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Who changed and who maintained their urban bike-sharing mobility after the COVID-19 outbreak? A within-subjects study

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Declaration of competing interest

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CRediT authorship contribution statement

Rudi Seifert: Conceptualization, Formal analysis, Investigation, Writing - Original Draft. **Maite Pellicer-Chenoll:** Software, Investigation, Writing - Original Draft. **Laura Antón-González:** Software, Investigation, Writing - Original Draft. **Miquel Pans:** Investigation, Software, Resources. **José Devís-Devís:** Conceptualization, Methodology, Data Curation, Writing - Review & Editing. **Luis-Millán González:** Conceptualization, Formal analysis, Writing - Review & Editing.

The COVID-19 pandemic has remarkably impacted urban mobility. All non-essential movements were restricted in Valencia (Spain) to contain the virus. Thus, the transport usage patterns of Valencia's bike-sharing system (BSS) users changed during this emergency situation. The primary objective of this study was to analyse the behaviour patterns of BSS users in Valencia before and after the COVID-19 outbreak, specifically those who maintained or changed their transport routines. A within-subjects comparison design was developed using a group of BSS users before and after the onset of the pandemic. Data mining techniques were used on a sample of 4,355 regular users and 25 variables were calculated to classify users by self-organising maps analysis. The results show a significant reduction (40%) in BSS

movements after the outbreak during the entire post-outbreak year. There was some recovery during the rest of 2020; however, this has yet to reach the pre-pandemic levels, with variations observed based on the activities performed in different areas of the city. Of the users, 63% changed their BSS use patterns after the onset of the pandemic (LEAVE group), while 37% maintained their patterns (REMAIN group). The user profile of the REMAIN group was characterised by a general reduction of approximately 35% of journeys during 2020, with a slight increase in morning movements compared to those made in the evening. These users also presented an equivalent number of cycling days to those of the previous year, reduced the number of connections and increased the network's density and the travelling speed. These results can be useful in estimating the percentage of people who do not vary their usual behaviour during emergencies. Finally, several policy implications are outlined based on the findings.

Keywords: Bike-sharing system, COVID-19; Valencia; Travel pattern; Urban mobility.

1. Introduction

The first case of pneumonia of an unknown origin was detected in December 2019 in Wuhan, China (Huang et al., 2020); subsequently, a new type of coronavirus called SARS-CoV-2 was identified as the principal cause of this illness, COVID-19. On 11 March 2020, the World Health Organization declared the virus to be a pandemic, forcing governments to take drastic measures on social distancing and human mobility to mitigate COVID-19 transmission. Strong correlations between these measures and decreased infections were observed during the first weeks after the outbreak (Badr et al., 2020; Xiong et al., 2020). However, people's daily lives were severely affected and there was a significant impact on the economy (Anoushiravani et al., 2020), environment (Khan et al., 2021), physical activity and sedentary time (Castañeda-Babarro et al., 2020), shopping (Tanveer et al., 2020), communications (Seufert et al., 2022), mental health (Usher et al., 2020) and transport (K. Kim, 2021). The pandemic had a particularly severe and radical effect on cities, specifically when the most severe measures and lockdowns were adopted. Some cities were forced to alter their urban dynamics and population distribution in relation to land use. For example, a survey-based research project carried out in the Chicago metropolitan area on general changes in mobility trends reported changes in long-established routines since shopping, commuting and business meetings were replaced by online alternatives (Shamshiripour et al., 2020). Romanillos et al. (2021) provided evidence of the changes in human activity due to the restrictions imposed in Madrid through mobile data analysis. Although people's activities were significantly reduced in every urban area analysed, those related to commerce, industry and health maintained their activities better than educational and leisure activities. Moreover, in countries such as Germany, half of the adult population went outside their homes for leisure and errands. In this case, young adults appeared to be more active than other age groups (Kolarova et al., 2021).

Urban transport was one of the sectors most affected by the restrictions on movements, although the impact varied depending on the type of transport. Specifically, public transport was drastically reduced because it provided ideal circumstances for virus transmission (M. Kim & Cho, 2021). Both the stations and the means of transport were regarded as places with a high risk of contagion due to the limited space available and the many surfaces that could aid in propagating the virus (Musselwhite et al., 2020). According to early post-outbreak estimations, public transport dropped as much as 80%–90% in major cities in China, Iran and the US and as much as 70% for some operators in the UK (Batsas, M., 2020). An Indian survey reported that

after the pandemic started, people reduced their unnecessary journeys and avoided public transport, taxis or other mass transport, while they walked and cycled more (Meena, 2020). Moreover, the demand for public transport in Budapest experienced the greatest reduction (80%), while cycling (23%) and bike-sharing (2%) experienced the lowest; however, private car use increased by 25% (Bucsky, 2020). According to Choi et al. (2023), citing a report by the Seoul Institute of Technology, there was a reduction of 32% in public transport movements in Seoul after the outbreak, with a reduction of 27.4% among subway users. In addition, a Polish survey found a reduction of 66% in the time spent travelling, regardless of age group and gender (Borkowski et al., 2021).

This paper is organised into eight sections. After this Introduction, Section 2 reviews relevant previous literature on bike-sharing systems (BSS) during the COVID-19 pandemic. Section 3 describes the study area, the database and the data analysis strategy, which includes self-organising maps (SOM) and linear statistics. Section 4 presents the general descriptive data pre- and post-COVID-19 outbreak, classifies the participants using SOM and analyses the changes in the use of the BSS as well as the differences between the participants who changed and those who maintained their normal BSS routines. Section 5 discusses the results obtained. Section 6 outlines some limitations of the study and suggests future research directions. Section 7 concludes this empirical research by presenting the paper's main contributions and Section 8 presents the policy implications of the main contributions of this study.

2. BSSs and the COVID-19 pandemic

Active modes of transport, such as walking or cycling, were encouraged during the COVID-19 pandemic to minimise the risk of infection (World Health Organization, 2020). Specifically, bicycles were recommended as they help users save time (Bullock et al., 2017) and allow them to avoid sharing a space with others, thereby reducing the risk of contagion. Thus, many authorities encouraged using BSS (Nikiforiadis et al., 2020) to alleviate public health risks associated with crowded public transport, which may explain the significant rise in bicycle use observed in different countries during the pandemic (Buehler & Pucher, 2021).

BSS systems had become increasingly popular in many cities over the previous 20 years due to their beneficial effects on the users' health, the ability to combine them with other modes of public transport and

their potential to reduce the use of motor vehicles and lower greenhouse gas emissions (DeMaio, 2009). During lockdown, BSS services in Boston, Chicago and New York provided free access to health workers and other essential personnel to promote the use of bicycles as a means of transport during the pandemic (Bouhouras et al., 2022), while some cities, such as Houston, Atlanta and New Orleans in the USA (Miketa & Sun, 2020) and Santander, Spain, suspended their BSS service (Aloi et al., 2020). Furthermore, in some cities, such as Bogotá, New York and Barcelona, bike lanes were extended, added to or made bike-friendly (or cyclable) streets. Furthermore, in Budapest and Oakland, BSS prices were reduced (Berezvai, 2022; Bustamante et al., 2022; Miketa & Sun, 2020).

Despite differences in political decisions, many cities worldwide, including Beijing, Boston, Budapest, Chicago, Coruña, London, New York and Seoul, experienced significant reductions in BSS use after the COVID-19 outbreak. However, follow-up recovery was observed compared with other modes of transport, although it did not always reach pre-pandemic levels, especially when BSS services re-opened or restrictions were relaxed (Bucsky, 2020; Heydari et al., 2021; Hu et al., 2021; J. Kim & Lee, 2023; Orro et al., 2020; Padmanabhan et al., 2021; Shang et al., 2021; Teixeira & Lopes, 2020; Xin et al., 2022). In addition, several studies, which used different data-gathering methods, agreed that BSS was more resilient than other forms of public mobility due to its versatility and flexibility, which enable it to recover easily from changes or shocks (Mattsson & Jenelius, 2015).

However, there were variations in BSS use during the pandemic due to mobility restrictions and the particular characteristics of each BSS and community network. For example, in Budapest, no clear recovery was observed in the number of BSS users after the initial increase in ridership at the onset of the pandemic (Berezvai, 2022). In Chicago, BSS usage followed an ‘increase-decrease-rebound’ pattern, with a pre-pandemic period coinciding with an increase and a pandemic period coinciding with a decrease and rebound (Hu et al., 2021). A spatiotemporal analysis revealed more detailed changes in different parts of Chicago. Areas with more white and Asian residents and fewer African–American residents reduced their BSS usage earlier, to a greater extent and recovered later. Open spaces and residential areas showed lower reductions and recovered earlier. The city centre and high-income areas presented an early increase with a delayed drop and recovery time. Isolated stations played a more important role in the pandemic, with a more relative pre-pandemic increase and less relative post-pandemic decrease. From the Beijing BSS data, Chai et al. (2021)

observed an overall reduction in bike usage of 64%, with a subsequent recovery of 15.9%, while bike-sharing experienced a reduction of approximately 40%. The early reductions especially affected underground train stations, high technology companies and shopping malls, while residential zones, supermarkets and hospitals were less affected. The subsequent recovery of bike-sharing was particularly observed in high-tech and ordinary companies.

