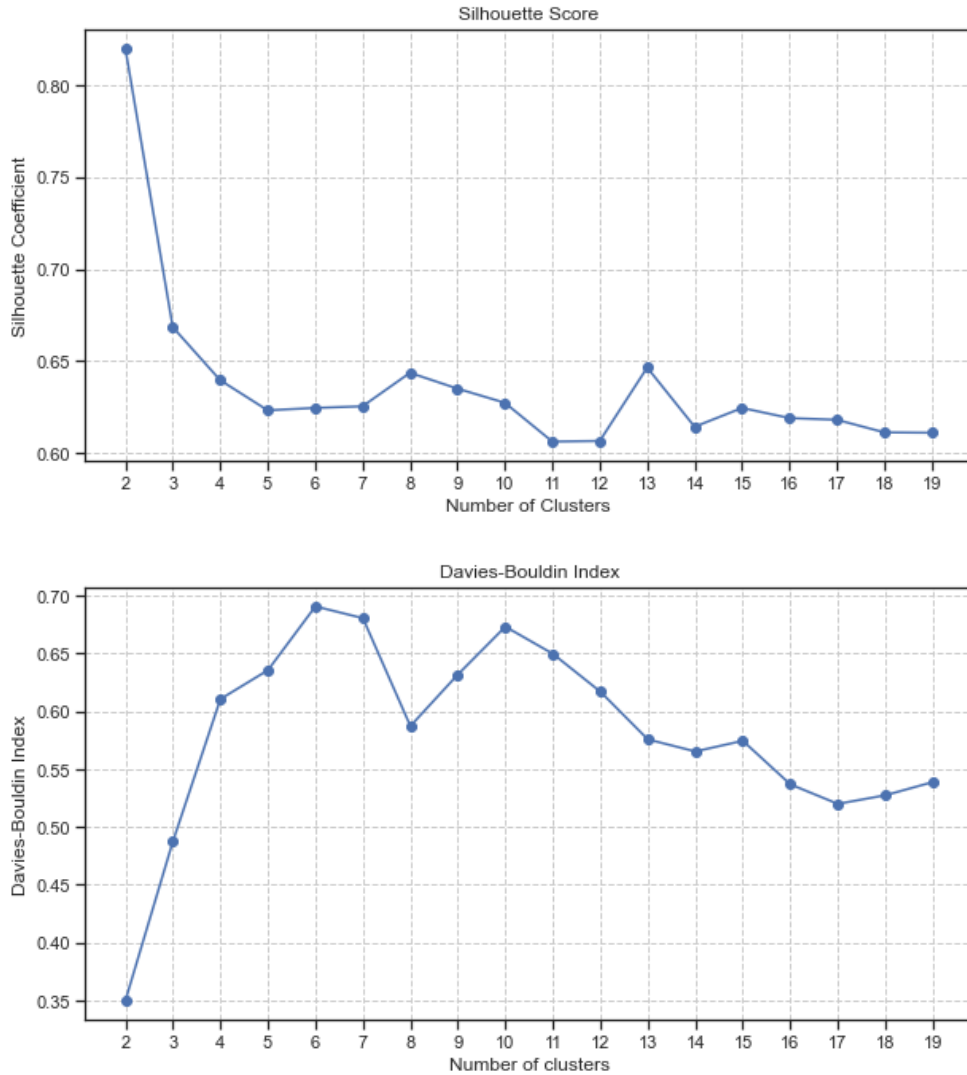
and 2020 objects were calculated concurrently for a better comparison. Thus, the same station will appear twice, resulting in 298 objects. Table 2 illustrates the input data.

**Table 1. Example of input data for the POI-station-level clustering**

STATION		0	1	2	3	4	5	6	7	8	station_year
0	23 Dry Dock Ave	49.000	0.000	0.000	3.000	0.000	30.000	0.000	0.000	0.000	23 Dry Dock Ave_2019
1	27 Dry Dock Ave	36.000	0.000	0.000	2.000	0.000	21.000	0.000	0.000	0.000	27 Dry Dock Ave_2019
2	88 Black Falcon Ave	33.000	0.000	0.000	1.000	0.000	18.000	0.000	0.000	0.000	88 Black Falcon Ave_2019
3	Airport	205.000	0.000	0.000	1.000	0.000	3.000	0.000	0.000	0.000	Airport_2019
4	Airport Terminal A	3.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	Airport Terminal A_2019
...	...	...	...	...	...	...	...	...	...	...	...
293	Wonderland	8.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	Wonderland_2020
294	Wood Island	27.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	Wood Island_2020
295	Woodland	16.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	Woodland_2020
296	Worcester Square	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	Worcester Square_2020
297	World Trade Center	6.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	World Trade Center_2020

#### 4.3.2. Cluster Validity of POI-Station-Level Cluster

In this section, DBI and SC are still utilized to identify the optimal number of clusters. Several prominent elbows indicate bad values of  $k$  for DBI, including 5,6, and 7. For SC, there is an increasing trend between 2 and 6, with seven falling back slightly. Consequently, 8 is the optimal number of  $k$ .

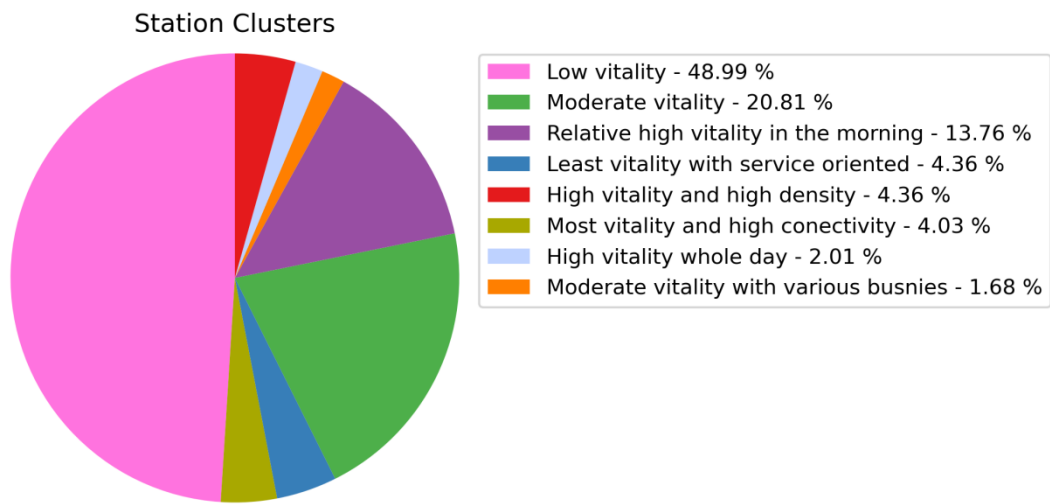


**Figure 11. Cluster validity indices for POI-station-level cluster**

### 4.3.3. Station-Level POI Clustering

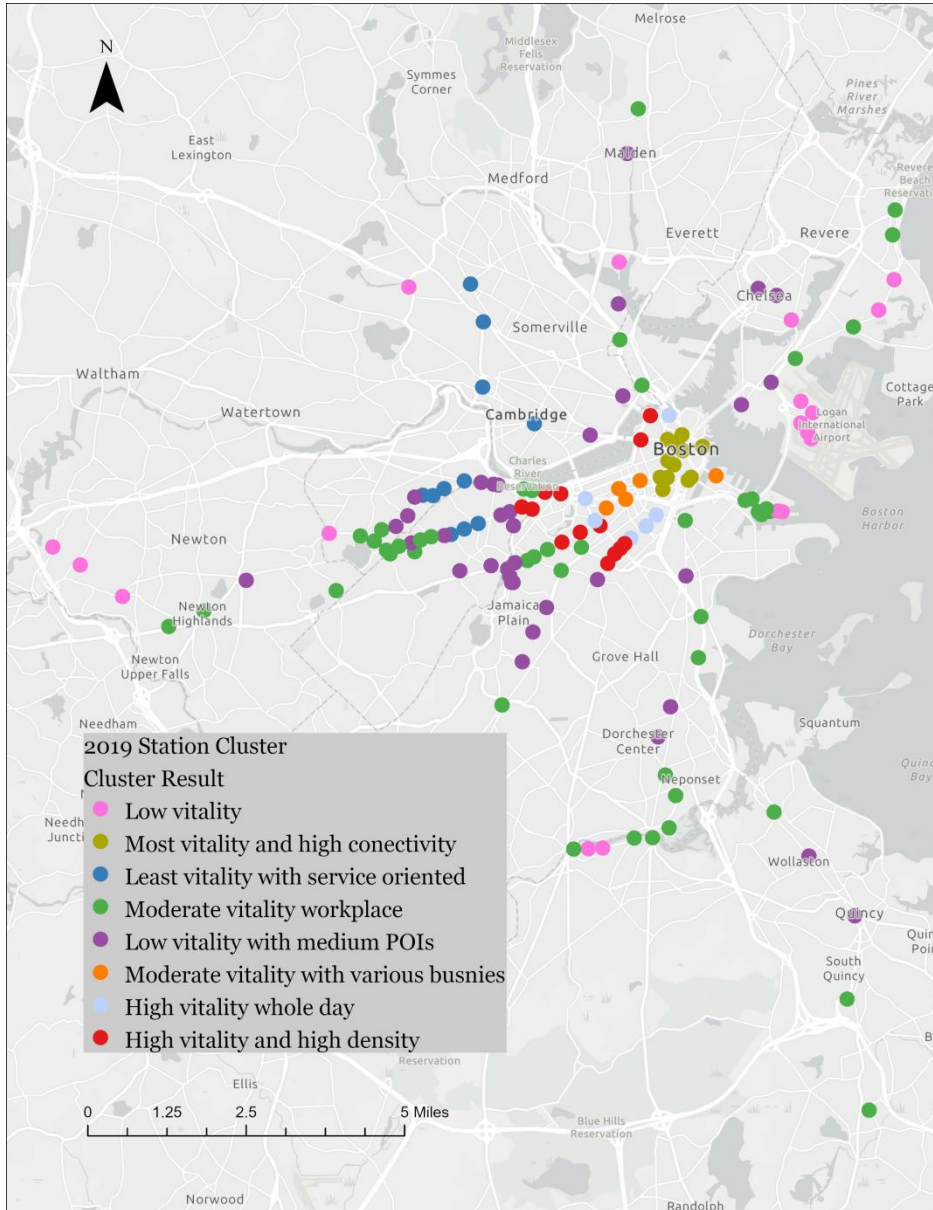
Figure 12 is a pie chart depicting the components of the station level clusters. *Low vitality* accounts for roughly half of all 298 observations in the Boston metropolitan area. Meanwhile, most transit stations are assigned to *Moderate vitality* and *Relative high vitality in the morning*. These stations have low vitality and little distribution of POI. No more than 15 percent of the stations are popular and contain a great number of

POI within their 15-minute walkable area.

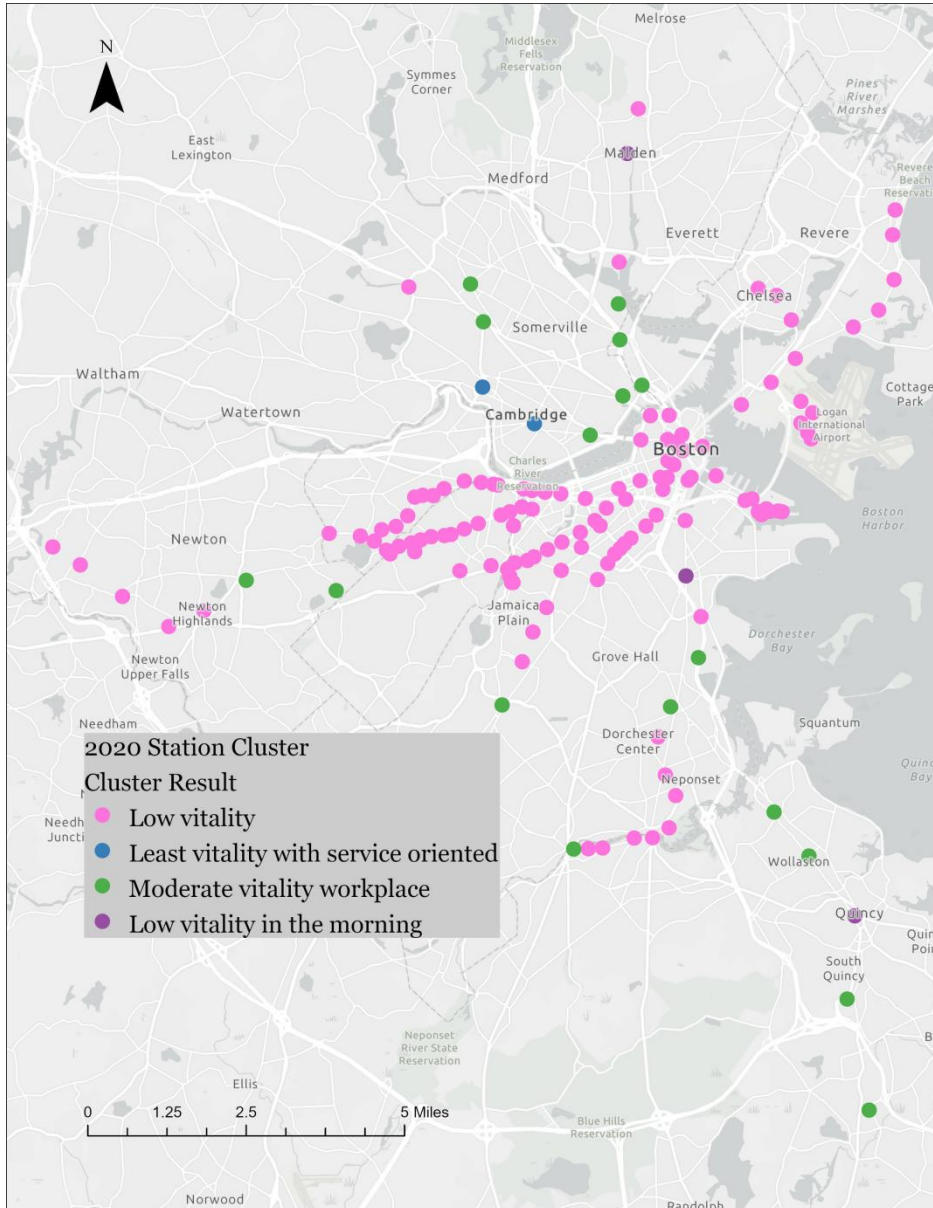


**Figure 12. Composition of the POI-station-level clustering. Note: For comparison purposes, in this pie chart and in the following maps, we use different colors to indicate each cluster ,and the combination is fixed.**

Figure 13 and Figure 14 depict the spatial distribution of these transit stations' clustering results in 2019 and 2020.



**Figure 13. Spatial distribution of POI-station-level clustering results in 2019**



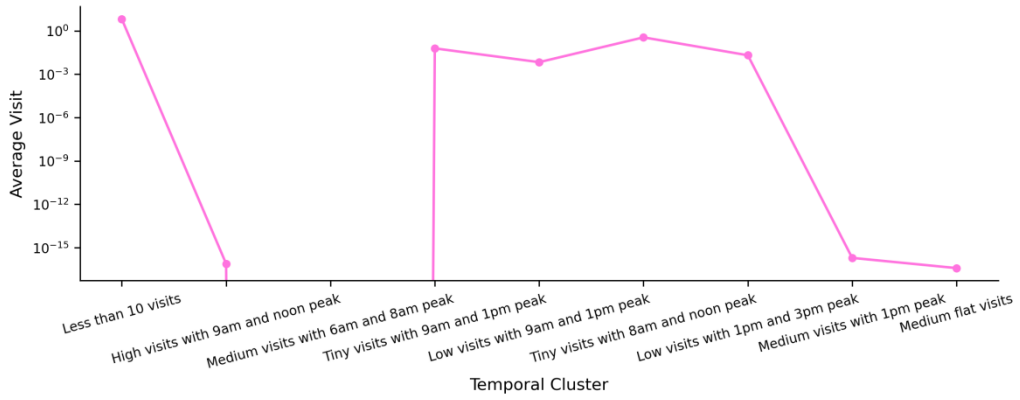
**Figure 14. Spatial distribution of POI-station-level clustering results in 2020**

Figure 15 demonstrates line plots of visit patterns for the *Low vitality* cluster; Figure 16 radar plots including socio-demographic and built environment data; and Figure 17 maps showing clustering results pre-and during the pandemic. The line graphs present the characteristics of each type of transit station by comparing the visit patterns of POI within a 15-minute walk of transit stations in the cluster. Since the

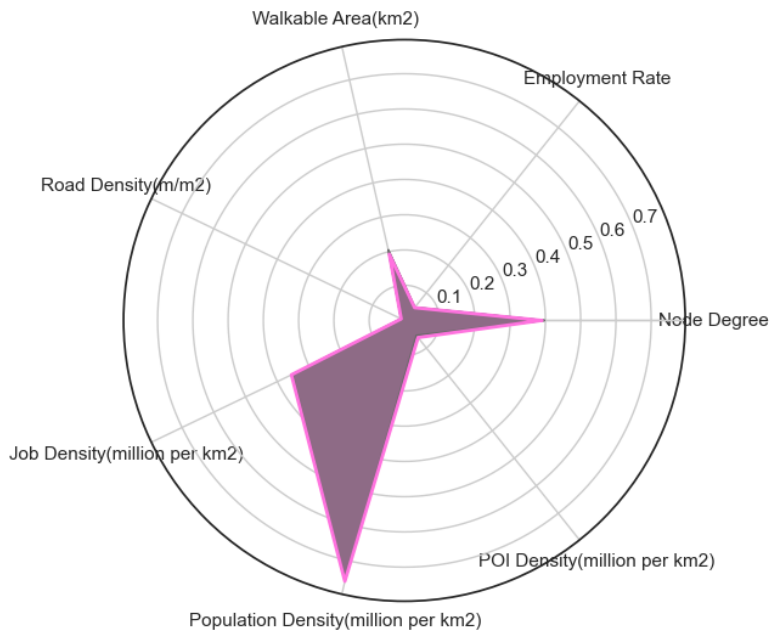
number of POI with different temporal cluster outcomes changes widely, the y-axis of the line graph has been transformed to logarithmic coordinates for clearer observation. The different colored lines on the radar plot represent the average value of each parameter for each cluster. In contrast, the grey region represents the average value of each parameter for all 149 transit stations. Due to the disparity in data magnitude, we normalized all parameters before generating the radar map, and the scores ranged from 0 to 1 as one moved from the center to the periphery. The labels represent the meaning of the parameters. The map on the right lists all the transit stations that belong to this cluster, and the uniquely colored dots on the distribution map indicate their positions, with the grey dots representing the remaining transit stations in this study.

*Low vitality* transit stations increased dramatically from 19 before the pandemic to 126 during the pandemic, suggesting that activity within the 15-minute walkable area of the majority of transit stations declined significantly. The primary temporal cluster types for the transit stations in this cluster were 'Less than ten visits' and a small number of POI with medium visits that peaked in the afternoon. Moreover, given that the number of transit stations in this cluster accounts for 85 percent of the total observations, the performance of socio-demographic data and the physical environment is comparable to the average. Before the pandemic, we discovered that these transit

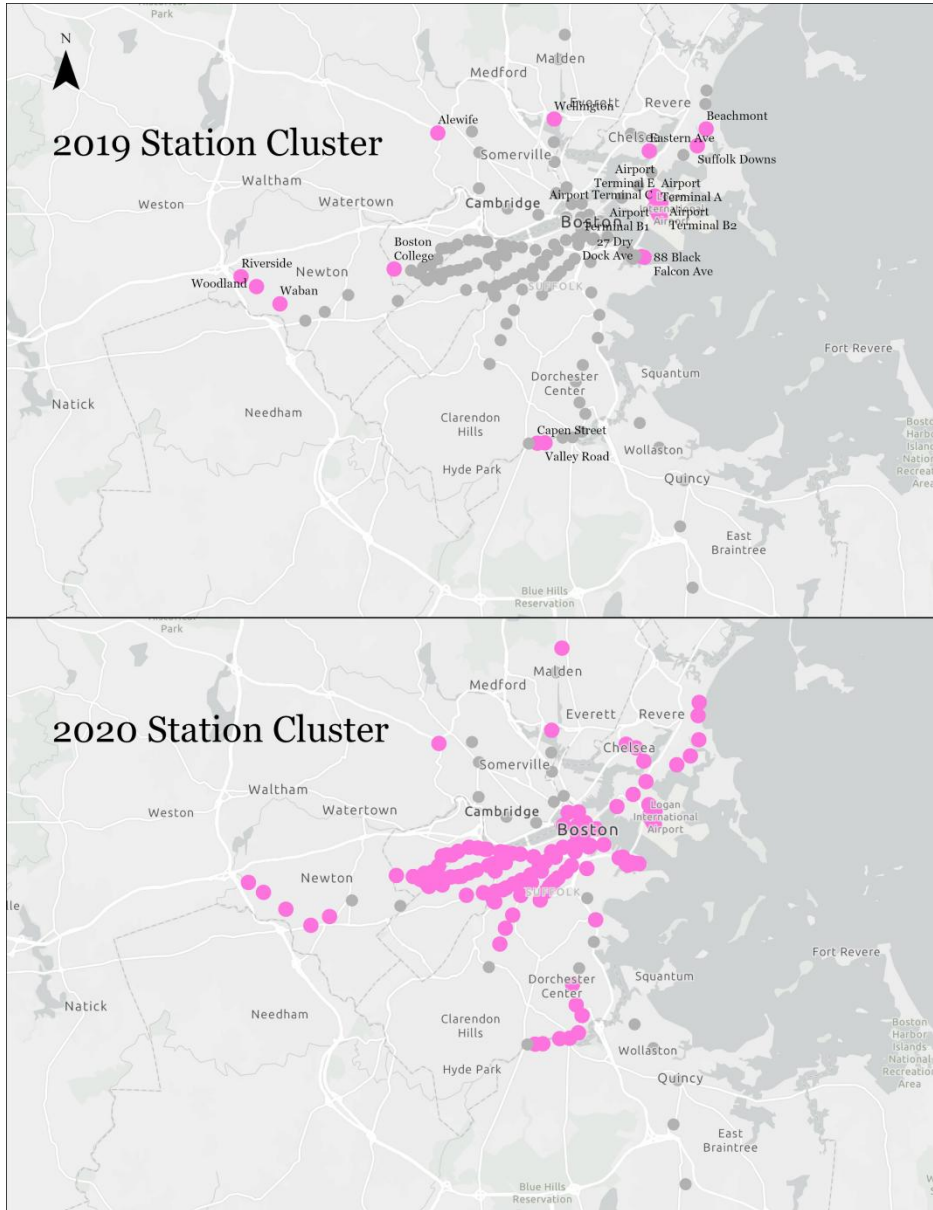
stations were primarily located in the city's periphery, such as the five transit stations located in the Logan Airport terminal.



**Figure 15. Visit pattern of *Low vitality* cluster stations.**



**Figure 16. Social demographic and building environment of *Low vitality* cluster stations**



**Figure 17. Spatial distribution of *Low vitality* cluster stations**

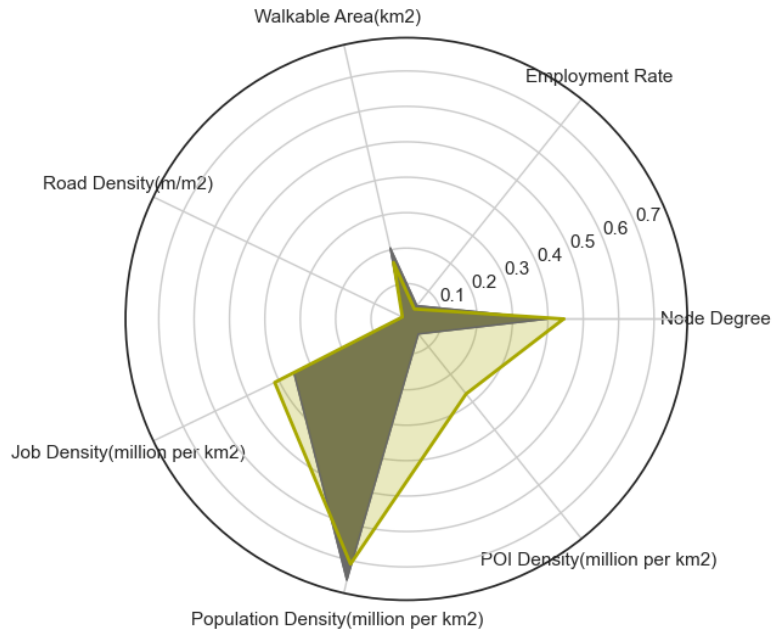
For most vitality and high connectivity, although the dominant type of the temporal cluster is 'Less than ten visits', many medium and high visitation POIs are located within a 15-minute walk of the transit stations of this cluster. The radar plot reveals that the cluster has a substantially greater job density around the transit stations but a lower employment and population density than the average, showing that the area

has numerous workplaces to accommodate residents from other locations. Moreover, the number of POI is much greater than average, with Accommodation and Food service and Art, Entertainment, and Recreation being the most visited business categories. Likewise, these transit stations perform above average in terms of the performance of the built environment. For instance, greater node degrees suggest easy transfer to other transit stations, contributing to the area's robust connectivity.

