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Public transport, social environment, and Bike Sharing System use to high school: A case study in València (Spain)

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ABSTRACT

Urban cycling provides significant benefits for both health and environment. Additionally, due to the demands of contemporary society, it serves as an effective way to promote healthy habits among adolescents. Since high schools (HS) are a primary destination for this age group, the social and environmental characteristics of these institutions can play a critical role in influencing the use of Bike Sharing Systems (BSS). Our study aimed to determine how various sociodemographic characteristics of HS influence BSS use for active commuting to school (ACS) in the city of València, Spain. A Self-Organizing Maps analysis were applied to generate HS profiles, followed by non-parametric analysis to compare these profiles based on HS typology. Four HS profiles were identified. Results indicated a higher use of BSS for ACS in public HS compared to private HS. Lower BSS use was observed in HS lacking public transport and BSS facilities, while private schools generally had better access to public transport resources. Regardless of the socio-economic status of the HS, equal access to public transport resources and BSS stations should be provided to both public and private institutions to foster an active lifestyle for all students. HS located in neighborhoods with low-to-moderate economic status and a moderate risk of vulnerability can still promote the use of BSS for ACS. However, disparities in the availability of resources for ACS are significant, often disadvantaging public HS and schools in the poorest and most vulnerable neighborhoods.

1. Introduction

The World Health Organization (WHO) recommends that children and adolescents engage in 60 min of moderate to vigorous physical activity daily (World Health Organization, 2010). However, obesity and low levels of physical activity are currently major problems among school-age populations in developed countries (World Health Organization, 2015). Active commuting to school (ACS) is one of the many solutions proposed to help school children increase their physical activity levels to meet WHO's fitness recommendations (Chillón et al., 2010). Specially, cycling offers a variety of health benefits such as improved cardiorespiratory fitness, reduced disease risk factors for disease and a significantly reduced risk of mortality from cancer, cardiovascular disease, or obesity (Oja et al., 2011). Longitudinal associations have been shown between cycling to school and weight status; particularly, the prevalence of overweight increased in students who stopped cycling to school (Bere et al., 2011). Bike Sharing Systems (BSS) particularly offer the ability to combine them with other modes of public transport (DeMaio, 2009) and also eliminates the fear of theft, storage and maintenance (Goodman et al., 2014). Thus, interventions such as the Go2school project created BSS stations for students and obtained positive results (Migliore et al., 2021). In addition, access to BSS has been found to be a strong predictor of using bicycles as an active mode of transportation to school (Estevan et al., 2018). Despite these positive findings, cycling represents a low percentage of journeys compared to other means of transport in different cities (European Environment Agency, 2019), as well as transport to and from schools (Estevan et al., 2018). Commonly, studies have attempted to identify factors that influence the use of BSS for school commute, such as the location of BSS stations around the high school (HS) (Estevan et al., 2018), students' access to a bus shuttling to and from the educational center (Rodríguez & Vogt, 2009), socioeconomic level of families (Molina-García et al., 2018; Pans et al., 2023) going to a public or private school (Babey et al., 2009), an so on.

Most of these studies have attempted to predict the use of BSS for ACS. However, these studies used linear analyses, which has certain limitations (Lu et al., 2014; Villarrasa Sapiña et al., 2023). A systematic review of the methodologies used to study this topic showed that linear

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analyses could lead to multicollinearity problems, proposing unstable estimates, and erroneously showing results with significant differences (Lu et al., 2014). Therefore, a subsequent study analyzed the interaction between factors influencing ACS, avoiding methodological limitations (Molina-García et al., 2018). Nevertheless, no non-linear analysis has been applied to analyze the use of BSS for ACS. Additionally, the literature has focused on students but has so far not been analyzed from the perspective of schools and their environment. This study proposes to analyze the use of BSS for ACS from the perspective of schools and their socio-economic environment through advanced analyses, such as a self-organizing map analysis (SOM) (Haykin, 1998). The purpose of this study is to generate high-school profiles to estimate the use of bike-sharing for school commutes, and use SOM analysis to understand the relationship among BSS usage, a school's socio-economic environment, and school type (public or private).

