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Research Paper

In Light of the Automated Fare Collection Data, How Did the Travel Patterns of Transit Riders in Tehran Change following COVID-19?

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Abstract

The spread of COVID-19 caused some problems in public transportation. The pandemic created new challenges for developing countries like Iran, where public transportation is already plagued by many problems. As a result of COVID-19 concerns, it was speculated that unpredictable travel patterns would result. Based on Automatic Fare Collection data, in which passengers use a smartcard to enter a stop, this study evaluates this speculation. The dataset includes one month of transactions for each of the three COVID-19-related years (2019, 2020, and 2021) in Tehran, the country's capital. By using time series clustering, it was found that a new pattern of travel has emerged. Before vaccination, most origins were in the eastern part of the city; whereas, in the new era, most of the origins are in the western part of the city. The peak hours have also undergone a significant change. Prior to the pandemic, the peak hour occurred between 7 and 8 o'clock in the morning, and demand reduced until the evening peak hour, but as a result of the new pattern, demand did not decrease significantly after 8:00:00, which resulted in new peak hours. It is anticipated that these changes will have a domino effect on Tehran's transit system as a whole. The system may not be able to handle the changes in behavior, as it was designed to deal with pre-pandemic behavior patterns. There is a need for rescheduling to resolve the problem. Additionally, the government should develop a long-term plan for restoring public transportation demand to its pre-pandemic level.

Keywords: Public Transportation, COVID-19 vaccination, Transit Ridership, Machine Learning, Time series clustering

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1. Introduction

Following the spread of COVID-19, transit systems revealed an important weakness: it was almost impossible to meet the social distancing without reducing capacity in most modes. Therefore, both users and drivers are at increased risk of contracting the virus. There has been a modal shift, a decrease in ridership, etc., in public transportation as a result of the risk (Zhang and Hayashi, 2022). Public transportation has been described as one of the sectors which has experienced significant changes as a result of the pandemic (Jenelius and Cebecauer, 2020). Numerous studies have examined the transportation consequences of the virus (Beck and Hensher, 2020; Beck and Hensher, 2020; Zhang and Hayashi, 2021; Das et al., 2021; Rothengatter et al., 2021). In the first few months following the outbreak, governments around the world attempted to limit the use of public transport, as well as the users themselves. Specifically, their modes of transportation changed (Zhang and Hayashi, 2022). As a result, the use of public transportation decreased significantly in many countries, from the developing countries to the developed countries. As Iran had been experiencing an economic crisis, the situation was even more critical. During the outbreak of the virus, Tehran, the capital of Iran, was considered to be one of the most dangerous areas of the world in terms of COVID-19 infection risk (Arab-Mazar et al., 2020). Thus, it seems necessary to study the impact of the virus on transportation, specifically public transportation in Tehran. Generally speaking, there have been three phases of the outbreak in Iran: before the first confirmed COVID-19 infection, after the confirmation, and after mass vaccination started. To the best of the authors' knowledge, no transparent statistics or analysis have been conducted regarding the effects of the virus on transit ridership patterns using smartcard data, in this case Automatic Fare Collection (AFC) data, in the country since the beginning of the outbreak. To explore how much the transit ridership, in the form of BRT, has been affected, this research presents some figures and analyzes them thoroughly.

The following are the main contributions and essentiality of this study:

1. The number of studies concerning the COVID-19's effect may appear to be high, but some scholars still believe that “there are limited studies on the impact of COVID on transportation”
(Mogaji et al., 2022).
2. There have been a few studies, to the best of our knowledge, in which AFC data has been used in order to understand behavior changes caused by outbreaks. It is true that a lot of precious works can be found regarding COVID-19 effects on different aspects of public transport, but most of them are based on survey data, whereas the results and conclusions in this paper are based on intelligent system data collection. Compared to other studies, this may be considered to be an advantage.
3. A number of papers (Mogaji et al., 2022; Abdullah et al., 2021; Mogaji, 2022; Kutela et al., 2021) have confirmed that most studies are conducted in developed countries. A country such as Iran is not considered to be a developed one. We can gain a better understanding of how the virus has affected transit users' behavior in developing countries through this paper.
4. When examining COVID-19 and its impact on Iranian citizens, it is important to remember one important aspect: the relatively late vaccination period in comparison with other countries. Thus, Iran's situation has become unique when compared to other nations. It is noteworthy that Iranians experienced 3 different time periods before, during, and after breakdown, in contrast to most countries that experienced before and after breakdown. The importance of this study is further enhanced by this special circumstance.

5. According to (Zhang and Hayashi, 2022), “how to evaluate the impact of the virus on transportation is still a problem, needed to be addressed”. As far as the authors are aware, no previous study has used time series clustering to examine how public transport travel patterns have changed as a result of COVID-19, so this paper adds to the literature from an analysis-method standpoint.

The remaining of this paper will be a "literature review” where the related studies concerning the topic of this paper are reviewed, then in the "methodology" section, the data and analysis are explained, and in “results and discussion”, the results of the analysis are discussed. In the "implication" section, the consequences of changes in travel patterns are explained. Finally, in the "conclusion" section, this paper is concluded and the possible directions of future studies are shown.

2. Literature Review

Since the beginning of the pandemic, many studies have been conducted to understand the effects of the virus on transit sector, most of which belong to the developed countries. In the US, it was found that transit riders were affected more seriously than non-riders in terms of trip making (Parker et al., 2021). A survey conducted in Toronto, Canada confirmed the existence of a decrease in transit ridership (Wang et al., 2020) and another study found that car ownership plays a significant role in this decrease (Loa et al., 2021). Observing a lower decrease in transit ridership in Seoul and Singapore compared to the US, Europe, and China led to the conclusion that ridership reduction is more affected by the severity and duration of lockdowns rather than infection rates (Xin et al., 2020). Others have pointed out measures such as physical-distancing as one of the most important reasons for reductions of service capacities (Limsawasd et al., 2022) which would naturally result in a decrease in ridership. This decrease has reached up to 90 percent in some areas (Gkiotsalitis and Cats, 2021). Another paper demonstrated that there is a relationship between the transmission of the virus and transit mobility (Cazelles et al., 2021). Using smartcard data and developing linear time series models, it was found that concerns of infection during commutation influences the transit ridership significantly (Giouroukelis et al., 2022). Some tried to give solutions for the COVID-related problems. For example, a paper (Zhao et al., 2023) after modeling the infection risk of riding transit, for the purpose of decreasing infection risk, proposed a new strategy called “split route” which may replace “capacity reduction strategy”. As mentioned earlier, in the developing countries like Iran, the knowledge about COVID-19’s effects on transportation is limited (Kutela et al., 2021) and most of studies are from developed countries (Cao et al., 2021; Benita, 2021). However, a survey in Iran showed that when it comes to public transportation, customer satisfaction with taxies were the highest during the pandemic (Shabani et al., 2022). In Ghana, it was examined if the social distancing and mask wearing was compiled in the country’s paratransit buses (Trotro). The results of compliance to the social distancing was promising, however, about mask wearing the situation was disappointing (Dzisi and Dei, 2020). In Bangladesh a survey was launched to study travelers’ behavior in the new normal situation and their tendency to choosing active modes after leaving public transportation (Zafri et al., 2021). (Lizana et al., 2023) used the AFC data of Santiago of the whole transit network to estimate the location of passengers' residences. Accordingly, they found that the return to public transport among Santiago's citizens is not homogeneous on a demographic basis. In an analysis of the GPS data obtained from the mobile phones of 101 volunteers, (Ciriaco et al., 2023) found that most trips were created for commuting during the pandemic. Based on an analysis of movit data for 87 cities around the world, (Nikolaidou et al., 2023) found that among developed countries, Italy and Greece have left public transportation more frequently than the average.

As it can be seen, one can barely find studies about developing countries in order to understand what exactly happened during the pandemic and after vaccinating. Besides, for a few countries such as Iran, data on mobility since the beginning of the pandemic presented by GOOGLE does not exist, which adds to the necessity of this study. Fortunately, the authorities agreed with giving us the smartcard data of the most populated BRT line in Tehran in three time intervals, so for the first time some insights can be given on this issue in Iran. Besides, as (Zhang and Hayashi, 2022) adequately put in their review paper, “Among the many unresolved questions, we think the most importation questions should be 1) how to address the impacts of Covid-19; and 2) when and how to recover to a ‘new normal’.” One of the goals of this paper is answering the first question in a developing country.

In this paper, ridership and travel patterns will be compared in 3 time intervals: before confirming the first COVID-19 infected case, after confirming, and after starting mass vaccination. We will analyze the most frequent used BRT line in Tehran, a line that connects the east and the west areas of the city (Lane 1, which connects stop Tehranpars to Payaneh Azadi and vice versa).

3. Methodology

3.1. Study Location

Figure 1 illustrates the case study. This paper focuses on the red line. As can be seen in the figure, this line connects the western and eastern parts of Tehran (the capital of Iran). The study covers three time intervals: October 22 to December 21 in 2019 and the same time intervals in 2020 and 2021. The paper might be criticized for studying only one BRT line, and therefore the following explanations may be necessary:

1. It is clear that access to a larger dataset, which would have allowed us to examine Tehran's entire transit system, would have resulted in a more insightful study, but unfortunately, unlimited access was not possible.
2. As this is the AFC data of the most important BRT line in the city, where more than 100,000 trips per day are taking place in a normal situation, this data still tells a lot about what has been happening in transit ridership in Tehran.
3. Tehran's transit system is very important due to the fact that this line connects the east and west with 27 stops in the westbound direction and 26 stops in the eastbound direction, with many stops located in the central business districts.
4. The purpose of this study is to determine whether COVID-19 has contributed to the development of new travel behaviors in the city's public transport system. In the event that evidence of changes in the most important BRT line in Tehran exists, it can be concluded that a new pattern is emerging in the entire system. A significant change in any part of the public transportation system will have a domino effect on other parts, since all modes of public transportation are interconnected. We can therefore assume that if we can demonstrate that the first line of the BRT system has undergone a significant change, then the rest of the system has been affected as well. The claim that travelers' behavior has been influenced by new-born patterns will therefore be confirmed.

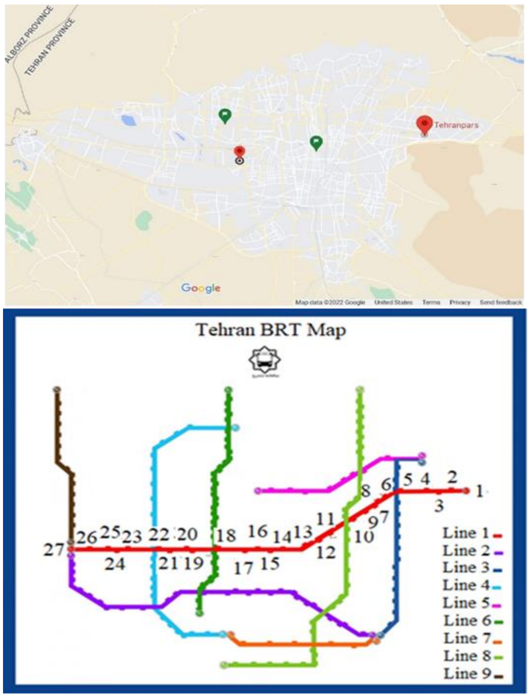

Figure 1. Line 1 of the BRT system in Tehran

Also, table 1 shows the name of stops from east to west.