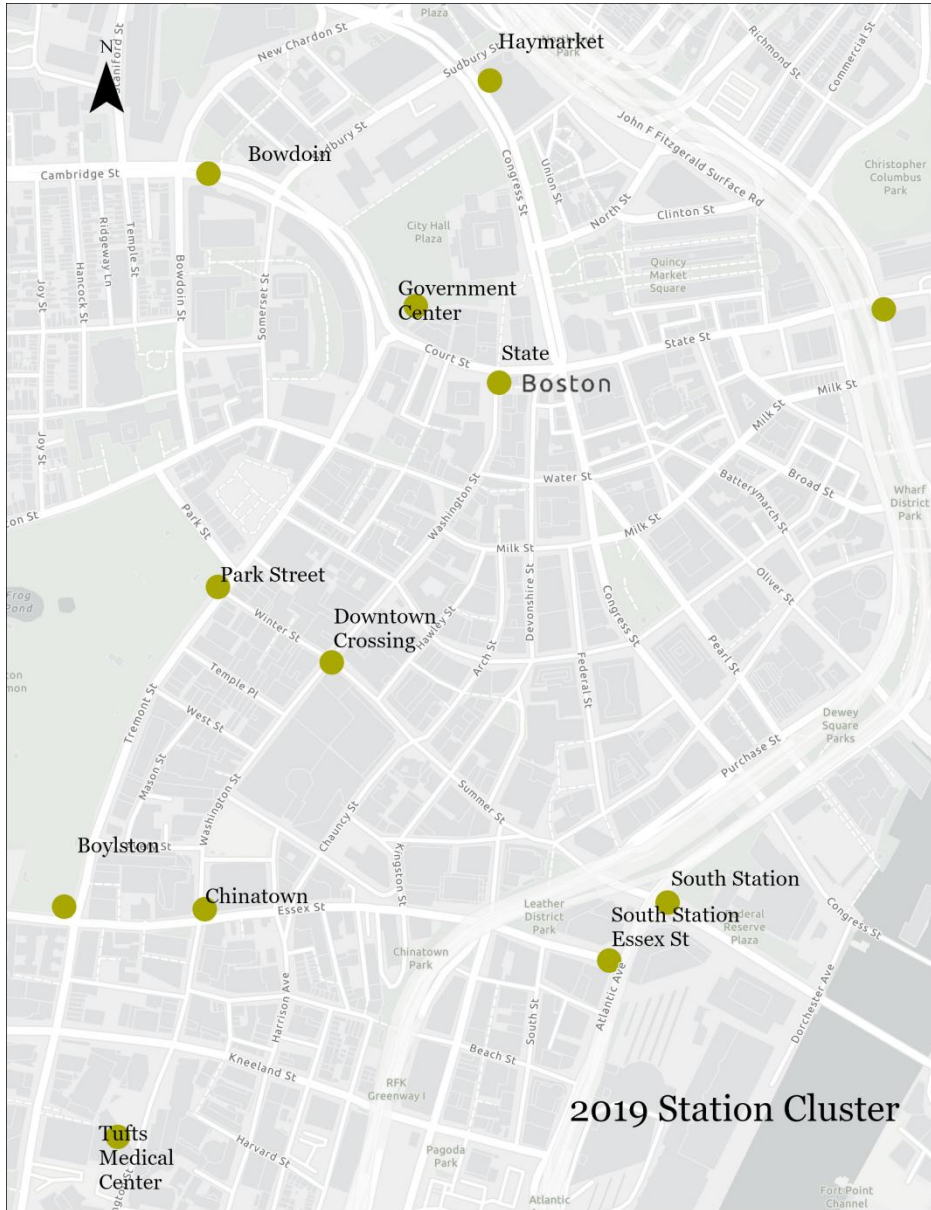
Nevertheless, these regions are not pedestrian-friendly, and the low walkability limits travel. The popularity of these twelve transit stations in the downtown area was high before the pandemic. In stark contrast, their cluster types shifted to *Low vitality* during the pandemic, the most drastic change in the vitality among the eight clusters.



**Figure 18. Visit pattern of *Most vitality and high connectivity* cluster stations.**



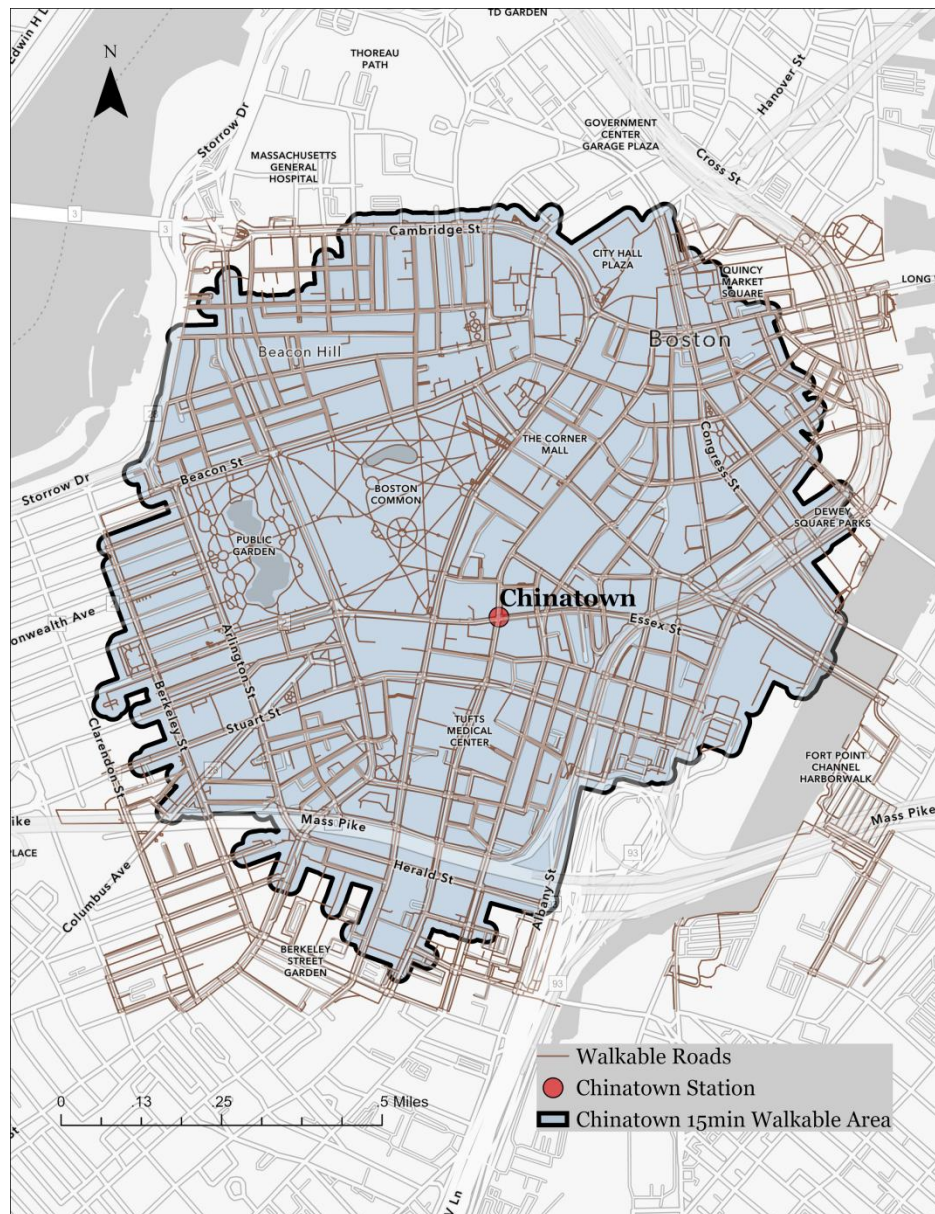
**Figure 19. Social demographic and building environment of *Most vitality and high connectivity* cluster stations**



**Figure 20. Spatial distribution of *Most vitality and high connectivity* cluster stations**

Although we perceive Chinatown as a highly walkable area, Figure 21 shows that this is not the case. Large transit hubs and the Bass River around Chinatown Station reduce the amount of walkable space. People cannot cross the crossroads on foot, and the limited number of pedestrian bridges precludes them from traveling further or approaching the transit station. Other stations in the area are facing similar problems,

such as Tufts Medical Center, Charles/MGH, and Downtown Crossing Station.



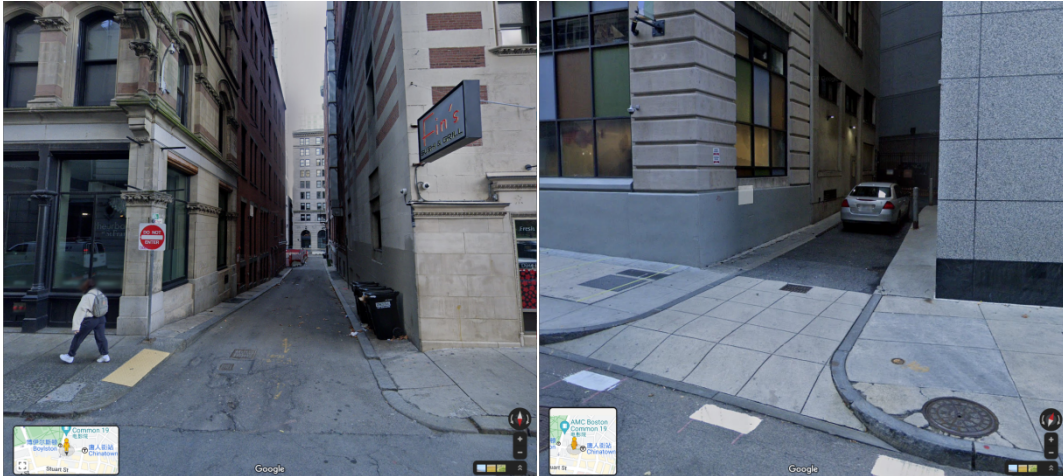
**Figure 21. Walkable area of Chinatown Station**

In addition, the road density of the street network in the area is not high. Boston Common and Public Garden are two parks that reduce normal walkable paths, and the high density of buildings and dead-end streets also contribute to the low density of the street network in the area. Often a single building takes up an entire block, making it

impossible for people to cross. Comparing the Google Map street view map, we can see that many internal roads, narrow roads, or dead-ends are excluded from the network density calculation, which is one of the limitations of this study.



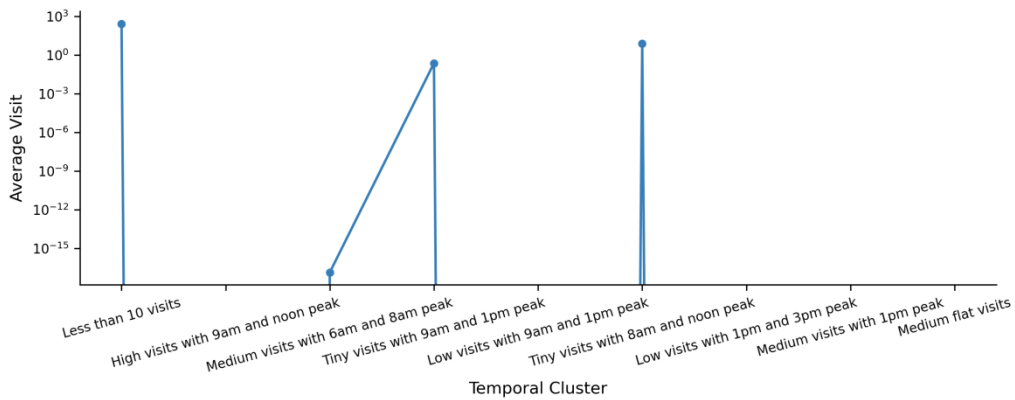
Figure 22. Google Map Streetview around Chinatown Station



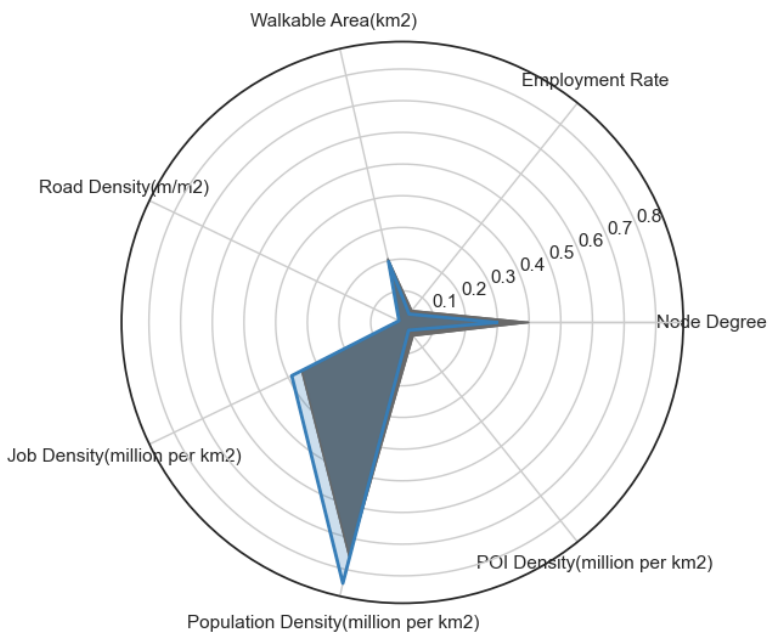
**Figure 23. Examples of narrow roads and dead ends**

For *Job and residential oriented*, the main types of temporal clusters are 'Less than 10 visits' and tiny visits, most of which occur between 6 a.m. and 8 a.m. and 1 p.m. With many Harvard and MIT students residing in the region, the job opportunities and population density surrounding these stations are above average. Additionally, the employment rate, POI density, and node degree averages are comparable, showing that residents in the region have access to similar services. Comparing the composition of transit stations in this cluster before and during the pandemic, only Harvard and Central Station out of the original 11 transit stations remain in the cluster, which I will explore more in the next section.

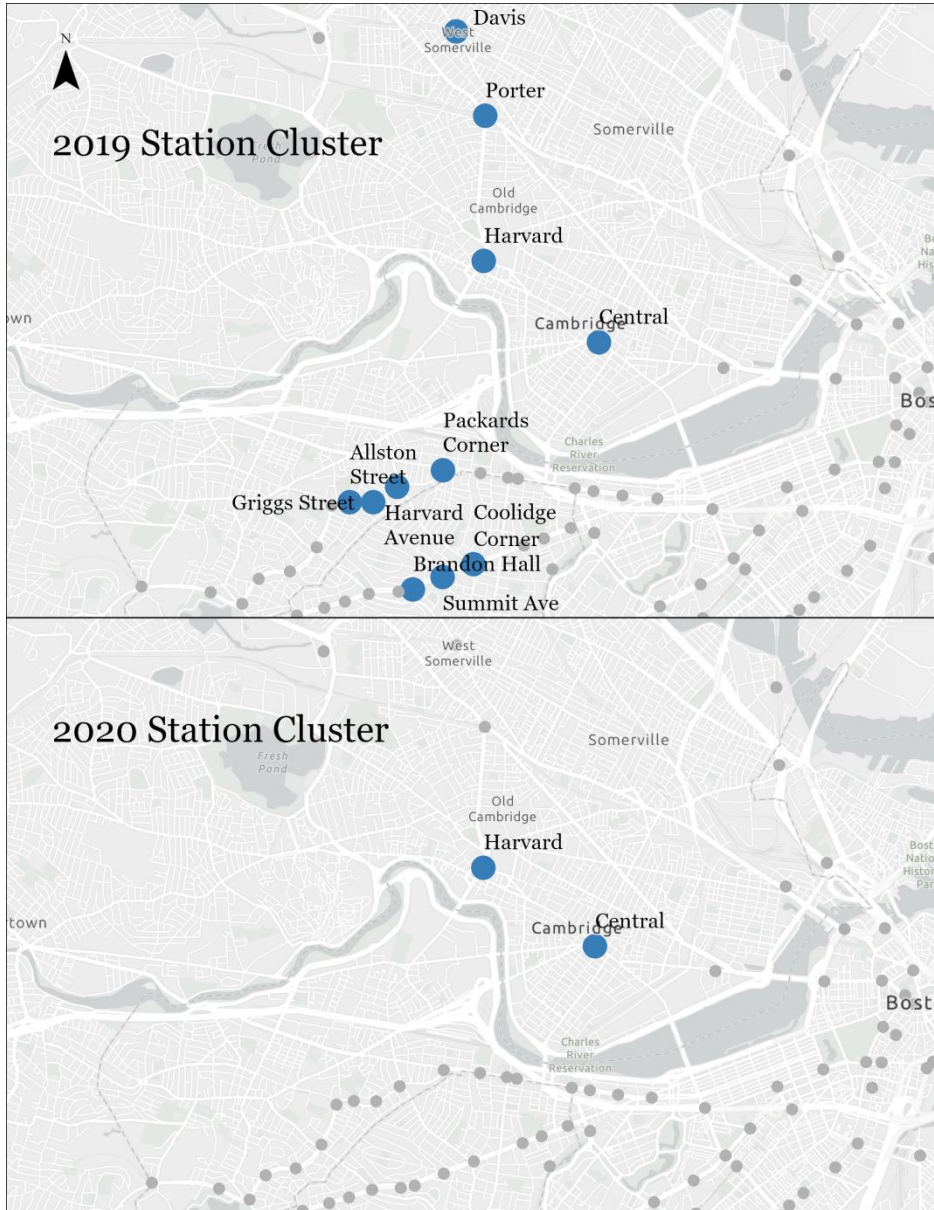
Surprisingly, the remaining nine transit stations increased in vitality during the pandemic, particularly Davis and Porter Station, whose cluster changed to *Moderate vitality*, indicating that people increased their visits to POI in the region.



**Figure 24. Visit pattern of *Job and residential-oriented* cluster stations.**



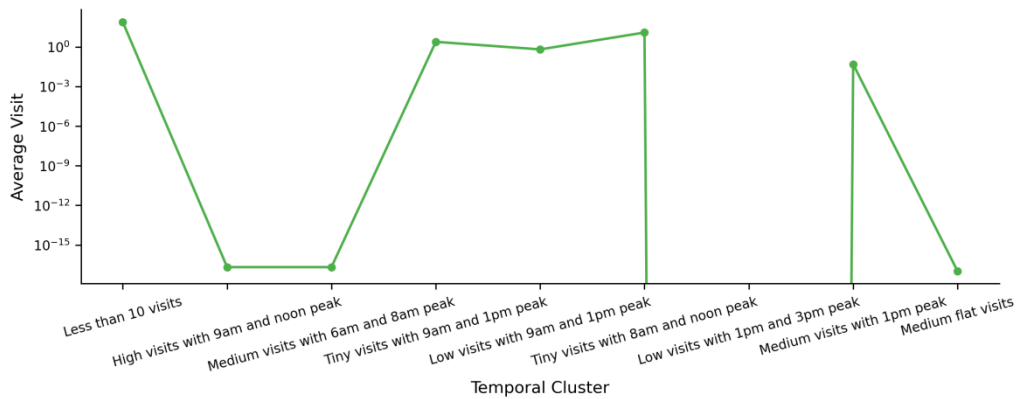
**Figure 25. Social demographic and building environment of *Job and residential oriented* cluster stations**



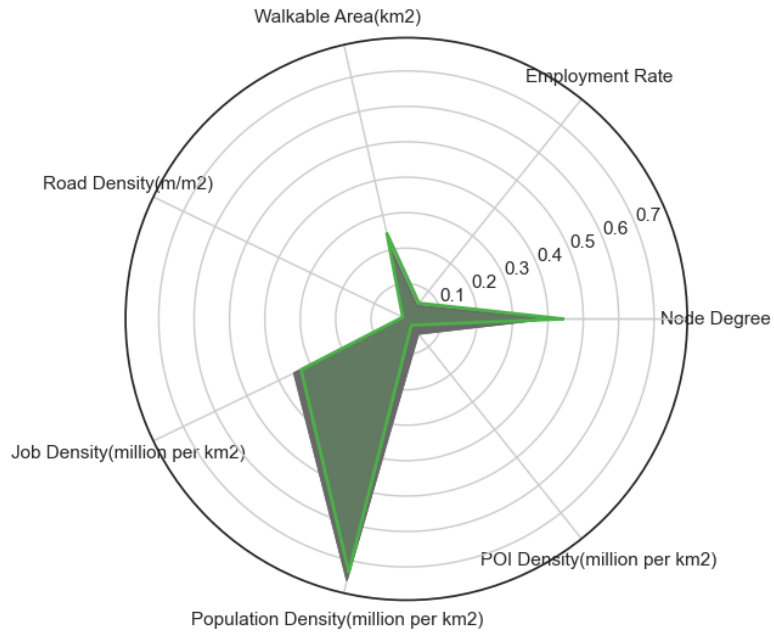
**Figure 26. Spatial distribution of *Job and residential-oriented cluster stations***

For *Moderate vitality*, in addition to 'Less than 10 visits' and tiny visits as the main types, the temporal cluster contains many POI with strong activity at 1 p.m. Regarding socio-demographic data performance, the cluster's transit stations have a slightly above average employment rate, but a drastically below average job density. The low employment rate at the transit stations suggests that most nearby residents travel long

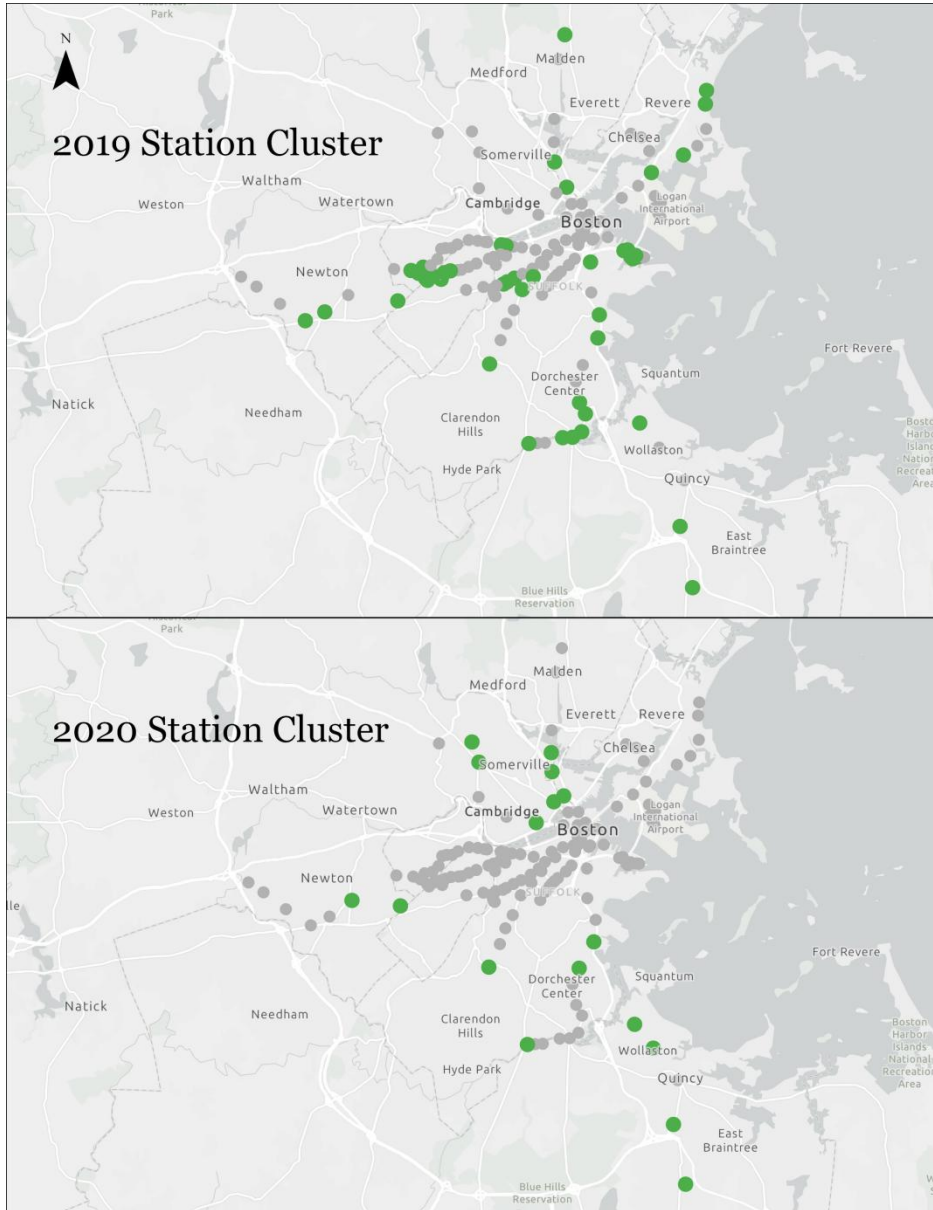
distances to reach their workplaces. The lower number of POIs indicates that residents have less access to services, facilities, and social activities. In 2019, there were 45 transit stations in this cluster; by 2020, there were only 17 stations. The cluster type of 36 of these transit stations changes to *Low vitality*, and 9 remain in this cluster. Besides, during the pandemic, 8 transit stations with low vitality pre-pandemic were also assigned to this cluster. These transit stations are typically situated on the outskirts of urban areas, with few services nearby.



