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# How learning to cycle influences lifestyle: An eight country pooled analysis and person-centered approach

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A R T I C L E I N F O

*Keywords:*
Cycling
Learning
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Age

A B S T R A C T

*Introduction:* Cycling plays a key role in the promotion of individual, community, and planetary health. However, no previous study has explored the interplay between the process of learning to cycle and cycling habits, adopting a person-centered approach. To understand which variables promote the learning process (i.e., acquisition) and lifelong bicycle use on a daily and recreational basis (i.e., engagement), the aim of this study was to identify different clusters of individuals with similar characteristics related to their cycling acquisition and engagement.

*Methods:* A cross-country pooled sample of 8542 individuals aged 28.9 ± 14.4 years (58.5 % female) was assessed via online questionnaire. A Self-Organizing Map (SOM) was used to classify and visualize the values of individuals in the variables tested.

*Results:* A K-means cluster analysis resulted in seven profiles. Participants in profiles characterized by a relatively old age to learn to cycle (i.e., 7-8 years-old; n > 1500 mainly from Mexico and the United Kingdom) typically learned to cycle on a conventional bicycle, were taught by their father, mother, or both, and mainly cycle for leisure. Participants in profiles characterized by a relatively young age to learn to cycle (i.e., 5 years old; n > 1500 mainly from Belgium and Finland)

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typically learned to cycle by using a wide variety of bicycles (i.e., balance-bicycle, two-training wheels, one-training wheel and conventional bicycle) and without guidance from a specific significant other.

*Conclusion:* The identified clusters highlight the diversity of cycling engagement across different demographics and geographic locations. The results provide valuable insights to plan and guide targeted policies and interventions to promote cycling as a mode of transportation and recreational activity.

## 1. Introduction

According to the latest United Nations sustainable development goals, cycling plays a key role in the promotion of individual, community, and planetary health (United Nations, 2015). From an individual health perspective, cycling enhances cardiorespiratory fitness (Larouche et al., 2014; Ramírez-Vélez et al., 2017) and fosters physical activity throughout the lifespan (Hulteen et al., 2018). Cycling for 20 min daily is associated with a 30 % reduction in the risk of type 2 diabetes and a 25 % reduction in cancer-related mortality (Dinu et al., 2019). Furthermore, cycling reduces carbon emissions, aiding in the fight against climate change (World Health Organization, 2022). Within communities, cycling is an active, affordable, inclusive, and eco-friendly mode of transportation that is increasingly being used as an alternative for the car, mainly for commuting (Heinen et al., 2010; Pucher & Buehler, 2017). Additionally, cities worldwide are adopting policies to promote cycling for its non-polluting nature (Braun et al., 2016; Hulteen et al., 2018).

To promote lifelong cycling, it's crucial to identify key variables promoting learning to cycle and sustained bicycle use (e.g., Cordovil et al., 2022; Goel et al., 2022; Heinen et al., 2010). A person-centered approach has emerged, providing valuable information on the strength of the associations between key variables that hinder the use of bicycles (e.g., Fraboni et al., 2022; Haustein & Nielsen, 2016). This approach identifies profiles of individuals with similar cycling habits, patterns, and behaviors (Ahmed et al., 2017; Magnusson, 1988). Identifying these profiles can inform policy development to promote cycling.

Previous studies on cycling behaviors using a person-centered approach, differed in the number and nature of identified profiles (Damant-Sirois et al., 2014; Haustein and Nielsen, 2016; Fraboni et al., 2022). This variation may be due to the wide variety of input variables including cyclist characteristics (e.g. background, motivation, and barriers), mobility patterns and geography. However, to the best of our knowledge, no previous study has explored the aspects related to the process of learning to cycle, combining it with bicycle use patterns, as a product or engagement in a cycling lifestyle, adopting a person-centered approach.

Appropriate input variables for clustering this process-product of learning (acquisition and engagement) may be theoretically framed by the bio-ecological systems approach, as depicted by Bronfenbrenner's Process-Person-Context-Time (PPCT) model (Bronfenbrenner, 1995; Bronfenbrenner & Morris, 2006). This framework has been used to better understand the profiles that can promote or hinder learning to cycle (Mercê et al., 2021) and the daily use of bicycles (Cordovil et al., 2022; Viola et al., 2021). At the individual level, sociodemographic and economic factors (e.g., age, gender, physical ability, education, income, employment status) are known to play a role in the adoption of the bicycle as a main mode of transport (Acheampong, 2017; Dill & Voros, 2007; Moudon et al., 2005; Parkin et al., 2008; Plaut, 2005; Shafizadeh & Niemeier, 1997; Wardman et al., 2007).

An important factor that influences learning to cycle is the type of bicycle that is used (Laukkanen et al., 2021; Mercê et al., 2021, 2022b). For this, several bicycles can be used such as the traditional bicycle with two lateral training wheels (B2TW) or the balance bike (BB). Children who use the BB approach acquire autonomous cycling on average 0.72–1.8 years earlier than children who use the B2TW. Two recent studies have investigated the effect of using these different bicycles on the age at which children learn to cycle, and both point to the BB as the most efficient one (Blommenstein & van der Kamp, 2022; Laukkanen et al., 2021; Mercê et al., 2022a).

In addition, other subjective individual factors (e.g., personal beliefs, attitudes, perceptions of safety, comfort, or perceived support from peers and family members) (Acheampong, 2017; Moudon et al., 2005; Underwood et al., 2014) are also significant for learning to cycle. Across generations, social support for learning has changed. Whereas older generations typically learned on their own or outside the family circle, the younger generation seems to learn under the guidance of a family member, with fathers being the most common person to teach their child in Canada (Brussoni et al., 2013) and both parents in multiple other countries around the world (Cordovil et al., 2022). In Australia, children most commonly learn to cycle in informal contexts such as playing with siblings and friends (Bonham and Wilson, 2012). In addition, expert training programs (e.g., in sports associations) have been considered successful in teaching children to cycle (Mercê et al., 2021). While these studies were conducted in specific countries, they likely reflect broader trends in cycling education and child development practices, as suggested by Cordovil et al. (2022).

At a more distal environmental level, factors such as the availability and quality of the cycling infrastructure, urban design, climate, topography (Cole-Hunter et al., 2015; Fuller et al., 2011), cost, time, safety (Wang et al., 2015), population density, land use diversity (Sun et al., 2017), the existence of a cycling culture and a sense of community within it (Rosas-Satizábal & Rodriguez-Valencia, 2019), and the adoption of public policies which promote and support bicycle-use (Zhao, 2013) are also determinants of the adoption of cycling habits across the lifespan. Furthermore, studies indicate that the use of bicycles varies from country to country. In high-cycling countries (e.g., the Netherlands, Japan, and Germany), cycling rates between work commuting and other trips tended to be more similar, whereas in low-cycling countries (e.g., Brazil, England and Chile), cycling to work was more common than cycling to other places (Goel et al., 2022). However, cycling is also impacted by season, especially in areas with high temperature differences between summer and winter months. In general, both cycling as a mean of active commuting and as a leisure time activity are most popular in the summer months (e.g. Miranda-Moreno & Nosal, 2011). Leisure cycling is more weather-dependent than active commuting (Chapman & Larsson, 2021; Zhao et al., 2018). In wintertime, cycling-friendly policy efforts, such as quality and maintenance of cycling infrastructure (Chapman & Larsson, 2021), as well as more individual effort and resources, for instance, specific winter gear are required (Galway et al., 2021; Lindqvist et al., 2019).