Table 1. The name of stops from east to west

Name	Number
T.Pars	1
Darioush	2
Khagani	3
Aboureihan	4
Ayat	5
NirHav	6
Vahidieh	7
Sabalan	8
Foroudgah	9
Fathana	10
BouAli	11
Montazeri	12
I.Hossein	13
Pole	14
Shariati	15
Darvazeh	16
Ferdosi	17
ValiAsr	18
Daneshgah	19
Enghelab	20
Gharib	21
Navab	22
Behboudi	23
Sharif	24
Moeen	25
Kgozar	26
PAzadi	27

3.2. Analysis Method

When sample sizes are large, the chi-square test is often used in the analysis of contingency tables. This test examines whether two categorical variables (two dimensions of the contingency table) are independent in influencing the test statistic (Ryabko et al., 2004). The term heat map refers to a 2-dimensional visualization technique that uses colors to indicate the magnitude of individual values within a dataset (Barter and Yu, 2018).

To analyze data some simple statistical methods along with time series clustering are employed. In this paper, time series clustering is used to understand possible pattern changes over the years.

A time series can be defined as a sequence of variable values which are ordered by time (Javed et al., 2020). Clustering is considered to be a popular unsupervised machine learning methods, in which data points are divided and those which are similar are put in same groups called clusters (Wu et al., 2009). Different methods of clustering with different kind of data including time series have been used widely in transportation studies (Asadi and Regan, 2021; Sundarkumar et al., 2021; Alonso et al; 2020; He et al., 2020; Almana et al., 2019; Chen et al., 2019; Aziz and Ukkusuri, 2018; Lane, 2021). Here there are several terms: clustering, time series data, clustering methods, time series clustering methods, evaluation the clustering and etc. Explaining and reviewing all of those concepts and methods, is beyond the goals of this study. Those who are interested to know more and deeper about the mentioned concepts can see (Aggarwal, 2015; Han et al., 2011). However, in this part we try to give some basics as concise as possible.

In this study the basic clustering algorithm is K-mean (MacQueen, 1967). This algorithm is popular among researchers (Ali et al., 2019). Some believe that this algorithm is one of the most accurate ones for time series clustering data (Paparrizos and Gravano, 2017). In K means clustering there is in fact an optimization problem in which the distance between cluster centers and the other points in a particular cluster is minimized. The distance is often calculated using Euclidean distance (Faloutsos et al., 1994). Equation 1 shows the formula for Euclidean distance D (T1, T2). Let T1 = ($T1_1$, $T1_2$, …, $T1_n$) and T2 = ($T2_1$, $T2_2$, … , $T2_n$) be two time series, then the distance would be:

$$d(T1, T2) = \sqrt{\sum_1^n (T1_i - T2_i)^2} \qquad (1)$$

The goal in time series clustering algorithms is minimizing equation (1). To calculate the distance between two points using Euclidean K-means, Euclidean distance is used. As stated by Muller (2007) and Rakthanmanon et al. (2013), DTW calculates an optimal match between two sequences (such as time series) with the following restrictions and rules: Every index from the first sequence must be matched with one or more indices from the other sequence, and vice versa, The first index from the first sequence must be matched with the first index from the other sequence (but it does not have to be its only match), The last index from the first sequence must be matched with the last index from the other sequence (but it does not have to be its only match), The mapping of the indices from the first sequence to indices from the other sequence must be monotonically increasing, and vice versa, i.e. if j > i are indices from the first sequence, then there must not be two indices l > k in the other sequence, such that index i is matched with index l and index j is matched with index k, and vice versa. A DTW barycenter averaging strategy is used in **K-means DBA clustering** (Petitjean et al., 2011; Chabchoub and Fricker, 2014). **K-shape clustering** is an accurate, efficient, and scalable time-series clustering algorithm that is invariant to shifting and scaling (Paparrizos and Gravano, 2017). In this algorithm, distance is measured and centroid computation is used to preserve the shape of the time series. In essence, this algorithm produces homogeneous, well-separated clusters by iteratively refining sequences linearly in number. It should be mentioned that in this paper the clustering analysis has been done using python.

3.3. Data

The purpose of this section is to provide more information about the dataset. Additionally, the data preparation process for the analysis will be explained.

3.3.1. Data Description

It is necessary to provide a detailed description of the data before explaining how to prepare for analysis. Tehran's Automatic Fare Collection (AFC) data consists of six columns: serial number, card type, line number, time, and reader number. As an example, Table 2 shows 10 rows of raw data.

Table 2. An example of the information included in the dataset

Serial	Card	Line	Date	Time	Reader
138821	132	2501	2020-12-07	13:12	1054
215125	132	2501	2020-12-06	17:12	1074
235077	132	2501	2020-12-03	09:12	1047
260341	132	2501	2020-12-08	12:12	1067
260405	132	2501	2020-12-02	08:12	1097
260405	132	2501	2020-12-02	12:12	1067
260405	132	2501	2020-12-02	12:12	1073
260405	132	2501	2020-12-03	08:12	1098
260405	132	2501	2020-12-03	12:12	1073

The first column of table 2 refers to the serial number. Cards are identified by their serial numbers. Each card has a unique serial number. It is possible to track every single passenger using this code. The second column lists the type of card. There are different types of cards available in Iran for different groups of people, which allows the government to provide discounts to certain groups of people, such as students, veterans, people who are unable to work, journalists, etc. Code 132 is the most common and belongs to people who aren't part of a special group. It could be argued that distinguishing between groups of users to see behavior changes should have been considered. If the dataset contains a large number of groups, it is a good idea to use this approach. The data used for this study contain a few observations related to special groups (in some cases, fewer than 100 transactions per day per group), but in order to draw concrete conclusions, it is necessary to analyze a large number of transactions for each group. It would have been possible to analyze each group separately if we had unlimited access to the whole AFC data. Furthermore, there might be a lot of veterans or students who use common cards, so even if there were enough transactions for every single group to be analyzed, the conclusions determined from analyzing each group separately would be unreliable.

Line number is the third column, date is the fourth, time is the fifth, and the last column is the reader number. AFC system of Tehran Transit System does not provide an exact time of use. The results are displayed in hourly intervals, with minute numbers indicating the month the card was used. During December, if a passenger uses their card at 10:26:32, the system would record 10:12. In November, if the card is used at the same time, it would be 10:11. Lastly, the last column displays the reader number for the particular transaction. By using this number, we are able to determine the origin stop. In Tehran's BRT system, the AFC system requires passengers to use their cards only in Origins, so the destination stops are unknown.

3.3.2. Data Preparation

Several preprocessing steps were performed on this dataset before analysis, including the detection of anomalies and their deletion, as well as the filling of missing values.

Readers' numbers in the studied line range between 1000 and 1098. Observations with reader codes greater than 1098 are not included in this line. As a result of operators' errors, the authors were provided with some observations with reader numbers that were not between 1000 and 1098. It was assumed that these observations were anomalous. In addition, when the data was sorted by serial number, date, and time, some observations had the same serial number, date, time, and reader number. Some passengers may have mistakenly used their cards more than once when entering the stop. To simplify the analysis, if there were, for example, three observations with the same serial number, date, time, and reader number, only one was considered and the other two were excluded.

The missing values were caused by the interruption of the AFC system for several hours in one day. Averaging the ridership of other similar days was used to fill these missing values (for example, if the observation with the missing value belongs to a particular hour within a work day, the ridership of other work days at that hour was taken into account). In order to fill in missing ridership values, average transactions with the same times, dates, and stops were considered. As a result of preprocessing, the data were ready for analysis.

4. Results and Discussion

The results of the analyses will be presented and discussed in this section. There are some tables that require explanations. According to Tables 3, 4, and 5, the number of passengers at each stop from 2019 to 2021 is shown in each row. These are statistics pertaining to the third month of autumn, Azar in Iranian calendar, which corresponds to November 22 to December 21 in the international calendar. It can be seen from the tables that there has been a dramatic change in ridership between 2020 and 2019, when the virus had not yet been confirmed to enter Iran.

In order to determine whether time has retained its influence over the ridership in all three tables, chi square tests were conducted. In each table, the real values (numbers in the table) were compared to the expected value for the entire table. According to table 6, the influence has not diminished, since the "chi-square statistics" for each year are above the critical chi-square even in 99.999 percent of reliability (alpha = 0.001). The degree of freedom for each year is also determined by taking into account that there are 27 stops and 17 hours (5 a.m. to 9 p.m.), so it will be 26 (27-1) stops times 16 (17-1) hours. This statistic has its minimum in 2020, which is after the outbreak and before vaccination. Nevertheless, it remains significantly higher than critical Chi-square. Table 7 follows the same explanations. However, there is an important difference: while in table 6, the real ridership values are compared to the expected ridership values in order to obtain the chi-square statistics (first column of the table), in table 7, the ridership for each year is compared with that of the other years. In fact, the expected values for each year are replaced by the actual values for the next year.

Table 7 shows that ridership differs significantly from year to year. Compared to 2019, the demand for 2020 has decreased significantly due to the pandemic. The demand for public transit in 2021 has increased significantly compared to 2020, since most passengers have received vaccinations and the transit system is about to go through a new normal period. Moreover, the difference in ridership between 2019 and 2021 is also significant. According to tables 3, 4 and 5, there are more passengers in 2021 than in 2020, but fewer than in 2019. However, in 2021, there has been an increase in ridership compared with 2020, but it is still significantly lower than in 2019 when the Iran pandemic hadn't begun.