**Figure 27. Visit pattern of *Moderate vitality* cluster stations**



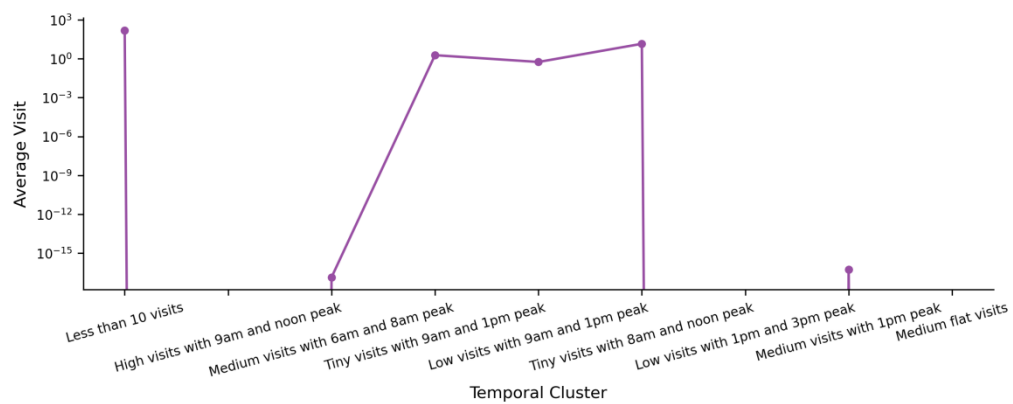
**Figure 28. Social demographic and building environment of *Moderate vitality* cluster stations**



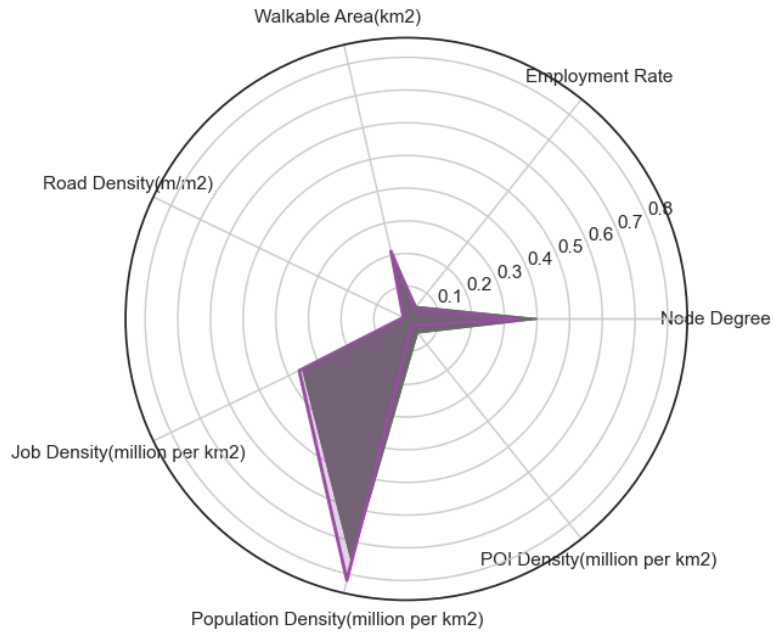
**Figure 29. Spatial distribution of *Moderate vitality* cluster stations**

*Relative high vitality in the morning* is quite similar to the *Job and residential oriented* in that both have low overall visits and morning visits to POI are concentrated. Yet, the former has a more diverse visit pattern than the latter, including some POI with low and moderate visits. Their performance is also fairly comparable in terms of the socio-demographic and built environment statistics. They have a slightly higher than

average employment rate and population density but lower POI density and node degree. Before the pandemic, this cluster's transit stations were primarily located in the uptown region, which is close to downtown, and people of this area typically commute to work there. Only three original 37 transit stations remained in this cluster during the pandemic: Andrew, Malden Center, and Quincy Center. Twenty-eight transit stations decreased their vitality and changed their cluster type to *Low vitality*, whereas six stations boosted their vitality and changed their cluster type to *Moderate vitality*.



**Figure 30. Visit pattern of *Relative high vitality in the morning* cluster stations**



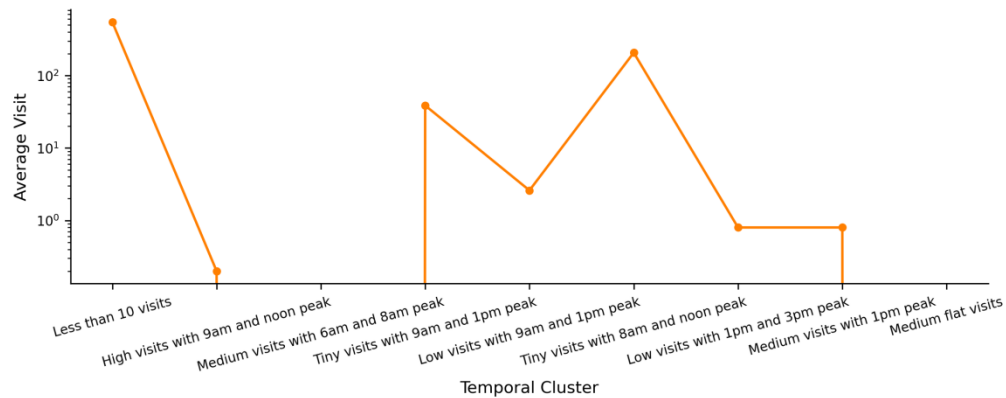
**Figure 31. Social demographic and building environment of *Relative high vitality in the morning cluster stations***



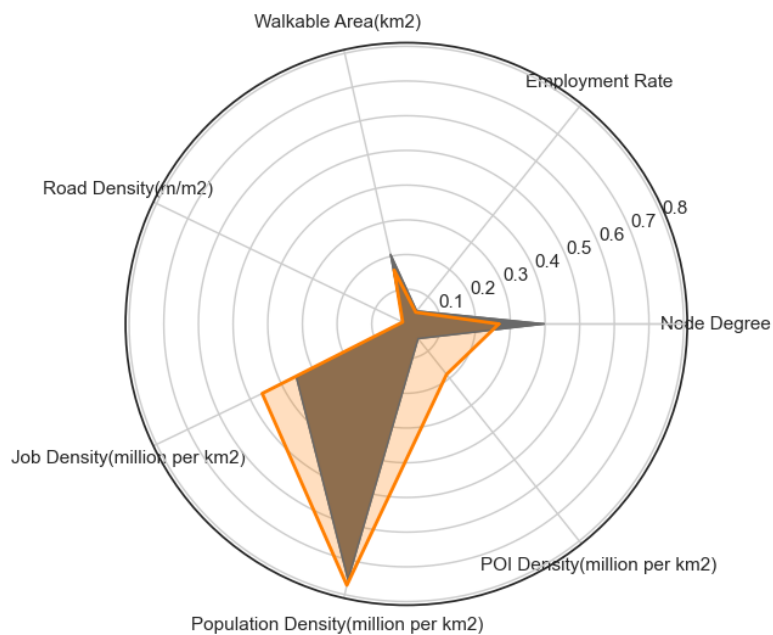
**Figure 32. Spatial distribution of *Relative high vitality in the morning cluster stations***

In addition to 'Less than 10 visits', facilities with significant activity at 1 p.m. give *Moderate vitality to various businesses* of the temporal cluster type. The density of POI within a 15-minute walkable area of these transit stations is well above average and extremely diverse. Similarly, these regions have higher-than-average employment rates and population density, which may be attributable to economic activity's greater scale and intensity. However, the low node degree of these stations makes convenient

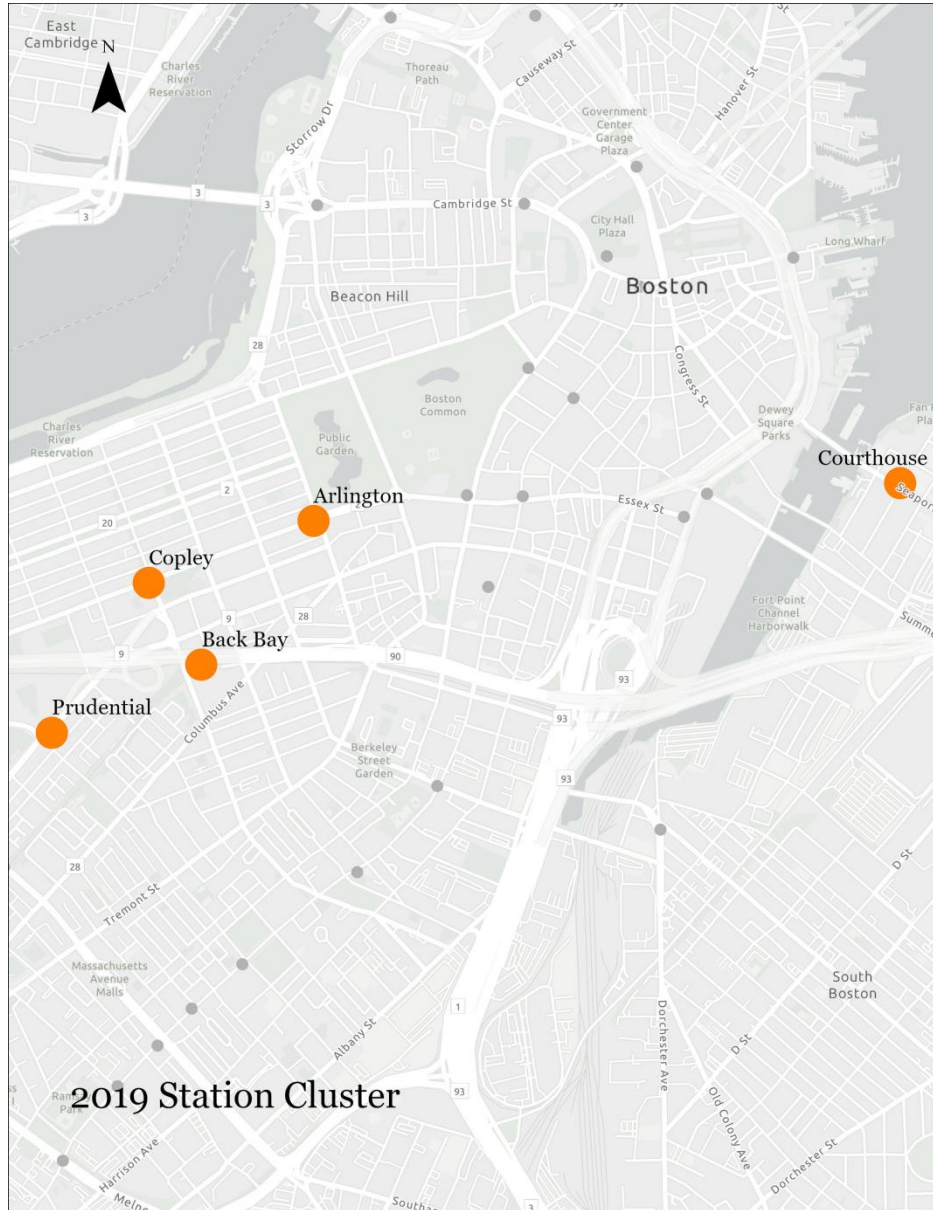
transfer impossible, and the pedestrian capacity is likewise inadequate. The spatial distribution of the five transit stations in this cluster is comparable to the pre-pandemic pattern of downtown areas with the *Most vitality and high connectivity*. Furthermore, their cluster type became *Low vitality* after the pandemic outbreak.



**Figure 33. Visit pattern of *Moderate vitality with various businesses* cluster stations**



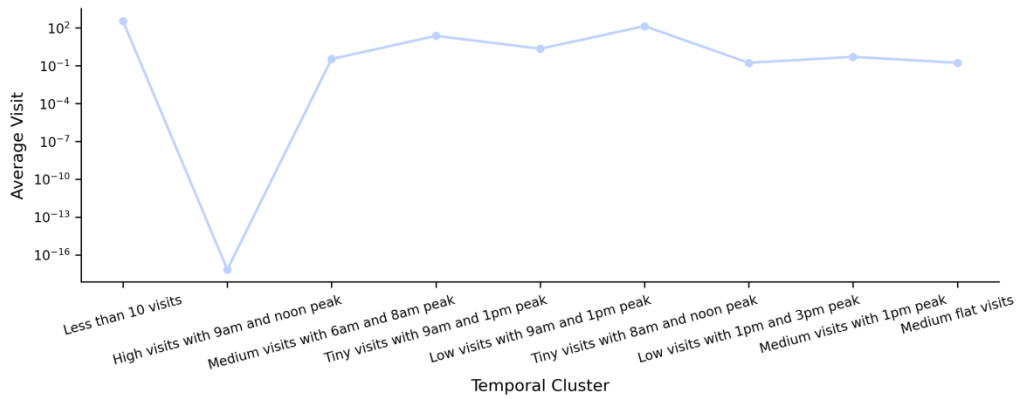
**Figure 34. Social demographic and building environment of *Moderate vitality with various businesses* cluster stations**



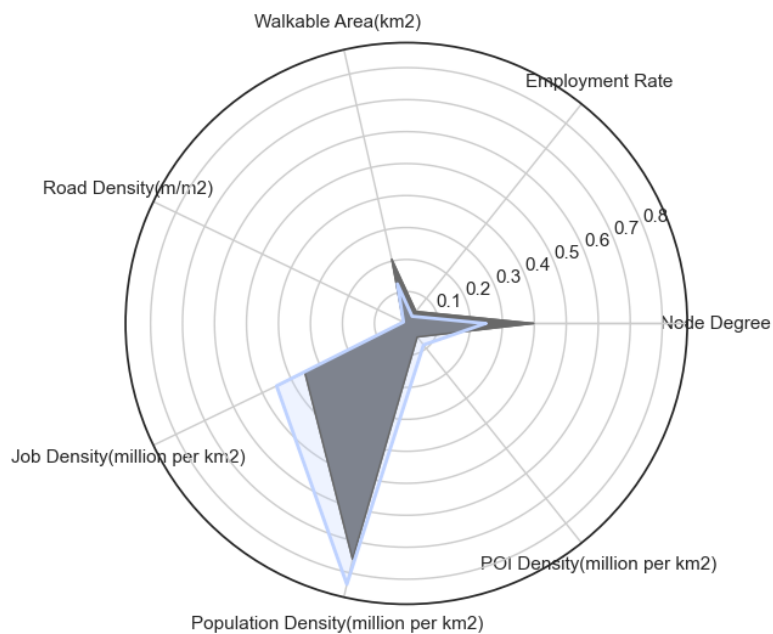
**Figure 35. Spatial distribution of *Moderate vitality with various businesses* cluster stations**

For *High vitality the whole day*, although there is fewer high-visitation POIs, it includes many POIs with various visitation patterns. It maintains a high level of activity throughout the day. The jobs, population, and POI density around the transit stations of this cluster are above average, indicating that the area is a mixed-use area with decent-sized business patterns that provide some job opportunities. Nevertheless, the

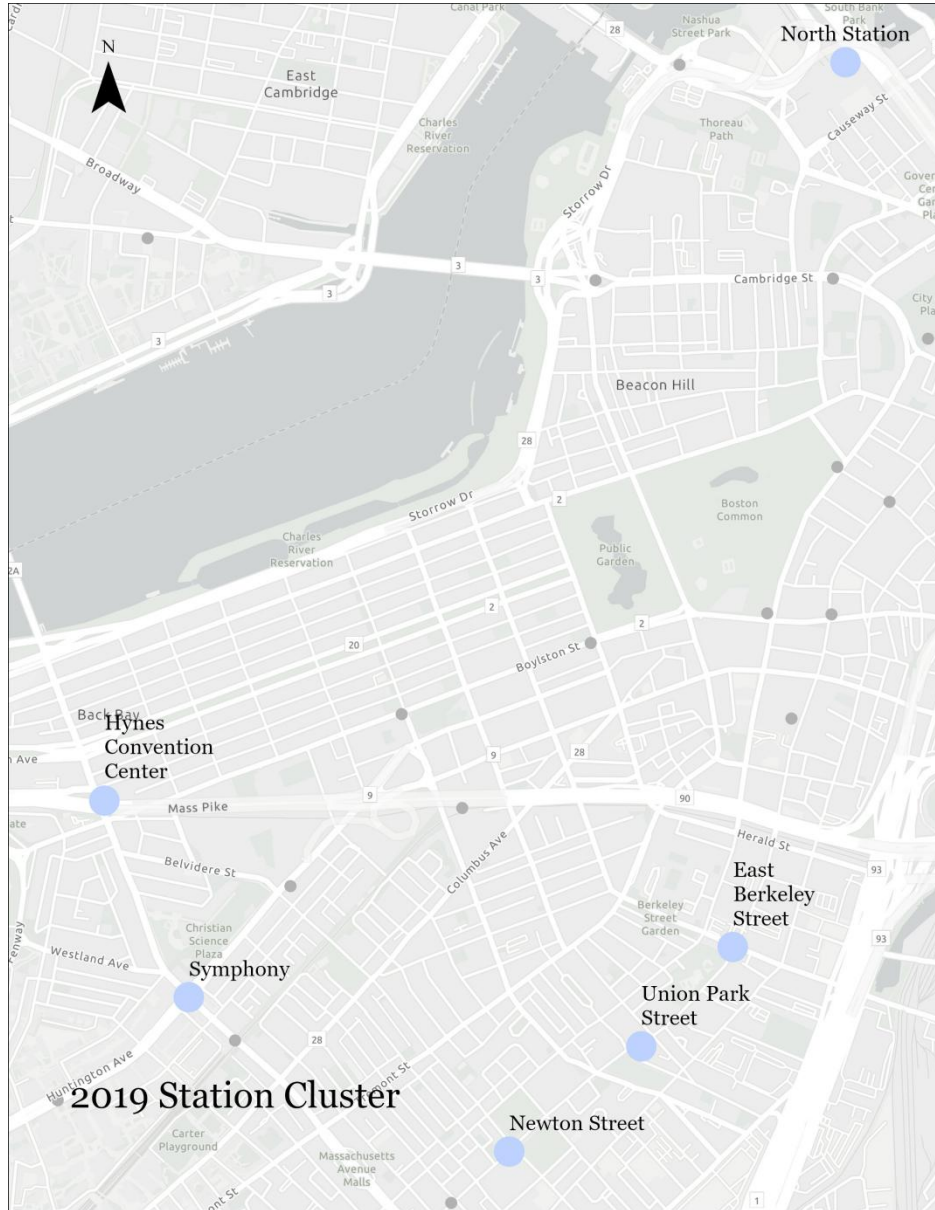
walking accessibility and node degree of the area is poor. Similar to the spatial and temporal dispersion of the two previously described clusters, the six transit stations of this cluster were only distributed in areas close to the downtown before the pandemic.



**Figure 36. Visit pattern of *High vitality whole-day* cluster stations**



**Figure 37. Social demographic and building environment of *High vitality whole day* cluster stations**

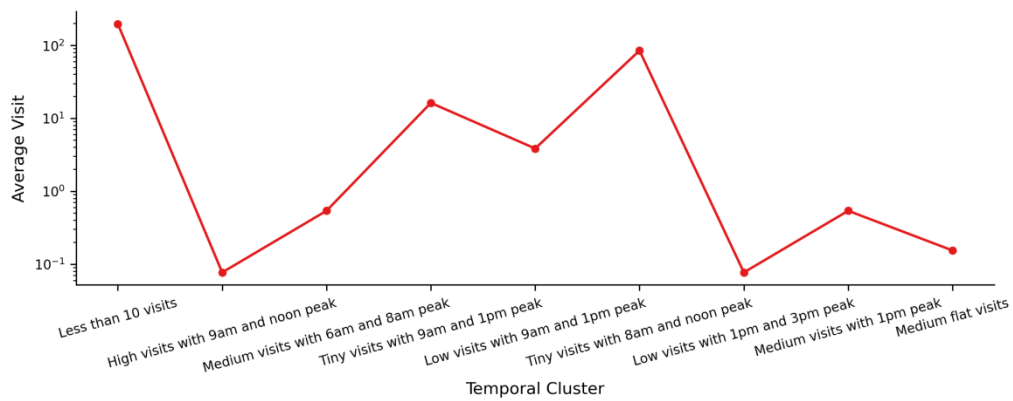


**Figure 38. Spatial distribution of *High vitality whole-day* cluster stations**

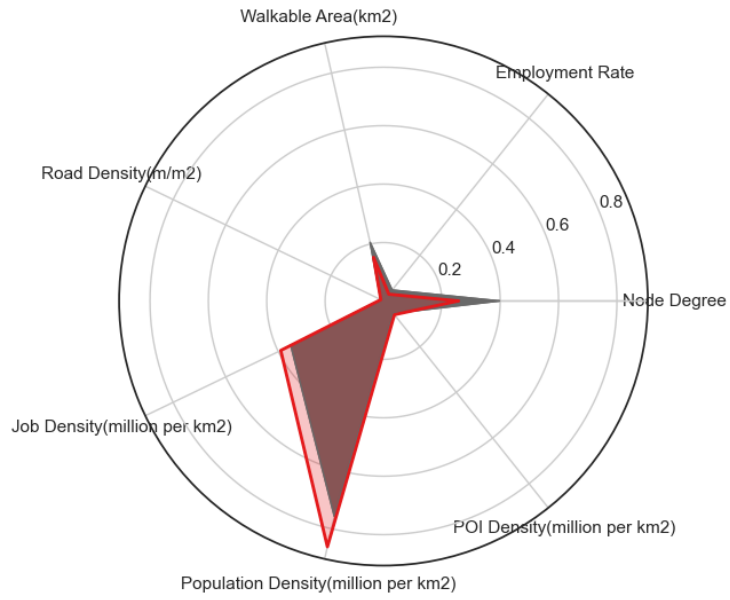
For *High vitality and institutional oriented*, it encompasses all visit patterns. In particular, its facilities are heavily utilized at 9 a.m. and noon. This type of station has a high job and population density but a lower than average employment rate and POI density. The land surrounding these stations is mostly utilized for religious, governmental, educational, and cultural purposes. For example, there are at least six

religious sites around Lenox St Station.

