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Behaviour associated with the presence of a school sports ground: Visual information for policy makers

Roman Vala *, Marie Valova, Pavla Drazdilova, Pavel Krömer, Jan Platos

Department of Computer Science, Faculty of Electrical Engineering and Computer Science, VŠB Technical University of Ostrava, 17. listopadu 2172/15, 708 00 Ostrava – Poruba, Czech Republic

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ABSTRACT

The planning and development of sports infrastructure is a complex process that has a broad and long-term impact on health and well-being in communities. It involves many different stake- holders and usually requires significant public or private investments. Its framework is outlined by policies that define the general social goals of such development. To ensure the maximum alignment between the goals and the development activities, it is important to support the policy making process by high-quality information based on real-world data and presented in a clear and focused way. This work introduces a new pipeline of methods for processing and interpretation of data on physical activity and lifestyle in adolescents. The data is extracted from the Health Behaviour in School-aged Children (HBSC) study and analyzed by modern machine learning methods. We identify behavioural patterns associated with the presence and absence of a school sports ground in different sex and age groups of adolescent in the Czech Republic. The patterns are presented by concise graphical models that ease their use by stake- holders without expert knowledge in sociology, statistics, mathematical modelling, etc. They enable intuitive visual assessment of situation in different regions and highlight the specific similarities and differences among them. Together, the proposed methods contribute towards objective evidence-based policy making in sports management and development.

1. Introduction

The physical environment, neighbourhood characteristics, and the availability of sports facilities have a large impact on the physical activity (PA) and physical inactivity (PI) of people (Sallis et al., 2016; Barrientos-Gutierrez et al., 2017; Halonen et al., 2015; Lee, Ju, Lee, Hyun, Nam, Han, & Park, 2016). The accessibility of healthy lifestyle options and an environment allowing for physical activity contributes to the reduction of peoples' Body Mass Index (Barrientos-Gutierrez et al., 2017). The vicinity of sports facilities has been associated with higher physical activity in people (Halonen et al., 2015; Lee et al., 2016).

The lack of physical activity has become a global problem and contributes to a whole range of severe civilization diseases. Because of that, the research on PA and PI is essential not only from the recreational and well-being points of view but most importantly from the perspective of global health (Sallis et al., 2016; Kalman, Hamrik, Sigmund, & Sigmundová, D., & Salonna, 2015; Bento & Dias, 2017; Haug, Torsheim, Sallis, & Samdal, 2008; Cardon, Labarque, Smits, & De Bourdeaudhuij, 2009; Althoff, Hicks, King, Delp, & Leskovec, 2017; Ǵaba, et al., 2018; Misener, 2020; McLean & Penco, 2020). Physical activity decreases with age. The increase in children's and adolescents' overweight and obesity is associated with many other civilization diseases. Therefore, it is clear that it is necessary to be physically active from an early age (Sallis et al., 2016; Bento & Dias, 2017; Haug et al., 2008). Regular PA in childhood and adolescence brings many advantages for immediate and future health. Among others, it contributes to the prevention of several chronic diseases that appear at a later age (Loprinzi, Cardinal, Loprinzi, & Lee, 2012).

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Despite an increasing interest of governments and decision makers in public policies related to sports, this area still faces a lack of evidence-based approaches that would utilize analytical models already used for decision making in other areas (Di Lu & Heinze, 2020). For example, it has been shown that policy makers have a rather limited idea about the connection of sport and tourism (Weed, 2006). Sport as a subset of PA plays a special role in the context of social policies. However, it is

* Corresponding author.
E-mail addresses: roman.vala@vsb.cz (R. Vala), marie.valova@vsb.cz (M. Valova), pavla.drazdilova@vsb.cz (P. Drazdilova), pavel.kromer@vsb.cz, jan.platos@vsb.cz (P. Krömer).

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often hard to identify the informal relationship between government-level social policies and the impacts of sport (Skille, 2009). Sport has an important social role and sports managers ought to work with a clear vision of its development and plan focused and sustainable interventions reflecting the needs of communities (Skinner, Zakus, & Cowell, 2008). It has been demonstrated (Bruner et al., 2016) that PA and, in particular, sport has a positive influence on the physical and psychical well-being of members of specific communities.