Since the pandemic's onset, variations in the time and duration of BSS use have been found in different cities worldwide. An increase in bike-sharing hire time and average travel duration was found in London, Beijing, Boston and New York, sometimes with short journeys (Heydari et al., 2021; Padmanabhan et al., 2021; Shang et al., 2021; Teixeira & Lopes, 2020; Xin et al., 2022). In Washington DC, more people were prepared to use the BSS for their complete commutes rather than just the final few miles (Chen et al., 2022), and trip distance was relevant to Barcelona BSS usage during the pandemic (Bustamante et al., 2022).

The above-detailed disparities in BSS use also include some socioeconomic inequalities in ridership after the outbreak, which probably existed prior to the pandemic but were exacerbated under the conditions created by the pandemic. For instance, bike-sharing appeared more prevalent in Chicago areas with more white, high-income, educated residents and with higher population densities (Hu et al., 2021). In addition, people from wealthier neighbourhoods in New York could better maintain social distancing than those in poorer areas with a high percentage of essential low wage workers (Pase et al., 2020). Prediction studies also indicated that higher-income and education levels of residents in Barcelona and Thessaloniki emerged as a relevant effect on BSS usage during the pandemic (Bustamante et al., 2022; Nikiforiadis et al., 2022). In fact, these results exacerbated the socio-demographic barriers for marginalised and vulnerable groups who lacked the capacity, accessibility and incentive to use bike-sharing services from pre-pandemic times (Teixeira et al., 2021).

According to socio-demographic variables, BSS use was moderately affected by the pandemic in different cities because it followed reducing pre-pandemic trends. For instance, weekdays attracted more BSS usage than weekends, although there was an increase during non-working days during the pandemic in Barcelona and Beijing (Bustamante et al., 2022; Chai et al., 2021). Men still tended to use the BSS more than women during the pandemic, but COVID-19 onset prompted an increase in women users in Barcelona, Spain and Shiraz, Iran (Bustamante et al., 2022; Shaer et al., 2021), with a similar frequency in Lisbon, Portugal

(Teixeira & Cunha, 2023). Younger individuals were more likely to use bike-sharing than older people, although an increase among older people was observed during the pandemic in Nanjing (Hua et al., 2021). Men showed a higher prevalence of bike ownership and were more inclined to use personal bikes than women when the BSS was unavailable. Conversely, women tended to combine the BSS with public transport and were more likely to use personal transport if the BSS was unavailable (Teixeira & Cunha, 2023). As in pre-pandemic research, women's behaviour appeared to be more influenced by a perception of environmental risks (such as injuries and accidents) and social insecurity (such as violence and harassment) (Graystone et al., 2022; Pellicer-Chenoll et al., 2021).

Several studies have also reported that the pandemic impacted infrastructure and the city environment, which greatly affected BSS usage among citizens. For instance, a survey conducted in Shiraz found that a people-friendly environment with mixed, diverse, dense and accessible land uses and bike-friendly infrastructure significantly affected active travel during the pandemic (Shariati et al., 2021). Other studies in Chicago and Seoul have noted that open spaces and green areas had a statistically significant positive impact on bike-sharing usage, while industrial areas had a negative relationship (Hu et al., 2021; Jiao et al., 2022). According to Kim and Lee (2023), outdoor spaces, accessibility to subway stations and bike lanes have significantly increased bike-sharing ridership since the COVID-19 outbreak. These findings highlight the importance of expanding public bike infrastructure to promote BSS and cycling, as found in other studies (Berezvai, 2022; Bustamante et al., 2022; Xin et al., 2022). In fact, Bustamante et al. (2022) considered the extension of bike-sharing duration and the transformation of streets into bike-friendly spaces as the most important political decisions made to promote the use of bikes in response to the COVID-19 pandemic.

Thus, the main purpose of this paper is to analyse the behaviour patterns of Valencia BSS users before and after the COVID-19 outbreak, particularly those who maintained or changed their transport routines. The specific objectives are to:

- Determine BSS users' mobility, including the number of movements and percentage of cycling days before and after the COVID-19 outbreak years.
- Classify BSS users based on SOM analysis and identify changes in their behaviour by analysing modifications in their clusters before and after the COVID-19 outbreak years.

- Characterise the profiles of BSS users who remained in their clusters and those who left by identifying differences in their pre- and post-COVID-19 outbreak habits across the 25 variables used for this purpose.

This study has three-fold importance. First, this is the first study, to our knowledge, that establishes the behavioural patterns of the same group of BSS users utilising objective data by comparing their pre- and post-COVID-19 outbreak behaviour. Previous research studies have conducted comparative studies on BSS usage pre- and during a pandemic, but not with the same participants at different times. This reduces their effectiveness in measuring the changes found, as the comparisons refer to different groups at two or more different times. The present study has identified changes through within-subjects comparisons of a group of Valencia BSS users, thus obtaining more precise and reliable measurements than between-subject comparisons. Second, the study focuses on characterising the types of users, especially those who changed and maintained their normal BSS routines, by identifying pre- and post-COVID-19 outbreak differences in the 25 variables used. Third, an innovative artificial network analysis based on machine-learning mathematical models has been applied, unlike the more traditional linear statistical analysis model. This approach is especially suitable for handling and analysing multiple data and variables. Moreover, according to Wang & Biljecki (2022), applying advanced analytical methods to establish behavioural patterns is crucial in urban studies as they represent the complex real world of urban systems on multiple scales through multi-source data integration.

3. Materials and methods

This paper follows a within-subjects comparison design of a group of BSS users before and after the onset of the pandemic, utilising data mining techniques. Figure 1 illustrates the study workflow and the different phases of the analysis performed.

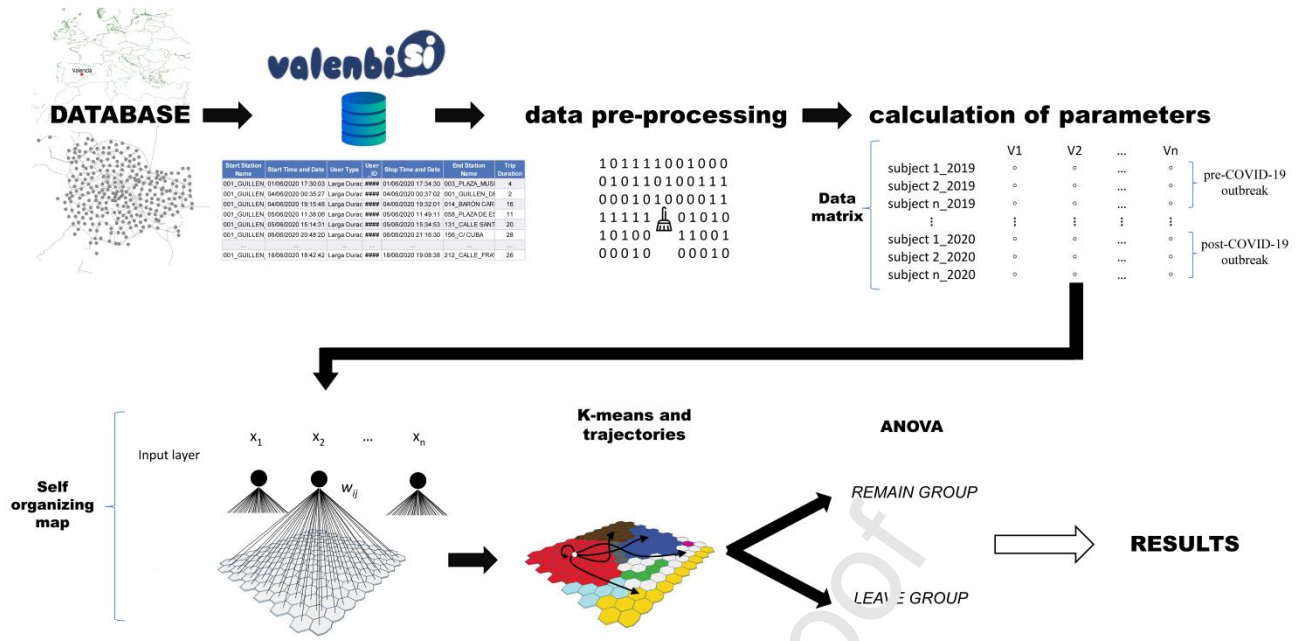


Figure 1. Workflow highlighting input data and analysis steps

3.1. Area of study and impact of the pandemic

Valencia, Spain, has had a BSS since 2010. Valencia is the third-largest city in Spain, located on the Mediterranean coast, with approximately 800,000 inhabitants and a population density of around 5900 inhabitants/km². Tourism is one of the main economic activities, partly due to the mild Mediterranean climate and a set of infrastructure focused on cultural tourism and entertainment. A detailed description of Valencia can be found in previous studies by Prytherch and Boira-Maiques (2009) and Pellicer-Chenoll et al (2021).