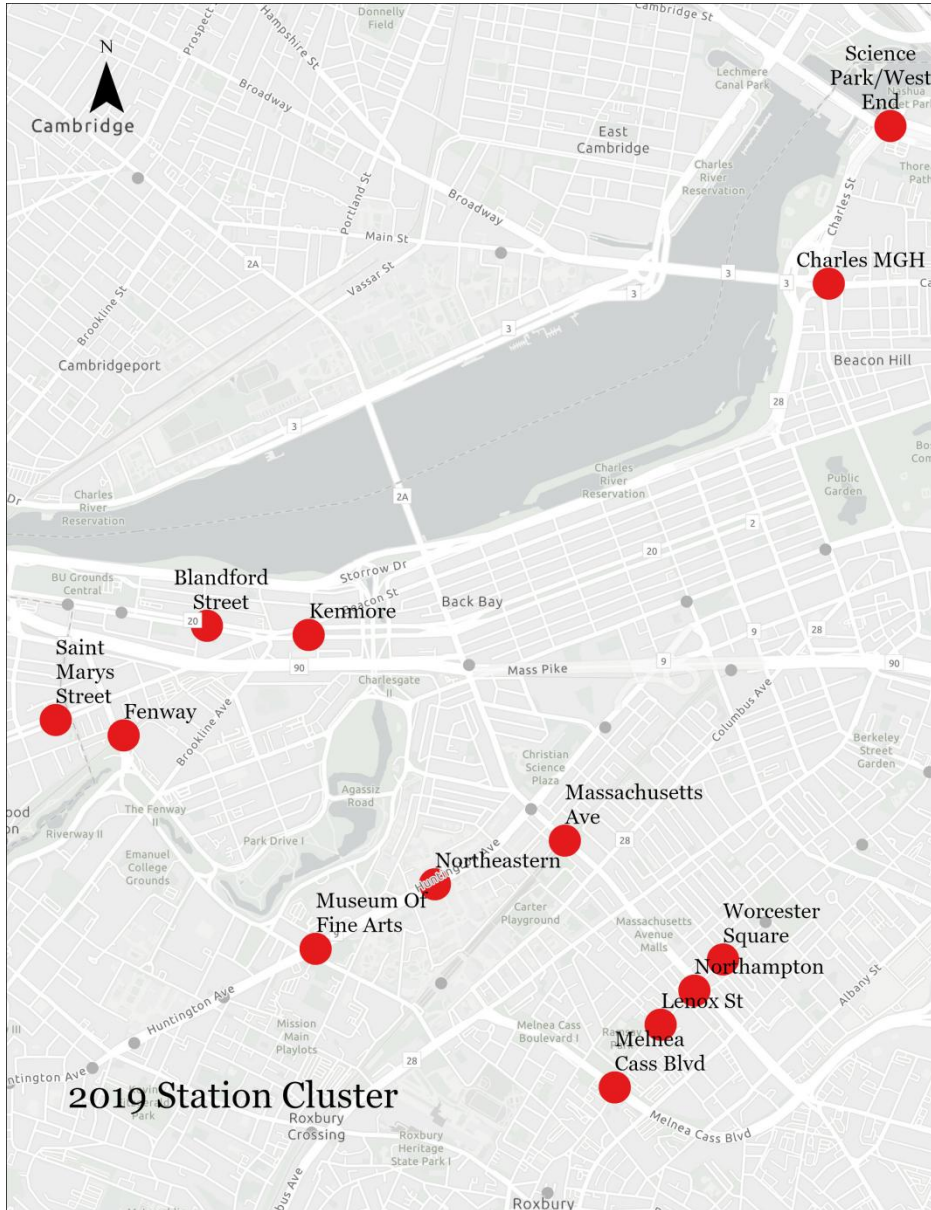
Moreover, several transit stations are located within Northeastern University and Boston University's campuses. Therefore, most of the area surrounding transit stations is occupied by structures such as libraries and offices. In addition, the cluster has numerous apartment buildings around the transit station, which may explain the high population density. In 2020, due to the influence of the pandemic, the cluster type of these transit stations shifted to *Low vitality*, mirroring the situation in which the other three clusters changed.



**Figure 39. Visit pattern of *High vitality and institution oriented* cluster stations**



**Figure 40. Social demographic and building environment of *High vitality and institution oriented* cluster stations**

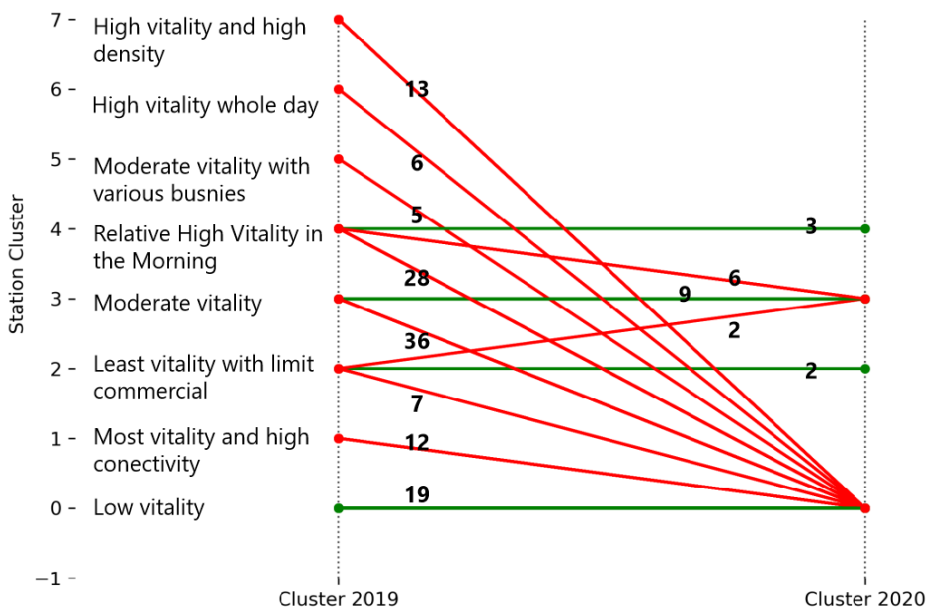


**Figure 41. Spatial distribution of *High vitality and institutional oriented* cluster stations**

#### ***4.3.4. Resilience Analysis of the POI-Station-Level Clustering***

Figures 42 compares the clustering results of 149 transit stations in the Boston metropolitan area in 2019 and 2020, with the red line showing a change in clustering and the green line indicating no change. We discovered that 107 transit stations

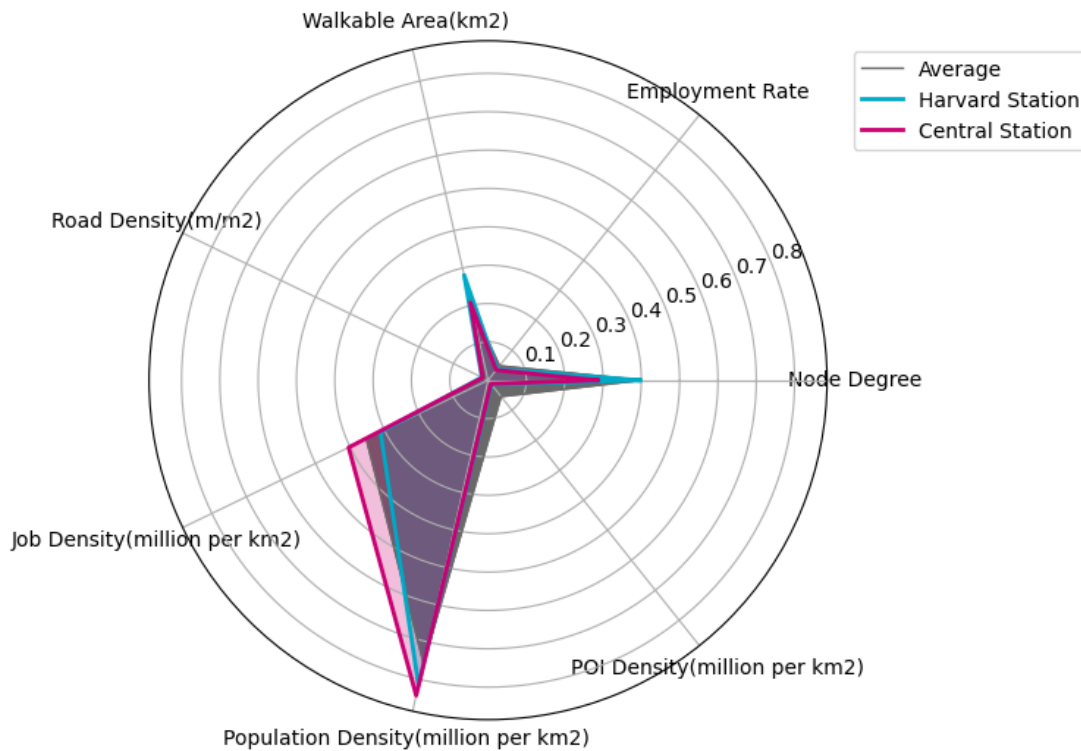
clustered from their original type to *Low vitality*, accounting for approximately 72 percent of all transit stations. Eight transit stations' clustering results changed to *Moderate vitality*, and the remaining 33 stations maintained their pre-pandemic clustering types. Nineteen of these transit stations with consistent clustering types have *Low vitality*. In the following paragraphs, I will focus on the remaining 14 transit stations since they demonstrate how the local environment maintains its resilience in the face of a pandemic.



**Figure 42. Comparing station cluster results between 2019 vs. 2020**

Harvard and Central Sq Stations are the two transit stations that retain *Job and residential-oriented*. Within a 15-minute walk of these two stations, the radar maps display information relating to the built environment and socio-demographics, with

different colors representing different stations.



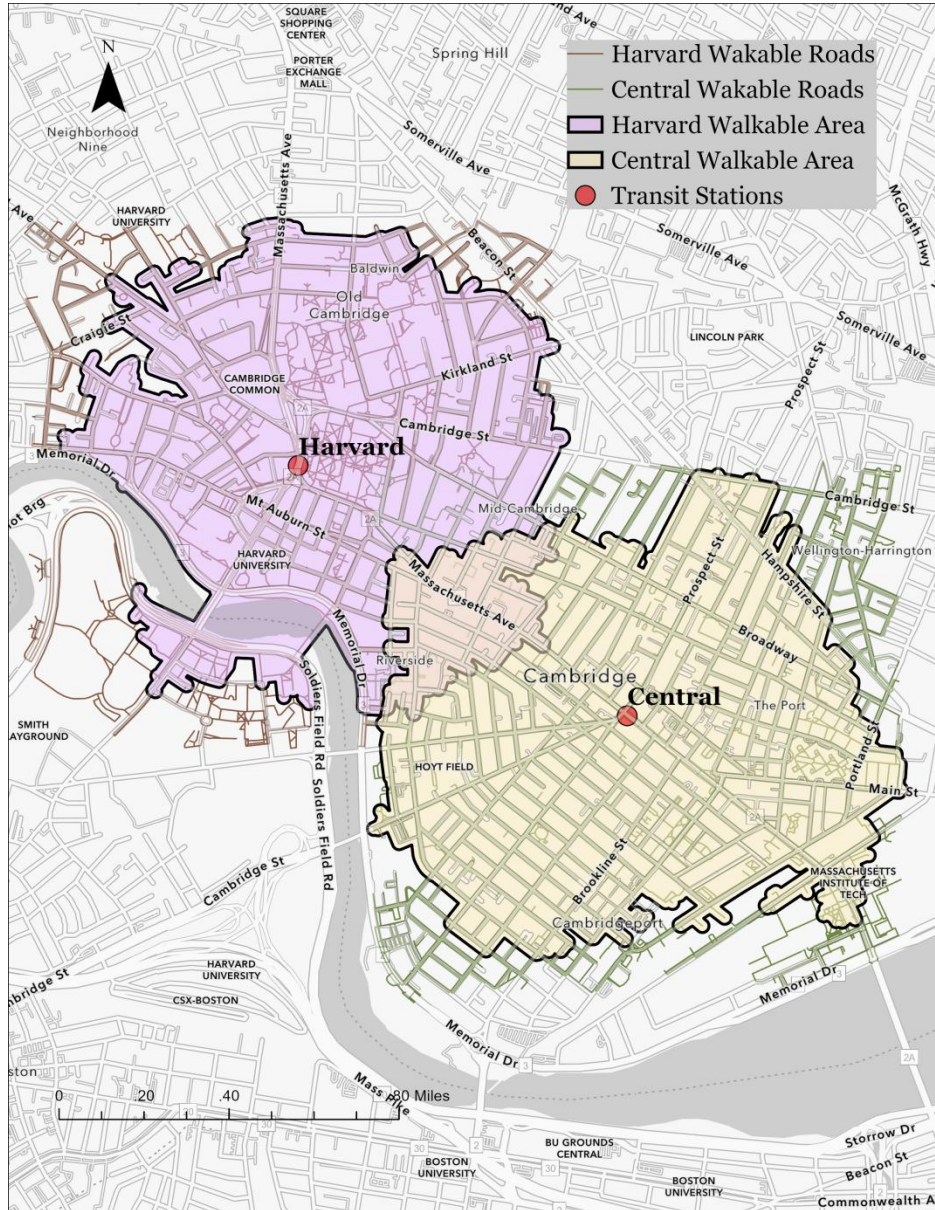
**Figure 43. Social demographic and building environment of Harvard and Central Station**

These two transit stations have a higher population density, node degree, and walkable area than the average Boston metropolitan transit station. Table 2 summarizes the 15 most walkable transit stations in Boston, with Harvard and Central Station ranking sixth and third, respectively. And Figure 44 displays the walkable area of these two stations. We also notice the high level of road connection surrounding Central Station, with few physical obstacles between the station and nearby locations, allowing people to travel farther from the station or to approach the

station more easily.

**Table 2. Top 10 stations by walkable area**

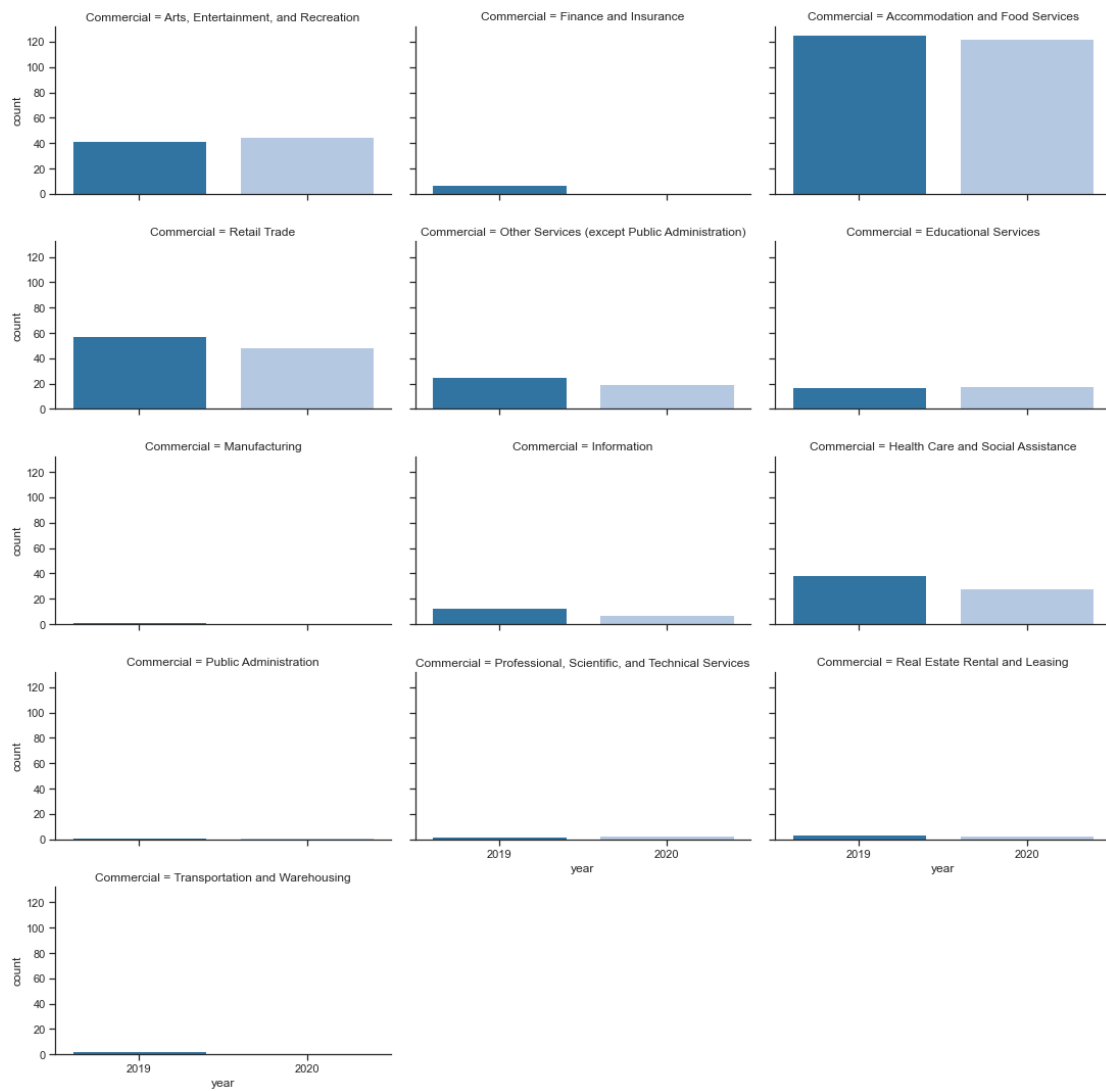
	<b>Station</b>	<b>Walkable Area(m2)</b>
<b>0</b>	Davis	3037589.843
<b>1</b>	Coolidge Corner	2954451.315
<b>2</b>	Boylston	2929830.756
<b>3</b>	Central	2916382.207
<b>4</b>	Government Center	2909948.658
<b>5</b>	Park Street	2869561.079
<b>6</b>	Harvard	2843623.562
<b>7</b>	Riverway	2762726.755
<b>8</b>	Andrew	2761919.935
<b>9</b>	Arlington	2761163.700



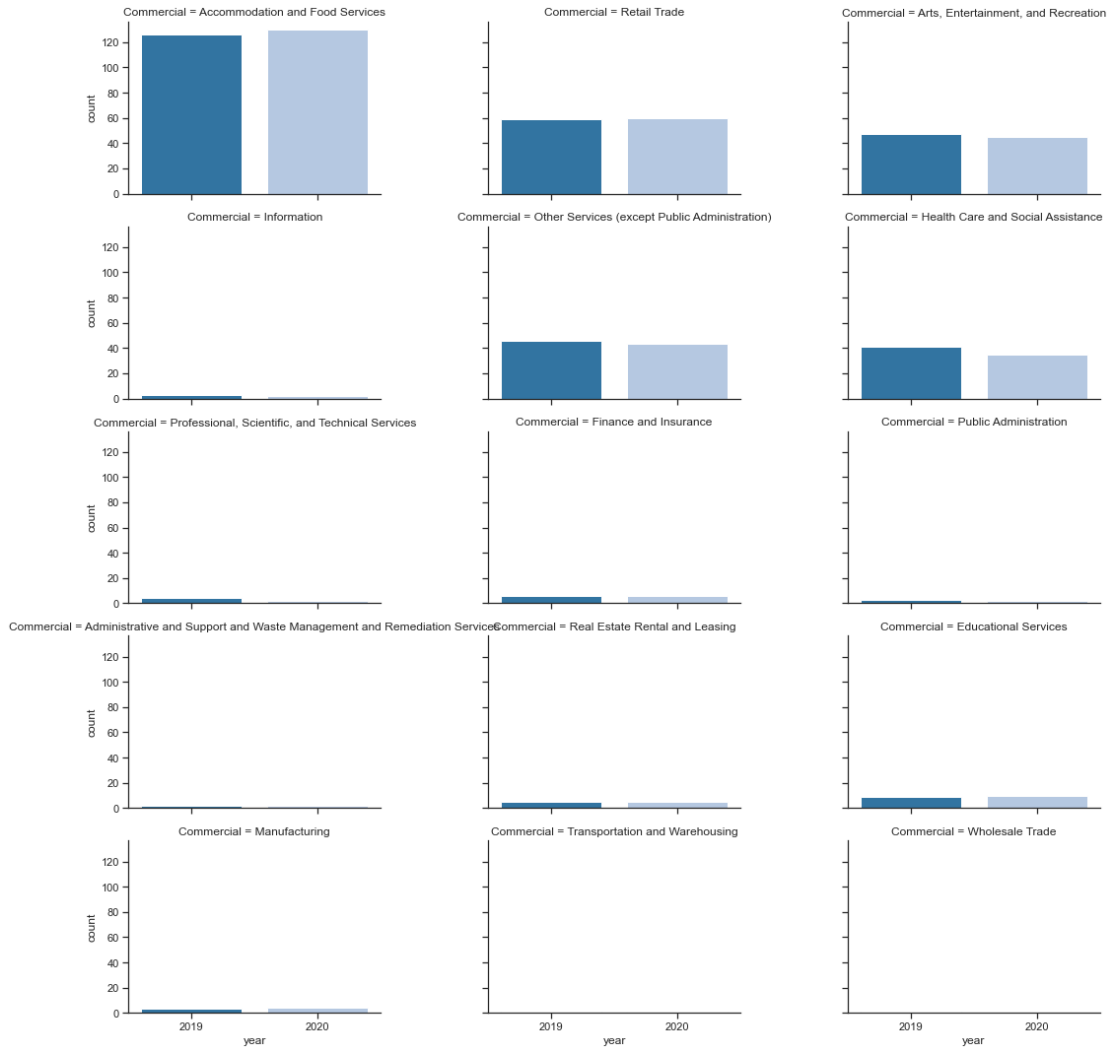
**Figure 44. Walkable area of Harvard and Central Station**

The bar charts in Figure 45 and Figure 46 depict the statistical distribution of the business types within 15-minute walking distance in Harvard and Central Station, respectively. The businesses with the biggest concentration near Harvard Station are 'Accommodation and Food Service', followed by 'Retail Trade,' 'Health Care and Social Assistance, and 'Art, Entertainment, and Recreation.' During the pandemic, the

number of these categories' POI decreased. In the surroundings of Central Station, 'Accommodation and Food Service' and businesses of a similar type to those found around Harvard Station predominate. In addition, there are numerous 'Other Services' in the vicinity of Central Station, like auto repair and maintenance, barber shops, and social advocacy organizations.



**Figure 45. Commercial type statistical distribution of Harvard Station**



**Figure 46. Commercial type statistical distribution of Central Station**

Nine transit stations maintain *Moderate Vitality*: Braintree, Chestnut Hill, Community College, Forest Hills, Mattapan, North Quincy, Quincy Adams, Savin Hill, and Sullivan Square Station. The figures for these nine stations, analyzed using the same methods as Harvard Station, can be found in Appendix. The employment rates near these stations are much higher, indicating that individuals commute to the region for work. Moreover, the most noticeable characteristic of these stations is that their

15-minute walkable area and node degree are significantly greater than the average for other transit stations—specifically, the Braintree, Chestnut Hill, and Sullivan Square stations.

Although the total number of POI of business types around these transit stations is lesser than that of Harvard and Central Station, the number of these two categories of businesses is equivalent near these stations. 'Retail Trade' around transit stations (such as Braintree, Chestnut Hill, and Savin Hill Station) surpasses 'Accommodation and Food Service', and the number increased in 2020. Besides, around Quincy Adams Station, 'Health Care and Social Assistance' is the most prevalent business type, followed by 'Other Service,' which is distinct from the other transit stations.

Three transit stations maintain *Relative high vitality in the morning*: Andrew, Malden Center, and Quincy Center Station. The study of the conditions around these three stations employs a similar methodology to the preceding section; the relevant figures are accessible in Appendix. These three stations feature above-average walking areas and a high degree of connectivity, facilitating easy transfers between transit lines. The four sorts, as mentioned earlier, of business types continue to predominate around these transit stations. In addition, the 'Health Care and Social Assistance' and 'Other Service' are more common at Malden Center and Quincy Center Station than other

transit stations.