Many studies have concluded that not only the presence of a school sports ground, parks, and playgrounds in the neighborhood but also the safety of their operation is positively connected to the physical activity of children (Pedroni et al., 2019; Ferreira et al., 2007; Roemmich, Epstein, Raja, & Yin, 2007). Sports grounds play an important role in the building and improvement of physical activity in people that live in their vicinity. They represent fundamental elements of public infrastructure for the exercise of fitness activities and an answer to the growing demand for physical activity (Zhu, Hou, & Wang, 2017).

Policy making has a major impact on sports development. It reflects social and community priorities and contributes to the definition and implementation of concrete actions to be executed in relation to sports in short and long-term horizon. It is a complex process that involves many stakeholders with different and often competing interests. Policy makers are exposed to various actors (advocates) supporting or opposing particular active or proposed policies. The goal of the advocates is to persuade policy makers towards certain opinions, often using exaggeration, over-interpretation, and other means of influence (Nelson, Hesse, & Croyle, 2009). In order to overcome the particular interests of advocates and to contribute towards objective evidence- based policy making in relation to the PA in adolescent, it is important to study, identify, and understand the factors that affect the PA in different groups of adolescent in different regions.

Although there is a substantial amount of local, regional, and global data on children's PA and PI (Sigmundová et al., 2019; Pedroni et al., 2019; Guthold, Stevens, Riley, & Bull, 2020; Ding, 2018), the identification of aspects that have a major impact on its level in certain time and place remains a complex problem (Samdal et al., 2007; Sallis et al., 2016; Larouche et al., 2019). In this work, we assume that the presence and absence of school sports grounds result in specific patterns in the health behaviour of adolescents. We extend the self-reported information about adolescents' health behaviour by external information about the availability of sports grounds in local schools. Then, we apply several machine learning methods to identify algorithms that are able to build accurate computational models of the behaviour of different sex and age groups (target groups) of adolescent located in regions of the Czech Republic. The models are further analyzed and variables (features) characterizing the behaviour of the target groups in associa tion with the availability of school sports grounds in different regions are identified. Finally, the variables are used to create concise visual profiles (fingerprints) that summarize the behaviour of the target groups in different regions. The visual profiles represent an important mean for communication of the extracted knowledge towards audiences without expert knowledge in sociology, statistics, mathematical modelling, data science, machine learning, and other involved disciplines.

The contribution of this work is twofold. First, it provides novel insights into the physical activity of adolescents in the Czech Republic in relation to the presence and absence of school sports grounds. Second, it proposes a new pipeline for a machine learning-based identification of important variables in complex high-dimensional social survey data, applied to a concrete research problem (physical activity in adolescents vs. availability of school sports grounds). It also introduces novel graphical methods for visual characterization of studied groups based on multiple variables at the same time and demonstrates their usefulness under several communication scenarios (comparison of two or more groups, identification of trends, and comparison of trends in multiple regions). As a whole, this multidisciplinary study demonstrates the usefulness of the proposed methods for evidence-based policy making and focused and efficient communication of rigorous information towards a general audience. It directly demonstrates the proposed methodology in a specific domain, discusses the findings, and shows the viability of the proposed visualizations in the context of several communication scenarios.

The rest of this article is organized in the following way. Section 2 provides a brief insight into current research on the impact of environment and policies on physical activity and provides the rationale behind the research focus of this work. Section 3 describes the data that was used and details the methods that were applied to extract and visualize relevant information from the vast survey data set. The results are discussed in detail in Section 4 and major conclusions are drawn in Section 5.

2. Impact of environment and policies on the physical activity in children and adolescents

The positive effect of the environment on the level of PA is well-known. Many studies confirm the fact that the living environment in the closest neighbourhood determines whether a person is physically active or inactive (Haug et al., 2008; Roemmich et al., 2007; Larouche et al., 2019; Zieff, Chaudhuri, & Musselman, 2016). An appropriate environment and its accessibility have the potential to significantly contribute to the PA of children (Sallis et al., 2016; Hyndman, 2017; Sandu, Chereches, Baba, Revnic, & Mocean, 2018). Most studies work with data obtained using questionnaires. Only few use directly measured PA values obtained by, for example, accelerometers. According to the Behavioural economic theory, children's choice whether to be physically active or sedentary is strongly affected by the examples observed in families. Inactive family contributes to a sedentary behaviour in child and a motivating living environment that encourages active alternatives helps to develop to a more active lifestyle (Roemmich et al., 2007; Dendup et al., 2020).