The first confirmed case of COVID-19 in Valencia was reported on 19 February 2020 (Romero García et al., 2021). Like other European cities, several legal measures were implemented to minimise COVID-19 cases and deaths. The first measures aimed to restrict citizens' movements while adding hygienic recommendations to create a barrier to contagion. Below is a brief summary of the measures adopted in 2020 by the Valencia City Health Department (2022):

- Lockdown or Phase 0 (15 March to 17 May 2020): All non-essential movements were restricted, with the exception of shopping for food or medicine, attending emergencies or going to work in an essential job. Schools and universities, bars, restaurants, discotheques, cafes, cinemas and retail outlets were closed. The BSS service was also closed during this period.
- Phase 1 (18 May to 31 May 2020): Journeys were allowed in cities within one's own province (Province of Valencia) but not outside. All other restrictions and exceptions were maintained as in Phase 0. Retail shops were re-opened and masks were recommended in public.
- Phase 2 (1 June to 14 June 2020): Journeys outside one's own province were still not allowed and physical activities could be conducted by different age groups at certain times. Masks were obligatory in public and closed spaces for all except children under six.
- Phase 3 (15 June to 20 June 2020): Travel was allowed within the Autonomous Community (consisting of three provinces). The time zones for physical exercise were eliminated, children's amusement parks were re-opened and large shopping centres were allowed to function with a limit to the number of customers at any one time.

3.2. Database and calculation of parameters

The database used in this study consisted of movement records of all users of the Valencia BSS from January 2019 to February 2021, divided into pre-COVID-19 outbreak year (1 January 2019 to 31 December 2019) and post-COVID-19 outbreak year (1 February 2020 to 31 January 2021). January 2020 was excluded as it was considered a transition month with no recorded cases in Valencia.

The data files contained 12 columns describing each user's movements, with over 500,000 trips per month. The analyses only used the member code (numerical), departure and return station (text), departure and arrival date (text: Day/Month/Year Hours: Minutes: Seconds) and travel time (numerical) columns.

Socio-demographic data for each user were stored in a separate, anonymised file from which four fields were extracted: member code (numerical), gender (nominal: male/female), age (ordinal: 1 = 'less than 26 years old', 2 = '26–55', 3 = 'Over 55') and post code (numerical).

Only individuals who used the BSS at least 25% of the days in 2019 (a minimum of 91 days per year) were analysed and those who made no trips in the pre- and post-COVID-19 outbreak periods were discarded. The final sample included 4,355 subjects and Figure 2 shows the gender and age distribution of the BSS users. Since other thresholds (e.g. 20%, 30%, 40%... of days of BSS use) can yield slightly different results from the ones reported in this study, readers can investigate these thresholds by accessing the data (Seifert et al., 2023).

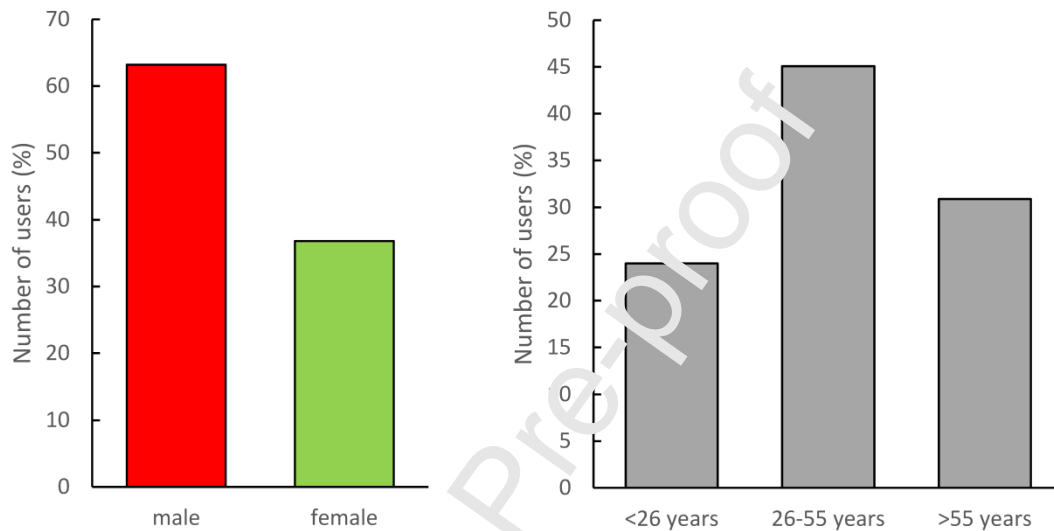


Figure 2. Gender and age distribution of BSS system users (n = 4,355)

The registers were pre-processed prior to calculating the parameters of users' behaviour. Registers exceeding the maximum usage time limit set by the BSS (30 minutes) by ten minutes were eliminated, as were those with duration of less than 5 minutes. Movements starting and ending at the same station were excluded from subsequent analyses, as were those without a final destination, such as bicycles not returned or sent for repairs.

After eliminating anomalous movements, 25 variables were calculated for all habitual users to characterise their behaviour. For this purpose, a script was written on MATLAB software (MATLAB R2021b, Mathworks Inc., Natick, USA). Separate calculations were performed for the pre-COVID-19 outbreak and post-COVID-19 outbreak years, as described below.

The first and second variables calculated were the total movements for each user and the percentage of days in the year they used the system. These variables represented the number of times the service was used each year.

Next, total movements and the percentage of movements during different seasons of the year, weekdays, weekends, mornings, evenings and nights were calculated. The average usage of the BSS was also determined for the different times of day when users had made at least half of their journeys.

The percentage of movements made by users who travelled the same route at the same time as others was also determined. The anonymous nature of the data prevented certainty in determining whether the journey was made alone or together. However, some logical rules were established and labelled as ‘Accompanied Movements’, which referred to movements where two or more users took bicycles at the same station within less than 2 minutes of each other.

Five variables were calculated after drawing a directed graph or digraph G consisting of a set of vertices V and a set of arcs E . The vertices were also called *nodes* or *points* and the arcs were called *directed edges* or *directed lines*. An arc is an ordered pair of vertices (v, w) , where v is the tail and w is the head. An arc $v \rightarrow w$ is said to go from v to w and w is adjacent to v . After eliminating loops (movements that begin and end at the same station) to draw the directed graph, all users’ movements were used and the adjacency graph was constructed. The number of existing cycles of each user was then calculated. A cycle exists in a graph when there is a non-empty path in which only the first and last nodes are repeated. Therefore, the percentages of movements that contained cycles of 2 or 3 nodes (e.g. Node1 \rightarrow Node2 \rightarrow Node3 \rightarrow Node1) were determined. The graph was also used to calculate the density, representing the ratio between the edges present in a graph and the maximum number of edges the graph can contain. Both the cycle percentage and density variables demonstrated the complexity of movements made by users. The percentage of times users followed the same route was also quantified.

Since movements were restricted in many time slots in 2020, the percentage of movements made in these slots was labelled as ‘irregular movements’. It should be noted that these movements did not exist in 2019. To enable comparisons, the value for 2019 was calculated for the days on which movements were prohibited in 2020.

Two variables were calculated based on the time and distance covered by users. The time taken was extracted from our registers, while the distance between stations was obtained from the Distance Matrix API (*Overview / Distance Matrix API*, n.d.). The latitude and longitude of the start and finish stations were entered and it was specified that the trip was made on a bicycle. These data were used to calculate the average kilometres covered in each journey and the average speed.

Four variables were calculated based on the zones visited by users. Before the analysis, stations located at least 65 m away from touristic points of interest or train or bus stations, sports centres, schools and leisure centres were geo-located (Lucchini et al., 2021). Then, the data published by the city council were used to locate them (*Portal de Datos Abiertos del Ayuntamiento de Valencia / Catálogo de Datos*, n.d.). These data were used to calculate the percentage of movements that ended at any of the above visit or connection categories.