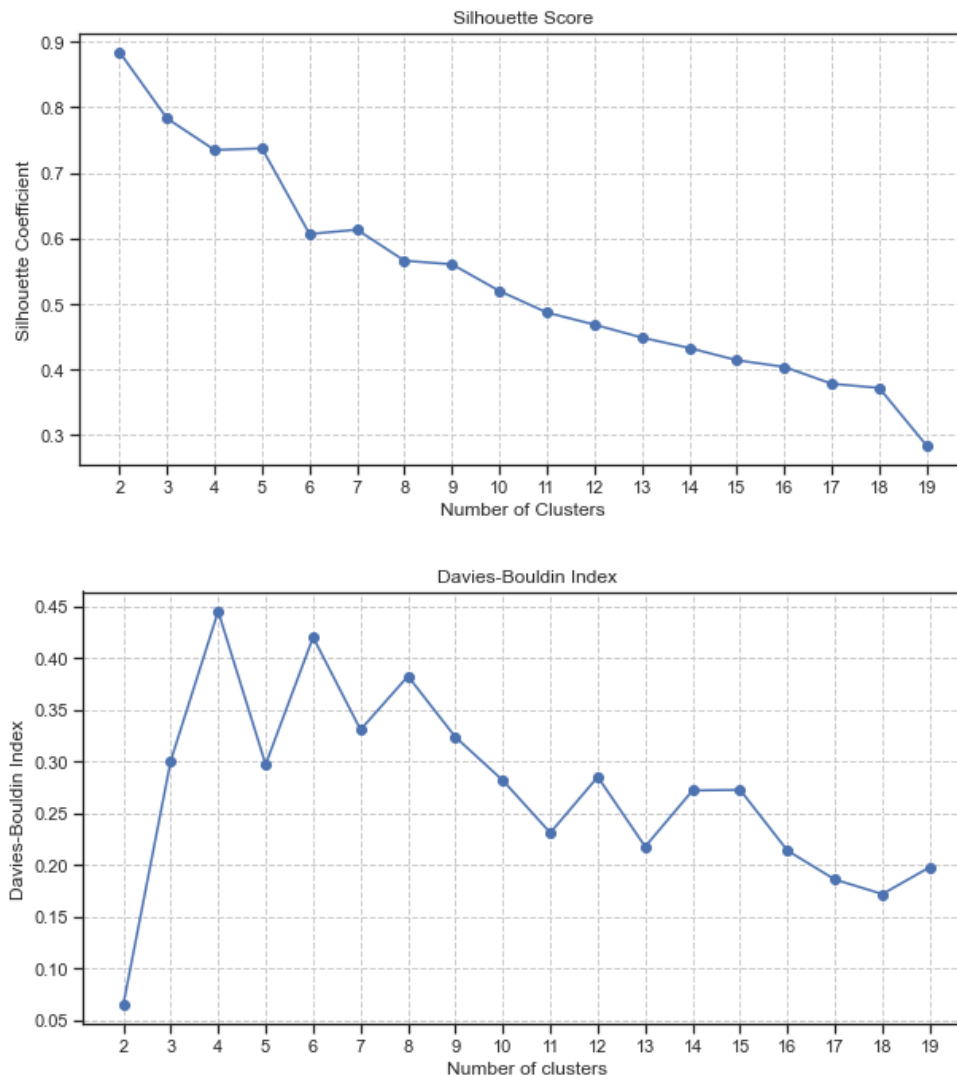
Different business types contributed to sustaining transit station resilience during the pandemic; therefore, I will conduct a cluster analysis of business types in the following study.

## 4.4. Commercial Types Clustering

### 4.4.1. Cluster Validity of Commercial Types Cluster

DBI and SC are utilized to find the ideal number of commercial-type clusters.

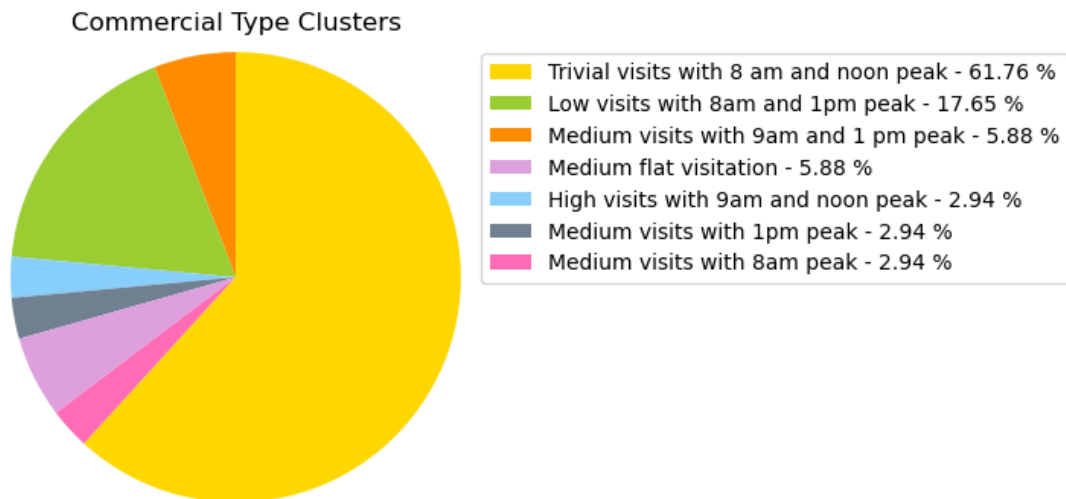
Similar to POI clusters, the present few elbows are meaningless and feature a one-tailed issue, despite producing better clustering results. Thus, we chose  $k = 7$  as the number of clusters.



**Figure 47. Cluster validity indices for commercial type level cluster**

#### **4.4.2. Clustering based on Commercial Types**

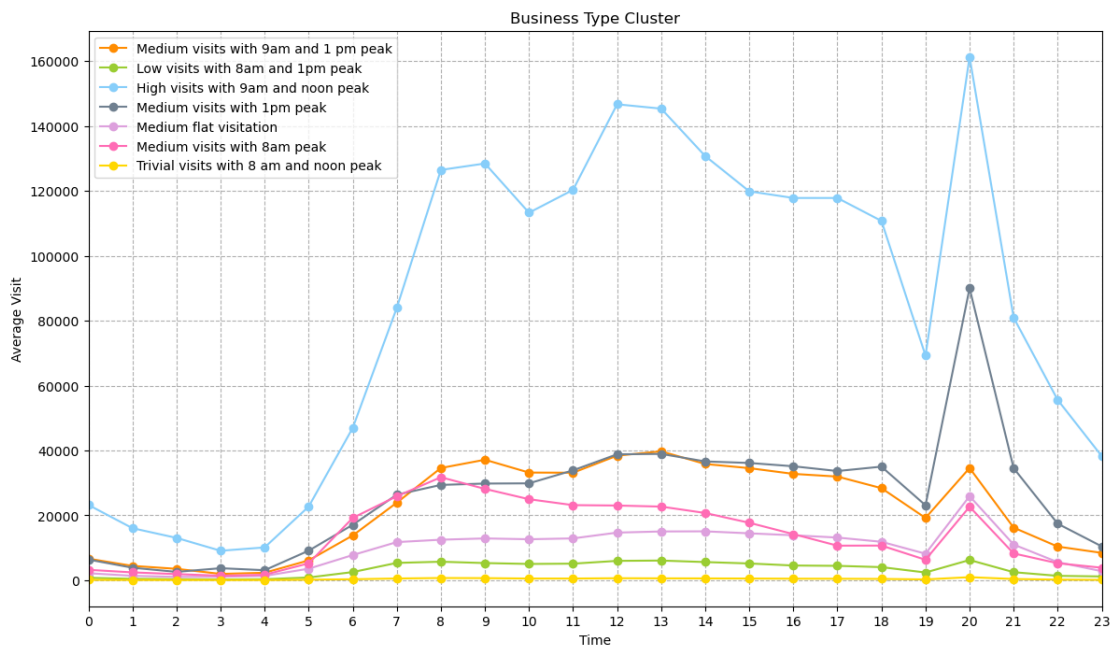
Figure 48 below illustrates the seven clusters' composition. The largest share is *Trivial visitation with 8 am and noon peaks*, which is more than half of the total observations, at approximately 62 percent. *Low visitation with 8 am, and 1 pm peaks* are the second-largest cluster; it includes about 18 percent of the observations. *Medium visitation with 9 am and 1 pm peaks* and *Low flat visitation* contains 6 percent of commercial types separately, *High visitation with 9 am and noon peaks*, *Medium visitation with 1 pm peak*, and *Medium visitation with 8 am peak* are the three most minor clusters, representing 2 percent of each.



**Figure 48. Composition of the commercial type clustering. Note: For comparison purposes, in this pie chart and in the following maps, we use different colors to indicate each cluster, and the combination is fixed.**

The line graph illustrates the daily variation in the number of visits to each cluster.

Most business types are given *Trivial visits with 8 am and noon peaks*, indicating many low-visited and unpopular business types near transit stations. In contrast, a negligible proportion of industries were visited regularly, such as *High visits with 9 am and noon peak*. The remaining clusters have comparable performance to the number of visits.



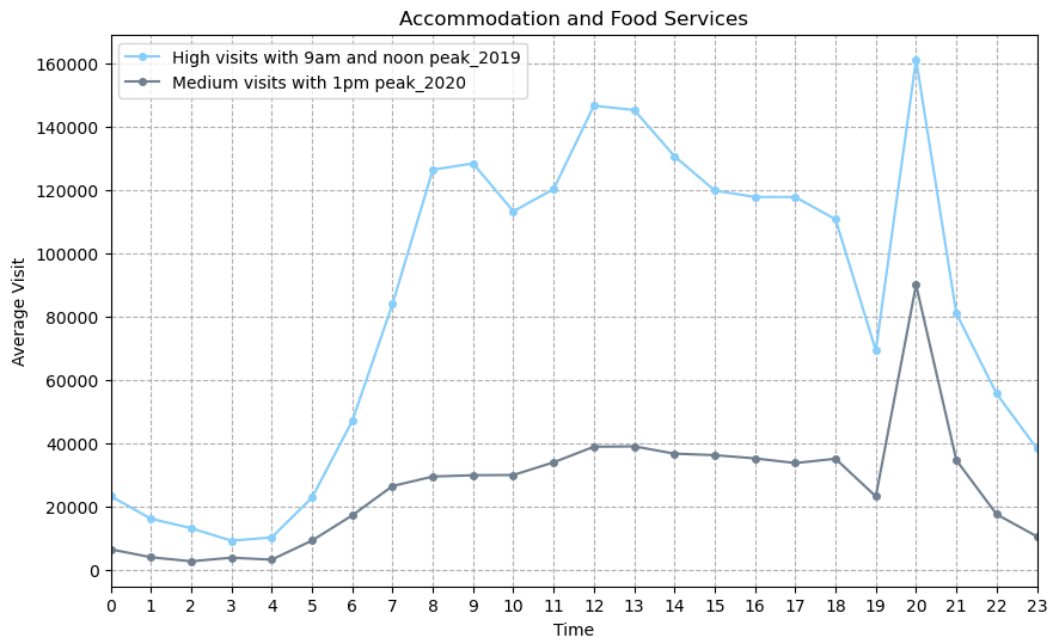
**Figure 49. Plot means of business type cluster**

Table 3 highlights how the visit patterns for various business types have shifted before and during the pandemic. Seven clusters altered their categories, and the remaining ten maintained the clusters to which they were initially assigned. These changes can be grouped into six scenarios. In the following paragraphs, we will discuss the features of change indicated by the clusters of these seventeen forms of businesses.

**Table 3. Comparison of results for commercial type clusters**

	<b>Commercial Types</b>	<b>Cluster 2019</b>	<b>Cluster 2020</b>
1	Accommodation and Food Services	High visits with 9am and noon peak	Medium visits with 1pm peak
2	Arts, Entertainment, and Recreation	Medium visits with 9am and 1 pm peak	Medium flat visitation
3	Retail Trade	Medium visits with 9am and 1 pm peak	Medium flat visitation
4	Educational Services	Low visits with 8am and 1pm peak	Trivial visits with 8 am and noon peak
5	Information	Low visits with 8am and 1pm peak	Trivial visits with 8 am and noon peak
6	Other Services (except Public Administration)	Low visits with 8am and 1pm peak	Trivial visits with 8 am and noon peak
7	Health Care and Social Assistance	Medium visits with 8am peak	Low visits with 8am and 1pm peak
8	Real Estate Rental and Leasing	Low visits with 8am and 1pm peak	Low visits with 8am and 1pm peak
9	Transportation and Warehousing	Trivial visits with 8 am and noon peak	Trivial visits with 8 am and noon peak
10	Utilities	Trivial visits with 8 am and noon peak	Trivial visits with 8 am and noon peak
11	Wholesale Trade	Trivial visits with 8 am and noon peak	Trivial visits with 8 am and noon peak
12	Administrative, Support, Waste Management and Remediation Services	Trivial visits with 8 am and noon peak	Trivial visits with 8 am and noon peak
13	Construction	Trivial visits with 8 am and noon peak	Trivial visits with 8 am and noon peak
14	Finance and Insurance	Trivial visits with 8 am and noon peak	Trivial visits with 8 am and noon peak
15	Manufacturing	Trivial visits with 8 am and noon peak	Trivial visits with 8 am and noon peak
16	Professional, Scientific, and Technical Services	Trivial visits with 8 am and noon peak	Trivial visits with 8 am and noon peak
17	Public Administration	Trivial visits with 8 am and noon peak	Trivial visits with 8 am and noon peak

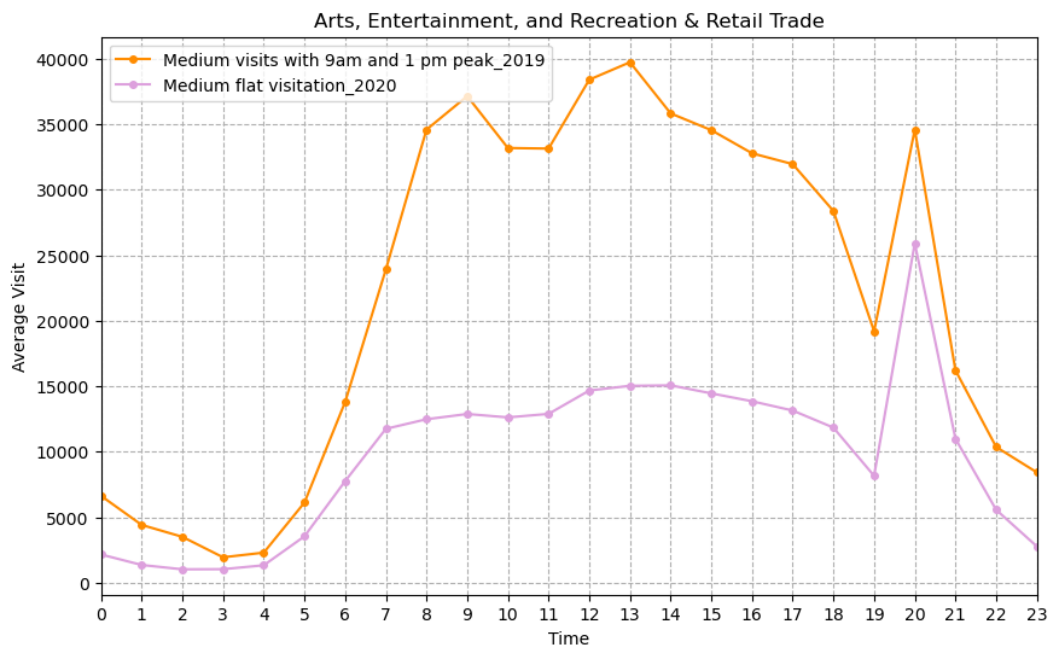
'Accommodation and Food Services' from *High visits with 9 am and noon peaks* to *Medium visits with 1 pm peak*. Before the pandemic, people visited this type of industry more frequently than other industries, and the peak hours to it were 8 a.m. and noon. During the pandemic, however, the number of visits plummeted dramatically to approximately 73 percent. Besides, the visitation showed a more moderate figure in the daytime but still increased remarkably at 8 p.m.



**Figure 50. Comparison of results for 'Accommodation and Food Services'**

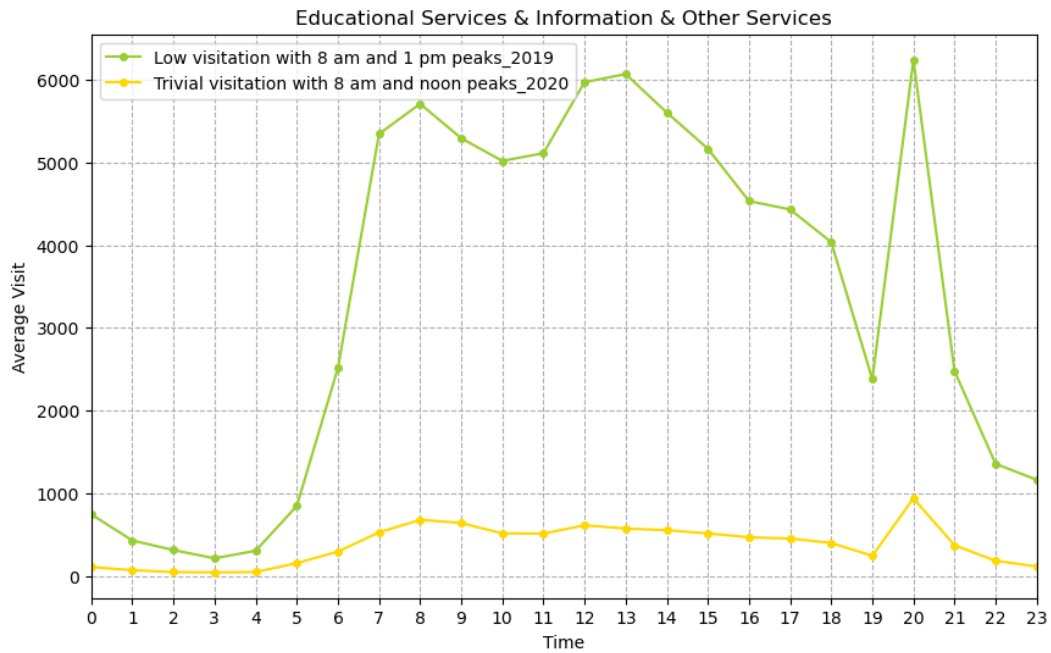
'Arts, Entertainment, and Recreation' and 'Retail Trade' from *Medium visits with 9 am and 1 pm peaks* to *Medium flat visitation*. Before the pandemic, these two business categories had moderate visitation with a slight increase around 9 a.m. and 1 p.m.

However, they were visited less frequently during the pandemic and did not demonstrate a distinct increase in a single day, except at 8 p.m.



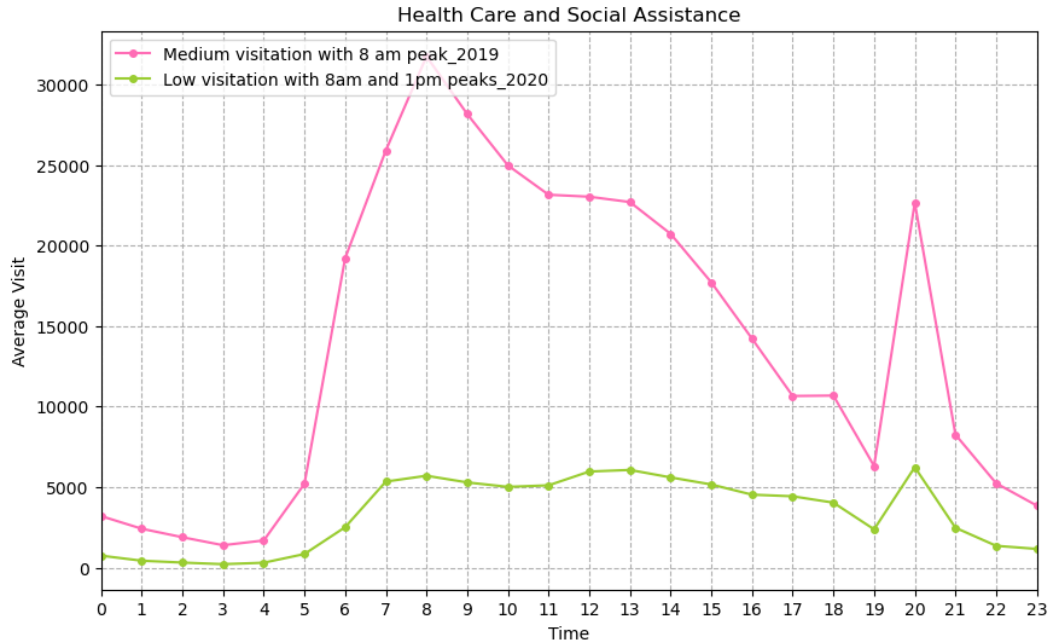
**Figure 51. Comparison of results for 'Arts, Entertainment, and Recreation' and 'Retail Trade.'**

‘Educational Services’, ‘Information’, and ‘Other Services’ from *Low visitation with 8 am and 1pm peaks* to *Trivial visitation with 8 am and noon peaks*. Before and during the pandemic, there were few visitors to these three sorts of businesses; after the pandemic broke out, there were even fewer. Nonetheless, the peak times for visits remain the same, with peaks around 8 a.m. and between noon and 1 p.m.



**Figure 52. Comparison of results for 'Educational Services,' 'Information' and 'Other Services'**

'Health Care and Social Assistance' from *Medium visitation with 8 am peak* to *Low visitation with 8 am and 1 pm peaks*. Before the pandemic, 'Health Care and Social Assistance' did not receive a high volume of visitors, and most individuals visited at eight in the morning. Surprisingly, however, after the pandemic broke out, its visitation declined. As a result of the pandemic's effects, fewer people visited.



**Figure 53. Comparison of results for 'Health Care and Social Assistance.'**

The remaining ten industries preserve their pre-pandemic clusters with extremely low visitor counts. 'Real Estate Rental and Leasing' cluster has always been *Low visits with 8 am and 1 pm peak*. The remaining nine business types were assigned to the least-visited clusters, the *Trivial visits with 8 am and noon peak*.

## 4.5. Commercial-Station-Level Clustering

### 4.5.1. Cluster Component within Commercial-Station-Level Stations

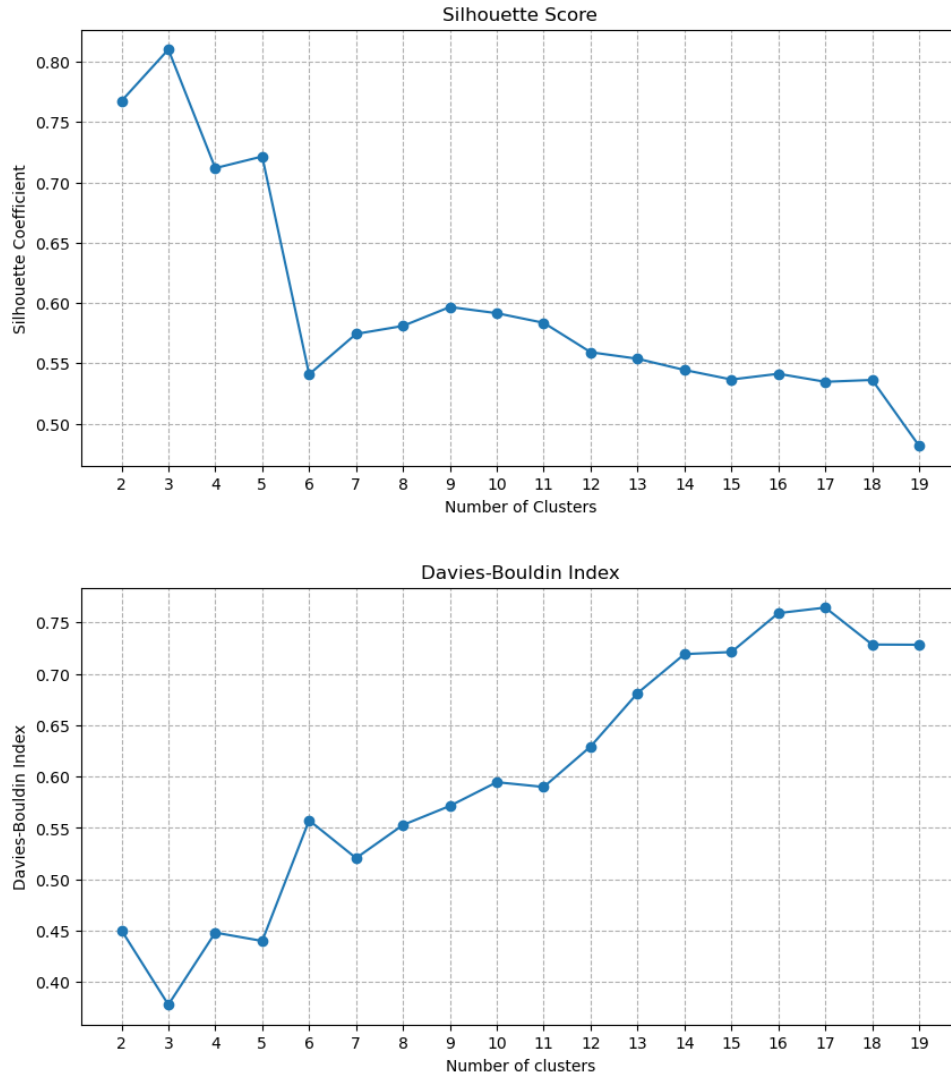
Similar to the clustering at the POI-station level, this clustering is parameterized by the number of commercial-type cluster results and combines 2019 and 2020 data for comparative. Table 4 displays an example of the data input.