Table 3. Total number of passengers in each stop in each time interval*for 1 month in 2019

	time																
Stop Name	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**
T.Pars	8143	22251	39732	29800	21418	17493	15033	14671	14848	14337	14592	15660	18616	17063	12212	7741	4684
Darioush	785	5413	8556	6885	5907	4595	3802	3061	2934	3276	2758	3108	3149	2672	1590	937	580
Khagani	3829	13676	25388	18444	13848	11051	9404	9186	9056	9559	8823	9392	10331	9306	6480	4210	2461
Aboureihan	701	4355	7684	5509	4673	3554	3054	2427	2376	2736	2177	2757	2637	2163	1278	744	514
Ayat	2026	7307	13592	9787	7761	6572	5750	5864	5736	6407	5755	5940	6579	6184	4361	3001	1787
NirHav	1133	6091	11729	8724	6761	5262	4414	4129	3755	4417	3621	3781	3930	2891	1934	1385	890
Vahidieh	1565	6622	11183	8499	6926	5583	5001	4610	4470	5271	4704	4794	5261	4240	3126	1718	1085
Sabalan	1731	7808	14431	10354	8189	6822	5638	5071	4662	6172	4422	5212	5117	3988	2552	1757	1008
Foroudgah	1130	5577	9686	7238	6169	5063	4468	4113	3627	3886	3629	3989	3970	2858	1853	1170	761
Fathana	1373	7211	13720	9369	7058	5566	4713	4469	4346	5604	4098	4840	4738	3706	2315	1564	888
BouAli	835	4020	7647	6041	5631	5263	4476	5534	3830	4735	5989	6045	5775	4271	2478	1074	673
Montazeri	1736	8071	15740	10969	8390	7107	6257	6940	6017	7272	6456	7413	6647	5686	3556	2240	1461
I.Hossein	1212	5308	10370	8632	7276	6221	5913	5846	5953	6242	6047	6503	6648	5954	4277	2888	2109
Pole	1078	5080	9134	7154	6155	5252	5015	5178	4989	5987	4714	5247	5258	4506	3132	2185	1219
Shariati	783	4170	7906	6202	5442	4837	4299	4608	4605	5854	4892	6315	6535	4598	3104	2148	1337
Darvazeh	663	3375	7431	5831	5166	4822	4746	5663	5899	6648	6713	8271	8542	7422	5376	3642	2448
Ferdosi	1581	7067	14293	10682	9534	9027	8898	9620	9681	11740	10351	14423	13860	10419	7380	4942	3120
ValiAsr	2201	9345	18820	15488	13517	12564	12699	14068	14280	16627	16309	20983	21883	19322	14918	10970	7114
Daneshgah	783	4766	9768	7495	6483	5981	6346	6747	6789	8748	8632	11662	10927	9096	7203	4050	1792
Enghelab	808	3811	8385	6809	5968	6183	6606	7276	7279	7738	7589	8790	9527	7751	6012	4434	2419
Gharib	802	4433	8931	6792	5708	4700	4479	4509	4318	5268	4532	5583	5873	4720	3120	2184	1210
Navab	2208	6797	14809	11102	8929	7789	7159	7276	7362	8649	8569	10306	10996	8394	5281	3908	2309
Behboudi	992	4253	8853	6508	5173	4696	4244	4487	3993	4752	4358	4951	4951	3690	2364	1704	1108
Sharif	973	5011	9779	7275	5659	4879	4359	4263	3995	4282	3845	5025	4642	3434	2106	1323	811
Moeen	716	3889	8174	5438	4336	3642	3254	3347	3076	3836	3333	4098	3732	3013	1968	1472	785
Kgozar	2341	8969	15872	11358	7885	5564	4460	3987	3728	4069	3433	4047	4142	3248	1803	1193	703
PAzadi	6472	15598	23107	16987	11254	8024	6534	6212	5740	6566	5807	5645	5579	4968	3343	2367	1362

*The numbers written in the top row of the table show the beginning of time interval, for example 5 means that the interval is (5,6), and etc.

Table 4. Total number of passengers in each stop in each time interval*for 1 month in 2020

	Time																
Stop Name	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**
T.Pars	4293	9464	14274	13181	9431	7409	6389	5591	6234	6824	6505	7318	9307	9056	6275	3382	1735
Darioush	341	1732	3036	3088	2018	1674	1228	1100	1054	1071	1076	1198	1496	1068	657	374	203
Khagani	2202	5349	8671	7546	5601	4263	3632	3165	3319	3682	3593	3980	4999	4725	3060	1732	815
Aboureihan	331	1808	3230	2749	1967	1404	1197	945	907	1044	949	993	1278	974	598	383	161
Ayat	1387	3391	5359	4474	3188	2586	2193	2037	2185	2309	2404	2549	3183	3044	2089	1213	570
NirHav	685	2591	5275	4686	3109	2407	1944	1557	1599	1629	1647	1657	1974	1520	954	611	260
Vahidieh	1044	3228	5297	4539	3218	2626	1981	1945	1917	1961	2003	2105	2535	2306	1345	716	332
Sabalan	994	3443	6039	5277	3608	2839	2289	1856	1777	1847	1959	2122	2457	1895	1167	700	283
Foroudgah	587	2071	4118	3768	2528	2127	1766	1521	1451	1386	1417	1679	1937	1380	847	410	198
Fathana	513	2814	5041	4206	3049	2229	1938	1607	1774	2053	1788	1687	1924	1624	1082	668	264
BouAli	546	1710	3462	2904	1936	1505	1306	1235	1137	1329	1201	1197	1435	1193	796	462	182
Montazeri	1052	3969	7270	5525	3745	2839	2505	2298	2238	2438	2217	2354	2684	2334	1649	1031	402
I.Hossein	677	2708	4647	4435	3189	2611	2776	2768	2717	2909	2983	3301	3770	3541	2504	1675	824
Pole	617	2054	3663	3393	2498	2255	2072	2110	2025	2298	2052	2236	2457	2177	1482	853	355
Shariati	445	1716	3093	2810	1999	1802	1685	1720	1775	2174	2177	2407	2750	2102	1431	816	324
Darvazeh	460	1929	3887	3274	2918	2849	3169	3577	3912	5087	4994	5703	6354	5157	3394	2280	934
Ferdosi	668	2563	4504	3874	3055	2822	2820	3017	3074	3806	3880	4378	4955	3850	2690	1586	522
ValiAsr	1127	4147	7312	6821	5221	4738	4790	5142	5478	6681	7366	8181	9910	8650	6414	4105	1421
Daneshgah	489	1801	3290	2944	2325	2087	2071	2135	2463	3859	3535	3806	4332	3777	2491	1311	484
Enghelab	539	2481	4449	4135	3579	3438	3748	3947	4175	4969	4974	5312	6419	5271	3874	2356	766
Gharib	502	1944	3859	3386	2498	1976	1769	1801	1776	2373	2105	2530	3110	2309	1505	921	276
Navab	1268	3722	6808	5623	4492	3485	3278	3116	3222	3948	4016	4741	5471	4225	2862	1780	758
Behboudi	590	2196	4335	3444	2690	2153	1858	1650	1755	1938	1858	2015	2295	1735	1106	629	272
Sharif	444	1948	3678	2817	2172	1644	1476	1345	1253	1511	1318	1503	1735	1223	793	454	152
Moeen	365	1869	3666	2796	2113	1607	1342	1106	1139	1272	1152	1246	1583	1154	724	446	156
Kgozar	1328	4634	7553	6448	4269	2774	2204	1806	1608	1776	1514	1692	1978	1557	953	629	243
PAzadi	3426	7615	10524	9154	5900	4012	2977	2631	2548	2461	2474	2464	2646	2308	1556	1038	545

Table 5. Total number of passengers in each stop in each time interval*for 1 month in 2021

	time																
Stop Name	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**
T.Pars	4084	12771	18532	15988	10816	8253	6733	6211	6598	6856	6969	7971	9334	9125	6921	4365	2754
Darioush	325	3078	4742	4246	3311	2485	1914	1691	1456	1281	1304	1449	1472	1029	781	462	265
Khagani	1217	6142	9208	7110	5583	4195	3392	3130	3154	3083	3262	2971	3187	2477	1585	1033	677
Aboureihan	524	3636	4423	3602	2649	1842	1392	1273	1253	1181	996	1016	1327	816	504	358	252
Ayat	2796	12010	18288	15165	9858	8087	6608	5986	6187	6137	5836	6236	6383	5159	4168	3111	2135
NirHav	970	4805	8651	6729	4176	3639	2582	2369	2214	2388	2042	2196	2279	1731	1282	789	586
Vahidieh	1046	4362	6053	4992	3319	2773	2417	2195	2154	2376	2198	2174	2080	1786	827	618	408
Sabalan	2068	6778	10078	8027	5697	4654	3740	3180	3147	3007	2827	3233	2854	2228	1496	923	544
Foroudgah	792	3844	6097	4876	3506	2791	2487	2418	2149	2109	1953	2088	2360	1624	1017	632	390
Fathana	613	2975	5234	3768	2324	1738	1557	1480	1510	1627	1505	1432	1468	1136	840	445	262
BouAli	630	2383	4335	3313	2081	2085	1942	2271	2020	2080	1605	1452	1457	1191	986	570	482
Montazeri	1162	4969	9161	6328	4157	3236	3220	3424	3126	3600	2999	2977	2671	2497	1942	1531	961
I.Hossein	948	3744	6615	5860	4095	4025	4227	4334	4798	5006	4981	5427	5958	5992	4718	3341	2247
Pole	616	2028	3075	2831	2474	2485	2698	2762	2756	3383	2904	3093	3300	2853	2102	1569	667
Shariati	435	1377	2636	2533	2141	2327	2603	3276	3852	5436	4808	5657	5278	3966	3006	2561	1924
Darvazeh	264	1693	3682	3453	3496	4001	5011	6112	6621	8029	8137	9591	9451	7589	5999	4870	3350
Ferdosi	364	709	1910	1927	2165	2730	3452	4002	4530	6621	6053	7023	7004	4963	4023	2873	2176
ValiAsr	1021	3466	6888	6720	5583	6074	7272	8599	9986	13044	14162	15957	17514	16467	13748	10526	6473
Daneshgah	236	1225	2466	2353	2329	2698	3196	3739	4504	7942	7388	8396	8469	7033	5229	3377	1656
Enghelab	867	3869	7542	7290	6420	6898	7774	8753	9279	11271	11453	11906	13856	11604	8895	6917	3825
Gharib	361	2007	4736	3690	2715	2574	2549	2746	2855	3671	3477	4425	4910	3657	2812	1791	880
Navab	1696	4819	8489	7738	5271	4938	4910	5067	5650	6635	6946	8240	9281	7013	5405	3905	2094
Behboudi	1363	5472	10227	7369	5330	4521	4285	4124	3773	4001	4087	4800	4975	3524	2387	1557	1139
Sharif	654	2605	4363	3486	2417	1993	1822	1656	1534	2268	1921	2168	2409	1679	1180	822	383
Moeen	1067	5892	10479	8335	5731	4309	3485	2918	2702	3076	2961	3264	3512	2988	1660	989	638
Kgozar	7244	22053	29487	22672	12978	7942	5990	5657	5469	5260	5287	5357	5345	4371	2895	1992	1044
PAzadi	11125	16291	22296	17384	11216	7911	6690	6310	5724	5743	6218	6044	6093	4992	3960	3179	2140

Table 6. Chi square test for each year

Chi-square statistics	Year	Degree of freedom	critical Chi-square alpha		
			0.05	0.01	0.001
139362.7	2019	26*16			
72759.6	2020	26*16	464.6	486.0	510.9
314730.1	2021	26*16			

Table 7. Chi square test for comparing ridership in each pair years

Chi-square statistics	Year	Degree of freedom	critical Chi-square alpha		
334542.7	2019 & 2020	26*16	0.05	0.01	0.001
199437.7	2020 & 2021	26*16	464.6	486	510.9
149053.9	2019 & 2021	26*16			

To gain a better understanding of how demand has changed, a heat map can be helpful. A heat map analysis can be performed by using the simple equation (2):

$$PCH_{ij(k+1)} = \left(\frac{a_{ij(k)-}\ a_{ij(k+1)}}{a_{ijk}}\right) \times 100 \ or\ PCH_{ij(k+2)} = \left(\frac{a_{ij(k)-}\ a_{ij(k+2)}}{a_{ijk}}\right) \times 100 \qquad (2)$$

Where:

$PCH_{ij(k+1)}$ = Percentage of changes in passenger numbers from year (k+1) to year (k)

$a_{ij(k)}$= Passengers at stop i at time interval j in year k

$a_{ij(k+1)}$= The number of passengers at stop i at time interval j in year k+1

k = 2019

If PCH is negative, it indicates that ridership has increased relative to year k at stop i and at time interval j, while if it is positive, it indicates that ridership has decreased. The results of calculating PCH for each stop at each time interval are shown in Table 8 for the years 2019 and 2020, 2019 and 2021, and 2020 and 2021. According to tables 8-10, red indicates a more severe change. A darker red color indicates more severe changes. In the cells of tables 8 and 9, the changes are more or less the same, whereas in 2020, due to the outbreak, the percentage of changes is high and demand has decreased substantially in many areas. As can be seen in the tables 9 and 10, the decrease in ridership in 2021 when compared to 2019 is comparable to the increase in ridership in 2021 when compared to 2020. Additionally, according to table 8, there is not a single cell in which the ridership has increased. The decrease in demand ranges from 23.48 to 83.27 percent with an average of 56.68 percent. Therefore, the ridership in 2020 has decreased by more than 50 percent as compared to 2019.Table 10, however, exhibits the most severe changes. It appears to be a different story entirely, namely that in 2021, as compared to 2020, night-time trips have increased, particularly in western stops (P.Azadi, Kgozar, etc.). Daytime trips in western stops have also seen an increase in passengers, indicating that transit riders' behavior has changed due to the outbreak, and in fact, the outbreak has created a new travel pattern. The increase in demand in 2021 compared to 2020 was at times as high as 490 percent, while the decrease in 2020 compared to 2019 was never greater than 80 percent. However, in some cases a decrease in ridership in 2021 compared to 2020 exists. On the one hand, there is a dramatic increase in some cells, on the other hand, there is a decrease in some cells.