The presence of school sports grounds, leisure time programs, and the time spent outside (Sallis, Prochaska, & Taylor, 2000) belong among positive correlates related to the physical activity of children up to the age of 12 and teenagers. Multiple research works have concluded that not only the presence of school sports grounds, parks, and playgrounds in the neighbourhood but also the safety of their operation and their design are positively associated with the physical activity of children (Roemmich et al., 2007; Pedroni et al., 2019; Ferreira et al., 2007; Otago, Swan, Donaldson, Payne, & Finch, 2009).

2.1. The effect of school sports grounds on PA

A school sports ground (Mårtensson et al., 2014; Dyment, Bell, & Lucas, 2009) usually fulfills the safety and vicinity requirements. We use the term school sports grounds as the playground next to the school (at least an asphalt playing area) which was detected from Google maps. It is an environment well known to the children and usually located in the neighbourhood (close to their residences). The school is among the most important environments for exercising PA. School sports grounds are associated with the daily physical activity of children during school hours in physical education lessons and during breaks. Besides supervised sports activities, unstructured physical activity consisting of outdoor free play during leisure time is also an essential factor in children's physical activity (Pedroni et al., 2019).

The relationship between sports facilities and physical activity has been analyzed in a number of studies (Halonen et al., 2015; Eriksson, Arvidsson, & Sundquist, 2012; Lee et al., 2016). The presence of the playground and its positive impact have already been demonstrated in the populations of preschool children (Cosco, Moore, & Islam, 2010). The study (Haug et al., 2008) showed that boys and girls from the schools with a higher number of sports facilities had 2.4 times higher PA (boys) and 2.1 times higher PA (girls) compared to the children from schools with a lower number of sports facilities. Results of a study

(Steinmayr, Felfe, & Lechner, 2011) indicate that there are also national differences in the level of PA in children and adolescents in large cities and in villages (small towns) depending on the distance from sports facilities. Factors such as gender and age of adolescents, employment status and level of education of parents, and household income are positively related to PA (Jongeneel-Grimen, Droomers, van Oers, Stronks, & Kunst, 2014). Many school sports grounds in the Czech Republic are or have been refurbished with a financial contribution from the European Union's financial instruments such as the European Social Fund. As a part of their sustainability requirements, they are required to remain publicly accessible for children and the general public for leisure activities after school hours. Therefore, school sports grounds have great potential to affect the PA of children across communities.

2.2. The importance of evidence for policy making

To increase the impact on the PA of children, the research on PA and initiatives for healthy lifestyle in adolescence are often transformed into policies to support investment in and creation of appropriate facilities for after school activities, healthy and safe communities, and, e.g., active transportation (Pate, Flynn, & Dowda, 2016). However, policy development and implementation requires a unique set of skills including communication, dissemination, and policy advocacy, that the practitioners in education, health, and local/regional community development often lack. Unclear policy objectives and insufficient or unclear information about the links between research, policy, and practice contribute to slow development and adoption of policies, too (Cooper et al., 2016). This work applies a series of steps based on data analysis, machine learning, and information visualization to identify health behaviour associated with the presence and absence of school sports grounds in 14 regions of the Czech Republic. The resulting behavioural models and visual profiles provide important objective insights into the changes in behaviour associated with the presence and absence of school sports grounds in different target groups and across the regions. Due to their minimum extent and graphical nature, they can be easily communicated towards various stakeholders and contribute to the clarification of policy objectives and expected impacts.

3. Methods

This study uses a combination of heterogeneous but complementary data from two distinct sources: a sophisticated and expert validated social survey among school aged children and adolescent (the HBSC study) and location-specific information extracted from orthophoto images collected from online map services. On top of that, a pipeline of machine learning and information visualization steps is performed in order to identify, extract, and display information important for the characterization of behavioural patterns associated with the presence of school sports grounds in a manner suitable for non-experts such as policy makers.

3.1. Data description and initial variable selection

The primary source of data used in this work is the HBSC study. It is an international study dealing with the health behaviour of school-aged children. It was collected through a questionnaire survey carried out among children in the schools. The survey is performed in more than 40 countries all over Europe and North America in a carefully designed and strictly controlled way according to an international research protocol (Inchley & Currie, 2016). The data set used in this work comes from the survey that took place in May and June 2018 in the Czech Republic. Participation in the survey was anonymous and voluntary. All parents were informed about the survey by the school management and had a chance to opt-out. Trained research assistants presented the questionnaires in the absence of the teacher during regular lessons. The data in the Czech Republic was collected with the help of an electronic questionnaire system in 2018.