2. Methodology

2.1. Participants

This cross-sectional study included a database compiled from the movement registers of BSS (Valenbisi) student users (aged 14–17 years) and the socioeconomic data of each neighborhood in València (Spain). The complete dataset of BSS users in the city from from August 1, 2018, to April 30, 2021, was obtained. From this dataset, we filtered the data to include only trips made by users aged 14 and 17 years. During the period of mobility restrictions due to Covid (15 March to 20 June 2020) (Seifert et al., 2023), face-to-face teaching was cancelled, and the student could not be outside. Therefore, this period has not been considered for the analysis of this study. In total there were 9468 users. The times of entry and exit to HSs were observed to select a time slot with entry movements (in the morning) and another with exit movements (in the afternoon), and to compile all movements that existed at that time by the selected users. For example, if the entry time was 9 am, the timeslot between 8:30 am and 9:00 am was determined. The number of students enrolled in these courses at each HS was also collected from the regional government's open data portal (https://dadesobertes.gva.es). Additionally, the number of students enrolled in these courses at each HS was collected (https://dadesobertes.gva.es). Based on this information, a several variables were calculated, such as the number and percentage of students using BSS for ACS, the total trips and time spent using BSS per student in each school for ACS, and the average trip time per student.

In addition, for each València neighborhood, we included the HS location, relevant socioeconomic data, and variables such as Average Neighborhood Income (ANI) and Neighborhood Vulnerability Index (NVI). The NVI is calculated using data from the National Institute of Statistics (INE) and is based on three dimensions of vulnerability indices: residential (average area per inhabitant of residential properties, cadastral value, and accessibility to housing), socioeconomic conditions (percentage of population without education, percentage of unemployment, and risk of poverty and social exclusion), and sociodemographic conditions (vulnerable population, vulnerable households, and immigrant population). A high NVI value represents no vulnerability, whereas a low value represents high risk of vulnerability. This information was extracted from the official database of the City Council of València (https://valencia.opendatasoft.com).

2.2. Instrumentation and procedure

The first step was to geolocate HSs and transport stations in València using the Q-Geographic Information System 3.22 software (QGIS, GNU General Public License) (Fig. 1A, B, and C). Once located, a radius of 200 m was generated around each HS to locate the public transport stations (BSS and bus stations) (Fig. 1D). Finally, only HSs with at least one BSS station within this radius were selected. Of the total of 102 HSs, 79 fulfilled these criteria. These were divided into private (fully private and semi-private) (53) and public (26) HSs (Fig. 1E). In this step, the following variables were obtained: number of BSS stations, number of bus stations, and bus lines (because each bus station may have one or more lines).

Once all the variables were extracted, a single matrix was generated in which each row referred to each of the 79 HSs. Each column contained one of the extracted variables as explained below.

- BSS station: number of BSS stations around each HS (200 m buffer)
- Bus station: number of bus stations around each HS (200 m buffer)
- Bus lines: total number of bus lines at bus stations around each HS (200 m buffer)
- BSS trip time (min): average trip time of BSS users
- Average neighborhood income (ANI) (€): Average income of the neighborhood where the HS is located
- Neighborhood Vulnerability Index (NVI): Vulnerability index of the HS neighborhood
- BSS trips: total trips made by BSS for commuting to HS per student, calculated from: total trips made by all students of a HS/total students enrolled at the HS.
- BSS total time (min): total time spent using the BSS for transport to HS per student, calculated as: total time using the BSS of all HS students/students enrolled students at the same HS.
- Student users (%): percentage of enrolled students who were BSS users
- HS typology: whether privately or publicly represented by 1 and 2, respectively

The collected data were subjected to SOM analysis. This unsupervised artificial neural network technique was used to establish relationships between the input variables and plot them on maps. These variables were used to classify HSs according to their similarity with respect to the inputs. The main propose of the SOM analysis was to transform an input signal pattern of arbitrary dimensions into a discrete two-dimensional map in a topologically ordered fashion. This type of analysis can be used to categorize or perceive relationships among a series of variables related to the studied problem (Pans et al., 2019). This technique has several advantages (Herrero-Herrero et al., 2017) such as identifying clusters with higher accuracy than commonly used clustering techniques (Budayan et al., 2009; Melo Riveros et al., 2019).

This analysis provided the ACS by BSS and sociodemographic profiles of the HSs. SOM was performed using MATLAB R2022a software (Mathworks Inc., Natick, MA, USA) and the SOM toolbox (Version 2.0) for MATLAB (Vesanto et al., 1999). Information regarding SOM analysis can be found in previous studies (Molina-García et al., 2018; Villarrasa-Sapiña et al., 2023).