Table 8. Heat map for comparing the changes in ridership (comparison between 2019 and 2020)

S/T*	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	47.28	57.47	64.07	55.77	55.97	57.65	57.50	61.89	58.01	52.40	55.42	53.27	50.01	46.93	48.62	56.31	62.96
2	56.56	68.00	64.52	55.15	65.84	63.57	67.70	64.06	64.08	67.31	60.99	61.45	52.49	60.03	58.68	60.09	65.00
3	42.49	60.89	65.85	59.09	59.55	61.42	61.38	65.55	63.35	61.48	59.28	57.62	51.61	49.23	52.78	58.86	66.88
4	52.78	58.48	57.96	50.10	57.91	60.50	60.81	61.06	61.83	61.84	56.41	63.98	51.54	54.97	53.21	48.52	68.68
5	31.54	53.59	60.57	54.29	58.92	60.65	61.86	65.26	61.91	63.96	58.23	57.09	51.62	50.78	52.10	59.58	68.10
6	39.54	57.46	55.03	46.29	54.02	54.26	55.96	62.29	57.42	63.12	54.52	56.18	49.77	47.42	50.67	55.88	70.79
7	33.29	51.25	52.63	46.59	53.54	52.96	60.39	57.81	57.11	62.80	57.42	56.09	51.82	45.61	56.97	58.32	69.40
8	42.58	55.90	58.15	49.03	55.94	58.38	59.40	63.40	61.88	70.07	55.70	59.29	51.98	52.48	54.27	60.16	71.92
9	48.05	62.87	57.49	47.94	59.02	57.99	60.47	63.02	59.99	64.33	60.95	57.91	51.21	51.71	54.29	64.96	73.98
10	62.64	60.98	63.26	55.11	56.80	59.95	58.88	64.04	59.18	63.37	56.37	65.14	59.39	56.18	53.26	57.29	70.27
11	34.61	57.46	54.73	51.93	65.62	71.40	70.82	77.68	70.31	71.93	79.95	80.20	75.15	72.07	67.88	56.98	72.96
12	39.40	50.82	53.81	49.63	55.36	60.05	59.96	66.89	62.81	66.47	65.66	68.24	59.62	58.95	53.63	53.97	72.48
13	44.14	48.98	55.19	48.62	56.17	58.03	53.05	52.65	54.36	53.40	50.67	49.24	43.29	40.53	41.45	42.00	60.93
14	42.76	59.57	59.90	52.57	59.42	57.06	58.68	59.25	59.41	61.62	56.47	57.39	53.27	51.69	52.68	60.96	70.88
15	43.17	58.85	60.88	54.69	63.27	62.75	60.80	62.67	61.45	62.86	55.50	61.88	57.92	54.28	53.90	62.01	75.77
16	30.62	42.84	47.69	43.85	43.52	40.92	33.23	36.84	33.68	23.48	25.61	31.05	25.61	30.52	36.87	37.40	61.85
17	57.75	63.73	68.49	63.73	67.96	68.74	68.31	68.64	68.25	67.58	62.52	69.65	64.25	63.05	63.55	67.91	83.27
18	48.80	55.62	61.15	55.96	61.37	62.29	62.28	63.45	61.64	59.82	54.83	61.01	54.71	55.23	57.00	62.58	80.03
19	37.55	62.21	66.32	60.72	64.14	65.11	67.37	68.36	63.72	55.89	59.05	67.36	60.36	58.48	65.42	67.63	72.99
20	33.29	34.90	46.94	39.27	40.03	44.40	43.26	45.75	42.64	35.78	34.46	39.57	32.62	32.00	35.56	46.87	68.33
21	37.41	56.15	56.79	50.15	56.24	57.96	60.50	60.06	58.87	54.95	53.55	54.68	47.05	51.08	51.76	57.83	77.19
22	42.57	45.24	54.03	49.35	49.69	55.26	54.21	57.17	56.23	54.35	53.13	54.00	50.25	49.67	45.81	54.45	67.17
23	40.52	48.37	51.03	47.08	48.00	54.15	56.22	63.23	56.05	59.22	57.37	59.30	53.65	52.98	53.21	63.09	75.45
24	54.37	61.13	62.39	61.28	61.62	66.30	66.14	68.45	68.64	64.71	65.72	70.09	62.62	64.39	62.35	65.68	81.26
25	49.02	51.94	55.15	48.58	51.27	55.88	58.76	66.96	62.97	66.84	65.44	69.59	57.58	61.70	63.21	69.70	80.13
26	43.27	48.33	52.41	43.23	45.86	50.14	50.58	54.70	56.87	56.35	55.90	58.19	52.25	52.06	47.14	47.28	65.43
27	47.06	51.18	54.46	46.11	47.57	50.00	54.44	57.65	55.61	62.52	57.40	56.35	52.57	53.54	53.45	56.15	59.99

Table 9. Heat map for comparing the changes in ridership (comparison between 2019 and 2021)

S/T*	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	49.85	42.60	53.36	46.35	49.50	52.82	55.21	57.66	55.56	52.18	52.24	49.10	49.86	46.52	43.33	43.61	41.20
2	58.60	43.14	44.58	38.33	43.95	45.92	49.66	44.76	50.37	60.90	52.72	53.38	53.26	61.49	50.88	50.69	54.31
3	68.22	55.09	63.73	61.45	59.68	62.04	63.93	65.93	65.17	67.75	63.03	68.37	69.15	73.38	75.54	75.46	72.49
4	25.25	16.51	42.44	34.62	43.31	48.17	54.42	47.55	47.26	56.83	54.25	63.15	49.68	62.27	60.56	51.88	50.97
5	-38.01	-64.36	-34.55	-54.95	-27.02	-23.05	-14.92	-2.08	-7.86	4.21	-1.41	-4.98	2.98	16.58	4.43	-3.67	-19.47
6	14.39	21.11	26.24	22.87	38.23	30.84	41.50	42.63	41.04	45.94	43.61	41.92	42.01	40.12	33.71	43.03	34.16
7	33.16	34.13	45.87	41.26	52.08	50.33	51.67	52.39	51.81	54.92	53.27	54.65	60.46	57.88	73.54	64.03	62.40
8	-19.47	13.19	30.16	22.47	30.43	31.78	33.66	37.29	32.50	51.28	36.07	37.97	44.23	44.13	41.38	47.47	46.03
9	29.91	31.07	37.05	32.63	43.17	44.87	44.34	41.21	40.75	45.73	46.18	47.66	40.55	43.18	45.12	45.98	48.75
10	55.35	58.74	61.85	59.78	67.07	68.77	66.96	66.88	65.26	70.97	63.27	70.41	69.02	69.35	63.71	71.55	70.50
11	24.55	40.72	43.31	45.16	63.04	60.38	56.61	58.96	47.26	56.07	73.20	75.98	74.77	72.11	60.21	46.93	28.38
12	33.06	38.43	41.80	42.31	50.45	54.47	48.54	50.66	48.05	50.50	53.55	59.84	59.82	56.09	45.39	31.65	34.22
13	21.78	29.46	36.21	32.11	43.72	35.30	28.51	25.86	19.40	19.80	17.63	16.55	10.38	-0.64	-10.31	-15.69	-6.54
14	42.86	60.08	66.33	60.43	59.81	52.68	46.20	46.66	44.76	43.49	38.40	41.05	37.24	36.68	32.89	28.19	45.28
15	44.44	66.98	66.66	59.16	60.66	51.89	39.45	28.91	16.35	7.14	1.72	10.42	19.23	13.75	3.16	-19.23	-43.90
16	60.18	49.84	50.45	40.78	32.33	17.03	-5.58	-7.93	-12.24	-20.77	-21.21	-15.96	-10.64	-2.25	-11.59	-33.72	-36.85
17	76.98	89.97	86.64	81.96	77.29	69.76	61.20	58.40	53.21	43.60	41.52	51.31	49.47	52.37	45.49	41.87	30.26
18	53.61	62.91	63.40	56.61	58.70	51.66	42.74	38.88	30.07	21.55	13.16	23.95	19.97	14.78	7.84	4.05	9.01
19	69.86	74.30	74.75	68.61	64.08	54.89	49.64	44.58	33.66	9.21	14.41	28.01	22.49	22.68	27.41	16.62	7.59
20	-7.30	-1.52	10.05	-7.06	-7.57	-11.56	-17.68	-20.30	-27.48	-45.66	-50.92	-35.45	-45.44	-49.71	-47.95	-56.00	-58.12
21	54.99	54.73	46.97	45.67	52.44	45.23	43.09	39.10	33.88	30.32	23.28	20.74	16.40	22.52	9.87	17.99	27.27
22	23.19	29.10	42.68	30.30	40.97	36.60	31.42	30.36	23.25	23.29	18.94	20.05	15.60	16.45	-2.35	0.08	9.31
23	-37.40	-28.66	-15.52	-13.23	-3.03	3.73	-0.97	8.09	5.51	15.80	6.22	3.05	-0.48	4.50	-0.97	8.63	-2.80
24	32.79	48.01	55.38	52.08	57.29	59.15	58.20	61.15	61.60	47.03	50.04	56.86	48.10	51.11	43.97	37.87	52.77
25	-49.02	-51.50	-28.20	-53.27	-32.17	-18.31	-7.10	12.82	12.16	19.81	11.16	20.35	5.89	0.83	15.65	32.81	18.73
26	-209.44	-145.88	-85.78	-99.61	-64.59	-42.74	-34.30	-41.89	-46.70	-29.27	-54.01	-32.37	-29.04	-34.58	-60.57	-66.97	-48.51
27	-71.89	-4.44	3.51	-2.34	0.34	1.41	-2.39	-1.58	0.28	12.53	-7.08	-7.07	-9.21	-0.48	-18.46	-34.31	-57.12