3.3. Self-organizing maps

We utilised unsupervised neural networks as SOM to convert the input signal pattern of arbitrary dimensions into a topologically ordered 2-dimensional discrete map. This is an innovative non-linear modelling data analysis method, especially suitable for handling multiple data when the equation explaining the relationship between the variables is unknown, as was the case in this study. Furthermore, this classification method produces better results than other methods such as traditional principal component analysis (Astel et al., 2007; Li et al., 2018).

We employed SOM analysis to classify study subjects according to various variables (Lasri, 2016). Each user had two sets of data variables characterising them at two points in time (i.e. the pre-COVID-19 outbreak year and the post-COVID-19 outbreak year). The system grouped similar behaviours in a nearby space. If the user followed the same behaviour in both years, they were classified in the same space. However, if their behaviour in both years differed considerably, the system classified the user in two separate spaces.

The SOM analysis was performed using MATLAB R2021b software (Mathworks Inc., Natick, USA) and the SOM Toolbox for MATLAB Version 2.0 Beta. The process began by building a neural network of nodes (also called neurons) whose size depended on the number of cases in the analysis. The input data matrix

contained 8710 cases (i.e. 4,355 subjects \times 2 years). To track the users' evolution in both years, each was assigned an identifier specifying the year the data referred to, following Ling and Delmelle (2016). Our network or grid was rectangular, 26 neurons high and 18 neurons wide. The neurons were hexagonal so that each one had six neighbours.

Each neuron was assigned a value (i.e. initialisation), which was carried out in two different ways: random initialisation when weight vectors were initialised with a small random value and linear initialisation when these vectors were initialised linearly along a subspace spanned by the two principal eigenvectors of the input data series.

The initially assigned weights were modified during the training process. In this study, we applied two different training algorithms (i.e. sequential and batch). During the training phase, each neuron in the grid competed to represent all input vectors or cases that compose the sample. The winning neuron in each case was the one with the smallest Euclidean distance between its weight vector and the input vector. It should be noted that the input vectors or cases were normalised between 0 and 1 before starting the training process to ensure that the scale of variables did not influence the SOM training.

Once the input data vector had been assigned to a neuron, the competitive process was followed by an adaptive process in which the weights of the winning neuron and its neighbours were modified and topologically ordered (i.e. ordering and convergence phases).

Eq. (1) provides the calculation used to train the neural network. It can be observed that after each iteration (k) the weights were modified according to the differences between the initial weights and the input vector, the neighbourhood function and the learning ratio (Figure 3).

$$w_j(k+1) = w_j(k) + \eta(k)h_{j,i(x)}(k)(x - w_j(k)) \quad (1)$$

Here, w_j denotes the weight vector of the j th neuron, η denotes the learning ratio, $h_{j,i(x)}$ denotes the neighbourhood function and x denotes the input vector. The neighbourhood function was employed to enable the winning neuron and its nearest neighbours to adjust their weights to resemble the input vector more closely than the neurons distant from the winning neuron. In this study, we tested four different neighbourhood functions: (i) Gaussian, (ii) cut Gaussian, (iii) Epanechnikov and (iv) Bubble.

The learning ratio is high in the initial iterations and gradually decreases to very small values, resulting in significant changes in neuron weights at the start of training, with successively smaller changes as the process advances.

The entire process was repeated 100 times because the final analysis result depends on random processes, such as initialisation and the order of input vectors. Therefore, repeating the process 100 times increases the likelihood of obtaining the best solution to the problem. As two different training methods, four neighbourhood functions and two initialisation methods were used, we obtained a total of 1600 SOMs (i.e. $100 \times 2 \times 4 \times 2$). The best SOM was the one that resulted in the lowest value when multiplying the quantification error by the topographical error. The former error expresses how well it represents the weight vector of neurons in cases belonging to each neuron and the latter relates to the position of the neuron values. The topographic error remains low as long as the nearest neighbours are more similar to each other than to more distant neurons.

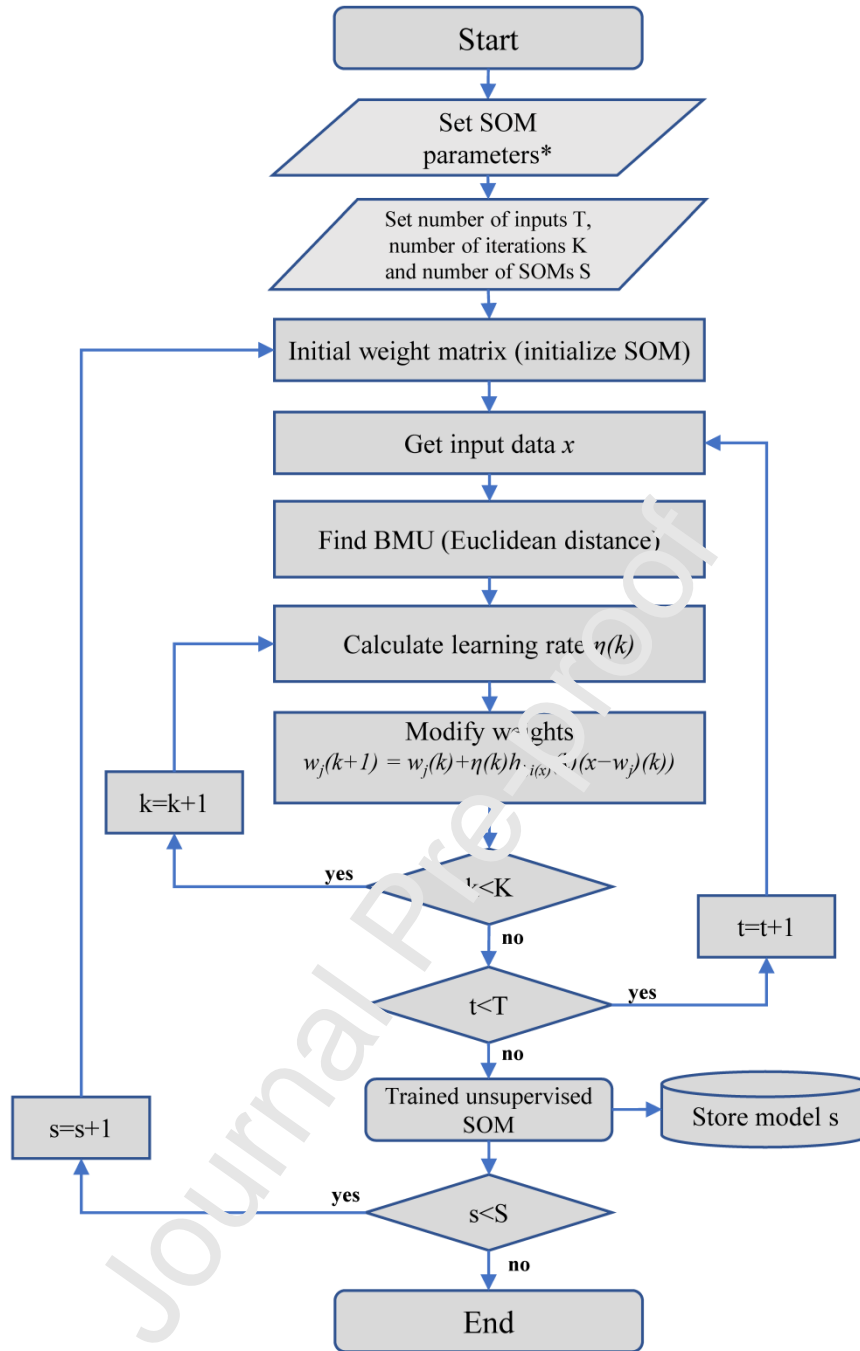


Figure 3. Flowchart for the unsupervised SOM algorithm. * We use the following parameters in constructing SOMs: initialisation = linear vs. random; training methods = sequential vs. batch; neighbourhood functions = Gaussian vs. cut Gaussian vs. Epanechicov vs. Bubble.

Among the different variables in our database, *gender* and *age* were not included in the SOM analysis but were used to label the neurons based on the number of subjects belonging to each gender.

Although the objective of SOM is to group cases with similar characteristics in the same neuron (i.e. each neuron represents a cluster); thus, a cluster analysis using a k-means method can be performed to obtain larger groups of people. To determine the appropriate number of clusters, we used the Davies–Bouldin index

(1979), which is commonly used to select the best solution. Generally, a smaller index indicates a better fit. For our study, we tested solutions with 2–10 clusters. Since the reduction in the index was less than one-tenth after six clusters (see Figure 4), we selected the 6-cluster solution, which provided the simplest solution with a similar error to the others.