The analysis was performed in three steps (Pellicer-Chenoll et al., 2015). First, the network was constructed using the number of cases and proportions of the two main eigenvalues of the dataset. Specifically, a network with 7 height x 6 width neurons was designed. Second, the initialization phase was initiated. For this purpose, *randomized* and *linear initialization* were applied to all the input variables to assign a weight to each neuron. Finally, the model was trained 100 times to obtain the best solution using *sequential* and *batch* algorithms (Oliver et al., 2018), and HSs with similar characteristics were located close in the neuron network (using *Gaussian, cut Gaussian, Epanechnikov*, and *Bubble* functions) (Estevan et al., 2019). Totally, 1600 SOM analyses were performed (100 times $\times$ 2 initialization methods $\times$ 2 training methods $\times$ 4 neighborhood functions). Subsequently, by multiplying the quantization and topographical errors, a map with minimum errors was obtained.

The neurons were classified into clusters using the *k-means* method. This method attempts to minimize the Euclidean difference between the input values of the days and centroids of the clusters (Kohonen et al., 2009). Finally, the number of clusters that provided the best solution was determined using the Davies–Bouldin index.

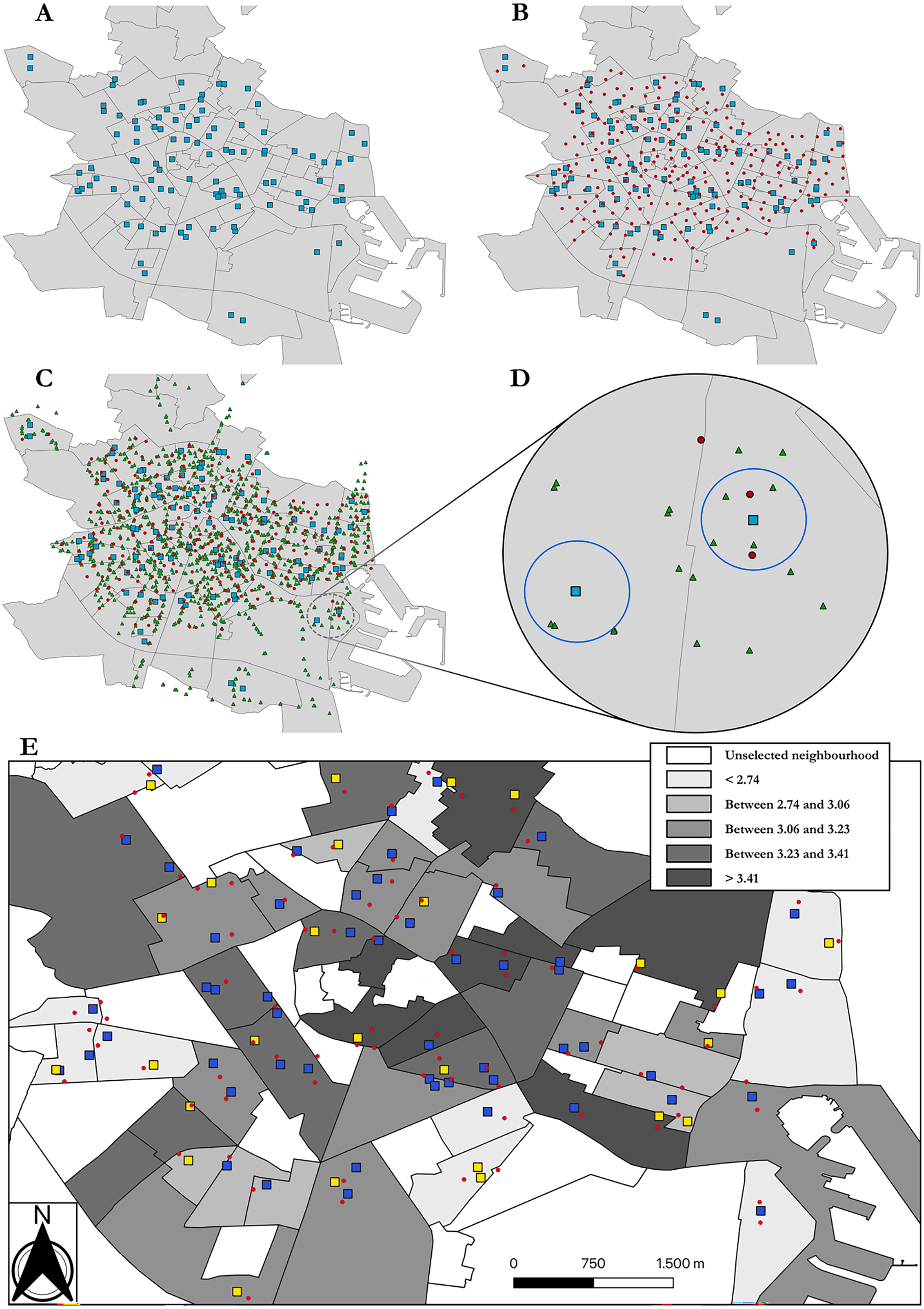

Fig. 1. Representation of geolocation procedure of HS, public transport and neighbourhood vulnerability studied. A) All high schools (cyan squares); B) Bike sharing system stations (red circles); C) Bus stations (green triangles); D) Perimeter of each high school (blue circles); and E) Vulnerability index of the selected high school neighbourhoods. The squares represent private (blue) and public (yellow) high schools. The red circles represent the selected bike-sharing system stations.