Table 10. Heat map for comparing the changes in ridership (comparison between 2020 and 2021)

S/T*	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	4.87	-34.94	-29.83	-21.30	-14.69	-11.39	-5.38	-11.09	-5.84	-0.47	-7.13	-8.92	-0.29	-0.76	-10.29	-29.07	-58.73
2	4.69	-77.71	-56.19	-37.50	-64.07	-48.45	-55.86	-53.73	-38.14	-19.61	-21.19	-20.95	1.60	3.65	-18.87	-23.53	-30.54
3	44.73	-14.83	-6.19	5.78	0.32	1.60	6.61	1.11	4.97	16.27	9.21	25.35	36.25	47.58	48.20	40.36	16.93
4	-58.31	-101.11	-36.93	-31.03	-34.67	-31.20	-16.29	-34.71	-38.15	-13.12	-4.95	-2.32	-3.83	16.22	15.72	6.53	-56.52
5	-101.59	-254.17	-241.26	-238.96	-209.22	-212.72	-201.32	-193.86	-183.16	-165.79	-142.76	-144.64	-100.53	-69.48	-99.52	-156.47	-274.56
6	-41.61	-85.45	-64.00	-43.60	-34.32	-51.18	-32.82	-52.15	-38.46	-46.59	-23.98	-32.53	-15.45	-13.88	-34.38	-29.13	-125.38
7	-0.19	-35.13	-14.27	-9.98	-3.14	-5.60	-22.01	-12.85	-12.36	-21.16	-9.74	-3.28	17.95	22.55	38.51	13.69	-22.89
8	-108.05	-96.86	-66.88	-52.11	-57.90	-63.93	-63.39	-71.34	-77.10	-62.80	-44.31	-52.36	-16.16	-17.57	-28.19	-31.86	-92.23
9	-34.92	-85.61	-48.06	-29.41	-38.69	-31.22	-40.83	-58.97	-48.10	-52.16	-37.83	-24.36	-21.84	-17.68	-20.07	-54.15	-96.97
10	-19.49	-5.72	-3.83	10.41	23.78	22.03	19.66	7.90	14.88	20.75	15.83	15.12	23.70	30.05	22.37	33.38	0.76
11	-15.38	-39.36	-25.22	-14.08	-7.49	-38.54	-48.70	-83.89	-77.66	-56.51	-33.64	-21.30	-1.53	0.17	-23.87	-23.38	-164.84
12	-10.46	-25.20	-26.01	-14.53	-11.00	-13.98	-28.54	-49.00	-39.68	-47.66	-35.27	-26.47	0.48	-6.98	-17.77	-48.50	-139.05
13	-40.03	-38.26	-42.35	-32.13	-28.41	-54.16	-52.27	-56.58	-76.59	-72.09	-66.98	-64.40	-58.04	-69.22	-88.42	-99.46	-172.69
14	0.16	1.27	16.05	16.56	0.96	-10.20	-30.21	-30.90	-36.10	-47.21	-41.52	-38.33	-34.31	-31.05	-41.84	-83.94	-87.89
15	2.25	19.76	14.78	9.86	-7.10	-29.13	-54.48	-90.47	-117.01	-150.05	-120.85	-135.02	-91.93	-88.68	-110.06	-213.85	-493.83
16	42.61	12.23	5.27	-5.47	-19.81	-40.44	-58.13	-70.87	-69.25	-57.83	-62.94	-68.17	-48.74	-47.16	-76.75	-113.60	-258.67
17	45.51	72.34	57.59	50.26	29.13	3.26	-22.41	-32.65	-47.36	-73.96	-56.01	-60.42	-41.35	-28.91	-49.55	-81.15	-316.86
18	9.41	16.42	5.80	1.48	-6.93	-28.20	-51.82	-67.23	-82.29	-95.24	-92.26	-95.05	-76.73	-90.37	-114.34	-156.42	-355.52
19	51.74	31.98	25.05	20.07	-0.17	-29.28	-54.32	-75.13	-82.87	-105.80	-109.00	-120.60	-95.50	-86.21	-109.92	-157.59	-242.15
20	-60.85	-55.95	-69.52	-76.30	-79.38	-100.64	-107.42	-121.76	-122.25	-126.83	-130.26	-124.13	-115.86	-120.15	-129.61	-193.59	-399.35
21	28.09	-3.24	-22.73	-8.98	-8.69	-30.26	-44.09	-52.47	-60.75	-54.70	-65.18	-74.90	-57.88	-58.38	-86.84	-94.46	-218.84
22	-33.75	-29.47	-24.69	-37.61	-17.34	-41.69	-49.79	-62.61	-75.36	-68.06	-72.96	-73.80	-69.64	-65.99	-88.85	-119.38	-176.25
23	-131.02	-149.18	-135.92	-113.97	-98.14	-109.99	-130.62	-149.94	-114.99	-106.45	-119.97	-138.21	-116.78	-103.11	-115.82	-147.54	-318.75
24	-47.30	-33.73	-18.62	-23.75	-11.28	-21.23	-23.44	-23.12	-22.43	-50.10	-45.75	-44.24	-38.85	-37.29	-48.80	-81.06	-151.97
25	-192.33	-215.25	-185.84	-198.10	-171.23	-168.14	-159.69	-163.83	-137.23	-141.82	-157.03	-161.96	-121.86	-158.93	-129.28	-121.75	-308.97
26	-445.48	-375.90	-290.40	-251.61	-204.01	-186.30	-171.78	-213.23	-240.11	-196.17	-249.21	-216.61	-170.22	-180.73	-203.78	-216.69	-329.63
27	-224.72	-113.93	-111.86	-89.91	-90.10	-97.18	-124.72	-139.83	-124.65	-133.36	-151.33	-145.29	-130.27	-116.29	-154.50	-206.26	-292.66

*the first columns in stop numbers and the first row is time of day

It may be helpful to refer to figure 2 in order to better understand the changes. The axis x represents the number of stops and the axis y represents the number of passengers. According to figure 2, the number of passengers at most stops is the highest in 2019. Nevertheless, there are a few stops where the number of passengers is higher in 2021 than in 2019. According to figure 2, one of these stops is stop 26, which is a western stop. Figure 2 confirms the results obtained by heat map analysis. The same applies to stop 27 as well. In stop 20, ridership has also increased from 2019 to 2020. A subway station is located nearby the BRT stop with the same name, Enghelab. This may be an important point regarding the changes, as it may imply that in the new normal situation the subway system has been affected too.

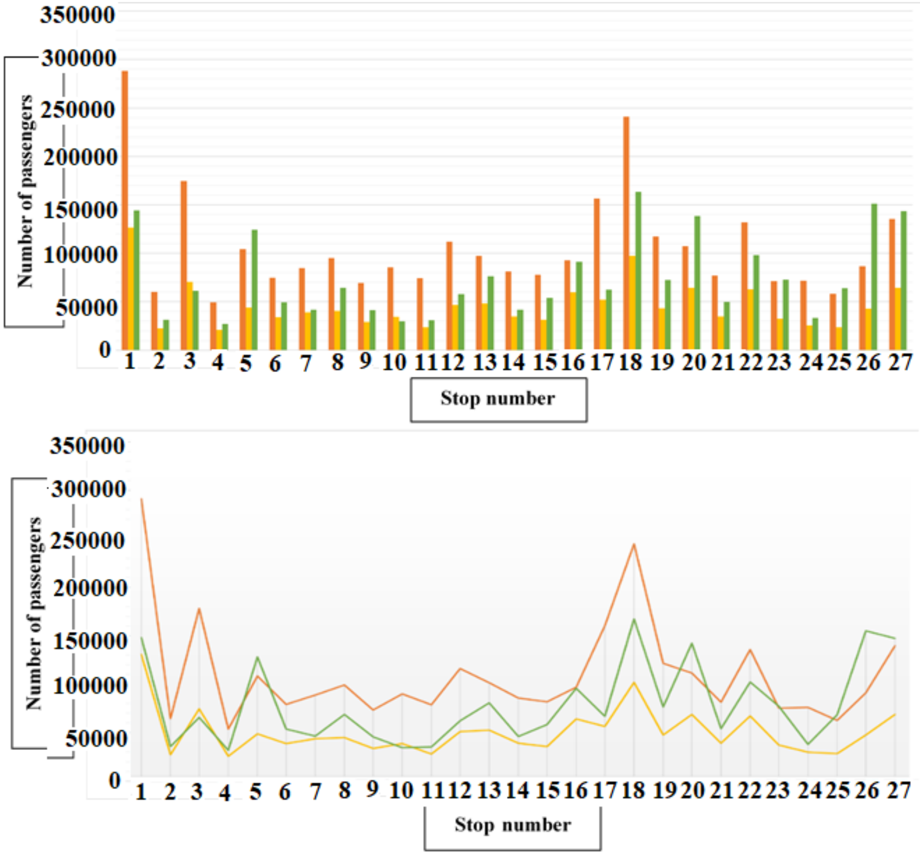

Figure 2. Total number of passengers in each stop at 2019 (red), 2020 (yellow), and 2021 (green)

Figure 3 illustrates the number of passengers per hour. For all stops, the number of passengers has been summed for each hour. There is not a single hour in this plot where ridership in 2021 or 2020 exceeds that of 2019. There may, however, be a difference in the slope of the changes.

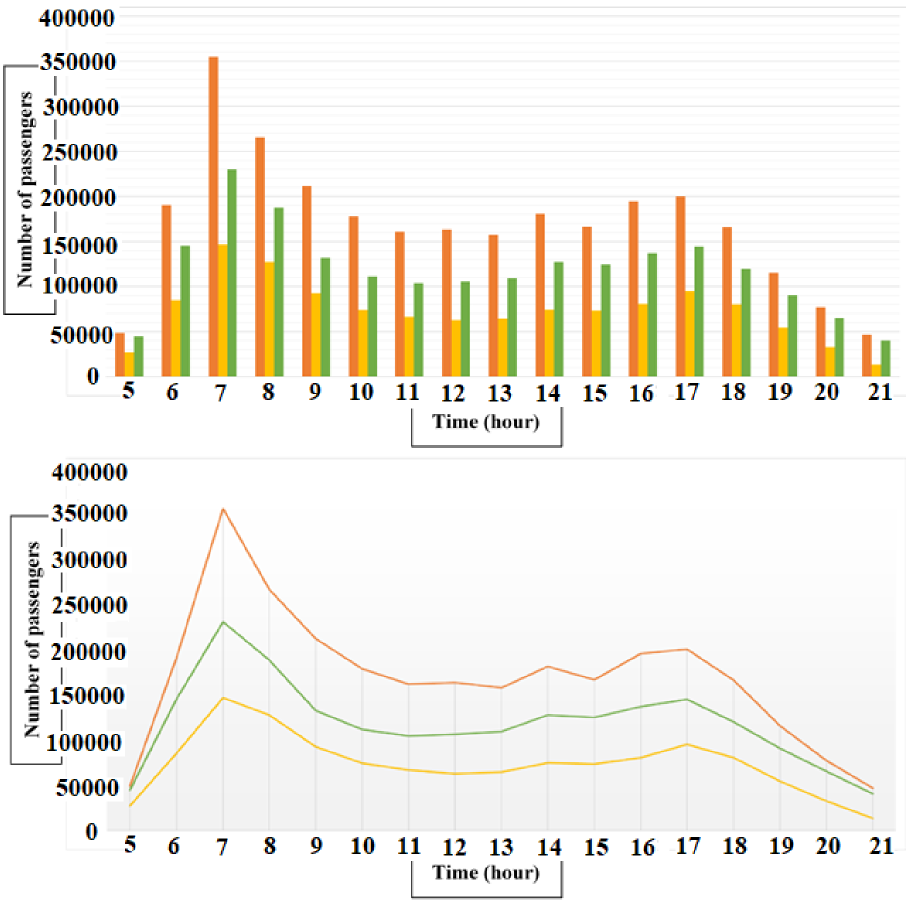

Figure 3. Total number of passengers in each hour at 2019 (red), 2020 (yellow), and 2021 (green)

A plot of the slopes of changes can be seen in figure 4. According to figure 4, each point in the vertical axis represents the total ridership at hour "t+1", minus the total ridership at hour "t". Although in most points, slopes have the same direction, but there are significant variations between them in many stops as shown in the figure. In stop 1, the slope of 2019 is significantly greater than the other two years, which means that the rate of change at 5 o'clock to 6 in 2019 is significantly different from that in 2020 and 2021.