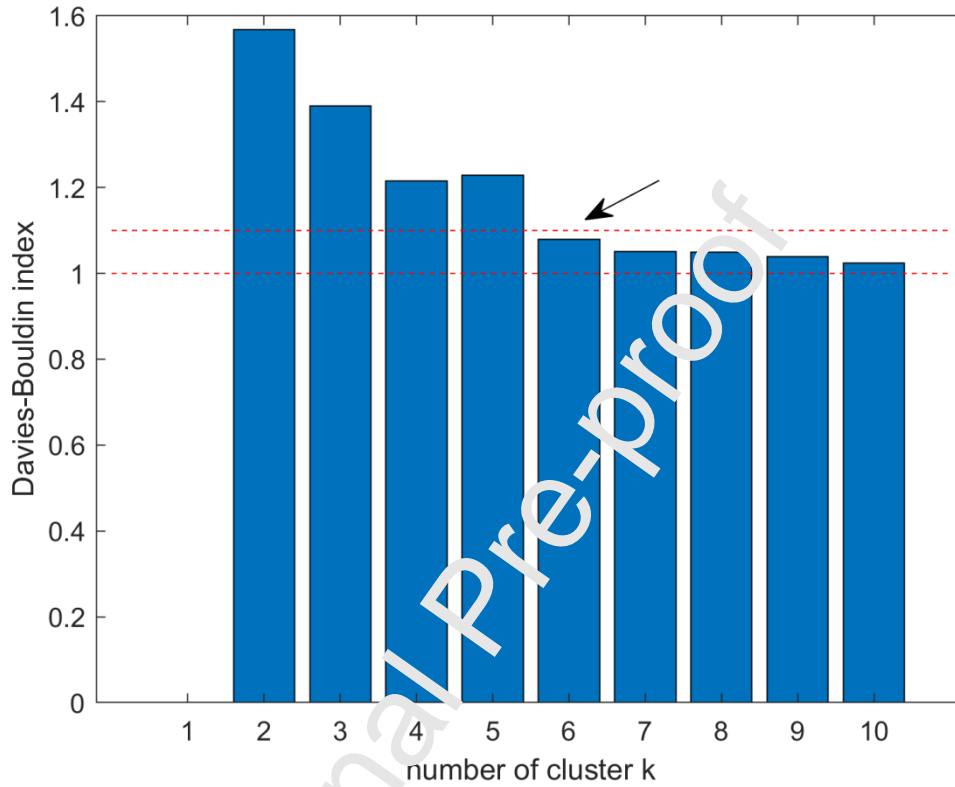


Figure 4. Davies–Bouldin index evolution regarding the number of clusters (*k*-means)

To determine the subjects' ability to move between clusters, the distance covered by each person on the SOM maps was calculated by taking the neuron they occupied in the pre-COVID-19 outbreak year and the ones they occupied in the post-COVID-19 outbreak year as reference points. The displacements were calculated using the Euclidean distance between the value of the neuron at the start and the value of the same neuron at the end.

Finally, a specific analysis was conducted on the number of users who changed clusters before and after the COVID-19 outbreak. Those who changed clusters were labelled 'LEAVE', while the group remaining in the same cluster was assigned the label 'REMAIN'.

3.4. Statistical analysis

Statistical analyses were conducted using SPSS for Windows V.26. Mean and standard deviation were calculated for all dependent variables. A mixed-model analysis of variance was performed to test the group effects (REMAIN vs. LEAVE), time (pre-COVID-19 outbreak vs. post-COVID-19 outbreak years) and the group \times time interaction for all 25 dependent variables. Post hoc analyses were conducted using multiple comparisons with confidence adjustment by the Bonferroni procedure as necessary. The alpha level was set at $P \leq 0.05$ for all analyses.

4. Results

4.1. General data on movements and cycling days pre- and post-COVID-19 outbreak

Before presenting our data, we must characterise the influence of the anti-COVID-19 measures on mobility in the city of Valencia. Figure 5 displays the epidemiological data from 2020 along with our data on the city's BSS and estimates of the population's location extracted from records available from Google (*COVID-19 Community Mobility Report*, n.d.). The epidemiological data are represented as absolute values (coloured in red). The BSS mobility values and Google mobility reports are expressed as percentage changes with respect to a reference value or baseline (i.e. a reference day represents a normal value for the day of the week, or the mean value of the 5-week period between 3 January and 6 February 2020).

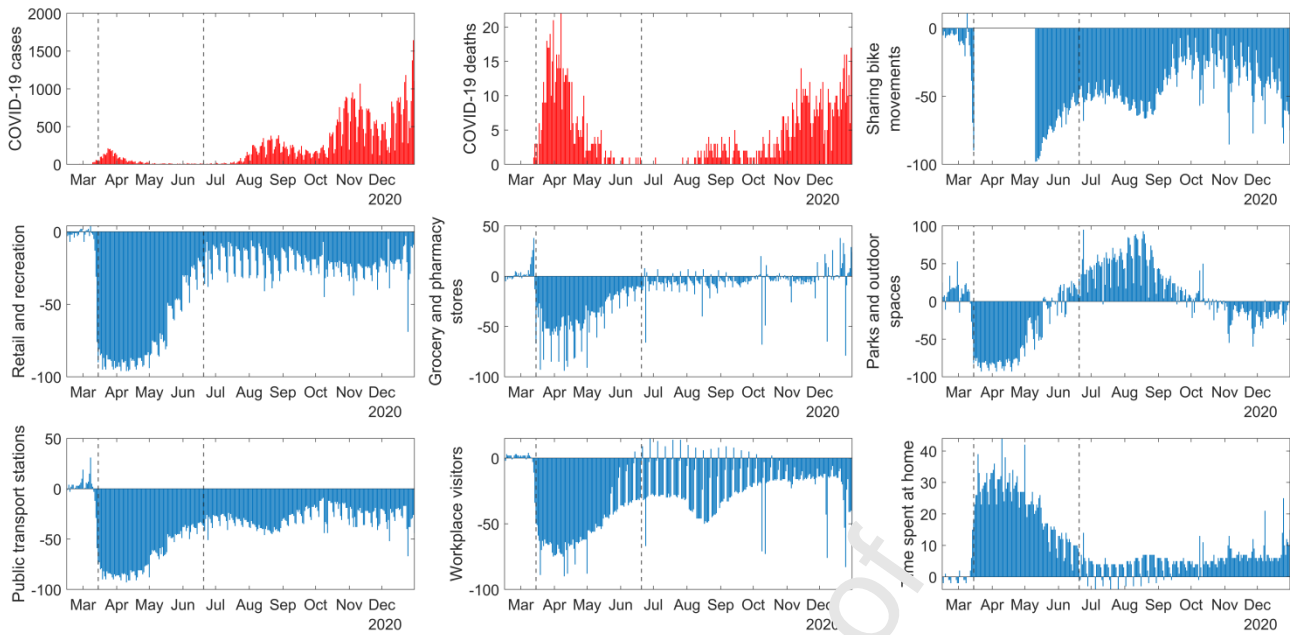


Figure 5. COVID-19 incidence and mobility in Valencia in 2020. Upper row (in red): COVID-19 cases diagnosed by PCR and deaths in the first year of the pandemic. Upper row (in blue): BSS movements as a percentage of baseline. Data for the period March 15-May 15 is blank due to suspended service. Second and third rows: movement tendencies according to Google Mobility Reports, as the percentage change regarding the reference value. Data are grouped in place categories, such as shops, leisure centres, supermarkets, pharmacies, parks, stations, workplaces and residential zones. Vertical dashed lines indicate the period in which government movement restrictions were in force (Phases 0–3).

Our database indicated a reduction of approximately 40% in the number of movements after the pandemic outbreak. In 2019 (pre-COVID-19 outbreak), there were a total of 3,159,890 movements, which decreased to 1,315,861 in the first year after the outbreak. The number of users who made at least one journey also decreased from 22,248 in 2019 (pre-COVID-19 outbreak) to 15,693 in the year after the COVID-19 outbreak.

A similar trend was observed among chronic users of the Valencia BSS ($n = 4,355$). The number of movements they made decreased from 1,344,965 to 693,907 ($p < 0.001$; $d = 1.05$) and the percentage of cycling days decreased from 41% to 23% ($p < 0.001$; $d = 1.31$), comparing the pre and post-COVID-19 outbreak year.

4.2. Classification of subjects by SOM

The overall patterns of movement suggest that the restrictions implemented at the local and national levels due to the pandemic influenced users' behaviour. To achieve the study's second objective, we employed an unsupervised neural network (SOM) to classify user behaviour. The resulting heat map and clusters are depicted in Figure 6. The heat map displays the locations where users were categorised, with fuller neurons indicating more users classified together. The user distribution was homogeneous, as users were evenly distributed throughout the space, with each user having a pre- and post-COVID-19 data vector.