2.3. Data analysis

Descriptive centrality data were obtained before the statistical analysis. The median and interquartile ranges of all input variables were calculated for each cluster in general and for the HS typology. These data were used to establish the effect of cluster membership (independent variable) on the characteristics studied (ACS by BSS and sociodemographic variables). Statistical analysis was performed using SPSS 25 software (SPSS Inc., Chicago, IL, USA). The Kolmogorov-Smirnov test was used to analyze the distribution of the variables. Given that the variables did not have a normal distribution, non-parametric tests were applied. Kruskal-Wallis tests were applied to establish the effect of the cluster on ACS by BSS and sociodemographic variables. Moreover, the Dunn-Bonferroni post-hoc test was applied to each pair of clusters. Mann-Whitney U-tests were applied to compare private and public HSs for every variable in each cluster. Finally, the chi-square test was used to check the distribution of HS typologies per cluster. A p-value of .05 was accepted as the significance level in all analyses.

3. Results

The SOM analyses are represented by nine component maps (one for each dependent variable), as shown in Fig. 2. The quantization error remains almost stable between four and six clusters. Within this range, four clusters (C1, C2, C3, and C4) were considered the best option because a small number of clusters would facilitate result comprehension.

The Kruskal-Wallis test showed a principal effect of clusters in the variables ANI (H3 = 45.49; $p < .001$), NVI (H3 = 46.27; $p < .001$), BSS trips (H3 = 29.47; $p < .001$), BSS total time (H3 = 30.55; $p < .001$) and student users (H3=10.71; $p < .05$). Pairwise comparisons with descriptive data of the variables in each cluster are shown in Table 1.

The representation of the HS characteristics of BSS for ACS and socioeconomic variables is shown in Fig. 3. This figure shows the minimum and maximum values, quartiles, and data density distribution for each HS.

Mann-Whitney U-tests showed significant differences between private and public HSs in C2, C3, and C4; however, there were no differences in C1. First, we observed a higher value in private HS than in public HS for the Bus lines variable (Z=-2.03; $p < .05$) in C2. Second, in the same line, a higher value in private HS than in public HS was observed for the Bus station variable (Z=-2.32; $p < .05$) in C3. Finally, a higher value in private HS than in public HS was observed for the Bus station (Z=-2.32; $p < .01$), Bus line (Z=-1.94; $p < .01$), ANI (Z=-.656; $p < .01$), NVI (Z=-.938; $p < .05$), and Student user (Z=-1.780; $p < .05$) variables in C4. Descriptive data and significant differences between private and public HSs in each cluster are shown in Table 2.

3.1. Differences in HS characteristics by typology in each cluster

Regarding typology distribution per cluster, a significant relation between cluster and typology by χ^2 test was shown (χ^2_3=15.21; $p < .01$). More private HSs were present in C1, C2, and C4 than public HSs. However, the number of public HSs was higher than that of private HSs in C3. Descriptive data are shown in Table 2.

4. Discussion

4.1. Principal findings from general data

This study illustrates the usefulness of SOM analysis for analyzing and comparing variables of the HS socio-economic environment and the use of BSS for ACS. In addition, it generated HS profiles showing different combinations of the variables' values.