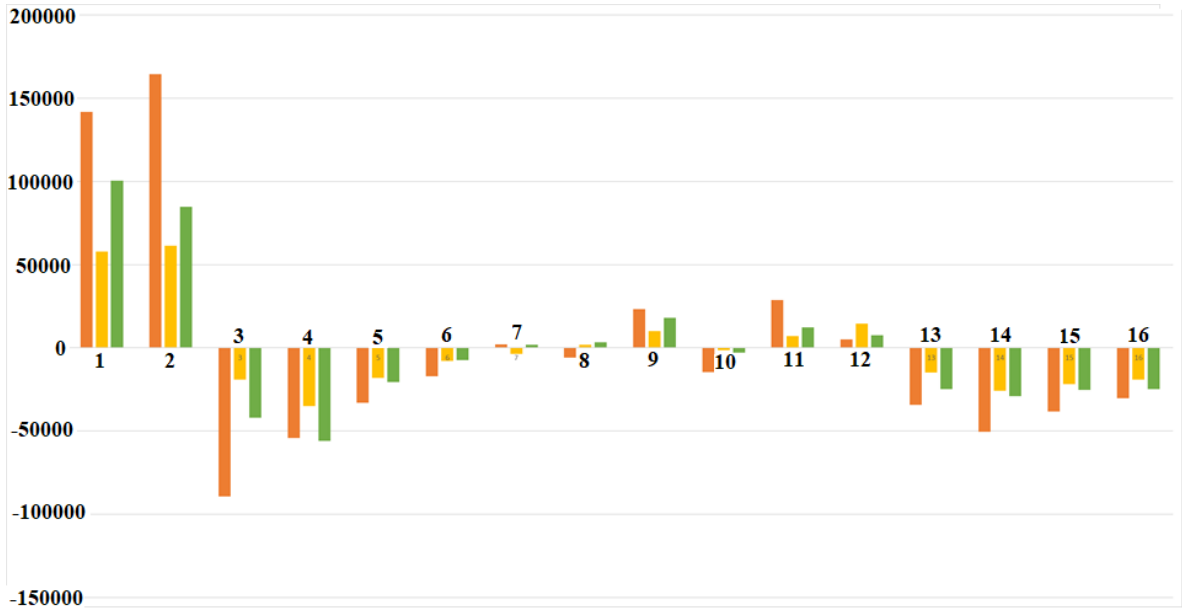

Figure 4. The slope of changes (passenger/ hour)

Figure 5 is the result of doing the same with stops. In order to obtain figure 5, the number of passengers is summed for every single stop and for all hours and days of each year. After this, each point on the vertical axis is equal to ridership in stop 's+1' minus ridership in stop 's' in a particular year. The result will be expressed in terms of passengers per stop.

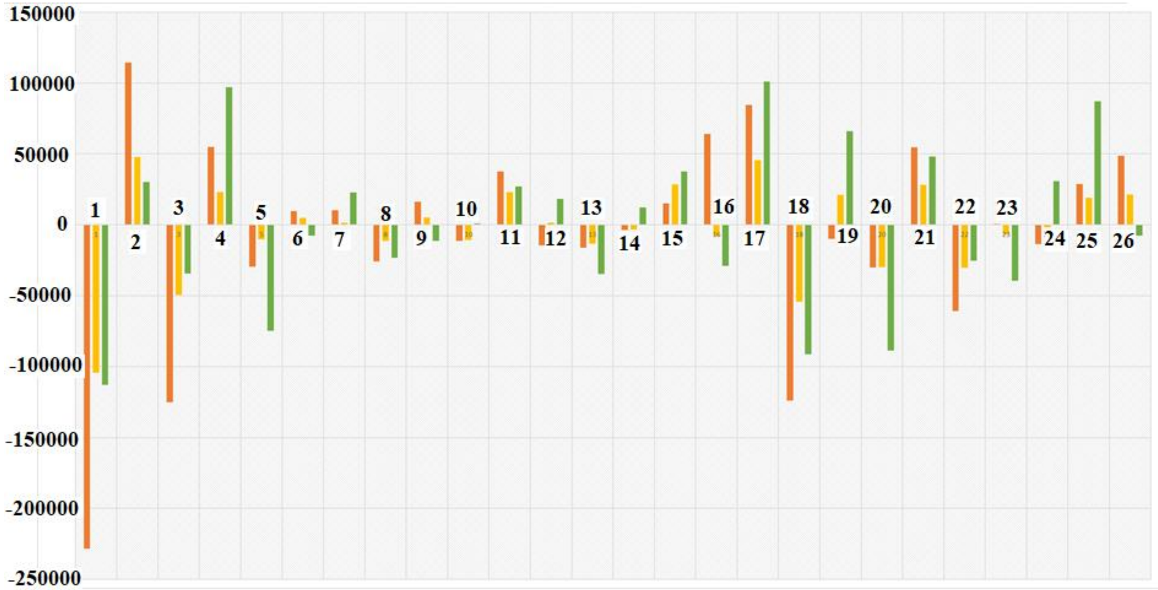

Figure 5. The slope of changes (passenger per stop)

As shown in figure 5, the slopes are completely different. There is once again a greater change in ridership from stop "s" to stop "s+1" in 2019. However, it is smaller in 2020 and 2021. A change may even occur in the opposite direction in some cases. According to Figures 2, 3, and 4, a more advanced analysis, such as time-series clustering, will be necessary in order to understand the new patterns. Since there is a variable (the number of passengers) that changes over regular courses of time, we can assume we are dealing with a time series. Table 8, and Figures 2-5 demonstrate that it is likely that there are similar patterns among the time series. Capturing and analyzing them may be helpful in finding and understanding emerging travel patterns among transit users. Therefore, it appears that there is a need for a more advanced analysis such as machine learning analysis. Because of the time series nature of the data we deal with in this study, it seems that time series clustering could be an appropriate choice. Also, to obtain the most logical and explainable results, different algorithms have been used. Because the number of passengers changes over time, we can consider the number of passengers in each stop at each hour as a time series. As a matter of fact, there is a periodic pattern in these series, so the question is: are there any significant differences between them? This may be answered by noting that there are 81 time-series (three years multiplied by 27 stops, in fact for every single stop, there is a time-series. Considering the fact that the data of three years is accessible, then for each stop, there are 3 time-series which means in total there are 3*27 or 81 time-series) in axis X, with each series consisting of 510 (17 hours multiplied by 30 days, in fact, in each day, the AFC data is recorded from 5 a.m. to 9:59 p.m. which is equal to 17 hours, and because each month consists of 30 days, then each time-series should have 510 (17*30) points) data points. The number of passengers is represented by axis Y. First it is needed to find the best time series clustering algorithm. In order to evaluate the clustering results so that we can select the most appropriate algorithm, several metrics can be considered. According to the literature the metrics should be Silhouette score (Ruousseeuw,1987) Davies-Bouldin index (Davis and Bouldin, 1973), Clinski-Harabasz index (Calinski and Harabasz, 1974). In order to choose the best algorithm, both the metrics and the theoretical background of the problem should be considered. First a silhouette analysis is carried out to find an estimation of the best choice for the number of clusters. Figure 6 shows the results of silhouette analysis visually. The analysis has been done assuming the number of clusters being 2, 3, 4, and 5. As it can be seen in figure 6, there is a red dotted line and rectangle-like shapes in which lengths are bigger than widths. For the best choice, the red vertical dotted line should intersect all those rectangle-like shapes. Also, the difference between the widths of those shapes should not be too much. Considering these conditions, it seems that three is the best choice for the number of clusters. However, for all algorithms, the clustering analysis was done using 2, 3, and 4 clusters, so that we make sure that we will choose the best option for the number of clusters according to the metrics as well. After trying different algorithms such as Euclidean K-means, DBA, Soft DTW, and K-Shape, and according to table 11, the DBA algorithm with 3 clusters was found to be the best choice. Because its scores, especially Davies-Bouldin score is better than the others (this score shouldn't be more than 1), and the other two scores are relatively good. It is somehow supported by earlier theoretical and statistical results too; because as suggested by the heat map analysis, there is a change in both ridership and passengers' behavior in the third year (2021), thus clusters of the last year should be different from 2019 and 2020. The three-cluster DBA algorithm, has captured this behavior; therefore, this algorithm seems to be more accurate. Also, the other two scores for this algorithm are not so different from that of the others. Thus, for the rest of the paper, DBA-K-means with 3 clusters will be considered and discussed. According to table 12 which is based on DBA-K-means algorithm, the time series in year 2021, when most people had received at least one dose of vaccines are significantly different. Based on the clustering results, the time series for 2019 and 2020 are more or less similar as they have been categorized by the same clusters. It means that after vaccination and in the new normal situation we have faced a new behavior.