**Table 4. Example of input data for the commercial-station-level clustering**

	STATION	Cluster 0	Cluster 1	Cluster 2	Cluster 5	Cluster 6	station_year	Cluster 3	Cluster 4
0	23 Dry Dock Ave	206.000	16.000	267.000	29.000	53.000	23 Dry Dock Ave_2019	0.000	0.000
1	27 Dry Dock Ave	180.000	9.000	186.000	15.000	38.000	27 Dry Dock Ave_2019	0.000	0.000
2	88 Black Falcon Ave	164.000	9.000	162.000	15.000	22.000	88 Black Falcon Ave_2019	0.000	0.000
3	Airport	135.000	100.000	164.000	28.000	28.000	Airport_2019	0.000	0.000
4	Airport Terminal A	6.000	0.000	16.000	0.000	0.000	Airport Terminal A_2019	0.000	0.000
...	...	...	...	...	...	...	...	...	...
293	Wonderland	0.000	8.000	0.000	0.000	28.000	Wonderland_2020	37.000	44.000
294	Wood Island	0.000	14.000	0.000	0.000	58.000	Wood Island_2020	63.000	42.000
295	Woodland	0.000	11.000	0.000	0.000	4.000	Woodland_2020	0.000	1.000
296	Worcester Square	0.000	216.000	0.000	0.000	692.000	Worcester Square_2020	1241.000	1094.000
297	World Trade Center	0.000	40.000	0.000	0.000	171.000	World Trade Center_2020	747.000	367.000

#### ***4.5.2. Cluster Validity of Commercial-Station-Level Cluster***

In this section, DBI and SC are still utilized to identify the optimal number of clusters. Similar to temporal cluster, I found that  $k = 7$  is the best alternative, as it allows the total number of observations in each cluster to be more dispersed and provides a relatively stable clutter.

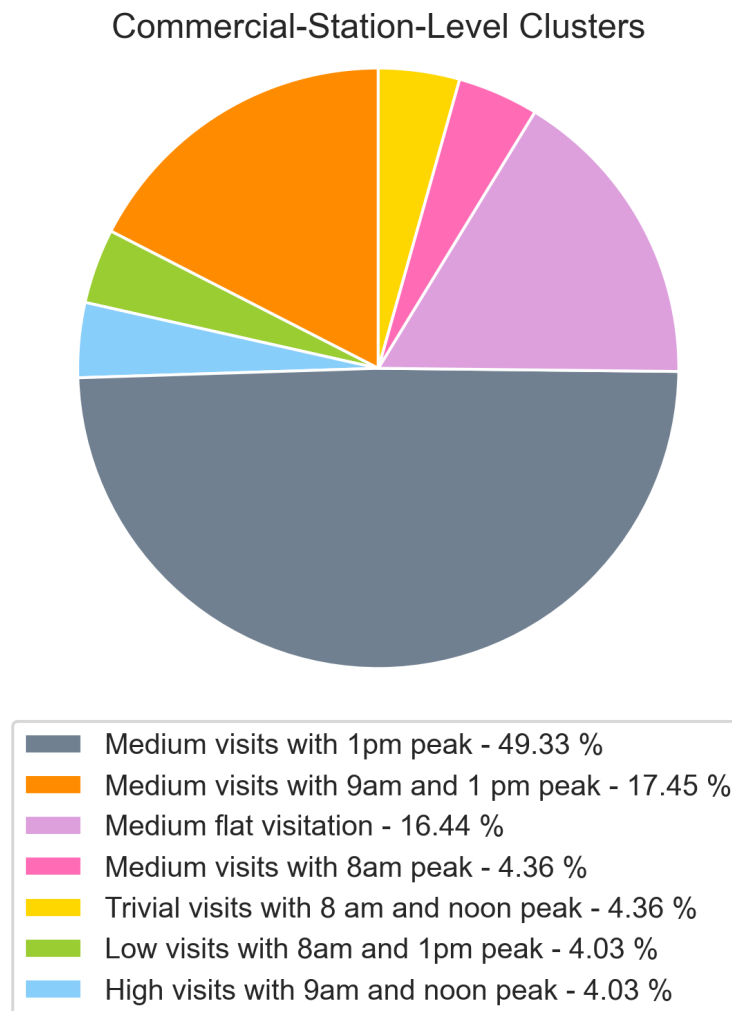


**Figure 54. Cluster validity indices for commercial-station-level cluster**

#### 4.5.3. Analysis of the Commercial-Station-Level Clustering

Figure 55 is a pie chart depicting the components of the station level clusters. Low and medium vitality accounts for most of all 298 observations in the Boston metropolitan area. Meanwhile, most transit stations are assigned to *Medium visits with 1 pm peak*. No more than 12 stations are more popular and contain more POI within

their 15-minute walkable area.



**Figure 55. Composition of the commercial-station-level clustering. Note: For comparison purposes, in this pie chart and in the maps that follow, we use different colors to indicate each cluster and the combination is fixed.**

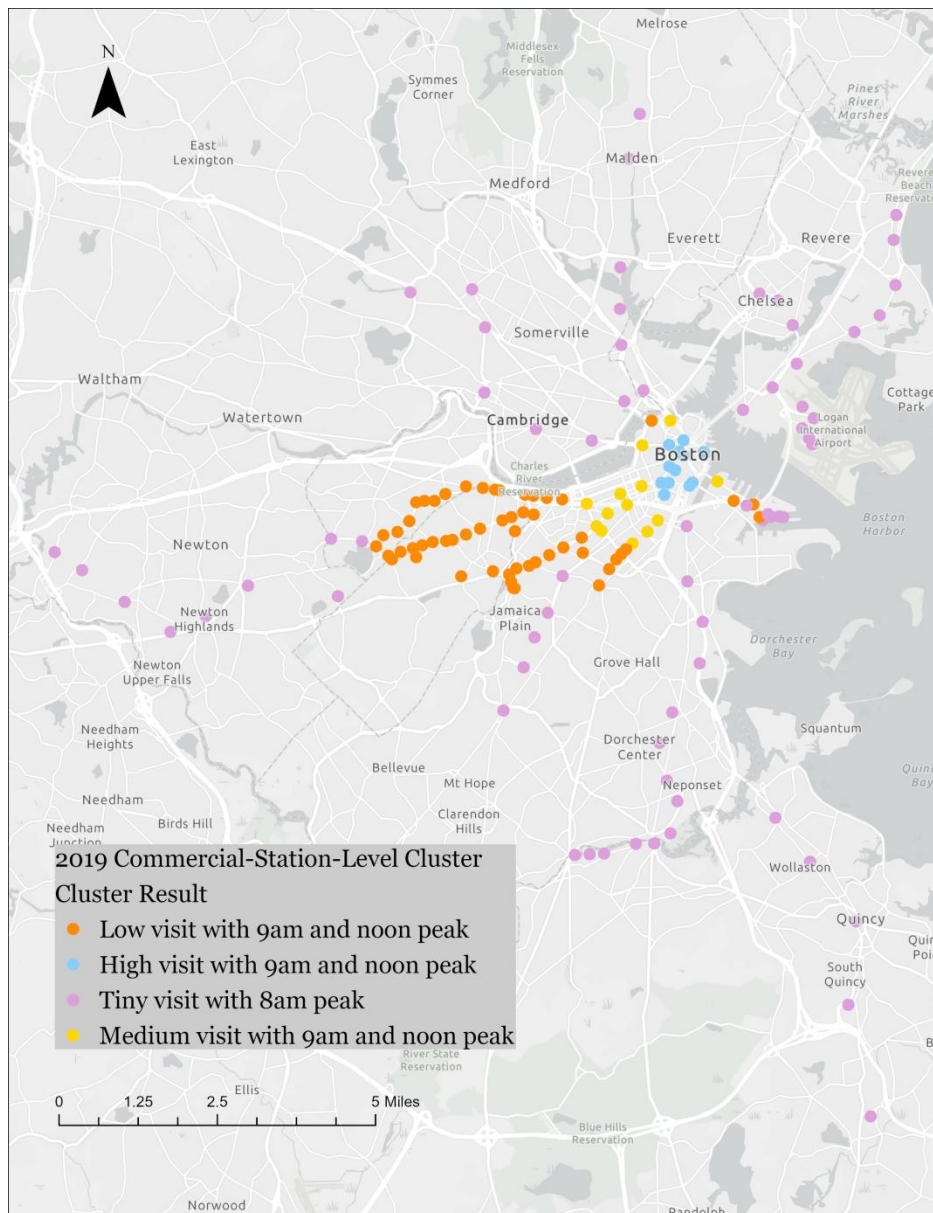
Figures 56 and 57 depict the spatial distribution of the clustering results at the commercial station level for these transit stations in 2019 and 2020, respectively. The commercial-station-level clustering results reveal a distinct spatial clustering, which I classify as central business district (CBD), downtown periphery (DTP) district, uptown,

and suburban areas. Except for those in suburban areas, visits to all transit stations fell.

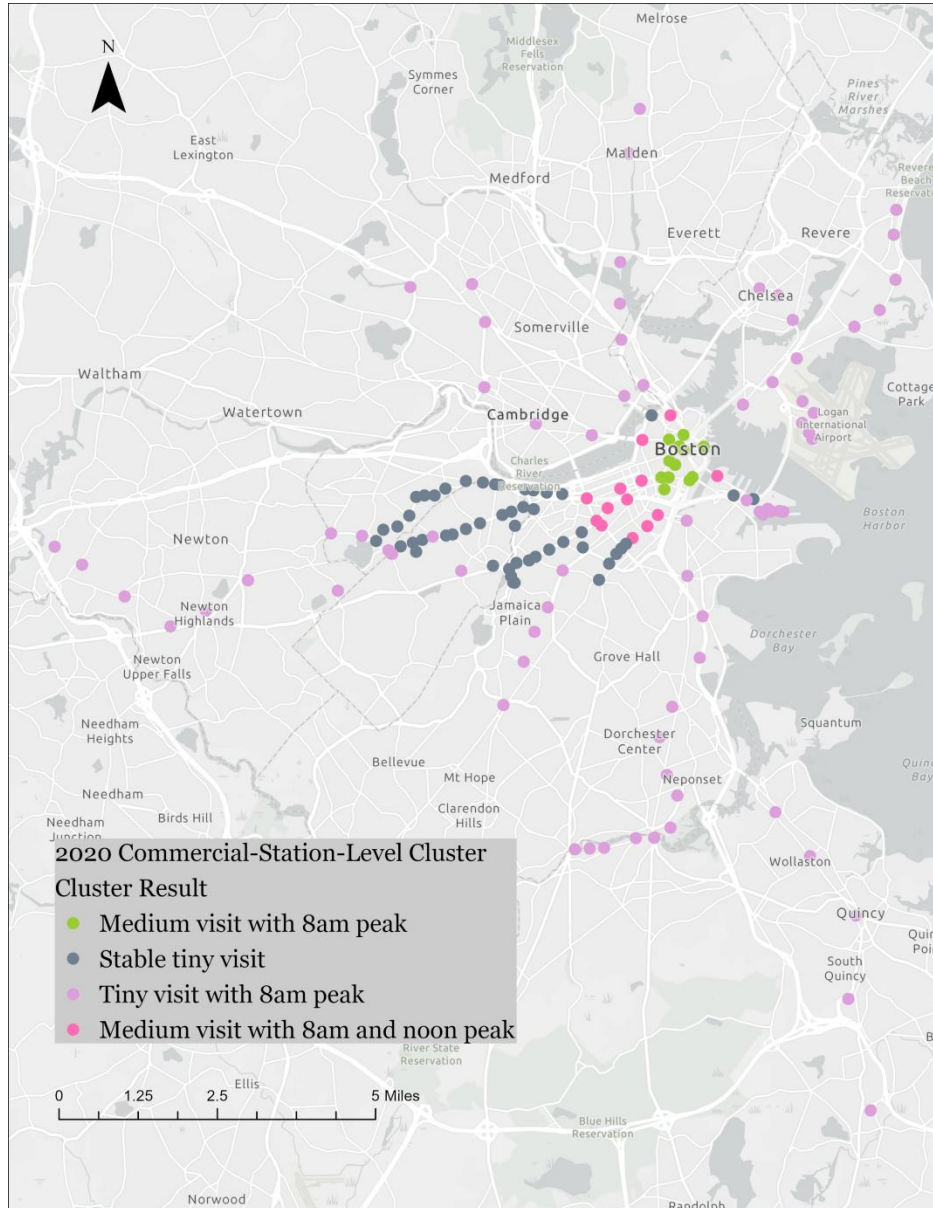
The transit stations in suburban areas maintained their clustering results despite little

daily visitation, with slight fluctuation. The following paragraphs will analyze the

changes in each region's transit station clustering.



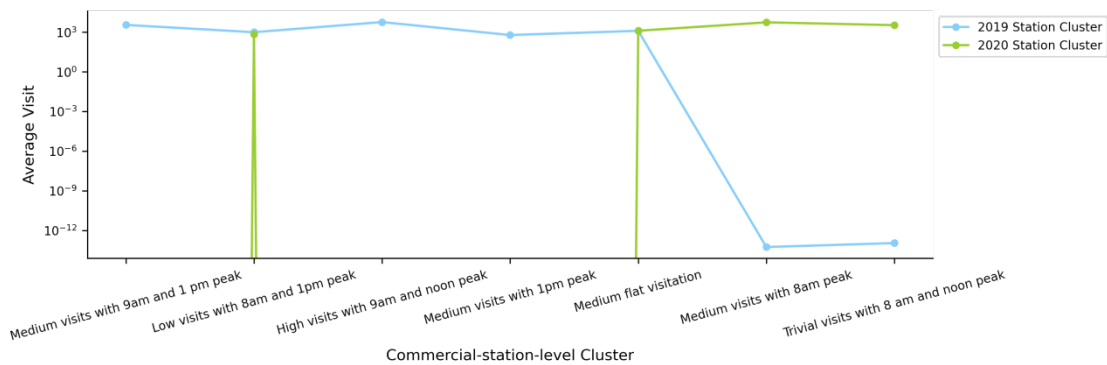
**Figure 56. Spatial distribution of commercial-station-level clustering results in 2019**



**Figure 57. Spatial distribution of commercial-station-level clustering results in 2020**

The clustering of the 12 transit stations in the CBD changed from *High visit with 9am an noon peak* to *Medium visit with 8am peak*. As illustrated in Figure 58, the timing of visits altered. Throughout the pandemic, the peak visitation time shifted from 9 a.m. to 8 a.m. While these stations maintained a higher foot traffic than others during the pandemic, visitation to all sorts of businesses decreased dramatically. Some *Low*

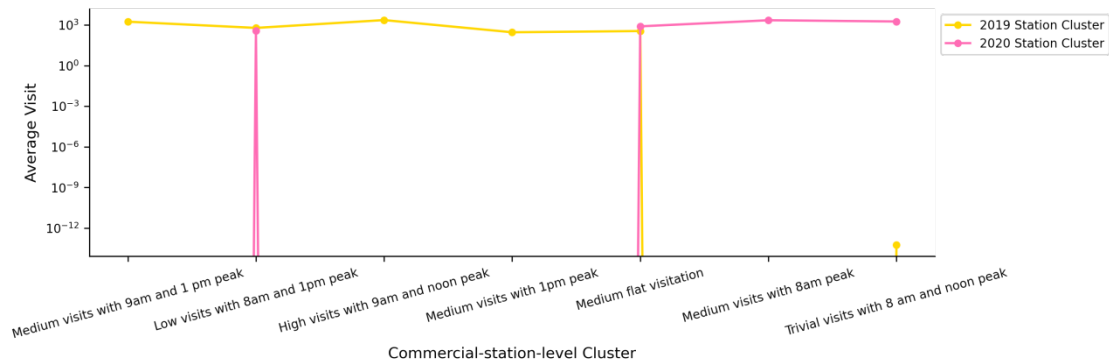
visits with 8 am and 1 pm peak and Medium flat visitation business types retained their pre-pandemic visit patterns, whereas numerous *Medium visits with 8am peak* and *Trivial visits with 8 am and noon peak* business types formed near these transit stations. Based on the results of the previous cluster analysis of commercial types, we know that the commercial types with the highest visitation are 'Accommodation and Food Services', and that the decrease in visits to this type of POI is the primary cause of the decline in popularity of downtown transit stations. Yet, the number of visits to certain businesses increased throughout the pandemic, including 'Arts, Entertainment and Recreation', 'Retail Trade', 'Information', and 'other service'. Besides, the access to 'Health Care and Social Assistance' saw little change.



**Figure 58. Visit pattern change in CBD**

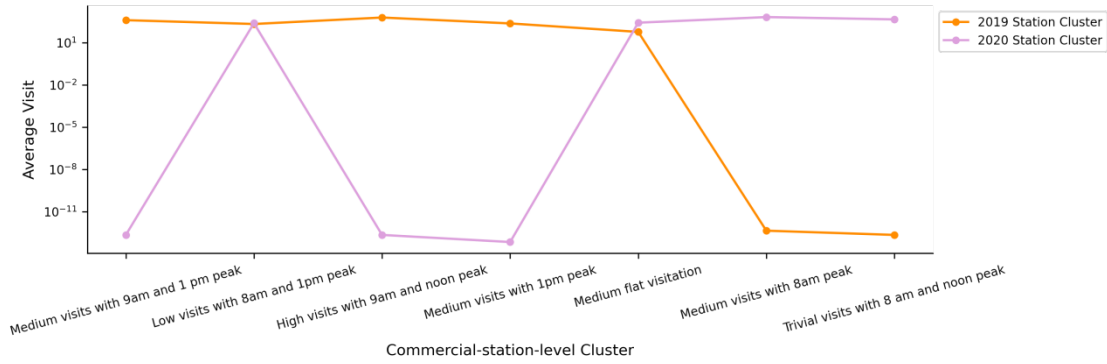
The clustering of the 13 transit stations in the DTP district changed from *Medium visit with 9am and noon peak* to *Medium visit with 8am and noon peak*. The vitality around the thirteen transit stations in the uptown area showed a similar change as

stations in downtown area during the pandemic, as shown by the visit patterns to the surrounding facilities. There was a preference for visits to business types similar to those in the downtown area, both before and during the pandemic. Nevertheless, the total visits to these three commercial types were relatively lower than in the downtown area.



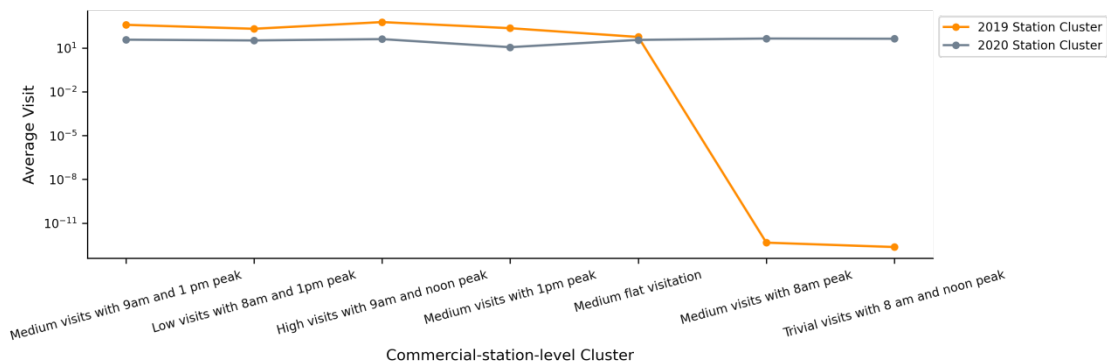
**Figure 59. Visit pattern change in DTP**

The clustering of the 49 transit stations in the uptown area changed from *Low visit with 9am and noon peak* to *Tiny visit with 8am peak*. Before and during the pandemic, the number of visits to the facilities surrounding these transit stations was minimal. Although the overall number of visits is substantially fewer than in the last two regions, most visits are also attracted by the four business types mentioned previously. In contrast to the first two regions, the suburbs experienced a large fall in the number of visit to the 'Accommodation and Food Services' around transit stations.



**Figure 60. Visit pattern change in uptown area**

It is interesting to note that the clustering results for five transit stations differ from the other transit stations in the area: Cleveland Circle, Reservoir, Washington Square, Brookline Hills and Design Center. These five transit stations shifted from *Tiny visit with 8am peak* to *Stable tiny visit*, suggesting that despite the low frequency of visits to these POI near transit stations, these visits remained relatively stable. Similarly, visits to these four industries near these transit stations grew.



**Figure 61. Visit pattern change in suburb area**

## **Chapter 5. Conclusion and Policy Implication**

### **5.1. Conclusion**

The worldwide COVID-19 pandemic has called for innovative knowledge and insights on how cities can respond more resiliently, especially for public transportation services. Different transit stations have varying levels of resilience when it comes to adaptation to changing habits and reducing the impact of visitation limitations. These critical discoveries can allow us to better understand which transit stations can be described as resilient. The findings imply that the visit patterns of POI and the vitality of transit stations in the Boston metropolitan area changed dramatically during the pandemic, which is verified by the results of two cluster analyses.

First, overall visits to POIs within a 15-minute walkable area of transit stations decreased dramatically during the pandemic, and daily visit patterns shifted significantly. Before the pandemic, peak visitation to these facilities occurred around 8 a.m., noon, and 1 p.m., yet these peaks vanished during the pandemic. This might be because more individuals switched to work from home (WFH), which reduces the need for travel. Despite the fact that visits around 8 p.m. decreased due to the pandemic, it was still the peak of the day.

Second, before and during the pandemic, Accommodation and Food Services was

the most popular type of business, followed by Arts, Entertainment, and Recreation and Retail Trade. Even though the impact of the pandemic has lowered the number of visitors to these businesses, they continue to receive a greater number of visits than other business types. In addition, visits to all business types were negatively affected by the pandemic, with the two business types, Accommodation and Food Services and Arts, Entertainment, and Recreation, being the most significantly impacted, indicating that the pandemic and social distancing policies have contributed to the decline in tourism. The requirement in social distancing and the transition to WFH have impacted access to amenities, decreasing the demand for transit facilities. During the pandemic, visits to educational facilities also fell dramatically. Despite this, individuals continue to use essential services such as grocery stores, health care, and restaurants, demonstrating that these essential services are crucial to individuals' daily lives.

From this study, we find that although the density of POIs around Malden Center and Quincy Center Station are low, there are numerous commercial types in these two areas. The majority of them are facilities that provide essential daily services. Therefore, it is necessary to highlight the variety of business establishments surrounding transit stations, particularly important retail establishments.

Third, the cluster analysis findings at the station level reveal that the vitality of

transit stations is strongly linked to their location. Prior to the pandemic, the number of visits to facilities around downtown transit stations was much greater than that of facilities around transit stations on the outskirts of the city. During the pandemic, the vitality of transit stations fell in all areas, but it was most severe around the 36 transit stations downtown. Most of these stations were surrounded by non-essential services and amenities such as shopping malls, office buildings, museums, schools, and places of worship during the pandemic. This shift in transit station vitality may be seen, for example, around Prudential Station, Northeast Station, and the Prudential Station.

Fourth, the COVID-19 influenced variations in activity distribution. Before the pandemic, activities were concentrated close to downtown transit stations, whereas activity was more spread spatially during the pandemic. Davis and Porter Station, both of which had weak vitality before the outbreak, drew more individuals to access there during the pandemic. These stations are typically found in the uptown region, where the majority of residents commute downtown for work, and individuals who need to telecommute during the pandemic, so they increase their access to services and facilities in the area.

In conclusion, the data-driven method demonstrates how we can evaluate the resilience of each transit station. Some of them responded well to the pandemic, while

others were disrupted. Either because services needed for daily life were not provided or because they were overly dependent on large influxes of people from elsewhere, and the changes in work patterns caused by the pandemic affected the original visit patterns.

## **5.2. Policy and Planning Implication**

Public transportation is a vital service that offers transportation to city dwellers. It is the most practical and affordable choice for many people, particularly those with low incomes. However, transit station vitality was severely impacted throughout the COVID-19 crisis. While people's mobility is limited by physical distancing, there is a potential to improve transit station vitality by planning and designing the structure of services and amenities surrounding transit stations. Consequently, the city must plan to increase the resilience of transit stations during the pandemic to mitigate the pandemic impact of people's accessibility and prepare for similar events in the future.

During the pandemic, we observed that home-ordering and telecommuting initiatives reduced visits to the office and leisure-intensive transit stations, whereas transit station vitality in the urban periphery increased. Hence, physical distancing alters the expectations for transit stations. It is beneficial to increase coordination between transit and land use planning, as well as comprehension of the availability of

the built environment to offer what residents demand. For instance, increasing connectivity around transit stations to grocery stores, medical facilities, and amenities required for daily life. Seniors and individuals with disabilities need more convenient and affordable access to these facilities.

Also, transit stations that maintained vitality during the pandemic, such as Harvard and Central Station, show the importance of walking accessibility and transit connections to the vitality of transit stations. In addition to the station's node degree, a popular station is typically accompanied by excellent external transit links. Hence, planners should consider increasing the accessibility around transport stations.