On the one hand, our results showed that HSs with C3 characteristics

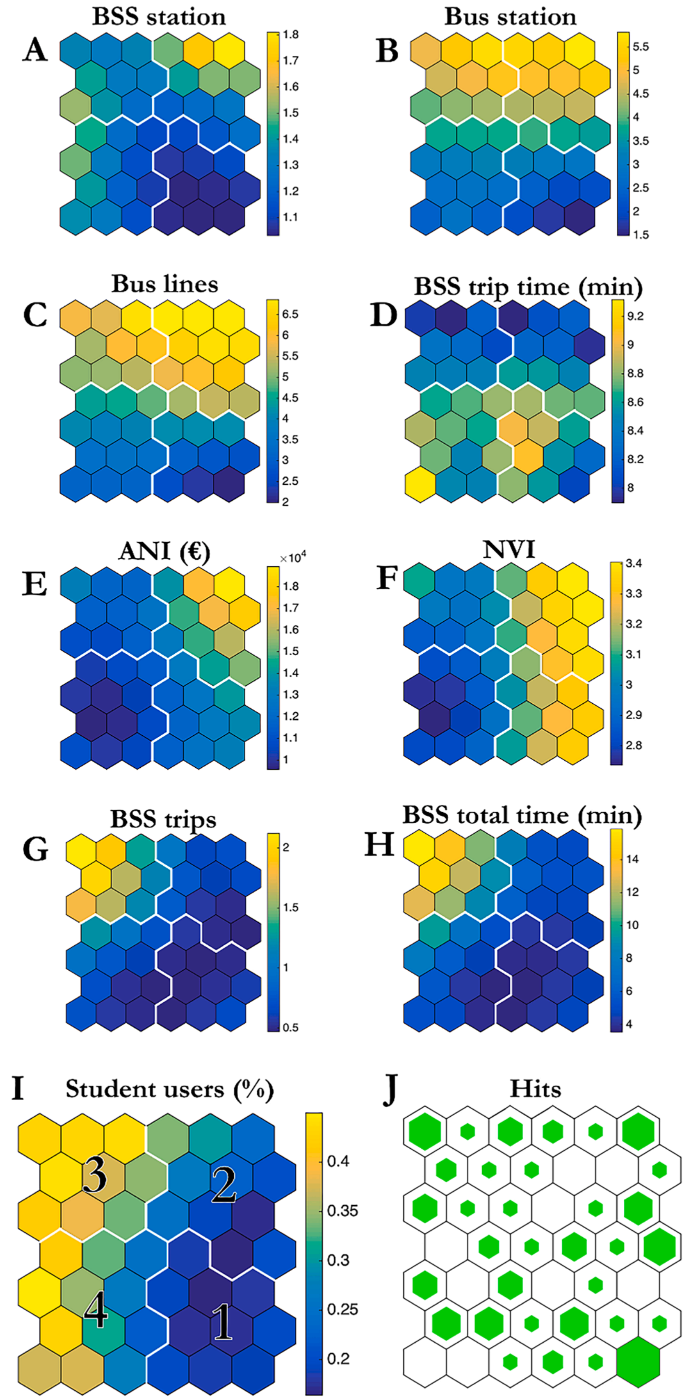

Fig. 2. Cluster differences.

are the ones that use BSS the most for ACS. So, these HS students who make the most trips and spend the most time using BSS represent the highest percentage of students using the BSS. Likewise, C3 has access to public transport, although lesser than the clusters with the highest ANI and NVI (C1 and C2), and more access than the cluster with the lowest ANI and NVI (C4). Moreover, C3 neighborhoods show a low to moderate annual income (ANI) and moderate NVI, which coincides with previous studies in which people with a low socioeconomic level exhibited a higher usage of BSS than people with a high socioeconomic level (Pans et al., 2023).

In contrast, the HSs with C1 profile were the ones that used the BSS the least for ACS. This profile has a fair amount of access to public transport, but limited access to BSS stations. However, their most

Table 1
Variables comparison between clusters. Data are expressed with median (interquartile range).

	BSS station	Bus station	Bus lines	BSS trip time (min)	ANI (€)	NVI	BSS trips	BSS total time (min)	Student users (%)
Cluster 1 (n = 22)	1	3.5	5	8.17	$12412.5^{C2,C4}$	3.2^{C4}	$.45^{C3}$	3.04^{C3}	5^{C3}
	(1)	(6)	(9)	(6.41)	(7080)	(.7)	(1.8)	(12.69)	(16)
Cluster 2 (n = 20)	1	4	5	9.00	16764.7*	$3.4^{C3,C4}$	$.51^{C3}$	4.72^{C3}	8
	(2)	(10)	(12)	(9.93)	(14295.29)	(.57)	(1.07)	(13.11)	(50)
Cluster 3 (n = 18)	1	3.5	4	7.79	11475.61^{C2}	3.06^{C2}	2.24*	15.07*	10^{C1}
	(2)	(9)	(10)	(12.11)	(12286.5)	(1.23)	(3.11)	(24.68)	(74)
Cluster 4 (n = 19)	1	3	4	7.66	$9622.3^{C1,C2}$	$2.74^{C1,C2}$	$.44^{C3}$	3.18^{C3}	7
	(1)	(8)	(11)	(10.79)	(3739.64)	(.59)	(1.61)	(9.81)	(27)

* Significant differences with all clusters. C1 indicates significant differences with cluster 1. C1 indicates significant differences with cluster 1. C2 indicates significant differences with cluster 2. C3 indicates significant differences with cluster 3. C4 indicates significant differences with cluster 4.