Although SOMs comprise a clustering system, when they have a large number of neurons, it may be beneficial to group them into larger clusters using a k-means algorithm, which in our case resulted in six clusters, determined by the solution with the lowest error.

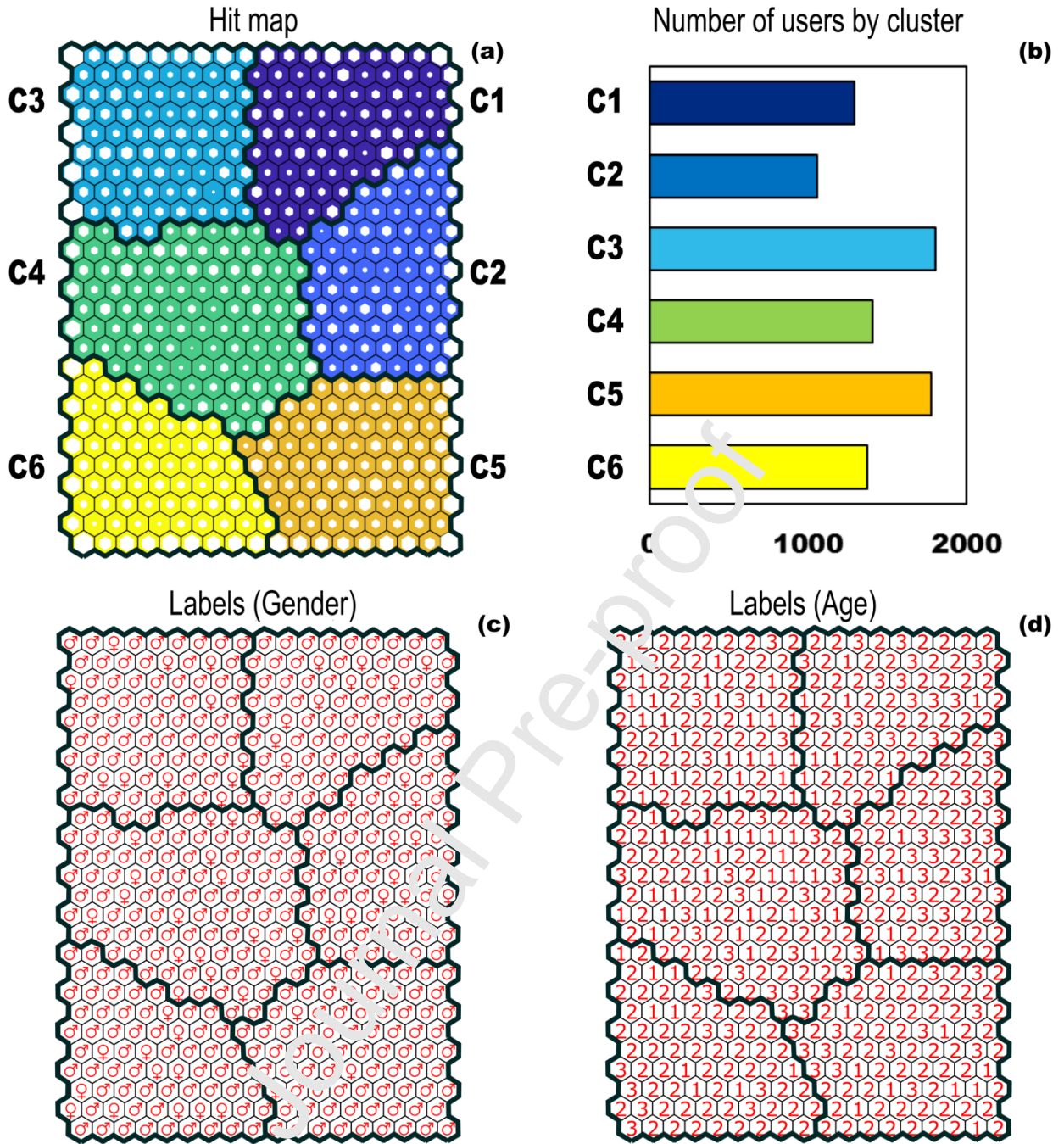


Figure 6. Hit map, number of users by cluster and labels ($n = 8,710$). (a) C1–C6 denotes cluster 1, cluster 2, ..., cluster 6; in every neuron, the bigger the white shadow the higher the number of users included. (b) The size of the bars shows the total number of users classified in each cluster. (c) Gender: ♂ = Male, ♀ = Female. (d) Age: 1 = 'Less than 26', 2 = '26–55', 3 = 'Over 55'.

4.3. Changes in usage behaviour

After classifying the users, we quantified the number of individuals in each cluster during the pre-COVID-19 outbreak year, as well as the number who remained in the cluster and those who left during the post-COVID-

19 outbreak year. Cluster C5 (see Figure 7) shows an example of such movements. This analysis was performed individually for all six clusters (C1–C6).

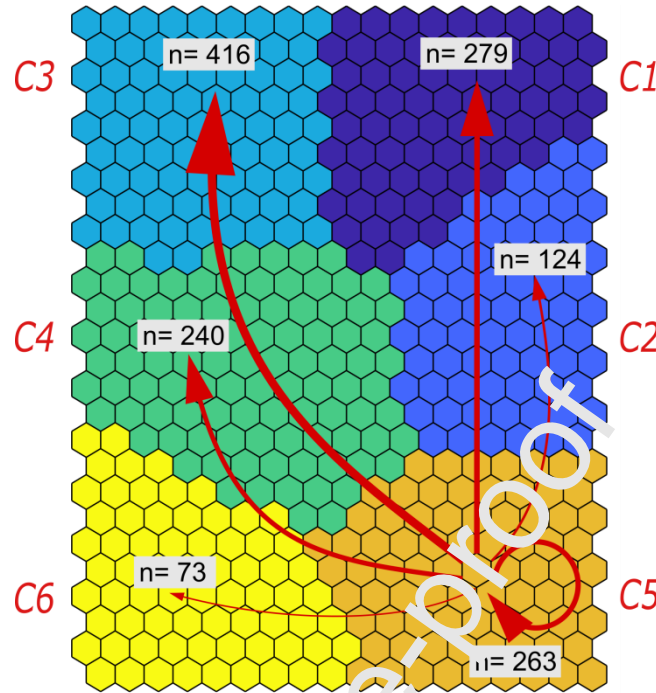


Figure 7. An example of change in cluster C5 during 2020. The size of the red lines shows the number of subjects that changed clusters in the post-COVID-19 outbreak year. The red circle shows the number of subjects classified in Cluster C5 in the pre-COVID-19 outbreak and post-COVID-19 outbreak years. Furthermore, n denotes the number of users who migrated from Cluster 5 to other areas, or who remained in it. Subjects that remained in the same cluster in both years were labelled the REMAIN group, while those who left were labelled as the LEAVE group. This analysis, given as an example, was carried out on all the clusters.

Considering the pre-COVID-19 outbreak year as the reference point, we observe that 63% of users altered their behaviour in the post-COVID-19 outbreak year (i.e. changed clusters), while 37% maintained their previous behavioural patterns despite the pandemic (i.e. remained in the same cluster). The upper panel of Figure 8 illustrates the number of users who either changed or continued with their previous behaviour in each cluster. As a result of these movements, the most densely populated cluster prior to the outbreak was C5, whereas C3 became the most densely populated afterwards. Since these clusters are topologically distinct, this indicates a significant change in behaviour for those who migrated from one cluster to another.

The lower panel of Figure 8 shows the inter-neuronal distances covered by users between the pre- and post-COVID-19 outbreak years. On average, the subjects from C5 covered the longest distance, indicating that

they underwent the most significant behavioural changes during this period. However, it should be noted that if a subject was classified in the same neuron in both years, the distance covered was 0, and if they migrated to the farthest neuron (e.g. from the lower right-hand corner neuron to the upper left-hand corner neuron), the distance value was approximately 27.