This study aims to identify different clusters of individuals with similar characteristics related to their cycling acquisition and engagement, while considering the multiple underlying factors affecting how we learn to cycle, and when we cycle, adopting a person-centered approach. The results following from this innovative research topic may be of value for the development of policies and person-centered specific interventions that promote and support cycling behavior across the lifespan. Specifically, a better understanding of profiles related to cycling acquisition and engagement can guide policymakers to improve cycling infrastructure, promote cycling education and training, and develop targeted interventions. For example, the results could help distinguish between interventions for (and specifically tailor to the needs of) individuals who never learned to cycle from those who know how to cycle but face practical or environmental barriers to put it into practice. Additionally, insights into the cycling clusters can help urban planners design more effective cycling infrastructure that meets the needs of diverse groups, ensuring accessibility for new cyclists, casual users, and regular commuters. Finally, the findings could inform policies that integrate cycling education into school curricula and community programs, ensuring that people learn to cycle at optimal developmental stages and are able to maintain cycling habits throughout their lifespan. This endeavor is paramount to achieving individual, community, societal, and planetary health and well-being.

## 2. Material and methods

### 2.1. Participants

The data were collected via an online survey targeted at adults aged eighteen years or older. The sample recruitment was open to any individual, not limited to sport contexts or cycling associations, with the aim of involving a large cohort and increasing representativeness and diversity within the research participants' groups. The survey included questions about the participant and their possible children. If the respondent had more than two children, they were asked to answer the questions in relation to both their oldest and youngest child. In total, we collected data on 10640 individuals from 29 countries. For this study, we only included data from countries that had at least $n \geq 300$ responses/cases. This resulted in a total sample of 8542 participants from 9 countries: Belgium ($n = 648$), Brazil ($n = 1265$), Croatia ($n = 343$), Finland ($n = 861$), Italy ($n = 1442$), Mexico ($n = 485$), Portugal ($n = 2008$), Spain ($n = 802$), and the United Kingdom ($n = 608$). For the whole sample (58.5 % female, 41.1 % male and 0.5 % unspecified), participants' mean (*SD*) age was 28.86 (14.28) years (range was 2.12–60.61years).

### 2.2. Procedure

The survey was available online for approximately one year from November 2019 to December 2020 (Ethical approval 22/2019 of the Ethics Committee of the University of Lisbon). It was available in ten languages: Croatian, Dutch, English, Finnish, French, German, Italian, Japanese, Portuguese and Spanish. Participation was voluntary and anonymous. Information about the research, including an open invitation to answer the survey, was disseminated through websites, social media channels (e.g. Facebook, Instagram, Twitter), email and paper magazines. Responses were collected on the server of the University of Lisbon as described elsewhere (Cordovil et al., 2022).

### 2.3. Instruments

The survey included questions concerning the process of learning to cycle, current cycling behaviors and other physical activity habits, and demographic background information. Answering took approximately 5–15 min. The respondents first answered questions concerning themselves, then the same questions about their children (with a maximum of two). The process of learning to cycle was inquired by questions about the age at which respondents learned to cycle, the type of bicycle used to learn to cycle [four dichotomous (yes/no) variables: a BB, a bicycle with two training wheels, a bicycle with one training wheel, and a conventional bicycle], and the person who taught the respondents how to cycle [eight dichotomous (yes/no) variables: father, mother, both, parents' friends, other family members, in sport activities, don't remember, and others]. The cycling habits (i.e., current reasons for cycling) were questioned by motive (three dichotomous (yes/no) variables: leisure, daily mobility, and commute to work/school) and frequency per season (two variables from 1 = never to 7 = all the days regarding bicycle frequency use in: summer, spring, and winter/autumn). The demographics included current place of residence (city/town), gender, and age.

### 2.4. Data analysis

Matlab R2021a program (MathWorks Inc., Natick, MA, USA) was used for the data analysis. Self-Organizing Map (SOM) analysis, which uses competitive, non-supervised artificial neural networks, was used for the study using the SOM toolbox (version 2.0) for Matlab. The main overall advantages are: i) SOM neurons or nodes are ordered into two-dimensional maps according to the distance between neurons in their weight vectors, ii) the weight vector of a neuron is representative of the participants' characteristics clustered in that neuron, iii) it establishes relationships among a large number of variables plotted on maps to improve the visualization and interpretation of the results, iv) is an unsupervised algorithm that is useful for non-linear models, as the relationships between the parameters in biological systems are typically non-linear (Pellicer-Chenoll et al., 2015), and v) the analysis did not decrease in power as more input variables or factors were included.

Moreover, SOMs offer a powerful alternative to traditional classification methods, particularly in analyzing complex, high-dimensional data. Unlike Latent Profile Analysis (LPA) or K-means clustering, SOMs do not require prior assumptions about the number of clusters or the underlying data distribution (Ferguson et al., 2020). This flexibility allows for the identification of nonlinear relationships and subtle patterns that might be overlooked by parametric approaches (Astel et al., 2007; Budayan et al., 2009; Melo-Riveros et al., 2019; Peiró-Velert et al., 2022). Additionally, SOMs provide an intuitive two-dimensional representation of the data, enabling the visualization of both global structures and local neighborhood relationships. This contrasts with LPA, which assigns individuals to discrete latent profiles without offering insights into the continuity or proximity of cases. Furthermore, SOMs are more robust to noise and collinearity, as they rely on an iterative competitive learning process rather than probabilistic modelling (Kohonen, 2013). Given these advantages, SOMs are particularly suitable for exploratory data analysis, revealing complex structures that would otherwise require multiple modelling assumptions in traditional classification techniques.

A brief introduction to SOM is provided below and readers who wish to expand on the information provided may refer to Estevan et al. (2019) and Oliver et al. (2016). The SOM analysis can be divided into three steps. First, a neural network is created in which the lattice size (i.e., 24 x 19 neurons in our study) depends on the sample size. The neural network is a set of neurons or nodes arranged in the form of a net. Each neuron or node is a vector with a value for each input variable (i.e., a weight vector). Therefore, each neuron is a vector with eighteen values, one for each input variable [i.e., the age at which one learned to cycle, bicycle use (i.e., cycling frequency in the summer and winter, and reasons to cycle: for leisure, mobility, or commute to work/school), type of bicycle used to learn to cycle (i.e., a BB, a bicycle with two training wheels, a bicycle with one training wheel, or a conventional bicycle), and the person who taught the participant to cycle (i.e., father, mother, both, parents' friends, family, in sport activities, don't remember, others)]. Each neuron should be interpreted as one mini-cluster, since during the training process of the SOM (see below) the neurons' weights are adapted to the data of the participants that fall in each neuron.