The original data set contained 13,377 individual responses. It was reduced to 10,994 responses of participants who answered all the required questions. The responses were collected at 227 schools located in 14 regions, labeled R1–R14 (label R0 represents the whole Czech Republic). The respondents were 1631 11-year-old boys, 1968 13-year-old boys, 1,927 15-year- old boys, 1,626 11-year-old girls, 1,950 13-year-old girls, and 1,892 15-year-old girls (see Table 2).

A group of 17 questions (variables) that are connected to physical and leisure activities was manually selected from the data set by sports and social science experts. The variables cover several areas related to active and inactive use of leisure time, namely: vigorous physical activity frequency (timeexe), participation in organized sports (OrgSp), TV/DVD/video watching on weekdays (PA1), TV/DVD/video watching at the weekend (PA2), playing computer games on weekdays (PA3), playing computer games at the weekend (PA4), computer use on weekdays (PA5), computer use at the weekend (PA6), TV/video watching with family (fc30), playing sports with family (fc37), physical activity over the past seven days (Physact60), the way the main part of the journey to school is done (PA10), the way the main part of the journey from school is done (PA11), membership in a youth organization (LS4), excuse from physical education (NQ PE), the time spent idling (NQ idle) and the size of the place of residence (NQ residence). The values of the variables were analyzed in association with the presence and absence of a school sports ground.

The procedure to obtain information about the presence of a school sports ground consisted of several steps. First, the addresses of the participating schools were extracted. Second, the precise geolocation of each school was obtained from the Google Maps service. The orthophoto imagery of school locations was then obtained from Google Maps. An example of the images is depicted in Fig. 1. After the orthophoto images were collected for all schools, each of them

was manually investigated by two researchers in order to identify whether a sports ground is present. When the information was not clear or there was a disagreement between the experts, another check on Google Maps as well as on a local satellite image service Seznam Mapy was performed. The results of the investigation were then added to the data set as a new binary variable.

3.2. Important variable learning and pattern visualization

The 17 variables manually selected from the 2018 HBSC survey form a self-reported description of the activities school-aged children in the Czech Republic execute in leisure time. They were chosen so that the intensity of physical activity (i.e., frequency and intensity of movement, sport) and the level of physical inactivity (i.e., the time spent on a computer playing computer games or online) of the respondents can be evaluated on their basis.

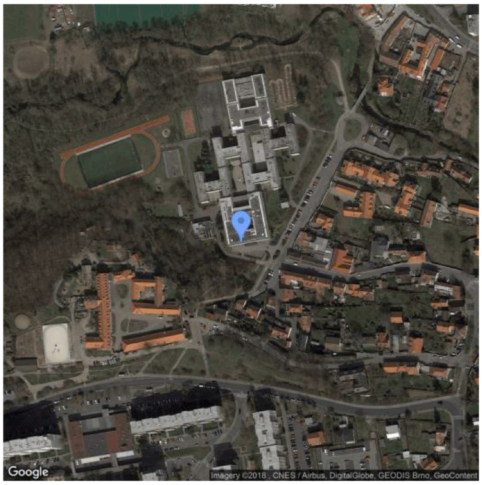
For each variable (question), the children picked one from a set of predefined answers. For the variable Physact60 (physical activity in the past seven days), the possible answers were the following: 1 = 0 Days, …, 7 = 6 Days. The variable timeexe (vigorous physical activity frequency) allows the reporting of 7 levels of vigorous physical activity frequency (1 = every day, …, 7 = never). While for Physact60, the

Table 1
Accuracy of the ML models on the data from the whole Czech Republic (R0). Higher is better. Accuracy = 1.0 represents the situation when the model learned the classification of all responses without errors.