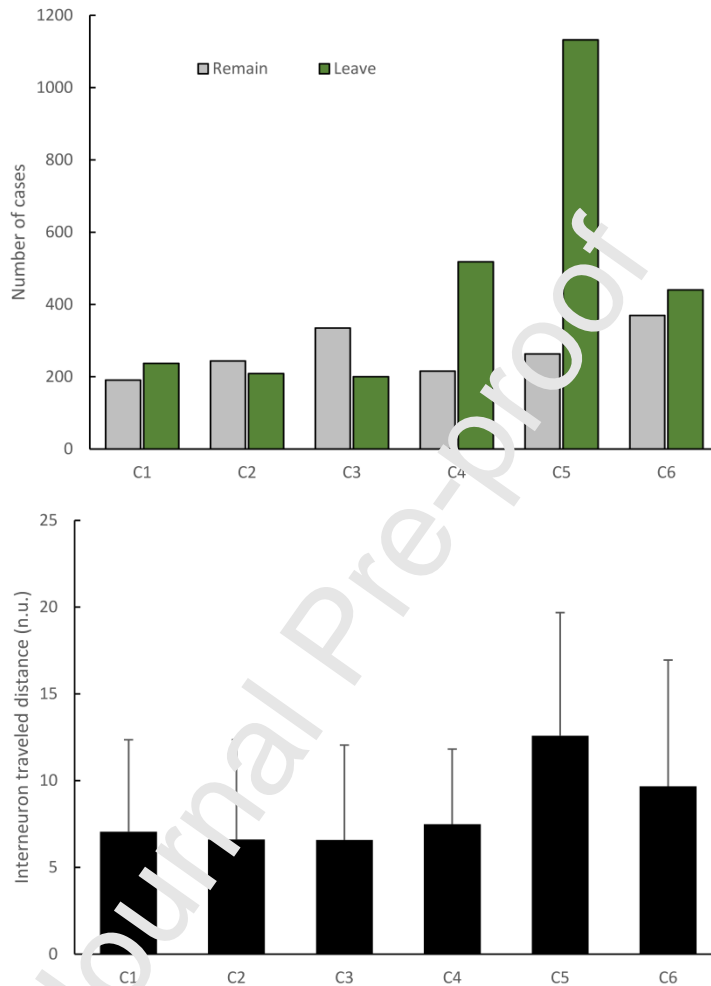


Figure 8. Residents and emigrants of different clusters after the upsurge of the COVID-19 pandemic. Upper panel: in grey users that stayed in the same cluster in the pre and post-COVID-19 outbreak years. Green represents those who emigrated to other clusters after the outbreak. Lower panel: inter-neuronal distances covered by the users between pre and post-COVID-19 outbreak years. Distance 0 means the user was classified in the same cluster in both years. Longer distances mean that the subjects were classified in different clusters far from each other. Error bars show standard deviation.

4.4. Means differences in the groups of individuals that remained in the same cluster and those who left it

After classifying the subjects and grouping them into either the REMAIN or LEAVE groups, the differences in the means between them were calculated for variables measured before and after the COVID-19 outbreak. The interaction between time (pre- and post-outbreak) and behaviour patterns (LEAVE vs. REMAIN)

revealed significant differences ($p < 0.001$). Of the 25 variables analysed, univariate contrasts of 15 variables showed significant differences ($p < 0.05$), as presented in Table 1. Both the REMAIN and LEAVE groups demonstrated significant changes in variables before and after the outbreak.

Total movements and the percentage of days the service was used decreased significantly in both groups, although the changes were more pronounced in the LEAVE group. Both groups showed increased movements during autumn and decreased during spring after the COVID-19 outbreak. The REMAIN group increased their morning movements and decreased their evening movements, whereas the LEAVE group did not. However, only the subjects in the LEAVE group demonstrated significant differences in weekday and weekend movement distributions.

In variables derived from the digraph, both groups reduced the percentage of cycles they carried out, increased the density of the graph and increased the percentage of times they took the same route. This indicates that each subject's graph became less complex, with fewer connections and streets they circulate.

Both groups showed a slight increase in their travelling speeds, with the increase slightly higher in the REMAIN group. Finally, the LEAVE group experienced a small reduction in the percentage of days they went to places related to education or leisure while no differences were found in the REMAIN group.

Regarding *gender* and *age* variables the percentage of men and women was similar in both groups (approximately 65% men and 35% women). Furthermore, a similar age distribution was also found in both groups, with approximately 45% of subjects between 26–55 years, 30% over 55 years and 25% under 26 years.

Table 1. Differences in means of the variables calculated between user's groups that remain and leave the clusters in the two years under study.

		LEAVE		REMAIN	
		M	SD	M	SD
Total movements (counts)	pre-outbreak	315.16*	(2.99)	298.15*	(3,89)
	post-outbreak	139.81	(2.54)	192.33	(3,30)
Days with movements (%)	pre-outbreak	41.57*	(0.22)	40.47*	(0,29)

	post-outbreak	20.54	(0.27)	26.67	(0.35)
Autumn movements (%)	pre-outbreak	32.95	(0.24)	34.20	(0.31)
	post-outbreak	34.84*	(0.35)	38.15*	(0.45)
Spring movements (%)	pre-outbreak	30.06*	(0.21)	28.34*	(0.27)
	post-outbreak	16.95	(0.29)	12.84	(0.37)
Weekend movements (%)	pre-outbreak	17.04	(0.21)	16.42	(0.27)
	post-outbreak	18.10*	(0.24)	16.05	(0.31)
Weekday movements (%)	pre-outbreak	82.96*	(0.21)	83.58	(0.27)
	post-outbreak	81.90	(0.24)	83.95	(0.31)
Morning movements (%)	pre-outbreak	31.08	(0.33)	32.31	(0.43)
	post-outbreak	30.69	(0.35)	33.56*	(0.46)
Night movements (%)	pre-outbreak	13.67	(0.25)	14.38*	(0.33)
	post-outbreak	14.15*	(0.27)	13.86	(0.35)
Cycle 2 (%)	pre-outbreak	33.04*	(0.23)	32.33*	(0.3)
	post-outbreak	28.87	(0.27)	31.03	(0.36)
Cycle 3 (%)	pre-outbreak	19.14*	(0.26)	16.92*	(0.34)
	post-outbreak	9.96	(0.25)	12.87	(0.32)
Graph density (n.u.)	pre-outbreak	1.89	(0.04)	1.28	(0.05)
	post-outbreak	1.67	(0.05)	1.67*	(0.06)
Movements on the same route (%)	pre-outbreak	20.43	(0.27)	24.26	(0.35)
	post-outbreak	20.98*	(0.28)	25.59*	(0.37)
Speed (km/h)	pre-outbreak	12.09	(0.04)	11.91	(0.05)
	post-outbreak	12.13*	(0.04)	12.09*	(0.05)
Movements ending at educational centres (%)	pre-outbreak	31.73*	(0.5)	29.84	(0.65)
	post-outbreak	20.11	(0.5)	29.56	(0.65)
Movements ending at leisure centres (%)	pre-outbreak	26.38*	(0.41)	26.97	(0.53)
	post-outbreak	24.87	(0.41)	27.39	(0.54)

*All groups show a significant time-by-group interaction ($P < 0.05$). *indicates significant differences ($p \leq 0.05$) pre vs. post-COVID-19 outbreak.*

5. Discussion

This paper is, to our knowledge, the first to establish pre- and post-COVID-19 outbreak behaviour changes in a group of Valencia BSS users, comparing objective within-subjects data. The main results obtained are linked to the three specific objectives defined at the beginning of this study.

The first main result refers to the significant reduction in BSS movements during the first months after the outbreak of the COVID-19 pandemic (Phases 0 and 1), followed by recovery during the remainder of the second year without reaching pre-pandemic levels. This is consistent with findings in many other cities worldwide (Bucsky, 2020; Heydari et al., 2021; Hu et al., 2021; J. Kim & Lee, 2023; Orro et al., 2020; Padmanabhan et al., 2021; Shang et al., 2021; Teixeira & Lopes, 2020; Xin et al., 2022). The reduction observed in Valencia was 40% throughout the post-outbreak year, which is similar to the 40% observed in

Beijing (Chai et al., 2021) approximately 32.35% reported in Chicago (Hu et al., 2021). However, it is far from the 2% observed in Budapest (Bucsky, 2020) and the 70% reported in New York (Teixeira & Lopes, 2020). The variation in Valencia BSS movements corresponded to national and local restrictions. A gradual recovery was observed after the end of the lockdown, from May until mid-August, followed by a small drop and a subsequent sharp rise until the end of 2020, but still below baseline levels. Although most areas of the city experienced a recovery in BSS movements, only shopping centres and pharmacies reached baseline levels, while parks and outdoor spaces experienced a substantial increase above baseline levels, specifically between June and October 2020. These variations illustrate how national and local restrictions impacted Valencia BSS usage and how usage patterns differed across various areas of the city, as observed by Hu et al. (2021) in Chicago.