Secondly, as the neurons start with empty weight vectors, a procedure is required to assign initial values to them. This procedure is called network initialization. During initialization, each neuron is given a preliminary weight vector with a value for each input

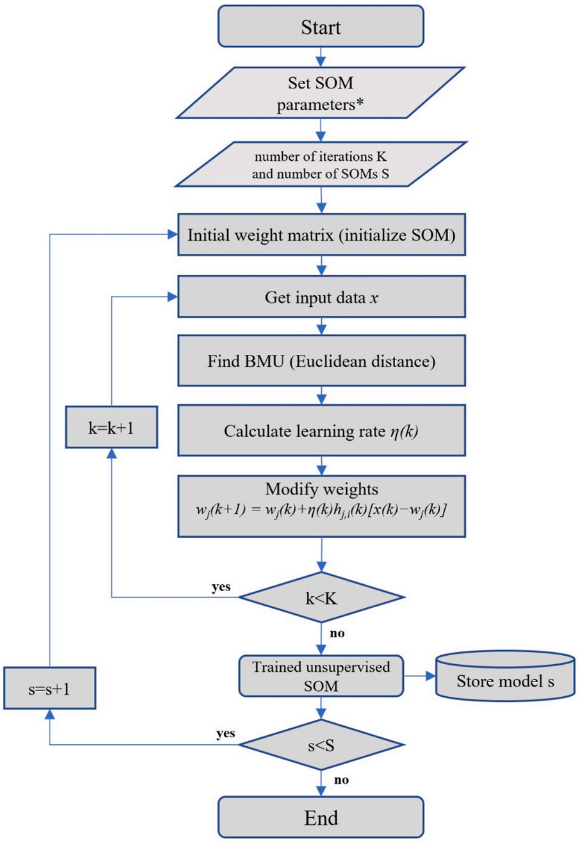


**Fig. 1. Flowchart for the unsupervised SOM algorithm modified from Seifert et al. (2023) with permission.** Here, k denotes time, x(k) is an input vector randomly drawn form the input data set at time k, $h_{j,i}$ denotes the neighborhood function around the winner unit j and η(k) is the learning rate at time k (Seifert et al., 2023).

variable. We employed two methods to initialize the neurons: i) random and ii) linear. In the first, small random values were assigned to each neuron's weight vector. In the linear initialization, the weight vectors were initialized in an ordered fashion along the linear subspace spanned by the two principal eigenvectors of the input data set.

Then, in a third step, the values of the neurons' weight vectors were adapted to the experimental data. To do that, the network is trained using the procedure shown in Fig. 1. Overall, training is an iterative process in which neuron weights are modified. The modification of the neuronal weights in each iteration depends on several factors. First of all, an input vector (i.e., a case or subject of the study) is presented to the network. Then, the neurons in the lattice "compete" (i.e., compare the Euclidian distance of their weight vector and the case values) to win the input vectors. The winning neuron is the one that achieves the smallest Euclidean distance between its weight vector and the input vector (i.e., neuron values are similar to the variable values of that case), so that the winning neuron's weight vector has the closest values to the input vector values. All the neurons in the lattice then adapt their weight values closer to the values of the input case. The magnitude of the adaptation depends on the learning ratio and the neighbor function. The learning ratio has a high value during the beginning of the training process and is gradually reduced as the training progresses and the neighbor function maximizes the adaptation of the winning neuron. The remaining neurons also adapt their weights according to this

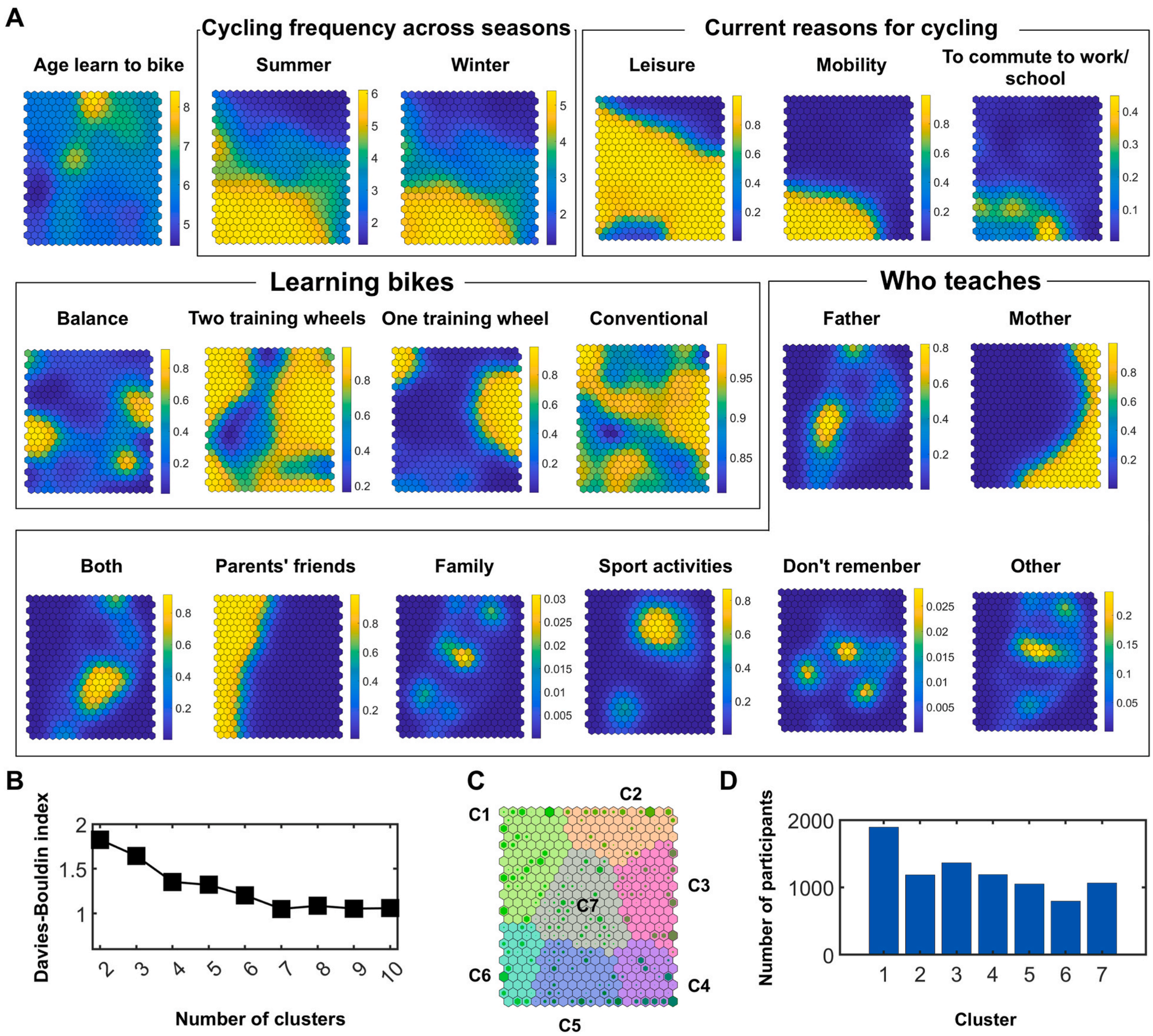


**Fig. 2. Self-Organizing Map Component planes and K-means clusters**. Layer A represents the component planes. There is a component plane for each SOM input variable. Individuals who are located in a neuron (hexagon) of the net remain in the same neuron in all the component planes. Thus, the profile of each neuron can be easily checked by analyzing its value in each component plane. Blue colors represent low values in the component planes while yellow colors represent high values. In layer B, the David-Bouldin index for K-means solution from 2 to 10 clusters are provided. The lower the index, the better the cluster solution. In layer C, the clusters are represented in the network space. Layer D represents the sample size of each cluster. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

function; the further away the neuron is from the winner, the smaller the adaptation magnitude. This process is repeated until the training process ends.