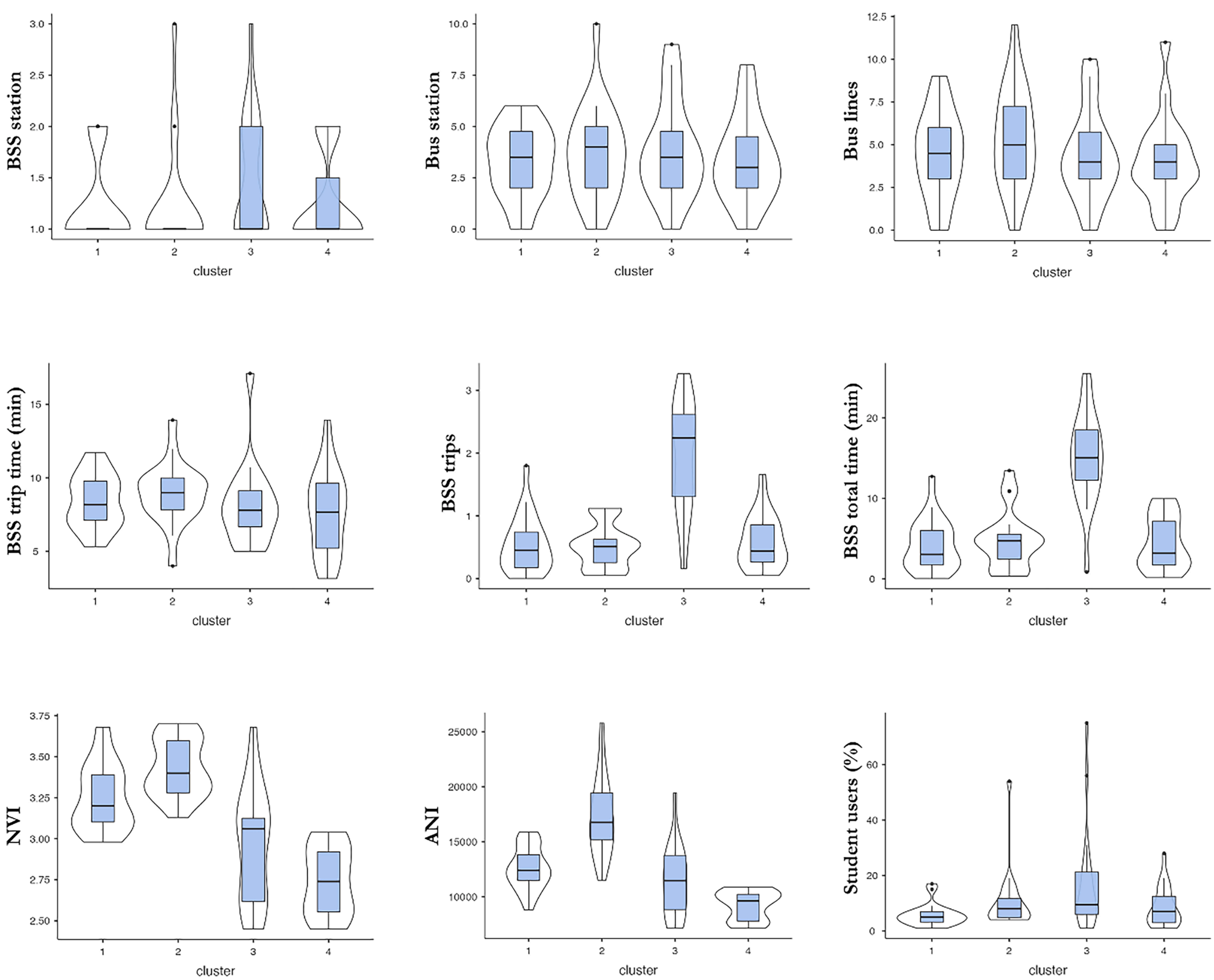

Fig. 3. Cluster characteristics for each variable. It is a combination of a box plot, which represents quartiles 1, 2 and 3, as well as the maximum values (upper and lower), and a violin plot to detail the density/concentration of data at each point on the y-axis.

notable characteristic is that they have a significantly stronger economy than C4 and a moderate NVI, although they have higher values than C3 for these variables (the profile with the highest use of BSS for ACS).