Alg.	boys	girls	boys	girls	boys	girls
LR	0.79	0.79	0.76	0.78	0.78	0.76
LinS	0.79	0.79	0.76	0.78	0.78	0.76
RbfS	0.93	0.92	0.93	0.92	0.92	0.90
DT	1.00	1.00	1.00	0.99	1.00	1.00
RF	1.00	1.00	1.00	0.99	1.00	1.00
ET	1.00	1.00	1.00	0.99	1.00	1.00

Table 2
Mean values of selected variables for the whole CZ (R0) and three regions – R4, R10 and R12. They are calculated separately for children in the presence and absence of a school sports ground. Data from regions are filtered by sex (boys, girls) and age (11, 13, 15). The third part of the table shows the statistical significance (p-value) of the difference between the mean values of the variables in selected groups of children in the presence and absence of a school sports ground. The shortcut Ph60 represents the variable Physact60. The chi-squared test was used to investigate the statistical significance of the differences between the behavior of children in the presence and absence of a school sports grounds. The level of significance, α, was set to 0.05 and values with $p < 0.05$ are highlighted by red color.

region: group	The presence of a school sports ground									The absence of a school sports ground									p-value P/A						
	PA1	PA4	PA5	PA10	NQ	idle	Ph60	fc30	cnt	PA1	PA4	PA5	PA10	NQ	idle	Ph60	fc30	cnt	PA1	PA4	PA5	PA10	NQ idle	Ph60	fc30
R0: boys aged 11	3.92	4.36	3.41	2.08		2.88	4.48	3.58	1281	3.81	4.01	3.91	4.31		3.11	4.15	3.23	350	0.105	0.849	0.387	0.075	0.690	0.494	0.664
R0: boys aged 13	4.28	5.18	4.21	2.15		3.04	4.39	3.38	1500	4.13	4.74	4.18	2.40		3.07	4.41	3.38	468	0.008	0.015	0.313	0.00	0.793	0.048	0.77
R0: boys aged 15	4.29	5.26	4.85	1.99		3.12	4.01	3.01	1500	4.16	5.15	4.70	2.07		3.14	4.09	3.01	427	0.808	0.614	0.587	0.021	0.641	0.864	0.067
R0: girls aged 11	3.50	3.01	3.20	2.01		2.79	4.40	3.45	1284	3.34	2.83	3.14	2.18		2.76	4.36	3.46	342	0.558	0.105	0.188	0.008	0.920	0.925	0.900
R0: girls aged 13	3.91	3.00	4.59	2.12		3.26	4.08	3.33	1521	3.94	3.26	4.62	2.15		3.27	4.22	3.3	429	0.253	0.003	0.139	0.218	0.543	0.503	0.941
R0: girls aged 15	4.15	2.71	5.49	1.96		3.52	3.53	3.19	1445	4.15	2.58	5.15	2.11		3.45	3.66	3.19	447	0.600	0.665	0.001	0.081	0.092	0.711	0.776
R4: boys aged 11	4.00	4.39	3.44	2.07		2.70	4.52	3.70	99	3.61	3.56	3.00	2.22		2.44	3.28	3.50	18	0.038	0.090	0.983	0.476	0.476	0.196	0.521
R4: boys aged 13	3.98	4.67	3.92	2.26		2.71	4.67	3.37	141	4.32	3.37	4.05	2.00		2.63	4.37	3.68	19	0.316	0.002	0.477	0.806	0.672	0.678	0.806
R4: boys aged 15	4.43	4.78	4.62	2.31		3.12	4.23	3.22	150	4.85	5.05	4.45	2.50		3.35	4.40	3.40	20	0.522	0.512	0.878	0.929	0.592	0.898	0.313
R4: girls aged 11	3.34	3.02	3.25	1.95		2.55	4.73	3.47	111	2.50	2.71	2.36	1.71		2.43	4.57	3.71	14	0.299	0.908	0.248	0.171	0.786	0.877	0.561
R4: girls aged 13	3.96	3.08	4.44	2.51		3.27	4.29	3.46	103	4.00	3.84	5.04	2.04		3.44	3.28	3.68	25	0.899	0.049	0.885	0.173	0.298	0.211	0.649
R4: girls aged 15	4.05	2.71	5.52	2.05		3.51	3.62	3.16	145	4.6	3.76	5.08	2.4		3.48	3.68	2.96	25	0.159	0.009	0.925	0.438	0.356	0.830	0.370
R10: boys aged 11	3.52	4.45	3.41	2.24		2.79	4.59	3.50	58	3.91	4.26	3.09	1.94		2.35	4.85	4.15	34	0.724	0.622	0.376	0.186	0.248	0.992	0.060
R10: boys aged 13	4.15	5.42	4.17	2.35		2.97	4.71	3.46	65	4.54	4.70	3.94	2.41		3.00	4.28	3.61	54	0.464	0.549	0.141	0.171	0.913	0.029	0.606
R10: boys aged 15	4.31	5.05	4.51	2.01		3.16	3.95	3.04	80	3.85	4.61	4.68	1.85		2.96	4.53	3.13	47	0.302	0.589	0.142	0.712	0.611	0.919	0.596
R10: girls aged 11	3.40	2.87	3.23	2.45		2.81	4.66	3.60	53	3.58	3.58	3.15	2.21		2.91	4.76	3.67	33	0.029	0.011	0.278	0.014	0.862	0.509	0.386
R10: girls aged 13	3.21	2.60	4.16	2.25		3.25	4.21	3.27	77	4.02	3.18	4.55	2.11		2.84	4.02	3.34	44	0.010	0.869	0.328	0.304	0.144	0.638	0.802
R10: girls aged 15	4.03	2.90	5.64	1.93		3.20	3.90	3.26	80	4.28	2.33	4.98	1.78		3.46	3.54	3.41	46	0.756	0.922	0.628	0.063	0.222	0.631	0.614
R12: boys aged 11	4.06	4.81	3.50	2.12		2.86	4.19	3.64	107	4.54	5.92	3.77	1.85		2.54	5.15	3.15	13	0.671	0.459	0.627	0.751	0.938	0.420	0.123
R12: boys aged 13	4.61	5.66	4.46	2.02		3.13	4.14	3.54	122	3.97	4.73	4.00	2.3		3.23	4.70	3.63	30	0.162	0.135	0.144	0.016	0.616	0.026	0.973
R12: boys aged 15	4.46	5.13	4.72	1.98		3.00	4.15	2.95	123	4.38	5.92	5.00	2.08		2.88	3.75	2.88	24	0.667	0.144	0.434	0.002	0.980	0.233	0.593
R12: girls aged 11	3.71	2.76	3.10	2.05		2.81	4.43	3.56	108	2.59	3.00	3.06	1.82		2.41	4.53	3.53	17	0.016	0.396	0.174	0.890	0.487	0.049	0.224
R12: girls aged 13	3.92	3.02	4.67	1.87		3.17	3.93	3.49	118	3.57	2.57	3.87	2.33		3.17	4.97	3.17	30	0.171	0.697	0.498	0.211	0.810	0.157	0.608
R12: girls aged 15	4.04	2.68	5.14	1.75		3.25	3.52	3.26	96	4.2	2.83	5.56	2.14		3.33	4.36	3.58	36	0.931	0.847	0.204	0.008	0.507	0.170	0.024