By way of summary, SOM can be understood as an unsupervised clustering tool that offers certain advantages over other techniques when dealing with complex and high-dimensional datasets. Each neuron (hexagon) represents a group of similar individuals, which in turn are similar to those assigned to adjacent neurons. Each neuron is represented by a set of weights reflecting the estimated value of each input variable for the cases grouped in that neuron (i.e., similar to centroids in cluster analysis).

Due to random factors in the SOM training and the different setting options of the training methods (i.e., batch or sequential), the initialization (i.e., linear and random) and the neighborhood function (i.e. Gaussian, cut Gaussian, Epanechicov and Bubble), 1600 maps were obtained. The best SOM was selected using the minimum product of quantization and topographic errors as criteria.

Cases with similar characteristics were grouped by the SOM in the same neurons (i.e., each neuron represents a cluster in itself). However, a cluster analysis is performed to establish larger groups of people. It should be noted that SOM groups cases in several neurons (i.e., 24 x 19 = 456 groups). Therefore, K-means clusters allow to classify of these neurons into larger groups than can be established as profiles. We used a *K*-means method to test the possibility of setting between 2 and 10 clusters. The best number of clusters was determined using the Davies–Bouldin index (Fig. 2B) and the clusters found are shown in Fig. 2C.

Once each subject was assigned to a neuron and a cluster, differences between clusters were analyzed in terms of the input variables, as well as the variables that remain outside of the SOM (i.e., age, sex, country). These analyses were carried out in RStudio (R Studio, Inc., part of the R statistical software package, version 3.2.2, Development Core Team, Boston, MA). For scale variables (i.e., current age, the age at which one learned to cycle, and cycling frequency across seasons), the normality assumption was checked (Shapiro-Wilks's test). If variables passed this assumption, a factorial ANOVA was applied with pairwise comparisons with Bonferroni

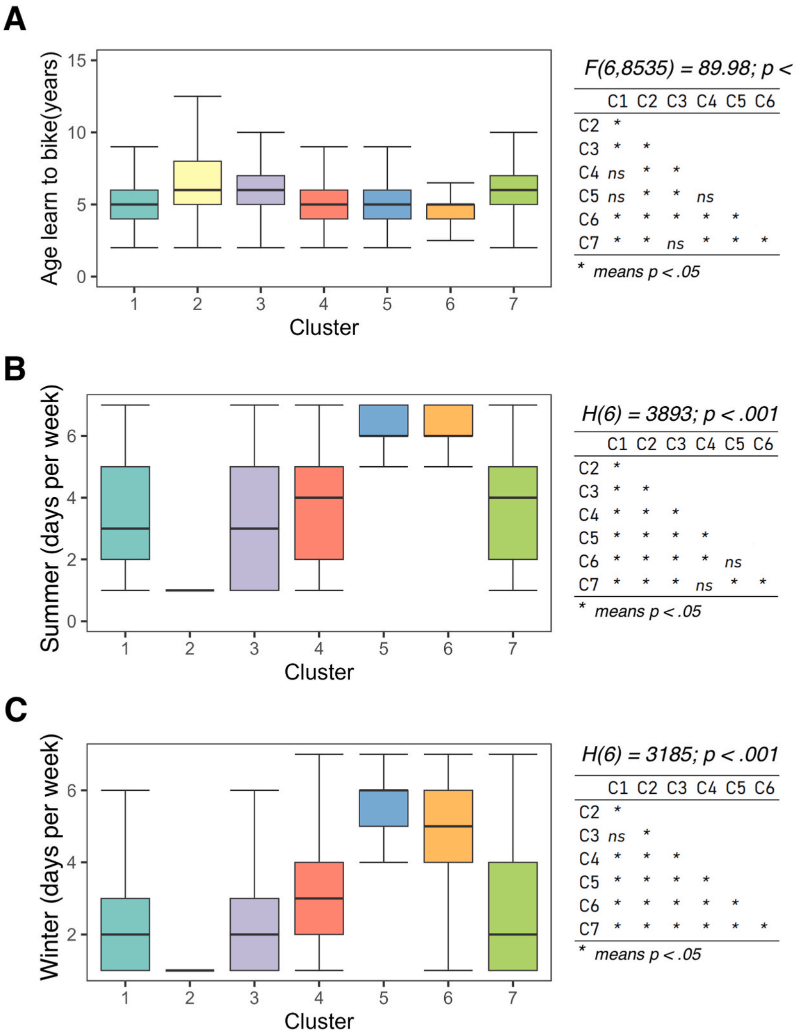


**Fig. 3. Boxplot of age at which children learn to cycle as well as summer and winter bicycle use**. At the right of the boxplots the statistical parameters of the effect of cluster as well as the pairwise comparisons between clusters are provided. Ns = non-significant; * indicate significant differences between clusters (p < .05).

correction. If not, Kruskal Wallis tests were performed with pairwise comparisons with Bonferroni correction. Regarding categorical variables [i.e., the current reasons for cycling (i.e., three categories that required a yes/no answer), the person who taught one how to cycle (i.e., eight categories that required a yes/no answer), the type of bike used to learn to cycle (i.e., eight categories that required a yes/no answer), sex (i.e., male or female), and country], associations with cluster membership were checked using a chi-square test. As there were 7 clusters, pairwise comparisons were carried out by means of chi-square tests by couples of clusters if necessary. The level of significance was set at $p < .05$.