Finally, the two remaining profiles (C2 and C4) show a similar level of BSS use for ACS to C1 but show higher centrality values in different variables (Table 1) of BSS use. Interestingly, these are the profiles with the greatest socioeconomic differences. C2 shows HSs with more economic resources and the lowest probability of vulnerability (i.e., highest NVI value), as well as greater availability of public transportation, and C4 shows those with fewer financial resources and a high risk of vulnerability.

If we focus on profiles with a high socioeconomic level and less vulnerability risk (C1 and C2), we can observe that the use of BSS for ACS is generally low. This may be because HS students living in high socioeconomic neighborhoods attend schools that are not close to their homes (Easton and Ferrari, 2015) and have access to motor vehicles (Chillón et al., 2010).

Through these four profiles, it is possible to gauge the demand for

Table 2
Comparative data between private and public HSs in each cluster. Data are expressed as the median (interquartile range). BSS, Bike Sharing System; ANI, Average Neighbourhood Income; NVI, Neighbourhood Vulnerability Index. *Indicates significant differences from the Public HS ($p < .05$).

	Cluster 1		Cluster 2		Cluster 3		Cluster 4	
Variable	Private	Public	Private	Public	Private	Public	Private	Public
N	17	5	18	2	6	12	12	7
BSS station	1 (1)	1 (1)	1 (2)	1 (0)	1 (1)	1 (2)	1 (1)	1 (1)
Bus station	4 (6)	3 (5)	4 (10)	2 (0)	5.5 (5)*	2.5 (9)	4 (7)*	2 (3)
Bus lines	5 (9)	3 (6)	5.5 (12)*	2 (0)	6 (6)	3.5 (10)	5 (10)*	3 (3)
BSS trip time (min)	7.48 (5.87)	9.45 (6.41)	8.58 (9.93)	10.66 (2.62)	7.04 (4.63)	8.27 (12.11)	7.56 (7.86)	8.48 (10.79)
ANI (€)	12121 (7080)	13421.33 (4851.83)	16088.45 (14295.29)	20833.25 (5171.5)	13689.19 (7689.14)	10693.72 (11509.71)	10222.84* (3403.97)	7679 (2919.78)
NVI	3.12 (.68)	3.31 (.68)	3.4 (.57)	3.55 (.31)	3.11 (1.08)	2.97 (.96)	2.85 (.52)*	2.52 (.52)
BSS trips	0.41 (1.8)	0.49 (.66)	0.5 (1.06)	0.85 (.56)	2.59 (1.99)	1.51 (2.79)	0.67 (1.54)	0.43 (.94)
BSS total time (min)	3.1 (12.69)	2.98 (5.85)	4.59 (10.59)	9.38 (8.14)	17.97 (13.67)	13.48 (24.68)	4.83 (9.04)	2.78 (9.35)
Student users (%)	5.38 (16)	4.72 (4)	7.12 (50)	12.19 (4)	18.66 (68)	7.84 (3.1)	8.57 (25)*	3.35 (8)

BSS based on the socio-economic conditions associated with an HS. A key finding is that students of HSs with fewer BSS stations nearby make less use of this system. Previous studies have shown that the presence of BSS stations encourages their use (García-Palomares et al., 2012). Similarly, an excessive amount of public transport around the HS seems to discourage and reduce ACS. These latter results seem to contradict studies that found a positive correlation between the proximity of bus stations and BSS stations (Faghih-Imani et al., 2014; Wang et al., 2018). However, this contradiction is predictable because the previous correlation occurs when people need to transfer along the trip (e.g., ride the bus for part of the trip and transfer to the BSS to continue the trip). In contrast, this study analyzes the departure and finish zones of a trip. In other words, whoever uses the bus in this zone does not use the BSS, and vice versa. In addition, it appears that there is no positive correlation between bus stations and BSS stations with BSS use among young people (Wang et al., 2018).

Regarding the average time for each trip (BSS trip time variable), no differences were observed between clusters. These results do not coincide with the study by Pans et al. (2023) where BSS users in València classified in lower socio-economic levels showed a longer time of use. This may be because this study was conducted in an adult population. However, the distribution followed the same trend as the ANI and NVI variables in the profiles, as they all had the same order, with C4 having the smallest value, followed by C3, C1, and C2 (the profile with the highest values). This may be because, in Spain, one of the first criteria for the admission of students to an HS is family income and different situations of vulnerability (i.e., large family, foster family, disability of the student or the student's relative, or victim of violence). Therefore, students with fewer resources and greater vulnerability prioritize choosing schools closer to their homes. In addition, the most frequent trip time among students was between 7 and 9 minutes, which in the city studied is equivalent to about 1.7–2.7 km and is in line with previous studies (Mandic et al., 2015).