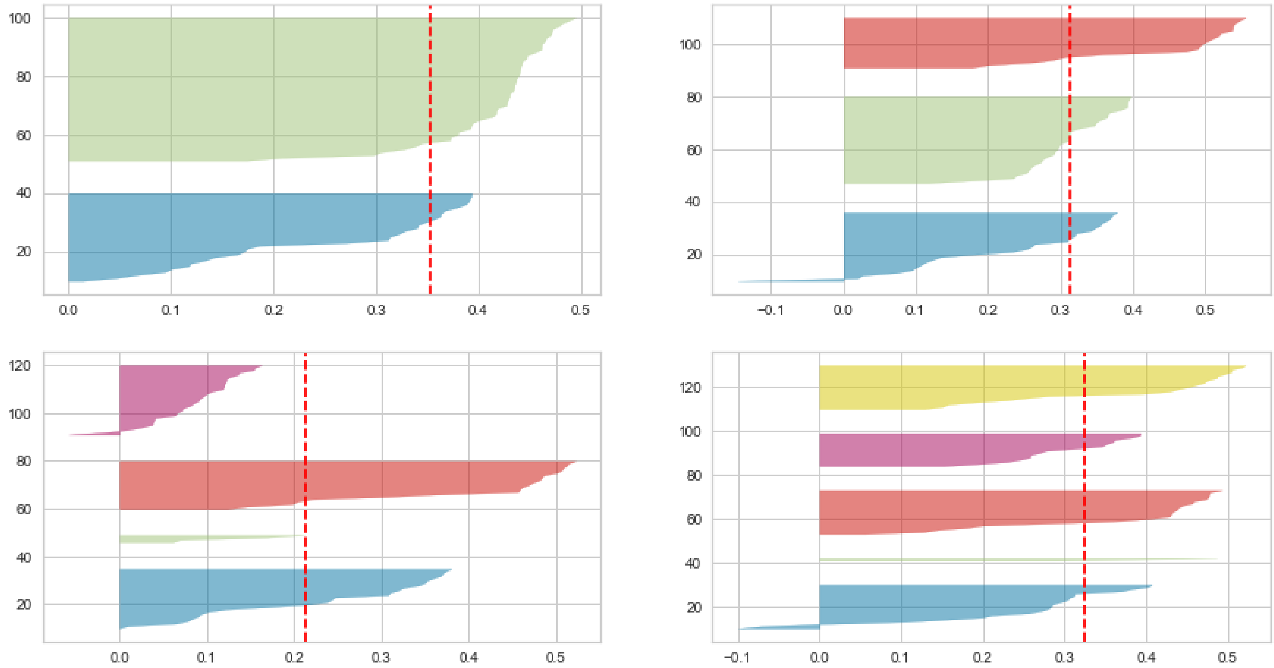

Figure 6. Silhouette analysis to find the number of clusters for K-means method

Table 11. Results of different time series algorithms

algorithms	Euclidean K means			DBA-k-means			Soft-DTW-k-means			KShapeClustering		
n_clusters	2	3	4	2	3	4	2	3	4	2	3	4
silhouette	0.35	0.32	0.21	0.35	0.33	0.30	0.35	0.24	0.24	0.35	0.24	0.26
Davies bouldin	1.26	1.14	1.72	1.26	1.10	1.81	1.26	1.97	1.88	1.26	1.81	1.97
calinski_harabasz	47.92	38.72	26.70	47.92	42.14	32.75	47.92	29.09	27.53	47.92	29.09	29.22

Table 12. Labeling each time series in each stop according to their cluster (DBA k-means)

Year/stops	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
2019	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
2020	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
2021	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	2	2	2	2	2

To provide a better explanation of the differences between three different trends in 3 clusters, an example of time series plots for each cluster is illustrated in figure 8. all three time-series belong to the 11th stop. As it can be seen in table 12, the time series data of stop 11 in year 2019, 2020, and 2021 belong to cluster 1, 0, and 2 respectively. Figure 8 is typical shape of each class and in fact a bigger and clearer picture of figure 7. In other words, to have a better understanding of figure 7, explaining figure 8 may be helpful.

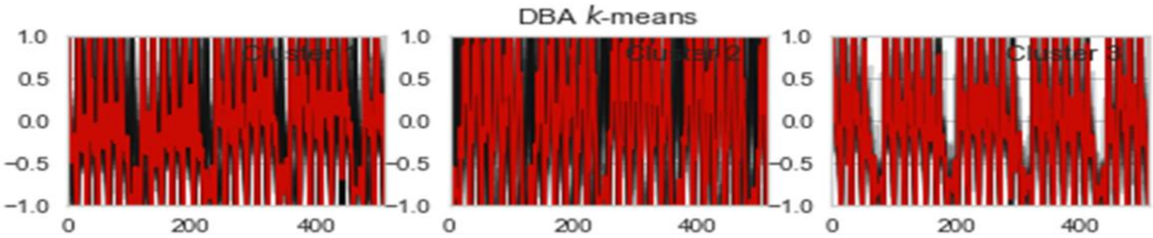

Figure 7. The visual results of the best clustering algorithm

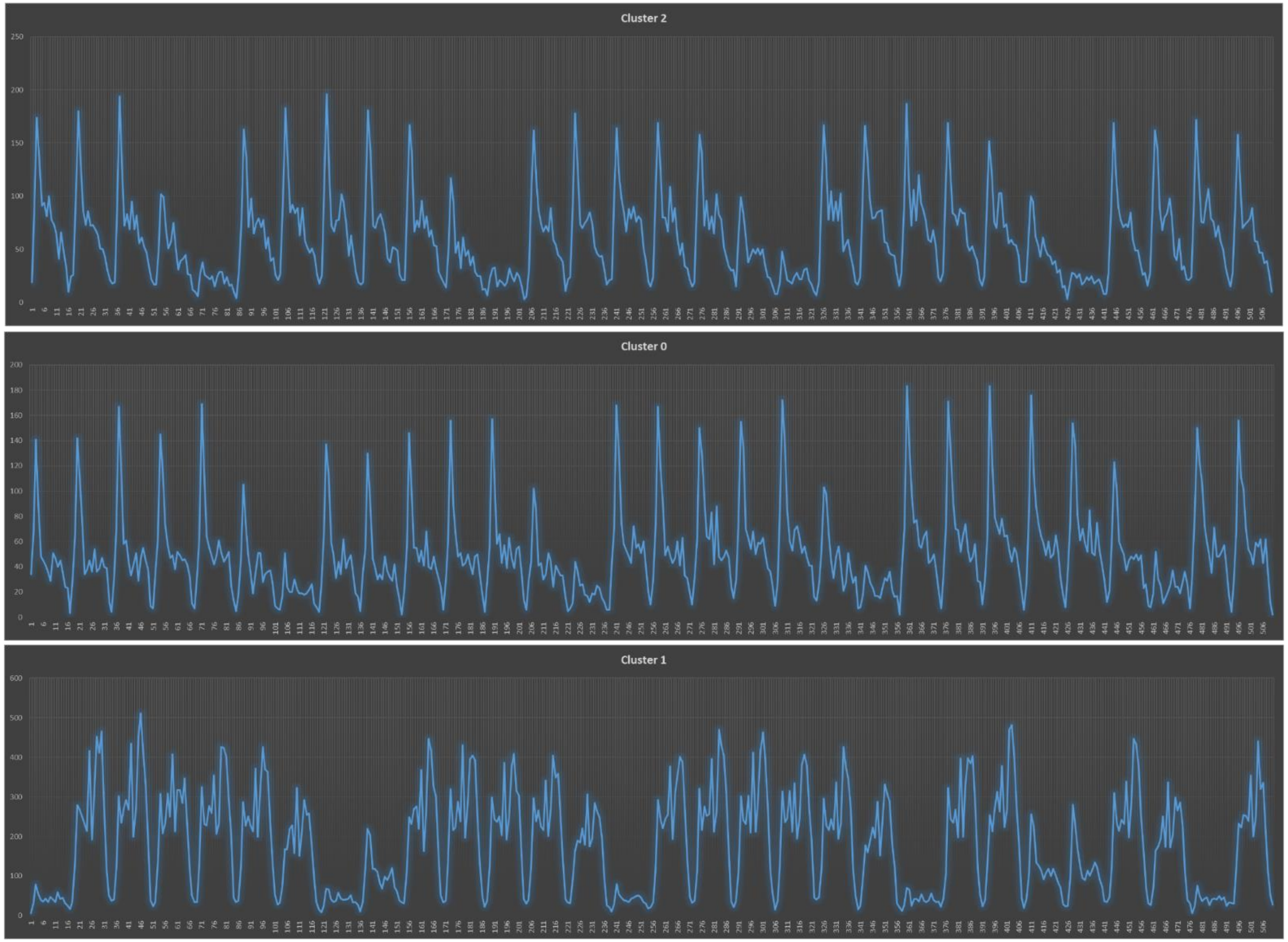

Figure 8. A representation for each cluster

For each of representative time-series in figure 8, ridership in one day is shown in table 13.

Table 13. Ridership in one day for each of representative time-series in figure 8

Time of day		5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Number of transactions	**Cluster 0**	31	69	167	111	58	61	43	33	42	51	29	47	55	45	37	9	7
	Cluster 1	41	126	302	235	272	292	267	435	199	268	454	511	411	323	198	39	24
	Cluster 2	19	86	194	120	72	83	69	95	69	82	56	61	53	47	35	22	17

In cluster 0, the number of transactions (ridership) starts to increase until the morning peak hour. The morning peak occurs in time interval (7,8) (indicated by 7 in the table). After the peak hour, the number of transactions decreases in almost each hour until we reach the evening peak. The ridership in this hour is less than that of morning peak. In cluster 1, although 7 o'clock to 8 is still the morning peak hour, however, when 'time of day' is 12, the number of transactions is more than that of 7 and at 16, it is even bigger. In fact, the evening peak hour has more transactions than the morning peak does. Therefore, in cluster 1, trends are different than cluster 0. In cluster 2, similar to cluster 0, there is one peak and that is the morning peak at 7 o'clock. However, there is an important difference, that is while in cluster 0, at 12, the number of transactions are small (one of the smallest among the members of cluster 0), while in cluster 2, at the same time interval, the number of passengers is one of the biggest among its counterparts. According to table 12, most of stops in new normal situation, belong to cluster 2, while before the pandemic their trends were categorized to be in cluster 0. It should be noted that as the smart card data in this study reveals, the demand in the new normal situation hasn't returned to pre-COVID-19 era. While in Thailand which is a developing country like Iran, a study (Thaithatkul et al., 2023**)** based on a survey at August 25, 2020 to October 9, 2020 concluded that once we transfer from pandemic to endemic, it is likely that the demand will return and if it doesn't completely return, it is because the government does not stop imposing some measures such as "working from home".

5. Implications

A consequence of this change will be the necessity of changing the headways between buses. The time schedule provided by the authorities for this line is shown in Table 14. As can be seen, the headways from 6 o'clock to 9 o'clock are all equal to one minute. The headway has been adjusted to two minutes between 9:00:00 and 14:30:00. For operators and managers, the first implication is the necessity of revising the time schedule. In fact, the demand at 12, for example, was expected to be much lower than at 7. The demand was supposed to be among the smallest of all 17 hours, but in the new normal situation, the number of transactions at 12 is one of the largest, so this schedule is no longer appropriate. To put it another way, headways have been calculated based on cluster 0 while now we are in cluster 2.

Table 14. Time schedule of line 1 of the BRT network in Tehran

From	To	Headway (minutes)
05:00:00	06:00:00	3
06:01:30	06:30:00	1
06:31:15	08:15:00	1
08:16:30	08:30:00	1
08:31:40	09:00:00	1
09:02:00	09:30:00	2
09:32:30	12:30:00	2
12:32:00	14:30:00	2
14:31:40	17:00:00	1
17:02:00	18:00:00	2
18:02:30	19:30:00	2
19:32:45	20:30:00	2
20:33:45	22:00:00	3

This BRT line is connected to Tehran's subway system by its 8 stops (P.Azadi, Moeen, Sharif, Navab, Enghelab, Vali-Asr, Ferdosi, and Darvazeh) which account for more than 33 percent (8 divided by the total number of stops which is equal to 27) of all stops. Some of these stops are so important. For instance, Darvazeh, is an intersection stop in Tehran's subway system. Figures 9 and 10 illustrate the metro's map of the city. Stop Darvazeh is shown as a green rectangle in both figures. The changes in ridership and travel patterns will affect the subway system too. In other words, the pandemic and the late vaccination may give rise to new travel patterns in the subway system as well, which definitely need to be addressed in terms of rescheduling and etc.