Furthermore, there is a particular need for bicycle and pedestrian infrastructure for low-income individuals since such infrastructure will give reliable, affordable, and convenient transportation options. Residents will not only be able to plan their travel with minimum COVID-19 exposure, but they will also be able to conveniently transfer between different forms of transportation from the first mile to the last mile.

As the pandemic's impacts persist, policymakers and planners should modify their strategies accordingly. We have seen the value of investing in transit stations in Boston's suburbs and surrounding communities. Low-income residents are forced out of the downtown area to live on the city's outskirts due to high housing costs.

Policymakers could alleviate these burdens by encouraging transit agencies to collaborate with transportation network companies (TNC) and non-motorized shared mobility companies to facilitate last-mile travel and develop sustainable multimodal transportation systems. This may encourage residents to use the transit station, allowing communities around them to stay resilient in a post-pandemic future.

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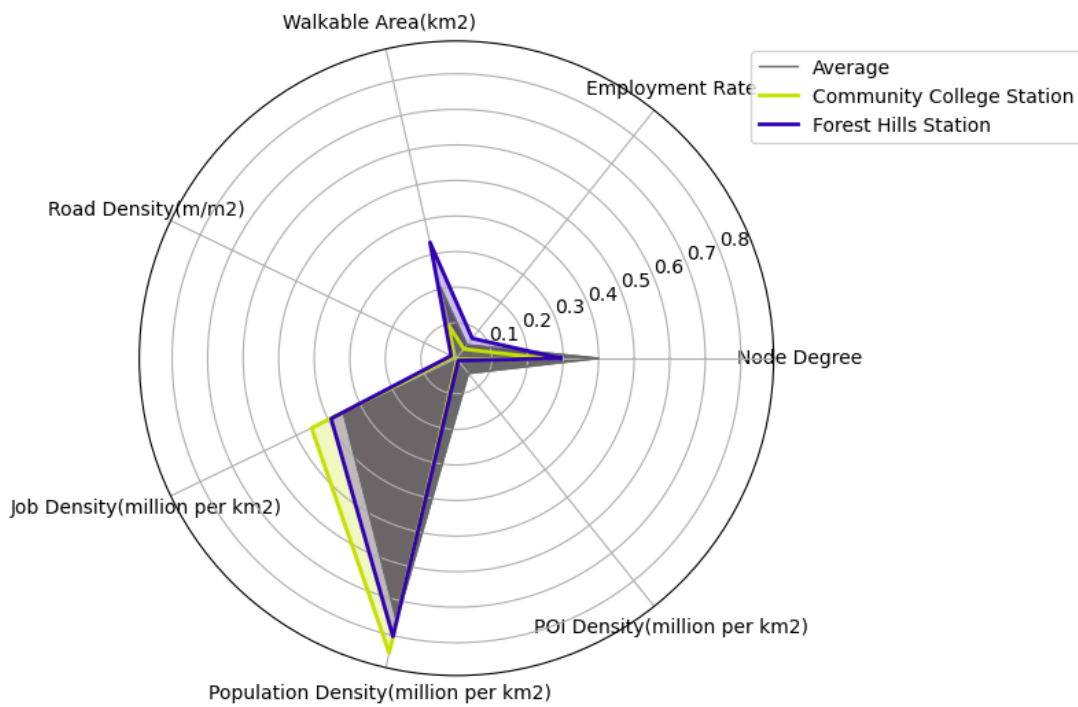
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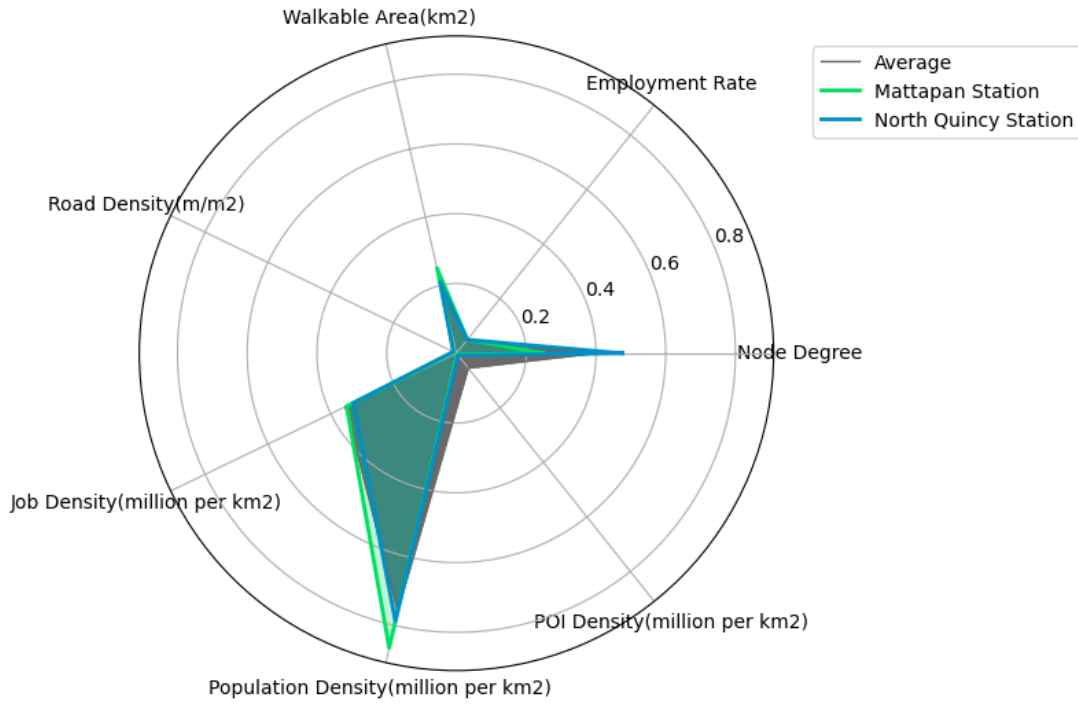
# Appendix



**Figure 62. Social demographic and building environment of Braintree and Chestnut Hill Station**



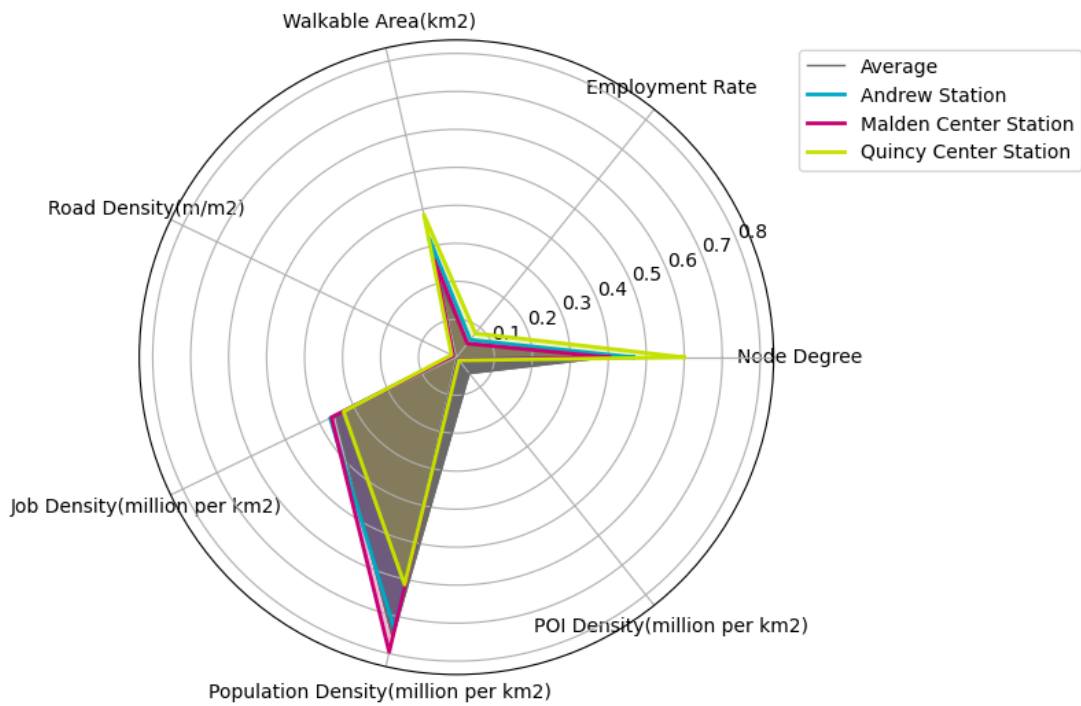
**Figure 63. Social demographic and building environment of Community College and Forest Hills Station**



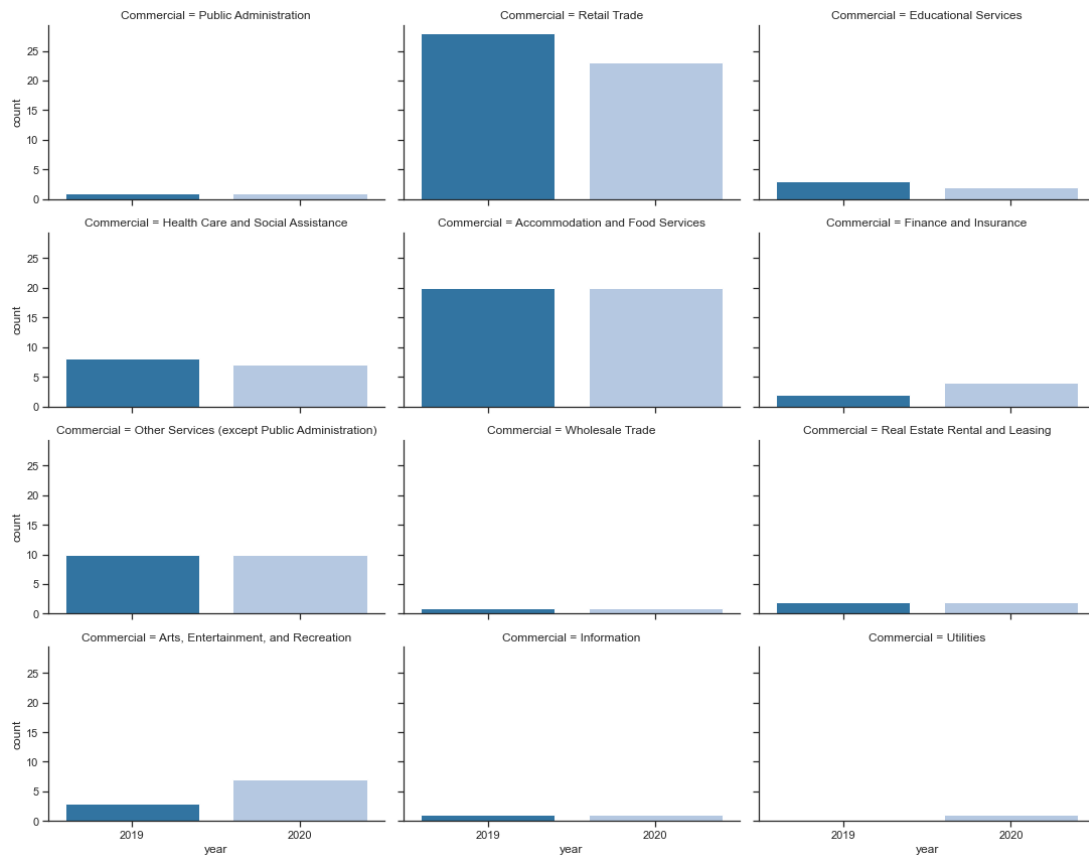
**Figure 64. Social demographic and building environment of Mattapan and North Quincy Station**



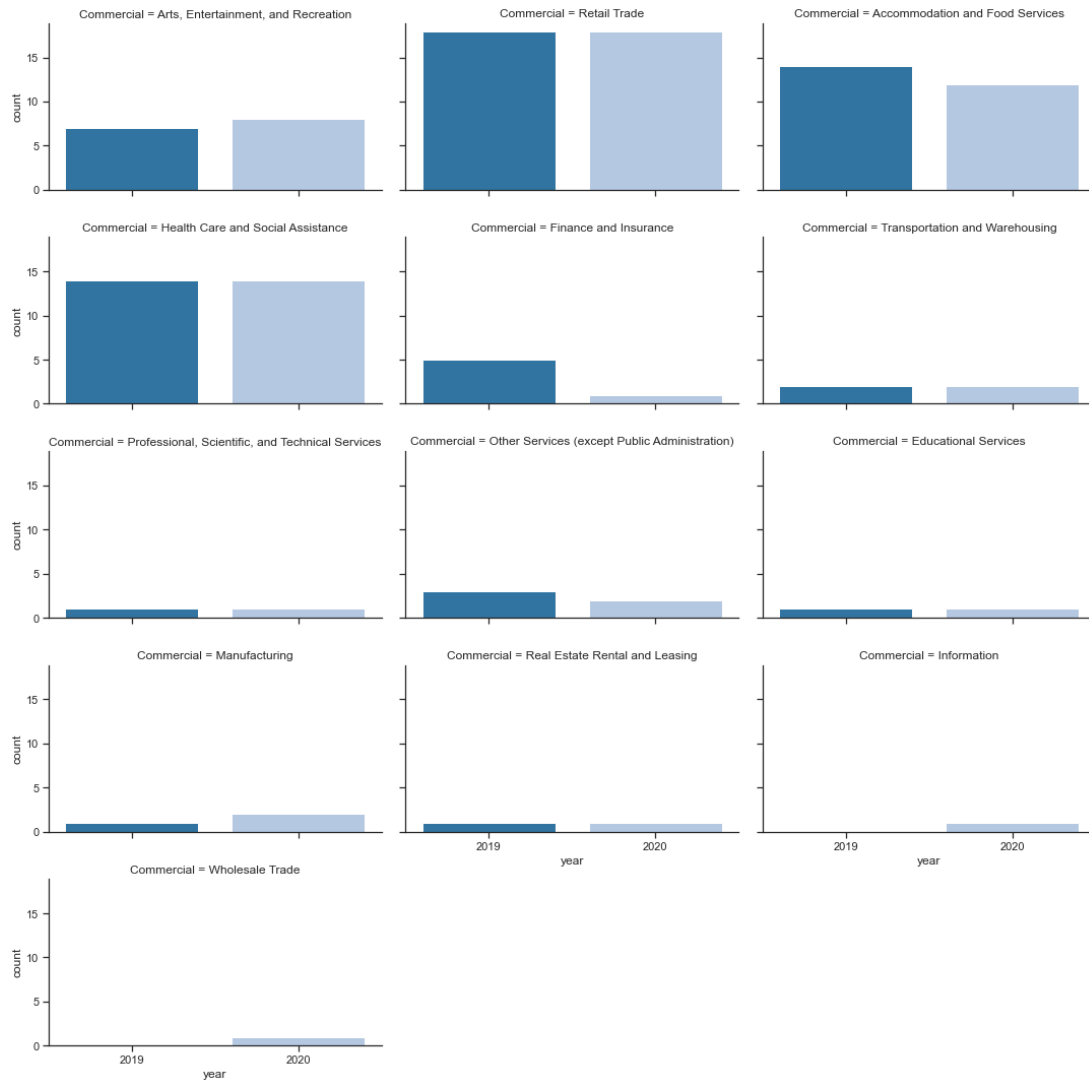
**Figure 65. Social demographic and building environment of Quincy Adams, Savin Hill, and Sullivan Square Station**



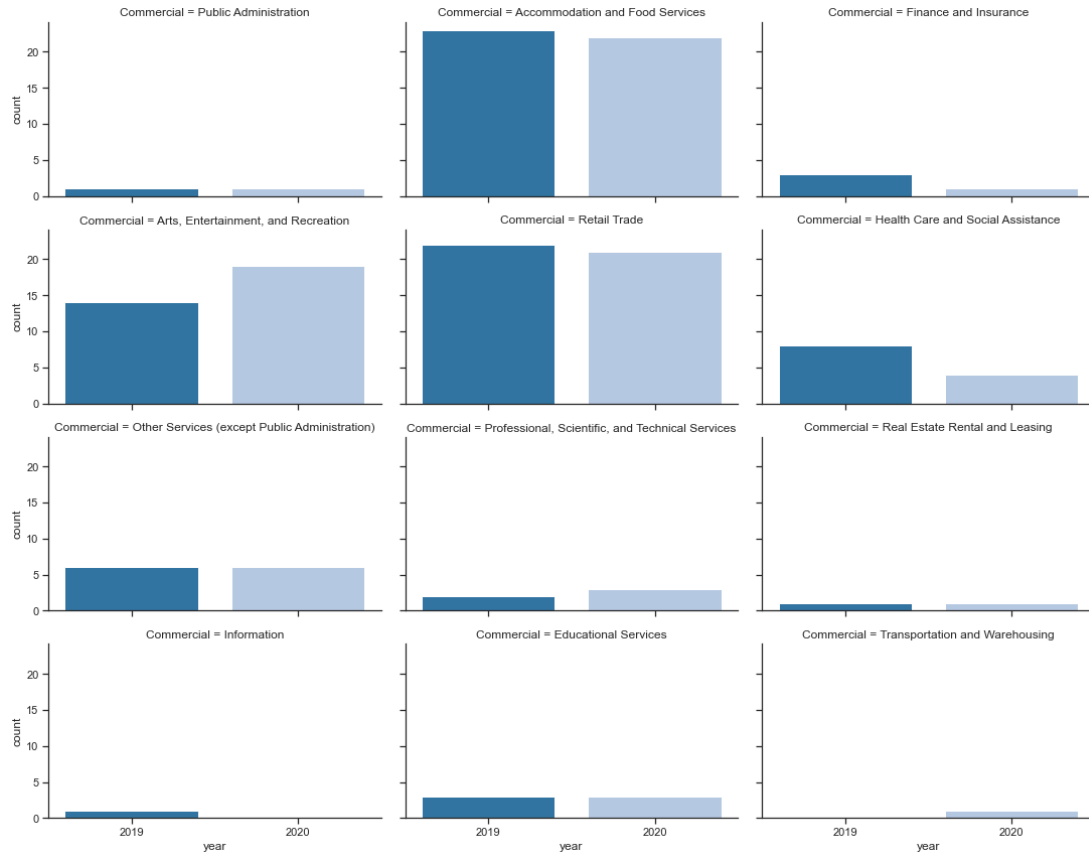
**Figure 66. Social demographic and building environment of Andrew, Malden Center, and Quincy Center Station**



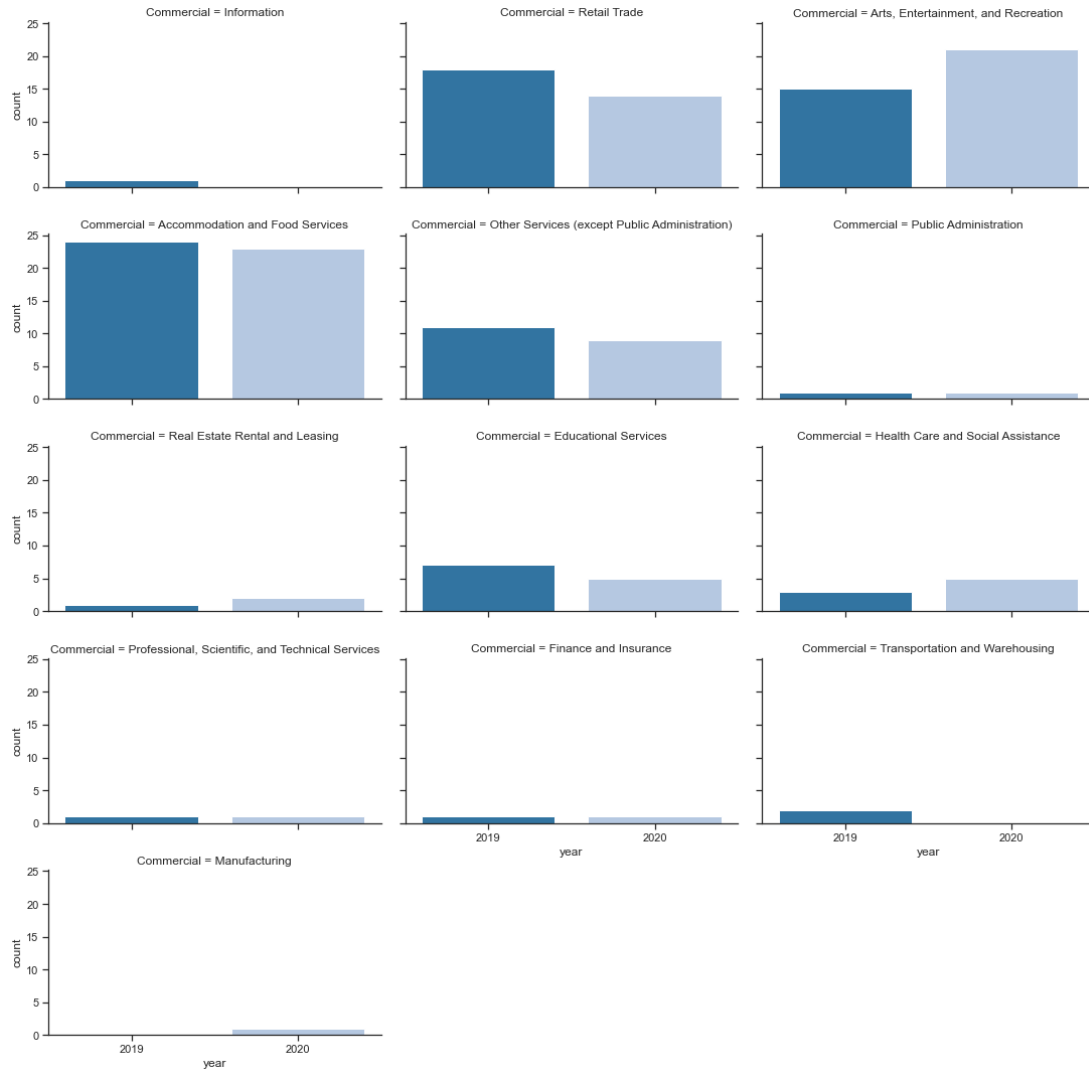
**Figure 67. Commercial type statistical distribution of Braintree Station**



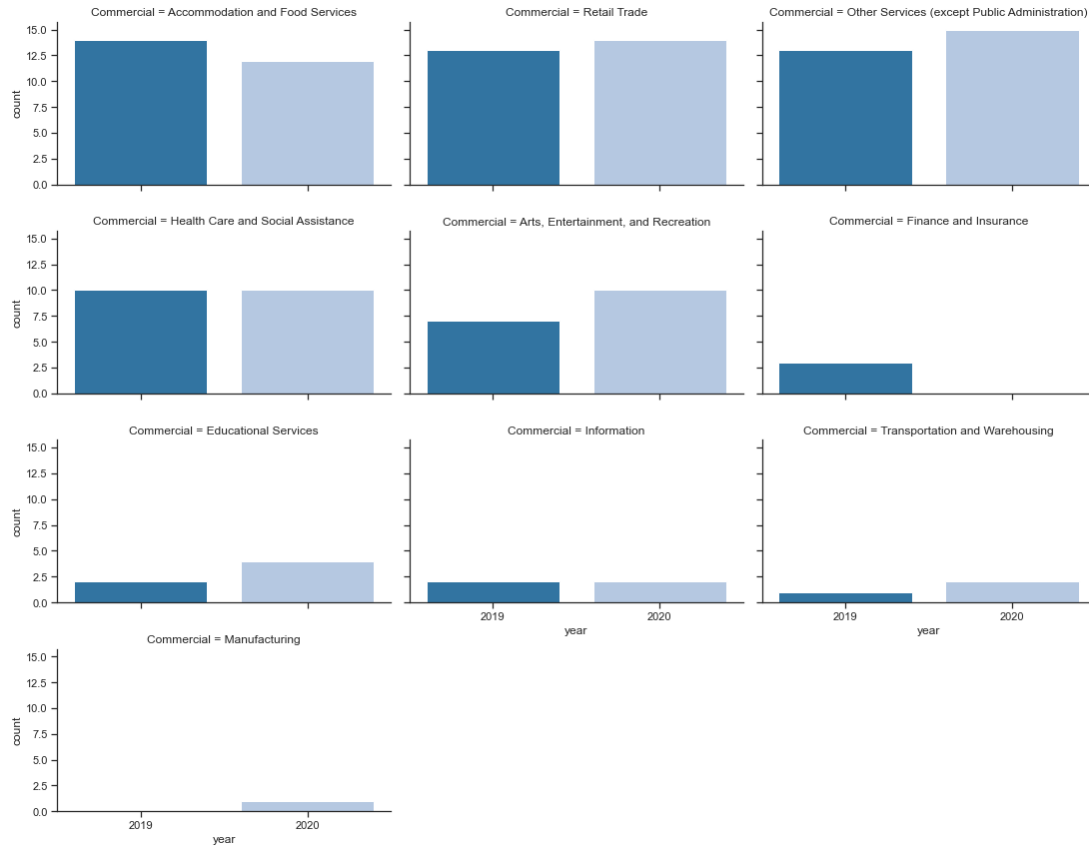
**Figure 68. Commercial type statistical distribution of Chestnut Hill Station**