Regarding HS typology, C3 is the unique profile with the highest prevalence of public HSs. Therefore, as C3 is the profile with the highest use of BSS for ACS, public HSs can be considered to be associated with more BSS use for ACS than private HSs, which is consistent with previous studies (Babey et al., 2009). If we focus on the typological differences between the HS profiles, we can find reasons to justify these results (Table 2).

First, it is remarkable that private HSs have more stations and bus lines than public HSs in all profiles. These results again emphasize the possible negative influence of public transport near the HS on ACS, highlighting the potential that the presence of public transport amenities favours its use to the detriment of the use of BSS. Second, considering the C4 differences between HS typologies, socioeconomic resources and vulnerability risk are relevant variables that can determine the use of BSS for ACS (Table 2). Specifically, HSs with high vulnerability risk, minimum economic income, and limited access to public transportation tend to be public schools and show the lowest use of BSS for ACS in all profiles and typologies. As we have seen, among the socio-economic factors between clusters, economic resources have been shown to vary. In some clusters it is people with higher incomes who show higher use as in the study by Bateman et al. (2021), but in others it is people with lower incomes who show higher use (Guerra et al., 2020). These results highlight the unequal distribution of resources in the city of València, disfavoring those with fewer economic resources, and thereby reducing the use of the BSS for ACS. In fact, it could be an additional reason why those with lower socioeconomic status are more likely to have poor physical health and higher incidence of mental health issues (Martínez, 2021). Thus, bringing resources to these students to encourage their BSS use will improve their health because of the benefits of BSS (Qiu and He, 2018). Duran-Rodas, et al (2020) found different results in the city of Munich, where they observed that their BSS follows the spatial efficiency and equity rules. They also point out that there is a lack of discourse on how and where resources should be located.

4.2. Implications for school health policy, practice and equity

Our study suggests promoting public policies that equitably offer public transport resources and bike-sharing stations to all students. The presence of facilities in the environment to use active or sustainable means of transport is key for the population to choose them. This avoids an uneven distribution of resources around the city. We have demonstrated that not all students have same transport amenities nearby high school. Other studies have shown that having BSS stations close to students' schools encourages bicycle use. However, as we observed, the resources are not offered equally. This study urges that public policies be geared towards greater equity in planning the distribution of resources to HSs.

In terms of school policies, students with fewer resources and a higher risk of vulnerability have indicated fewer trips and shorter trip time. Therefore, HSs with such students should implement campaigns to promote the use of BSS to reap its benefits.

In addition, this work provides a new perspective for studying ACS through a novel analysis method in the field, such as SOM. This new approach extends the paradigm commonly used to study ACS and demonstrates the usefulness of applying non-linear analysis in this area.

4.3. Limitations and futures studies

Owing to the characteristics of València, such as the Mediterranean climate low slope of the land, and the absence of rainfall for a large part of the year, it is difficult to extrapolate these results to less concentrated environments, to other cultures or even to the resident population in these cities. Furthermore, no attention has been paid to the existing infrastructure near schools, such as the type of cycle lanes (segregated or non-segregated), which could influence cycling. Therefore, it is recommended that this issue be studied in different cities worldwide, considering the infrastructure in each neighbourhood where the HSs are located. In addition, future studies should include information on this to identify different patterns between private cycling and BSS use. Moreover, analyse those high schools that do not have such transport facilities around them.

5. Conclusions

To conclude, by incorporating the specified resources—one BSS station and three to four bus stations—into the public transport and BSS network, alongside a low-to-moderate economic profile and a moderate vulnerability risk, the use of BSS for ACS could be effectively promoted in the studied city. However, the disparity in the availability of resources near HSs and neighborhood locations is highly relevant to ACS. Specifically, the poorest and most vulnerable neighborhoods and public HSs are the most disadvantaged when it comes to BSS use. Therefore, HSs with these characteristics should improve policies that promote the use of BSS for ACS and improve the health of our adolescents.

CRediT authorship contribution statement

Israel Villarasa-Sapiña: Writing – review & editing, Software, Methodology. **Miquel Pans:** Writing – review & editing, Supervision, Funding acquisition. **Laura Antón-González:** Writing – original draft, Investigation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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