As a result of a decrease in demand, the government's income will decrease. Both the subway and BRT systems in Tehran are operated by the government itself. With the government spending a high amount of money to provide subsides for the transit system, a decrease in ridership may have resulted in too much losses. This is a new economic problem in a country that already had been suffering from economic recessions.

There may be positive implications too. In the new pattern, for example, the differences between the first-highest demand hour and the other high-demand hours are less severe. This fact can be viewed as an opportunity to lower congestion at both stops and vehicles which will result in higher customer satisfaction and lower perceived travel times during peak hours.

Dramatic decreases in transit ridership might have led to a radical modal shift from public to private transportation modes. This is true about the situation of many countries such as India (Dai et al., 2021). As a result, the traffic congestion in highways will be exacerbated.

It is necessary for the government to make transit’s demand return to pre-pandemic situation by certain policies of promoting public transportation. One of the important issues is public opinion on public transport. According to China’s experiences, disinformation about public transport and exaggeration the risk of infection negatively influenced public opinion **(Wang and Gao, 2022).** Therefore, the authorities need to be aware that in order to return demand to the pre-pandemic era, an appropriate plan for promoting public transport is crucial.

Encouraging people to use active transport modes (bicycle, walking and etc) could be another solution. It makes those who have changed their mode from public transportation, replace it by active transport instead of cars. There are also some other implications such as increasing the air pollution due to modal shift, changing travel time reliability, and etc.

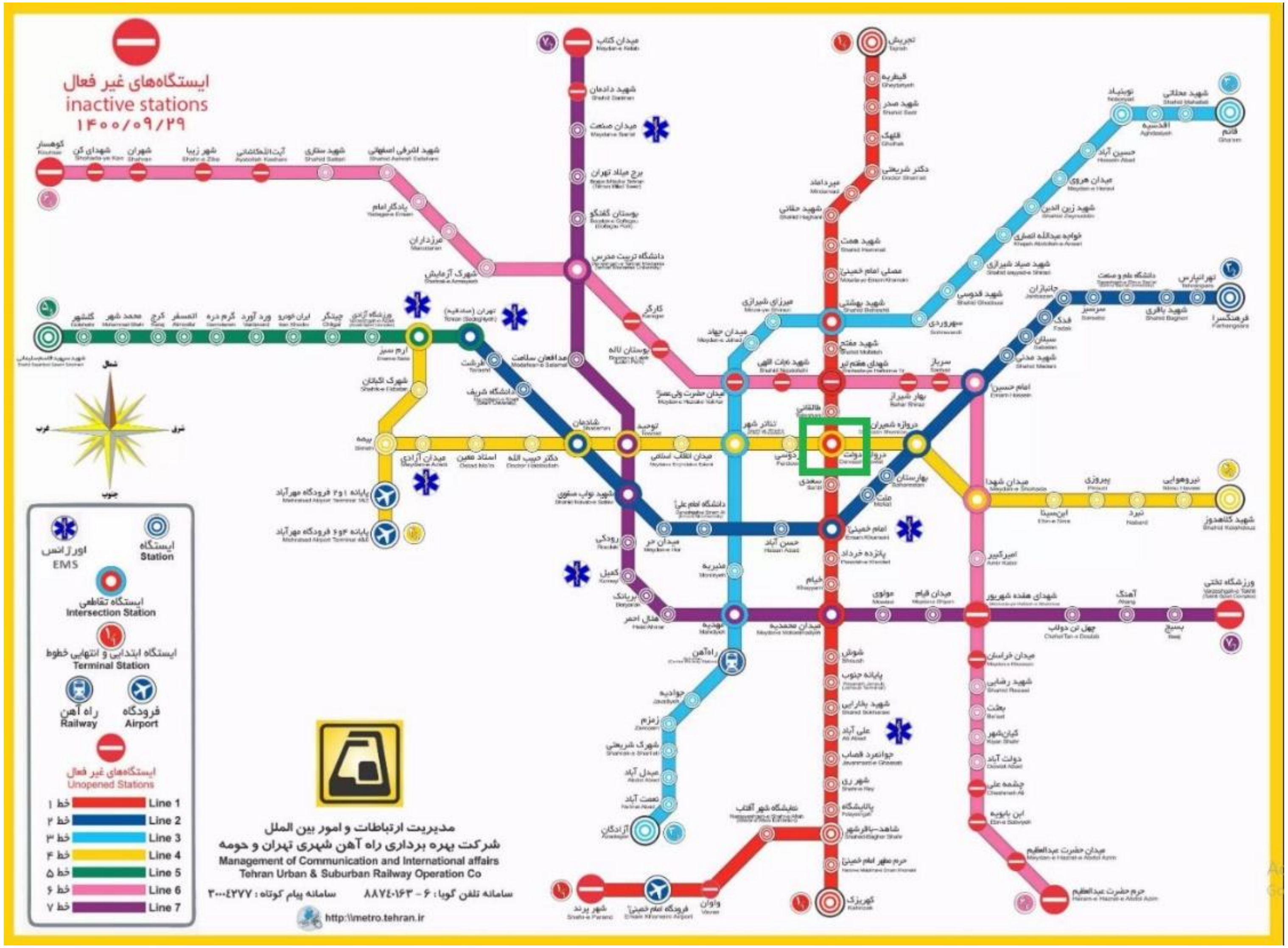

Figure 9. Metro's map of Tehran

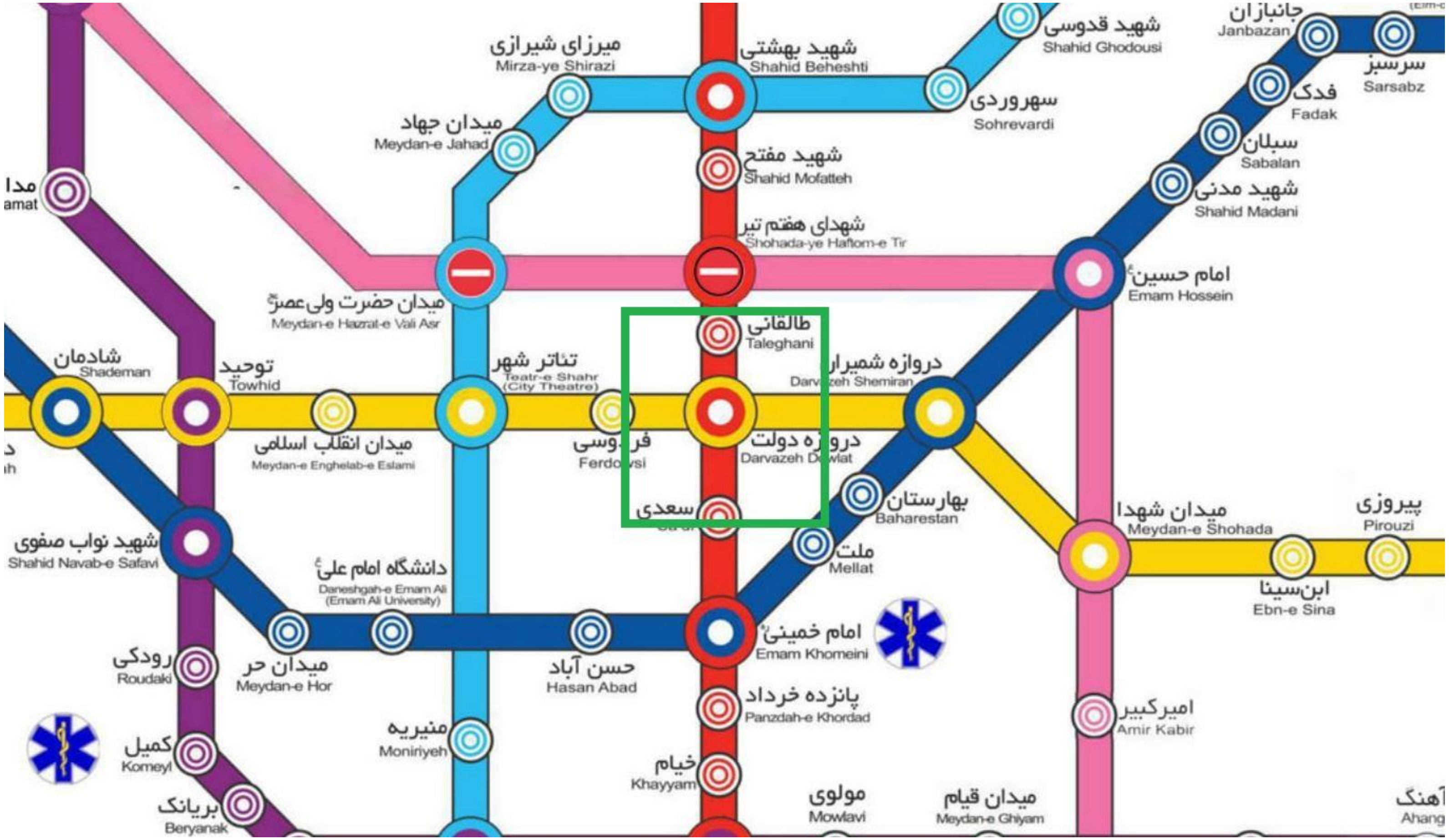

Figure 10. The subway station of Darvazeh

6. Conclusion and Future Research Direction

To determine whether there are new travel behavior patterns following the outbreak of COVID-19 in public transportation in Tehran, the capital of Iran, this study utilized a data-based approach. An analysis of the smartcard data of line 1 of Tehran's BRT system was conducted. There are nine BRT lines in total, but this is the most populated line. With 27 stops, the line connects the eastern and western parts of the city. After COVID-19, the situation is more complicated, according to this study. There was also a dramatic decrease in ridership. According to the results of a time-series analysis performed using four different algorithms, including Dynamic Time Warping (DTW), a new travel pattern in public transportation has emerged as predicted. After mass vaccination and the establishment of a new normal situation, a new pattern has emerged compared to that which existed before and during COVID-19. It is reasonable to assume that Iranians experienced three time intervals rather than two: before spreading, after spreading, and before vaccinating, after vaccinating. From the perspective of transportation behavior, this particular situation has not previously been addressed in such a developing country in this manner. According to this paper, it is necessary to analyze more closely the transportation issues caused by COVID-19 in Iran, particularly public transportation. From a transportation planning point of view, this study indicates that a new planning for public transport in Tehran is crucial to ensure that the system will be able to cope with the new situation. Since the system was not designed to handle this new situation, it is reasonable to view the change as a disease. Before making any decisions, it is urgently necessary to determine how deep the disease has penetrated the body of Tehran's transit system by studying its entire structure. There are several areas for further research in this subject area, but it seems that there is an immediate need to analyze changes in ridership or new travel patterns regarding public transportation in Tehran at a network-level. In fact, the AFC data of Tehran's entire transit system can provide more insight into the changes in travel behavior following COVID. This study also indicates a significant decrease in demand for public transport users, and based on the fact that those who have left this mode may have chosen to travel by car, future studies may examine ways to restore demand to the pre-pandemic levels. It is also possible to assess the users' attitude towards those ways and solutions.

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