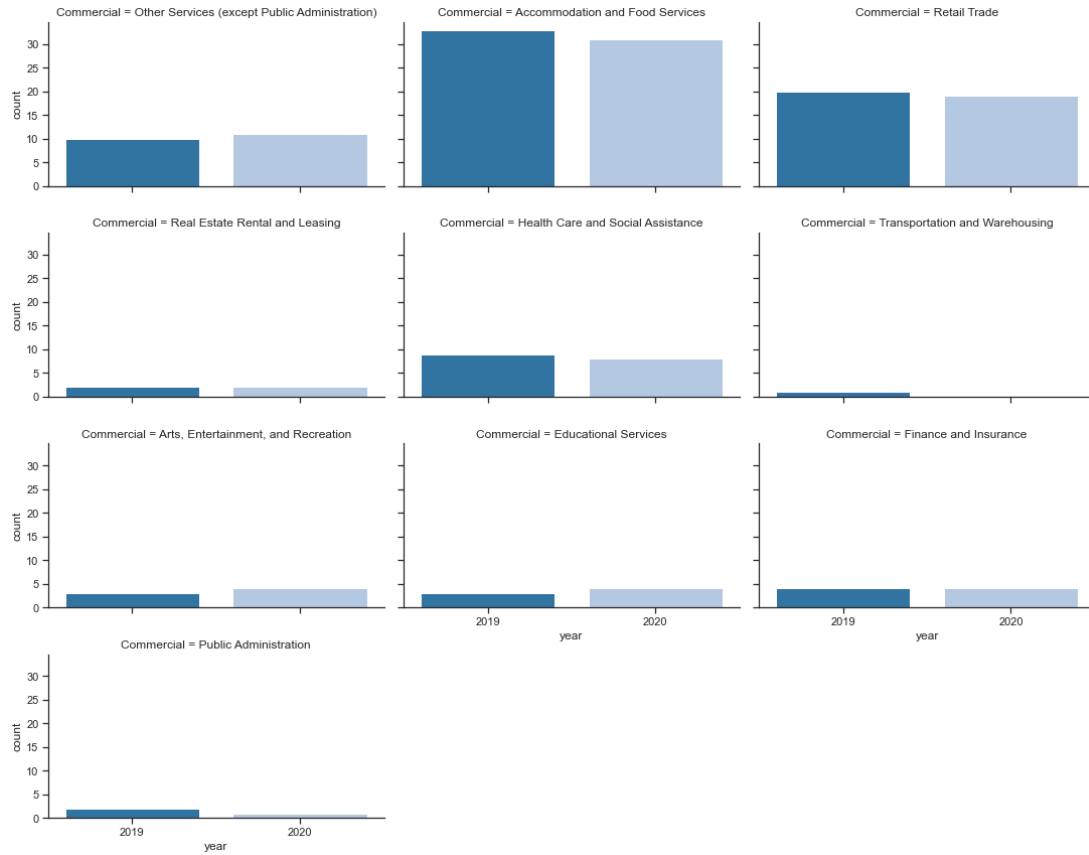
**Figure 69. Commercial type statistical distribution of Community College Station**



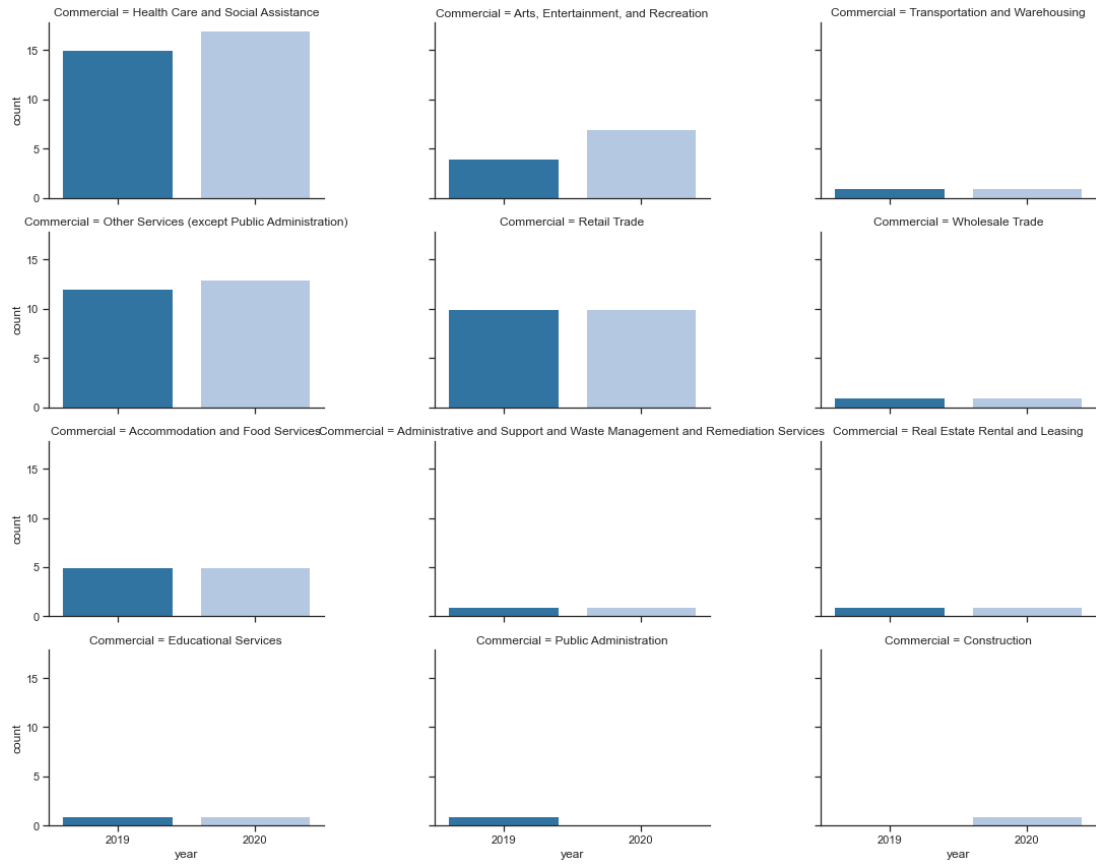
**Figure 70. Commercial type statistical distribution of Forest Hills Station**



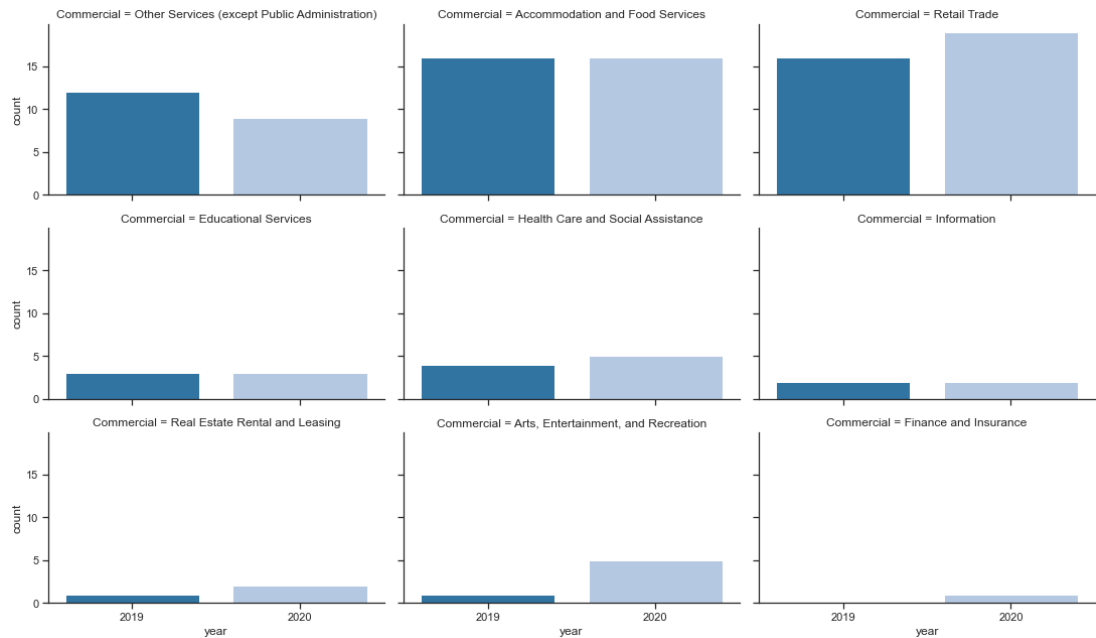
**Figure 71. Commercial type statistical distribution of Mattapan Station**



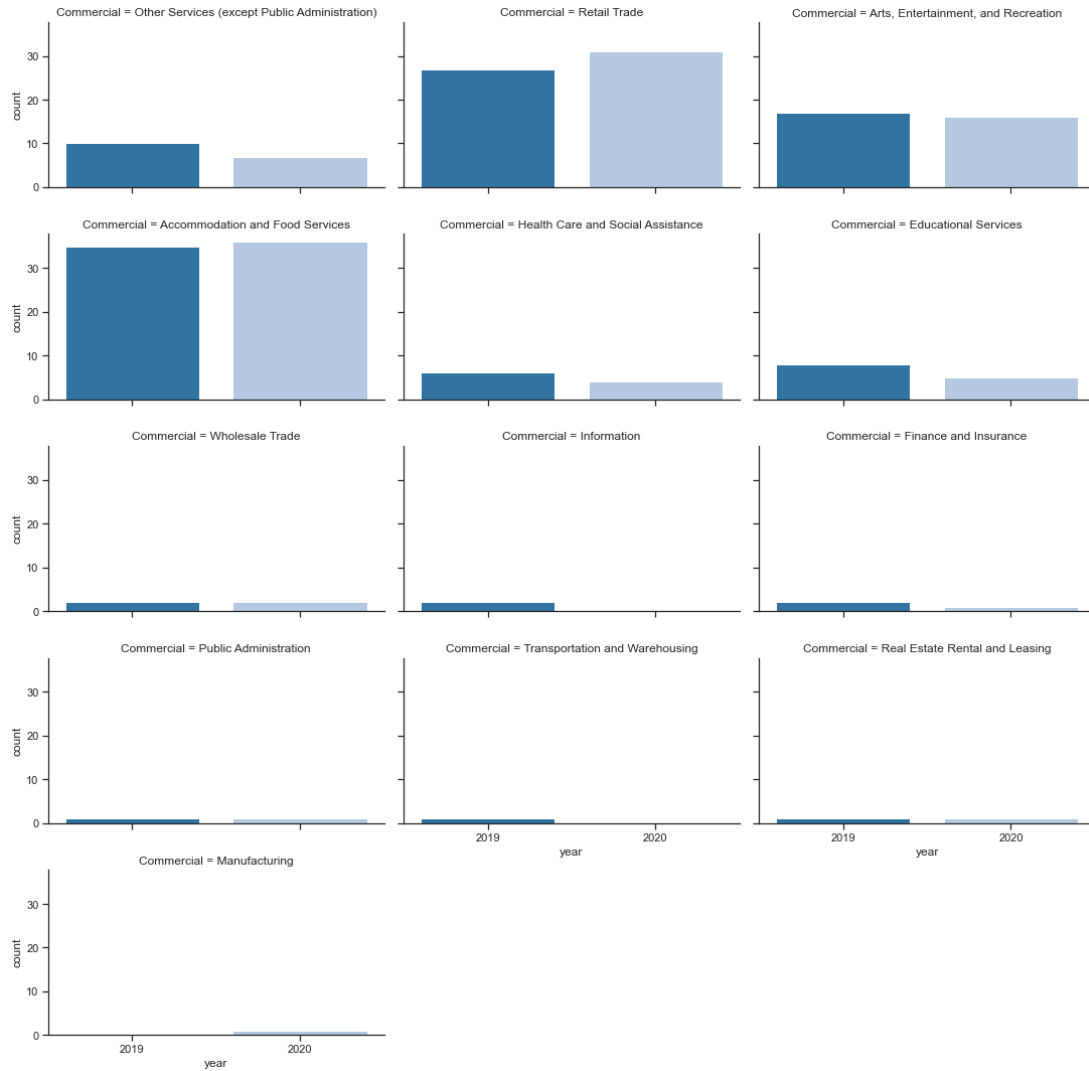
**Figure 72. Commercial type statistical distribution of North Quincy Station**



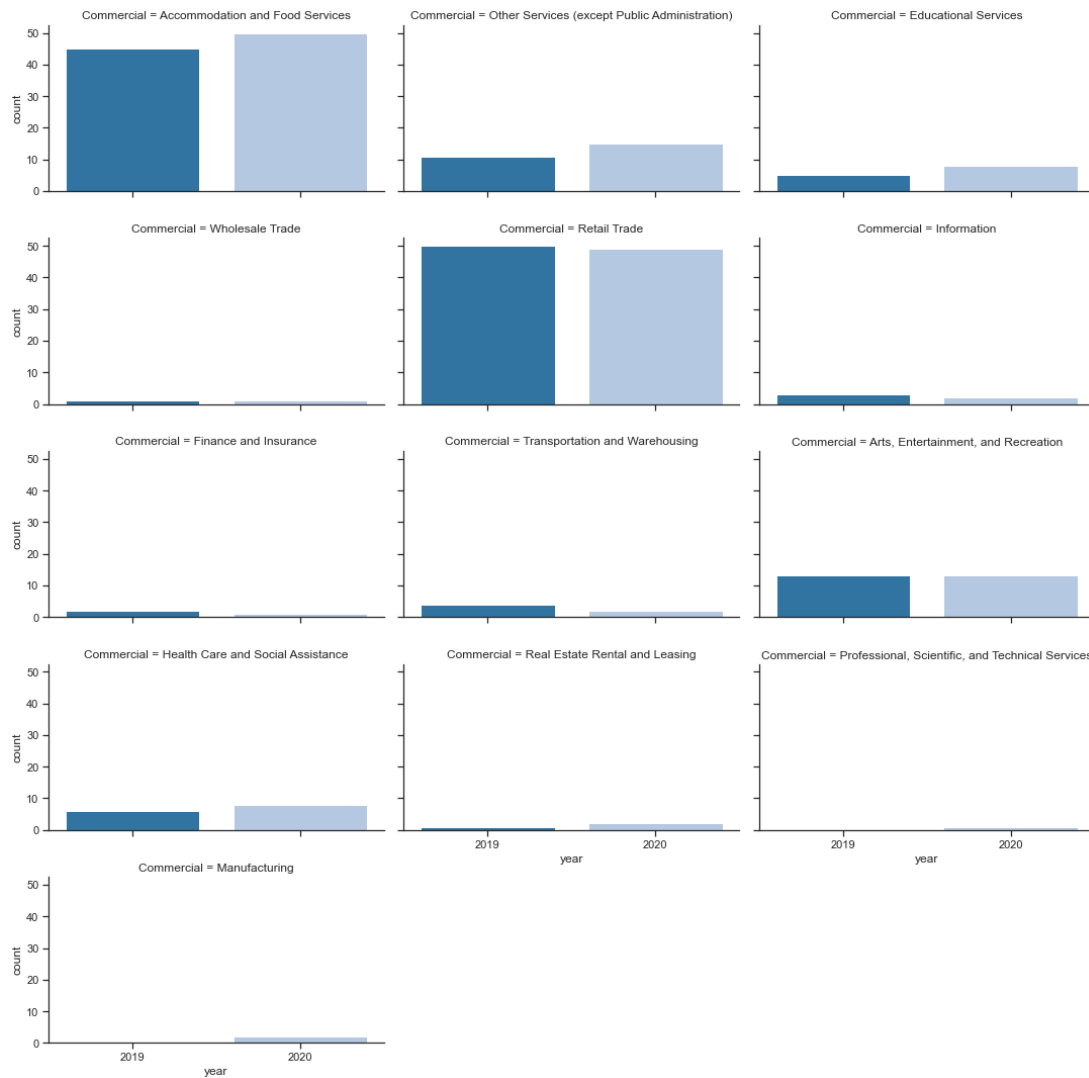
**Figure 73. Commercial type statistical distribution of North Quincy Station**



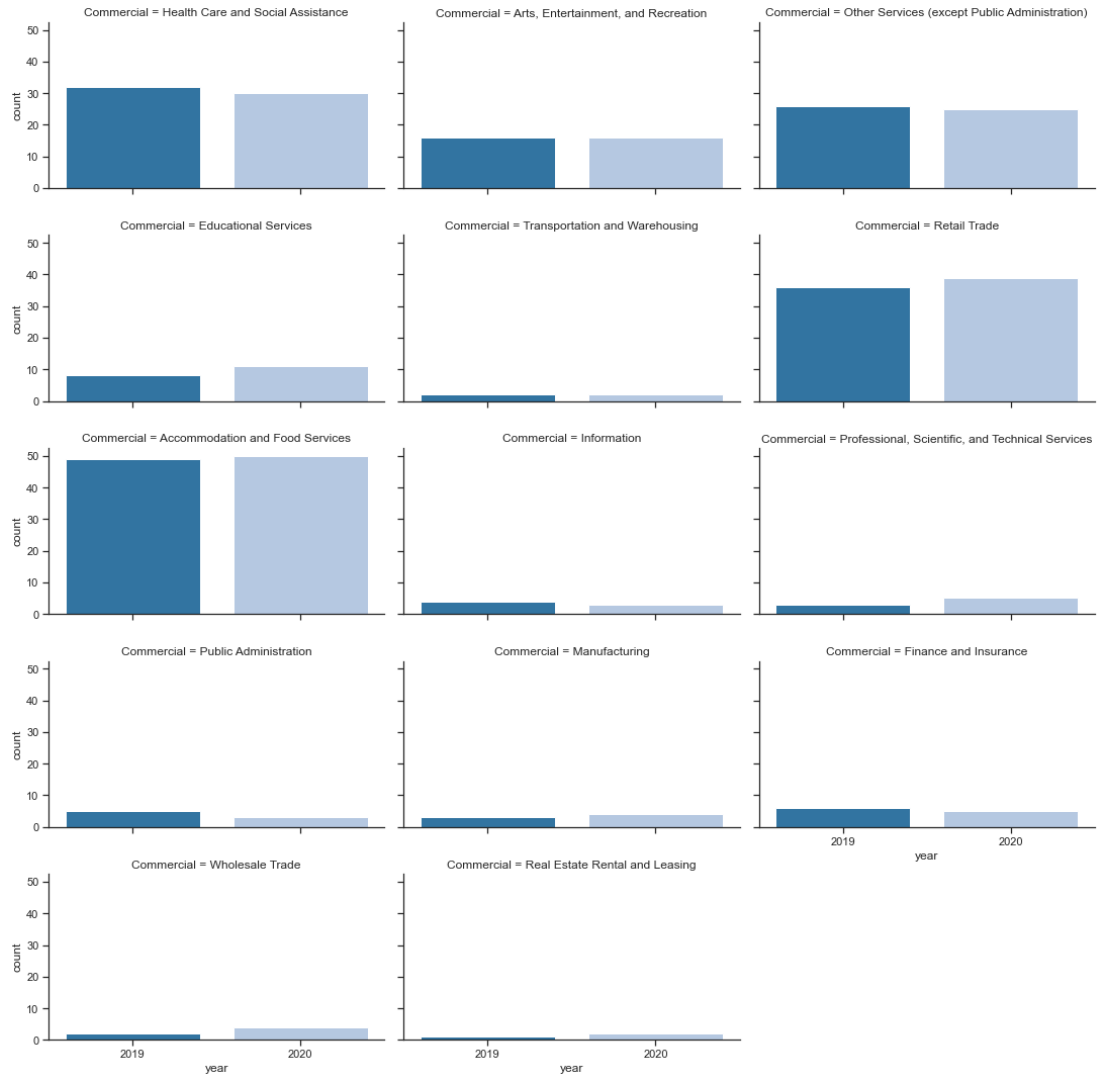
**Figure 74. Commercial type statistical distribution of Savin Hill Station**



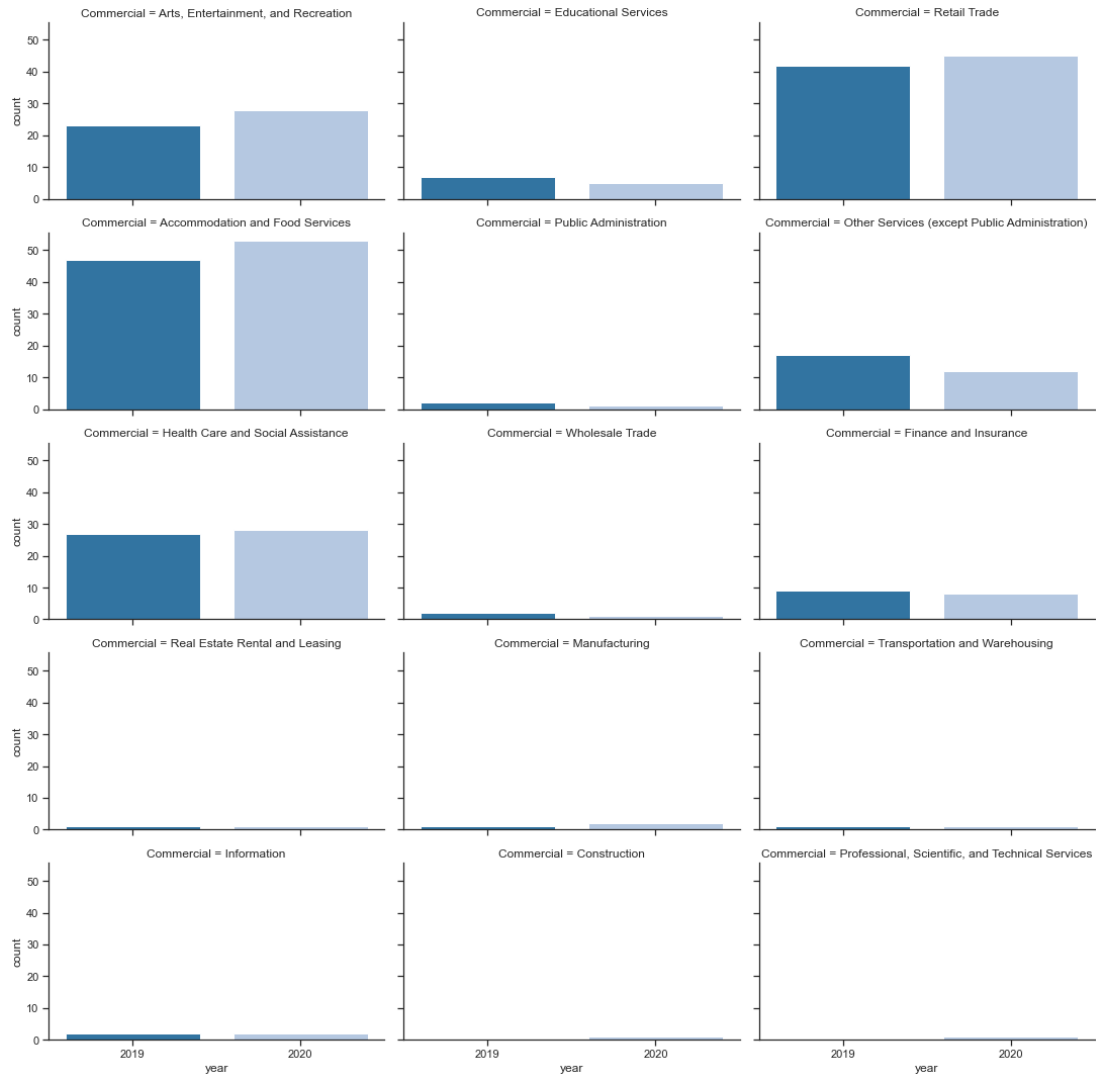
**Figure 75. Commercial type statistical distribution of Sullivan Square Station**



**Figure 76. Commercial type statistical distribution of Andrew Station**



**Figure 77. Commercial type statistical distribution of Malden Center Station**



**Figure 78. Commercial type statistical distribution of Quincy Center Station**