Beyond the dynamics of BSS usage and how the pandemic affected cycling patterns, the second objective of this study was to classify BSS users' behaviour and identify changes based on modifications of their clusters in pre- and post-COVID-19 outbreak years. Our analysis shows that 63% of users altered their BSS usage patterns following the onset of the pandemic, while 37% maintained their behaviour or made only minor changes. This percentage of users who made minimal changes to their mobility routine aligns with some previous studies conducted in Portugal. For instance, the study by Costa et al. (2022) in Lisbon found that 39% of those surveyed did not change the number of bicycle journeys they made before and after the first few months of confinement. Similarly, Teixeira et al. (2022) found that 35% of Lisbon BSS users were not particularly affected by the pandemic. These findings suggest that a considerable segment of the population responded to the restrictions by making fewer changes to their cycling mobility than the rest in response to the numerous changes in 2020. However, the variables analysed in this study do not directly identify the underlying reasons for this behaviour or indicate whether this behaviour influenced the dynamics of the pandemic. It is possible that many of those who did not change their behaviour belonged to essential professions and had already been using BSS before the pandemic and continued to do so after the outbreak. Moreover, in practical terms, it is important to investigate their behaviour to discover the details that would allow the promotion of BSS or avoid undesirable consequences for the health of the general population in exceptional situations, such as a pandemic.

The third main result, linked to the third purpose of this paper, indicates that the users belonging to the 37% in the REMAIN group of Valencia BSS users, like the 63% in the LEAVE group, were affected in 15 of the variables out of the 25 that were analysed. The main difference is that the former group made minor changes pre and post-outbreak that did not alter their general behaviour patterns (i.e. they did not change clusters). Although the changes were minor, it is crucial to understand what actually changed in this group's behaviour since it will help us create the profile of the people who composed the REMAIN group. Thus, it can be seen that the REMAIN group reduced their movements and the number of journeys by only approximately 35% during 2020. This group of users had an equivalent percentage of cycling days as in the previous year, even though there were legal restrictions on movements for four months. Conversely, the LEAVE group reduced their movements by around 56%, indicating a more drastic change in their routines.

Regarding the time slots of the day, the REMAIN group made minor pre and post-outbreak cycling behaviour changes, with a slight rise in morning movements compared to those made in the evening. This result is consistent with the findings of Fernández-Pozo et al. (2022), who found the disappearance of evening peak hours after confinement compared with the pre-outbreak period. Moreover, this was the only change in the routine of the REMAIN group after the COVID-19 outbreak, probably due to a series of night-time limitations in the months after the restrictions of Phases 1–3 that caused a displacement of some night-time movements towards the daylight time slots.

The analysis of digraphs reveals that both groups (especially the LEAVE group) reduced the complexity of the network formed by the total BSS movements made in 2020. Additionally, the users followed more predictable routes during the pandemic (Lucchini et al., 2021), simplified the number of connections and increased the network's density. This suggests that they made journeys to fewer stations but to those important to them and gave up most of their unscheduled journeys. Finally, we observed a slight increase in travelling speed, possibly related to the time of day of the journey, as previous research indicates that morning and weekday movements are typically faster (Jensen et al., 2010).

6. Limitations and future studies

Certain limitations emerged that should be considered when interpreting our findings. As previously mentioned, our data were obtained from BSS records and did not include all bicycle movements made in Valencia. Some citizens may have used their own bicycles to avoid using shared materials during the pandemic. However, this did not affect our results since we only compared BSS users in both years of the study (pre- and post-COVID-19 outbreak). It is important to note that our study only provides information on BSS movements and should not be used to extrapolate overall bicycle movements in Valencia. Moreover, we used a limited number of socio-demographic variables, such as gender, age and postcode, which makes it difficult to provide a detailed explanation of the Valencia BSS behaviours of both groups (REMAIN and LEAVE). In future studies, it would be necessary to increase the number of sociological variables and use a mixed-method approach that includes objective movement data, surveys or users' interviews. Additionally, the labelling of the REMAIN and LEAVE groups should be considered cautiously since the former consisted of people who remained in the same cluster before and after the COVID outbreak. This does not imply that their before and after data vectors did not vary but rather that the variations were not significant enough to assign them to a different cluster. A more restrictive view of our data (e.g. only assigning users who did not change their neurons to the REMAIN group) could slightly impact our findings. Future studies should also focus on this subgroup of the population, which appeared to be more 'resilient' to the changes, as it may be people, who belonging to essential professions, were already using this means of transport before the state of emergency. Future studies should identify and closely examine their different sociological, economic, medical and psychological characteristics. The results of such studies would help those responsible for directing health policies to design contingency plans in future emergencies or pandemics, maximising the positive aspects of their behaviour and reducing any risks detected in this population subgroup to a minimum.

7. Conclusions

This study aimed to determine the behaviour patterns and changes in Valencia BSS users before and after the COVID-19 outbreak, focusing on the city dwellers' emergency response patterns.

The first general conclusion is a drastic reduction in BSS movements, established at 40% during the entire post-outbreak year. Recovery was observed during the rest of 2020, but pre-pandemic levels were not achieved; moreover, there were variations depending on the activities in different areas of the city.

A second important conclusion relates to the 63% of BSS users who substantially reduced their patterns of use after the onset of the pandemic (LEAVE group) and the 37% who either maintained their behaviour patterns or made only slight changes (REMAIN group).

Finally, the third conclusion referred to characterising these two groups of BSS users. The LEAVE group showed a profile characterised by a substantial reduction in movements and the percentage of cycling days, while the REMAIN group displayed a minor reduction of 1/3 of the movements and journeys during 2020. Unlike the LEAVE group, the REMAIN group increased their morning movements and reduced their evening movements. The users of the REMAIN group were also active on an equivalent number of cycling days as the year before (excluding lockdown days), simplified the number of connections and increased the network density as well as travelling speed.

The REMAIN group's continued use of BSS in the year following the COVID-19 outbreak is likely due to the safety of bicycles as a means of transportation. Unlike public transport, bicycling allows for more physical distancing between riders, which may explain why users in the REMAIN group maintained their BSS behaviours. Therefore, the decision of these people not to change their habits was likely the correct one. However, from a sociological perspective, it is surprising that a significant percentage of the population continued with their usual routines after the COVID-19 outbreak, given the high numbers of deaths and cases of contagion that occurred in this period.

8. Policy implications

The conclusions of this study provide insight into how people commuted around the city of Valencia during the COVID-19 pandemic, which may be similar to the behaviour in other cities. This information can be useful for evaluating what happened and contribute to the decision-making of professionals, researchers and politicians involved in urban cycling and public health at the local and national levels. Furthermore, these conclusions can help justify the investments required based on evidence, although we acknowledge that it is not a common practice in Spain or elsewhere.

Specifically, we highlight the most important implications of our results. A general implication arises from the first conclusion, where BSS was revealed as a relevant means of transport in Valencia, as well as in many other cities, during an extreme and disruptive situation like a pandemic; however, no action was taken after the outbreak to increase the frequency of use. Beyond being sustainable and environmentally friendly, BSS is a mode of transport that avoids crowded public systems when social distancing is an important issue for public health. This is a new argument for policymakers to extend and improve BSS services in cities, making them accessible to the widest possible range of citizens. BSS managers should also consider increasing the flexibility of the BSS to avoid concentrations or high densities of movements in certain areas with high demand during pandemics, as infectious diseases will likely occur more frequently. This is a significant challenge, as disruptive events occur within short periods, requiring quick and flexible decisions to make the appropriate adaptations for new circumstances.

Another important implication is linked to the second and third conclusions, which are related to the two emerging groups of BSS users when comparing pre- and post-COVID-19: the largest LEAVE group, which significantly changed their cycling behaviour with a special reduction of movements and the smaller REMAIN group, which maintained their behaviour. Both groups should be considered in urban information campaigns and public health actions in future pandemics and disruptive events, without forgetting the REMAIN group, which apparently did not accept the restrictions but is probably composed of essential workers. BSS managers should ensure the maintenance and cleanliness of cycling infrastructure during future pandemics to cater to the needs of these groups of users.

The feasibility of the policy implications will depend on actions derived, including reducing prices or providing free access to the BSS, creating new bike-friendly spaces or reducing riding density in certain areas of the city. In addition, some actions to promote the use of BSS in emergencies would encourage healthy, environmentally friendly habits that could be maintained only during the emergency period. Other actions will take more time and exceed the disruption periods but can be essential for long-term improvement linked to the infrastructure, such as new and separate bicycle lanes, broad paths, pavement markings, clear guidance at intersections and more hubs and parking areas. All these actions derived from the policy implications can be achieved soon in Valencia and other cities.

Further improvements are desirable to achieve a wider and more flexible ridership network to better prepare for future disruptive events. However, more research is needed to further elucidate these two groups in the post-COVID-19 outbreak, which can aid decision-making in future disruptive events and the role played by BSS in cities.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Highlights

Neural network analysis was employed to classify the behaviour of bike sharing users

A within-subjects comparison was performed between the pre- and post-outbreak periods

A decrease of ~40% in movements was observed in the year following the outbreak

Of the users, 63% changed their behaviour and 37% remained the same

Public mobility campaigns should target both groups, especially the latter

Journal Pre-proof