(a) A sports ground is present

(b) A sports ground is absent

Fig. 1. Orthophoto images obtained from the Google Maps service.

highest numerical value (code) of an answer corresponds to the highest possible intensity (frequency of exercise), the variable timeexe is encoded in an opposite way. The answer with the lowest code indicates the highest possible frequency. For a better comparison, especially of visual representations (see Fig. 2), the answers for timeexe, fc30, fc37, and NQ idle were re-coded so that the higher answer codes correspond to the higher real-world values. The ranges of selected variables used in the table 2 are: PA1, PA4, and PA5 (1 = never, …, 9 = 7 h and more), PA10 (1 = active, …, 5 = passive), fc30 and NQ idle (1 = never, …, 5 = every day). Finally, the values of the responses were column-normalized to the range [0, 1] due to the requirements of the used data–processing methods (Yuan & Soucy, 2011).

In total, 10,994 individual survey responses were used for a machine learning-based analysis. The analysis was performed in order to seek evidence whether the presence and absence of school sports grounds can be associated with specific patterns in children's behaviour. Its goal was to find out what are the variables associated with the behavioural patterns and how the patterns change across individual regions of the Czech Republic. The machine learning (ML) approach is based on the assumption that if the data contains patterns that can be associated with the presence and absence of a school sports ground, a model (classifier) can be trained to classify it with respect to this criterion.

3.2.1. *Important variable learning*

It is reasonable to expect that potential behavioural patterns differ for boys and girls and among the three investigated age groups (Pedroni et al., 2019). Because of that, standalone models (classifiers) were in all regions sought for every target group.