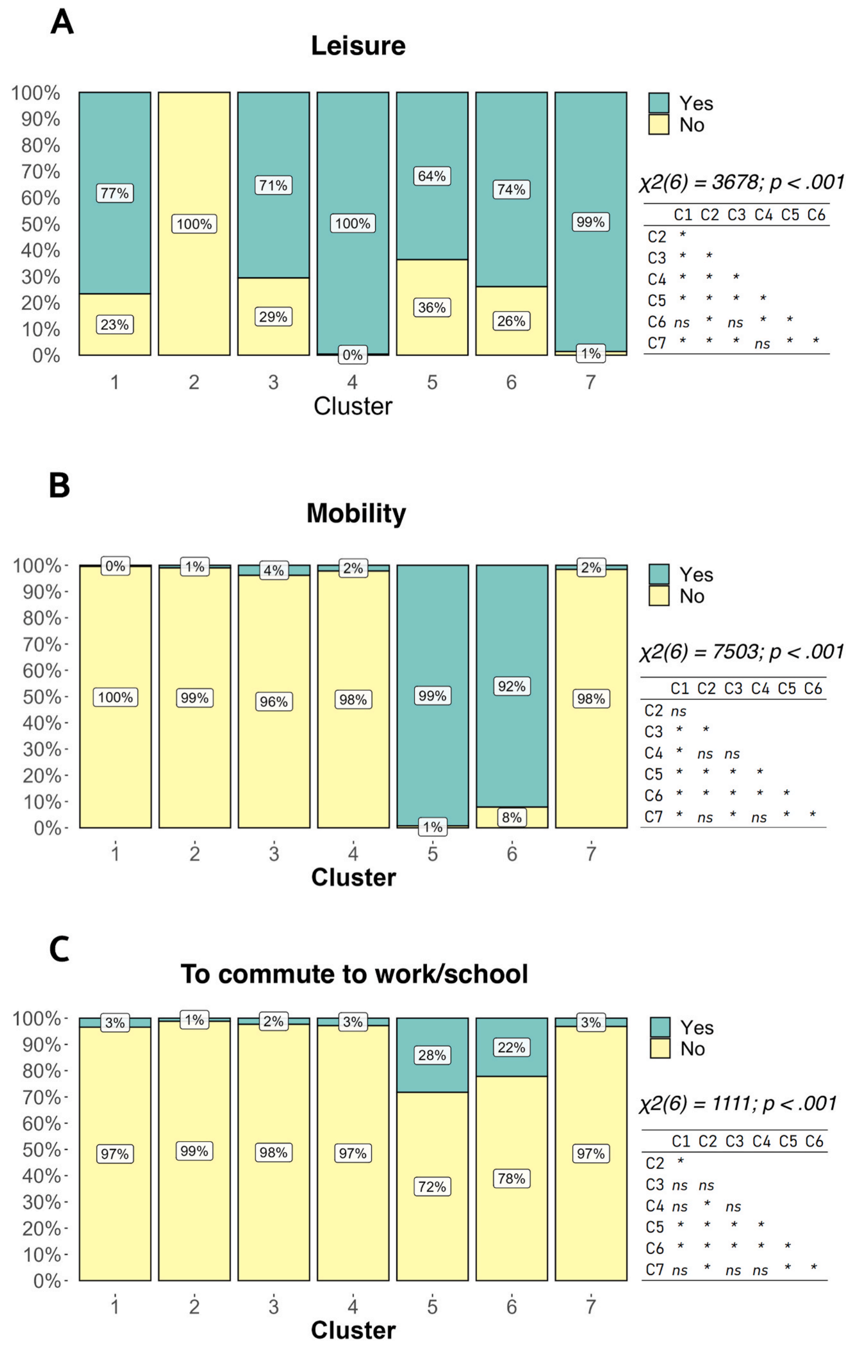


**Fig. 4. Chi square test and pairwise comparisons between clusters in the variables related to the reasons for cycling**. At the right of the stacked bars the statistical parameters of the association between the clusters and the variables as well as the pairwise comparisons between clusters proportion are provided. Ns = non-significant; * indicate significant differences between clusters (p < .05).

## 3. Results

### 3.1. Self-organizing maps and clusters

Fig. 2A shows the component planes for each input variable of the SOM analysis. To accurately interpret component planes, it is essential to understand the functioning of SOMs. As described in the previous section, the SOM is a tool that enables clustering participants with similar characteristics in a two-dimensional space (each component plane has two dimensions). In other words, individuals who share greater similarities are grouped within the same neuron (a hexagon in the component plane). Adjacent neurons (depicted in hexagons) represent participants that are quite similar to each other, whereas, as the distance between neurons increases, the represented participants become more distinct. Within this two-dimensional space, multiple component planes are defined, each corresponding to one of the SOM's input variables. In each component plane, a color scale is used to visualize the value assigned to each neuron for a given variable.

The K-means analysis revealed that the seven-cluster solution was the one with the lowest Davies-Boulding index (Fig. 2B). The representation of these clusters in the neuronal network according to the use of the bicycles as well as its learning-to-cycle process characteristics are provided in Fig. 2C. Each cluster groups several neurons that share similar characteristics and therefore represent people with similar variable values. To recognize each cluster characteristic, the shape in Fig. 2C must be projected to each component plane in Fig. 2A. Finally, the sample size of each cluster is shown in Fig. 2D.

To learn to interpret the maps, five of the seven clusters are as follows: the two groups of neurons in the upper right corner that correspond to cluster 2 (labeled as C2) and 3 (C3) are characterized by those who learned to cycle later (6-7 years-old; SD = 2–3 years) on a traditional (two or one wheel and conventional) bicycle and were taught by their mother, father, or both. They are mainly females who either do not cycle (C2) or cycle mainly just for leisure purposes (C3). Another profile is found in the upper left cluster 1 (C1) which is composed mainly of young females who learned to cycle at 5 years old with support of parents' friends. They used a diversity of bicycles to learn to cycle, and they predominantly ride their bikes in the summer for leisure purposes. Finally, in the lower left corner corresponding to clusters 5 (C5) and 6 (C6) profiles are represented by people who use their bicycle for mobility and the frequency of use is the highest in both summer and winter. Participants in cluster 5 and 6 learned to cycle using a wide variety of bicycles (i.e., BB, two-training wheels, one-training wheel, and conventional bicycle). Both clusters contain mainly Finnish males that were taught to cycle by family members (mother, father or both) or – in cluster 6 specifically-by friends of their parents.

### 3.2. Clusters characteristics according to the input variables

The comparative analysis for the age of learning to cycle, bicycle use in the summer and winter (Fig. 3), leisure cycling and daily transport by bicycle (Fig. 4) is reported in boxplots with a main effect of the cluster in each variable. Pairwise comparisons revealed multiple significant differences among clusters, as shown in the tables on the right.

Due to their key characteristics in terms of age of learning to cycle and the current period and reason for cycling, the clusters which

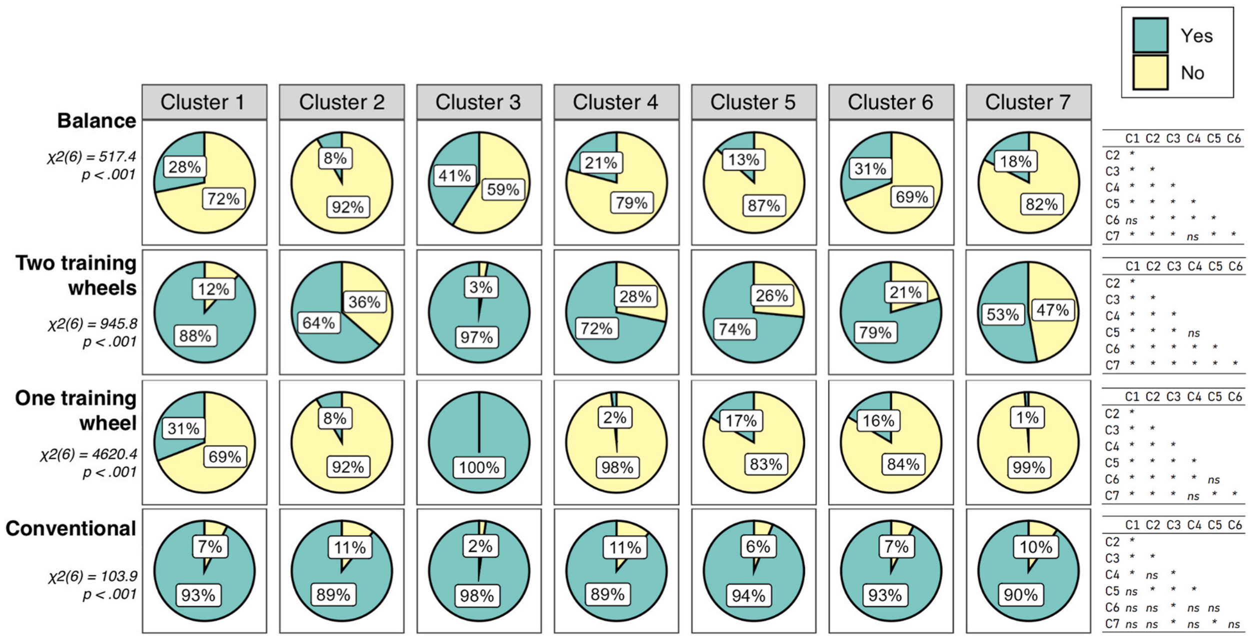


**Fig. 5. Proportion of people that use each kind of bicycle during its learning acquisition in each cluster**. At the right of the pie charts the pairwise comparisons between clusters proportion are provided. Ns = non-significant; * indicate significant differences between clusters (p < .05).

correspond to the highest and lowest use (clusters 5 and 6 vs clusters 2 and 3, respectively) are explained in depth. Cluster 2 followed by cluster 3 are characterized by participants who were the oldest to learn to cycle (Fig. 3A) and who currently don't tend to cycle regularly, neither in summer (Fig. 3B) nor in winter (Fig. 3C), not for leisure (Fig. 4A), nor for mobility (Fig. 4B) nor for going to school (Fig. 4C). Alternatively, individuals in clusters 5 and 6 are those who were the youngest to learn to cycle and who typically use the bicycle a lot, both in summer and winter, usually to go to work/school, and mainly for mobility purposes.

Regarding the rest of the clusters, participants in cluster 1 had the youngest average age compared to the participants of other clusters, they have the third lowest bicycle use in winter and summer, they do not cycle for mobility nor to commute but mainly for leisure. Participants in clusters 4 and 7 had the highest proportion of leisure time cycling.

There was a significant association between cluster membership and the type of bicycles used to learn to cycle. Fig. 5 shows the proportion of people using each type of bicycle during the learning acquisition. The majority of clusters were characterized by the use of different types of bicycles to learn to cycle. Conventional bikes and bikes with two training wheels were the most used among all the clusters. For instance, those who cycle the most (clusters 5 and 6) mainly learned to ride their bikes on conventional bikes and bikes with two training and sporadically on bikes with one training wheel and balance bikes. Those who cycle the least -such as clusters 2 and 3- also used bikes with two training wheels and conventional bikes; interestingly, those in clusters 2 and 3 showed the lowest and

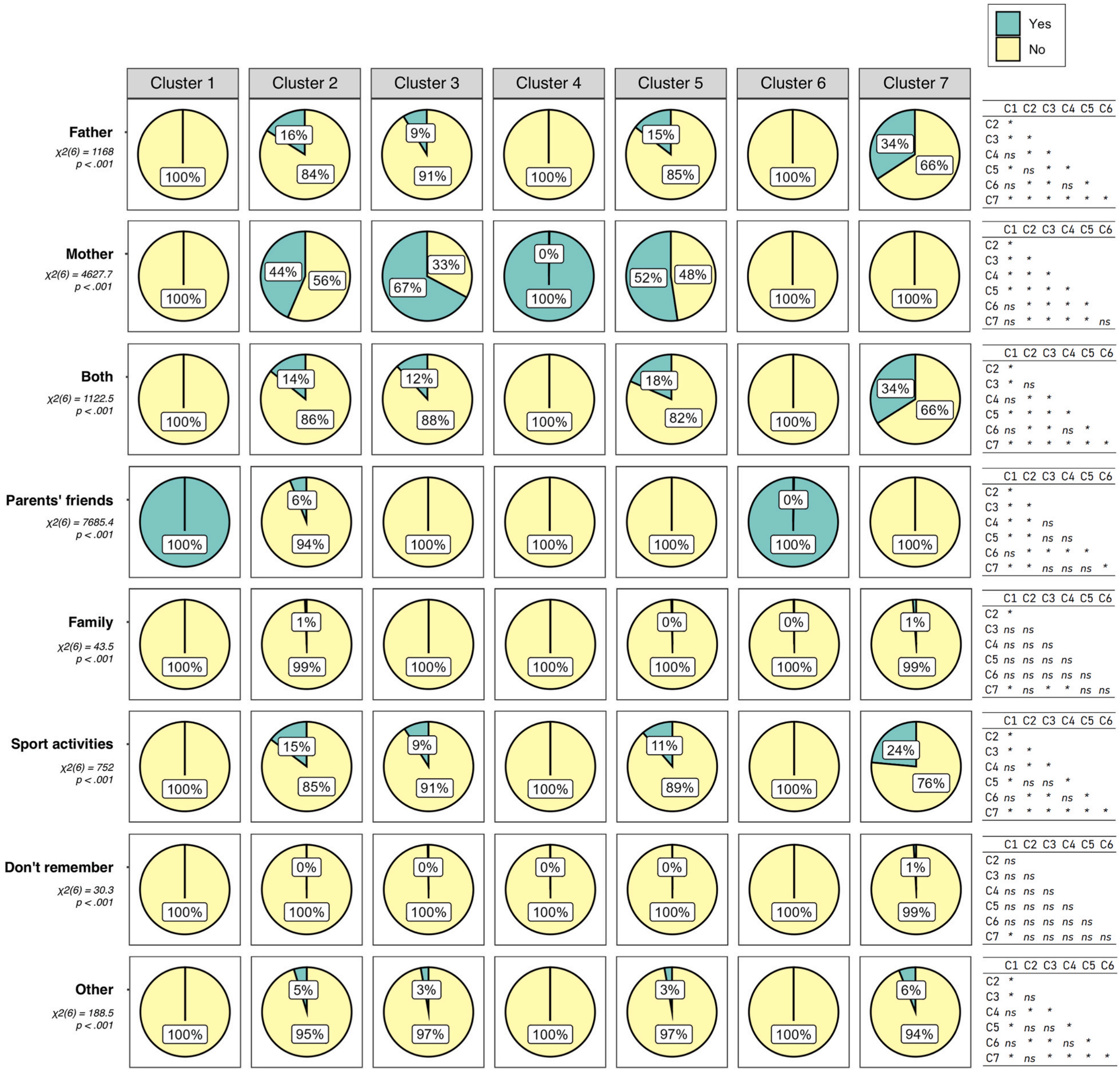


**Fig. 6. Proportion of people that learned to cycle with different type of teacher**. At the right of the pie charts the pairwise comparisons between clusters proportion are provided. Ns = non-significant; * indicate significant differences between clusters (p < .05).

highest proportion of the use of balance bikes to learn, respectively.

There was an association between cluster membership and the significant other who taught participants to cycle (Fig. 6). In clusters 2, 3, 4 and 5 the mother was the most important significant other who taught them to cycle. Parents' friends were important significant others to teach in clusters 1 and 6. Finally, some participants in cluster 7, but also clusters 2, 3 and 5 learned to cycle in the context of sports activities they participated in.