First, the complete data set, covering all 14 regions, was analyzed. A battery of machine learning methods including Linear regression (LR) (Hayes & Montoya, 2017), Support-vector clustering (SVC) with linear kernel (LinS) (Chauhan, Dahiya, & Sharma, 2019), SVC with radial basis func- tion kernel (RbfS) (Begg & Kamruzzaman, 2005), decision tree (DT) (Breiman, 2017; Yan- nakoulia et al., 2016), random forest (RF) (Biau & Scornet, 2016) and extremely randomized trees (ET) (Geurts, Ernst, & Wehenkel, 2006) was used to learn models separating the target classes. The classifiers were for every target group trained on the complete data set with all 17 variables as inputs. The results of the learning are summarized in Table 1.

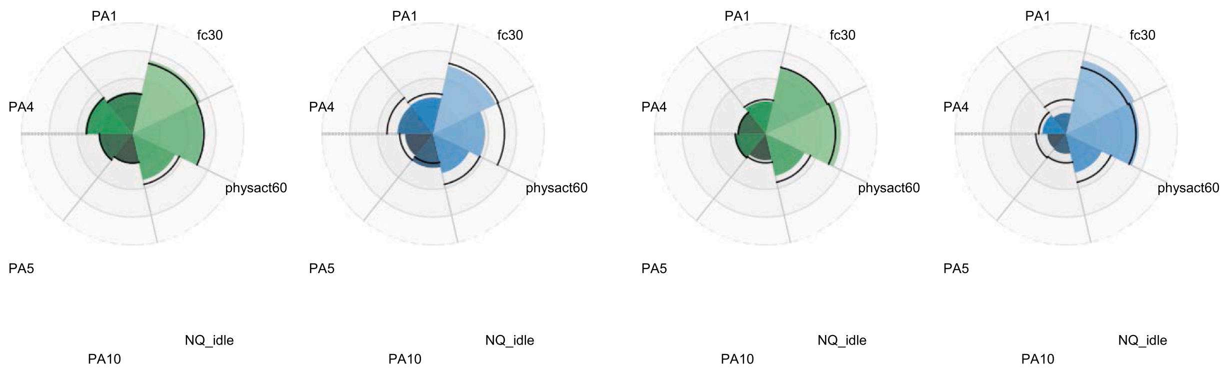
The results show that models obtained by machine learning can distinguish between the behavioural patterns of children in the presence and absence of a school sports ground. However, the decision boundary is non–linear (linear regression and SVC with linear kernel fail). It also shows that the differences between the behaviour in the presence and absence of a school sports ground can be for all target group perfectly expressed by the models DT, RF, and ET. The only exception is the group of 13-year-old girls for which no model perfectly dividing the group with respect to the absence and presence of school sports ground was found. That indicates that the 17 manually selected variables contain sufficient information to distinguish the behaviour of children in all sex and age groups except the one mentioned above. DT was selected as the most lightweight algorithm from the most successful ML algorithm family to be used in the remainder of the experiments.

It is reasonable to expect that behavioural patterns associated with the presence and absence of a school sports ground, although diverse across geographical regions, will be more coherent within them. A lower number of variables will be needed to model the behaviour of the target groups inside a single region. In order to test this hypothesis, the data set was split according to the geographical regions, and standalone classification models were for each target group learned in every region, respectively. Independent DTs were trained for every combination of 5, 4, and 3 variables, respectively, and their classification accuracy was evaluated.

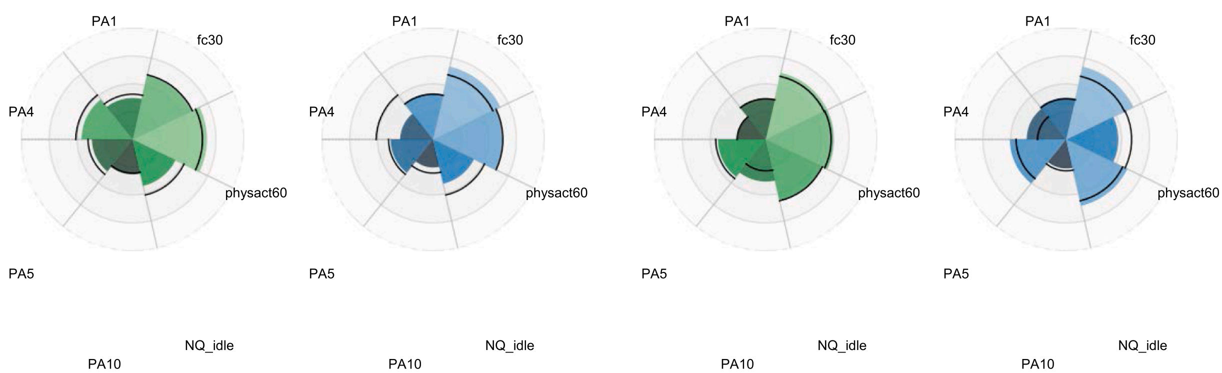
The accuracy of the DT with the best classification ability was calculated for each target group in every region. The results showed that 3 variables are not enough to obtain perfectly accurate models (accuracy = 1.0) for the vast majority of regions. The experiments also showed that 4 variables are sufficient for all regions but not for all target groups and 5 variables are necessary to obtain accurate models for all target groups in every region. A further analysis of the best models showed that the 5–tuples of variables that yielded the best DTs in different regions are, in all cases, not identical. Altogether, the following seven variables were used by the best DTs found for every target group in every region: NQ idle, PA1, PA4, PA5, PA10, Physact60, fc30. This shows that only 7 variables (out of the 17 manually selected ones) are in the HBSC data set needed to discover the behavioural patterns associated with the presence and absence of a school sports ground for each target group in every region.