### 3.3. Differences between clusters in variables not included in the SOM

A main effect of cluster membership was found between clusters for age, sex and country (Fig. 7). The largest proportion of females

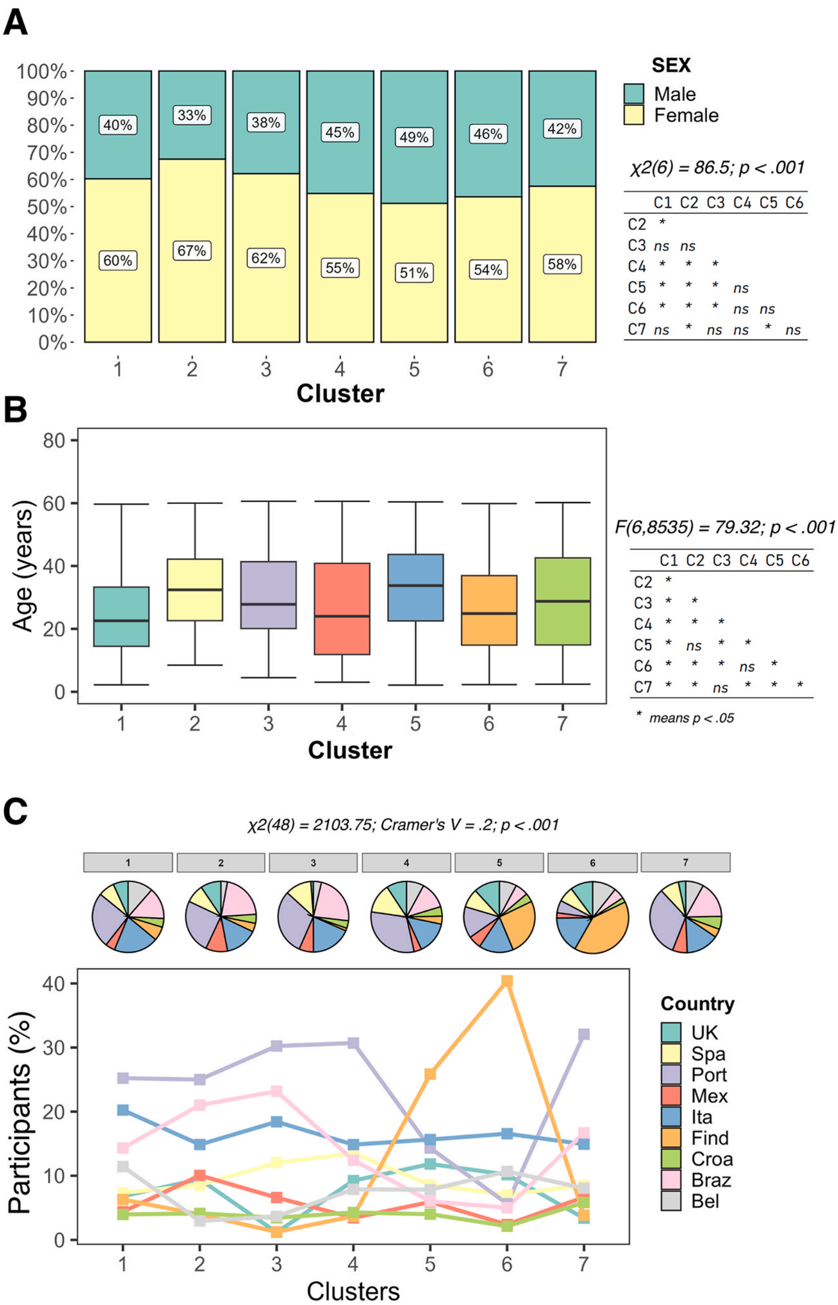


**Fig. 7. Differences between clusters in sex, age and country**. At the right of the layers A and B the pairwise comparisons between clusters proportion are provided. Ns = non-significant; * indicate significant differences between clusters (p < .05). Layer C represents the percentage of participants per country in each cluster.

was found in clusters 2 and 3, whereas clusters 4, 5 and 6 show a similar proportion of females and males. Participants in clusters 2 and 3 were among the oldest (31.6 ± 11.2 and 30.3 ± 13.5 years-old, respectively) and included high percentages of people from Portugal, Brazil, Italy and Mexico or Spain, respectively. Clusters 5 and 6, relatively old and young profiles, respectively (33.3 ± 13.7 and 26.3 ± 14.0 years-old), had a high proportion of people from Finland.

## 4. Discussion

The aim of the present study was to identify distinct clusters representing individuals from eight different countries with similar characteristics related to their cycling habits (acquisition) and behaviors (engagement). Applying a person-centered approach within a bio-ecological framework allowed us to gain more insight into some of the learning-to-cycle acquisition (i.e., the age at which one learned to cycle, the type of bicycle used to learn to cycle, and the person who taught one how to cycle) and engagement (i.e., current reasons for cycling, and cycling frequency across seasons). Our analyses showed that the seven-cluster solution was the best one (i.e., it had the lowest Davies-Boulding index). Clusters 2, 3, 5 and 6 are the most interesting in terms of practical implications to promote cycling as these clusters include people who either barely cycle or who cycle regularly but for different purposes. The differential preferences and practices observed across the clusters may be reflective of broader socio-demographic trends. For instance, gender disparities in cycling habits (Garrard et al., 2008) suggest that women may have unique concerns such as safety and the practicality of cycling with children, which could influence their cycling frequency and the cluster they fall into. Similarly, age and socioeconomic status have been identified as significant factors influencing cycling engagement, with younger individuals and those of higher socioeconomic status more likely to cycle (Heesch et al., 2012). These findings underscore the importance of tailoring cycling promotion strategies to cater to the diverse needs and constraints of different demographic groups.

### *4.1. Learning-to-cycle acquisition*

The results showed a significant association between cluster membership and the type of bicycle used during the learning phase. Recent research (Blommenstein & van der Kamp, 2022; Mercê et al., 2022a) has shown that children who learn to cycle with a BB learn to cycle independently at a younger age than those who practice on a bicycle with training wheels (or a combination of a BB and a bicycle with training wheels) (Chow & Ha, 2024). This finding is partially supported by our study as participants in Cluster 2, who typically did not use a BB, were the oldest of all clusters to learn to cycle. One possible explanation for the low use of BB in this cluster, is that people in this group were, on average, significantly older (i.e., 35.3 years) than people in the other clusters (i.e., 23.8–31.6 years), and it has been shown that the use of a BB as a training tool was significantly less popular in the 1960s–1980s than it was in the 1990s and early 21st century (Mercê et al., 2022a). Interestingly, none of the identified clusters showed a combination of BB and conventional bicycles. The majority of clusters were characterized by the use of different types of bicycles to learn to cycle. Conventional bikes and bikes with two training wheels were the most used among all the clusters. For instance, those who cycle the most (clusters 5 and 6) mainly learned how to cycle on conventional bikes or bikes with two training wheels but also practices on bikes with one training wheel and BB. Those who cycle the least (i.e., clusters 2 and 3) also used bikes with two training wheels and conventional bikes; interestingly, those in clusters 2 and 3 showed the lowest and highest proportion of the use of BB to learn, respectively. This may be a future trend, given recent evidence that BB may be more efficient for learning, or may even replace the need for bicycles with training wheels altogether (Becker & Jenny, 2017), and the increasing popularity of BB as a training tool for children and adults to learn to cycle.

We also found a significant association between cluster membership and the person(s) who taught participants how to cycle. Most clusters were characterized by a variety of different teachers, with one or both parents being the most common teachers. However, Cluster 1 had the highest percentage of participants who learned to cycle through organized sports activities. Furthermore, all participants in Cluster 6, and most participants in Cluster 7, learned to cycle exclusively with the help of their parents' friends. It is unclear which, if any, distinguishing characteristics of these two clusters might explain their heavy reliance on family friends to teach children how to ride their bicycles. Participants from Belgium and Italy were well represented in these two clusters. Perhaps certain cultural characteristics that distinguish these two countries from the other participating countries may play a role.

Strikingly, almost all participants remembered who taught them to cycle. This underscores the importance of learning to cycle. Curiously, it may be that a BB does not require any one to teach a person how to cycle, because it affords a self-organized learning acquisition, exclusively depending on velocity, as probable control parameter (Mercê et al., 2022b). Probably, more important than the person who teaches one to cycle (due to their diversity), is the opportunity of practice and the availability of equipment.

### *4.2. Cycling engagement*

The results showed a significant association between cluster membership and cycling engagement. Participants in Cluster 3 barely used their bicycles. This was similar for summer and winter or across purposes. Participants in this Cluster 3 were on average one of the oldest (>6 years) when they learned to cycle. It is very likely that cycling was not a common mode of mobility at home (Hulteen et al., 2018) and as such the habit of using a bicycle was not developed early on in life. Changing habits later in life, in this case changing to more active mobility by using a bicycle, has been proven to be challenging (e.g., Muñoz et al., 2013). Additionally, most participants in this cluster are from Mexico and Brazil. These countries are the only two non-high-income countries included in this study and buying a bicycle for children (or adults) might not be a priority in families. Participants in Cluster 5 showed the highest bicycle use across summer and winter and including all purposes. This might be explained by the location and circumstances facilitating cycling as active mobility (de Vries et al., 2010). Most participants in this cluster are in Finland, a country scoring well on active transportation according to the Global Matrix of Physical Activity Report Cards (Aubert et al., 2018). Also, children's independent mobility, closely linked to active mobility, is prominent in Finland (Shaw et al., 2015). This independent mobility links back to the community and built environment as the spatial properties and features can make a place more or less inviting for active mobility (Withagen et al., 2012). This might also explain the low or average age of learning to cycle (4.5–5.5 years) of participants in this cluster, as the built environment also influences whether or not the place is inviting and suitable for learning to cycle (Willis et al., 2015).

### 4.3. Strengths, limitations, and future research

It is important to acknowledge that the current study was not without limitations. First of all, we used a convenience sample, which may potentially skew the results towards certain demographics or characteristics and limits the representativeness of the findings within each country. However, given the substantial sample size with participants from various countries and continents, we feel confident that the findings of this study can be generalized to broader populations. Furthermore, by including data from other continents than Europe, this study surpasses prior research and provides a more comprehensive understanding of cycling processes and behaviors worldwide. A second limitation was the use of retrospective self-report surveys. This practice, even though commonly used for this type of research, is susceptible to recall bias, as participants may not or inaccurately recall past events or experiences, which could impact the validity of the collected data. Future research should include longitudinal studies to strengthen our current knowledge on the dynamic nature of cycling habits across the lifespan.

This study has also some considerable strengths. As mentioned before, our robust and extensive sample size from various countries in different continents. In addition, we believe that the innovative analytical methods that were used in this study offer valuable new insights and potentially transformative implications for the field of cycling education and active mobility research.

### 4.4. Practical implications

The person-centered approach situated within a bio-ecological framework and the accompanying SOM analysis enabled the emergence of seven clusters, each characterized by a distinct combination of cycling acquisition and engagement habits. These findings have significant implications for policy, education and practice, both in terms of what each cluster reveals as meaningful learning to cycle and sustain cycling practices across the lifespan, and when considering the interdependent dimension shared between acquisition and engagement tendencies.

Considering the former, to promote lifelong cycling, both starting at an early age (e.g. before the age of five years) and using BBs are important. Therefore, it is important to support parents with knowledge, skills and the right circumstances (e.g., a safe environment) that help them to teach their children to cycle in a fun and supportive manner. Additionally, educators, teachers and other significant adults in the children's lives should be made aware of the role they can play in teaching children to cycle. Given the increasing time children spend in childcare and at school, these settings might play an important role in teaching children to cycle thereby promoting lifelong cycling. For this, professionals in both settings need to be equipped with the right skills and knowledge to support children in learning to cycle. If people either learn to cycle at a later age, have forgotten how to cycle, or do not dare to cycle anymore, it is important to be aware of the barriers they perceive to (re)start cycling. Existing programs, e.g. the "cycle friends" initiative in Belgium that provides people with a 'cycling buddy', can help to increase the amount of people using bicycles.

As for the latter, focusing on the interdependencies shared between learning to cycle (acquisition) and contemporary daily life cycling engagement experiences, our findings reveal a "promising cluster". In this sense, the conjugation of proximal processes (e.g., using BB to learn how to cycle) with more distal influences (e.g., policies that promote a safe street design for cycling) might led to more favorable conditions to create, foster and optimize cycling mobility and habits as viable and meaningful options across the lifespan. The relational approach to cycling acquisition and engagement is crucial to provide valuable information and meaningful data for policy developers, at a national and local level, to devise legislation that actively supports the creation of cycling friendly urban environments and infrastructure. Simultaneously, at a more hyper-localized level, understanding such interdependencies provides educational entities (individual, such as parents, and collective, such as schools) and to municipality experts (such as urban planners), a more flexible and diverse action course to support and engage in more fruitful present acquisitional cycling opportunities, together with a more promising lifelong engagement in cycling practices.

In this sense, the bio-ecological person-centered approach to cycling, and the innovative SOM data analysis that comes with it in the present study, proves to be beneficial and a promising perspective to support national and local authorities in their quest and ethical imperative to comply with the new sustainable development goals, related with promoting healthy, resilient and sustainable communities.

## 5. Conclusion

This study aimed to understand the multifaceted nature of cycling habits and the factors that influence them. The identified clusters of learning and cycling practices shed light on the diverse profiles of cycling behavior through different demographics and geographic locations. The study's findings highlight significant associations between cluster membership and various factors, including the age at which individuals learn to cycle, the types of bicycles used for learning, the person who taught them to cycle, and their current cycling engagement. These results provide crucial insights for policymakers and urban planners to design targeted policies and interventions that encourage cycling, such as improving cycling infrastructure, promoting early cycling education with balance bikes, and addressing cultural barriers to cycling. By designing and tailoring policies to the needs of various demographic groups and geographic regions, local governments can enhance sustainable mobility efforts and foster cycling as a mode of transportation, as well as a recreational activity.

## CRediT authorship contribution statement

**Isaac Estevan:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **An De Meester:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Investigation, Data curation. **Sanne L.C. Veldman:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Cristiana Mercê:** Writing – review & editing, Writing – original draft, Validation, Investigation, Conceptualization. **Marco Branco:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Frederico Lopes:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **David Catela:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Elina Hasanen:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Arto Laukkanen:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Patrizia Tortella:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Cristina Sá:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Boris Jidovtseff:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Ricardo Fujikawa:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Xavier García-Massó:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Rita Cordovil:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

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## Data availability

The authors do not have permission to share data.

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