3.2.2. *Behavioural pattern visualization*

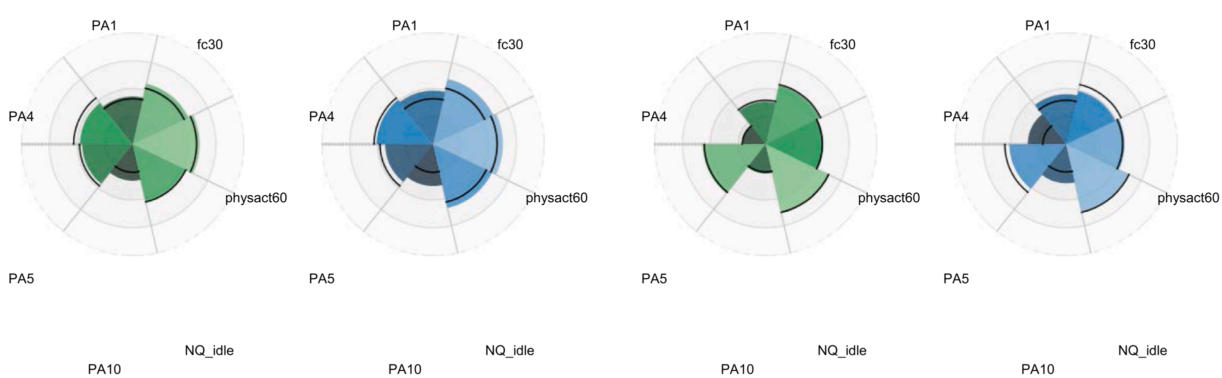
Based on the 7 variables identified by machine learning, visual *fingerprints* of the behaviour associated with the presence and absence of a school sports ground were created for all target groups in every region. The fingerprints are in the form of circular plots that allow concise graphical representation of multiple categorical variables at the same time. They clearly illustrate the differences between the behaviour of the target groups within and across the regions. An example of the fingerprints is shown in Fig. 2. In each fingerprint, blue sectors illustrate the



(a) Boys aged 11 (b) Girls aged 11



(c) Boys aged 13 (d) Girls aged 13



(e) Boys aged 15 (f) Girls aged 15

Fig. 2. Fingerprints of target groups' behaviour in region R4. Presence of a school sports ground (green) vs. its absence (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

behaviour of the group in the absence of a school sports ground and green sectors correspond to the behaviour of the group in its presence. The subfigures in Fig. 2 show the fingerprints for each target group. The country-wide means of all selected variables and all specific groups are highlighted in the pictures by black arcs.

The fingerprints provide a suitable mean for further communication of the results. They allow an easily understandable graphical representation of the differences and/or similarities in the behaviour of different target groups. This is especially useful for policy making when rigorous and objective evidence needs to be presented to different stakeholders of the policy making process. Several ways the fingerprints can be used to point out the relationships and trends among target groups are shown and discussed in section 4.2.

4. Results and discussion

The main outcomes of this study, i.e., the knowledge about the behaviour of school-aged children and adolescents associated with the presence and absence of school sports grounds in different regions of the Czech Republic and the pipeline to discover and visualize the behavioural patterns from data, are discussed in this section. Together, they illustrate the validity and usefulness of this evidence-based approach for policy making.

4.1. Findings about adolescents in the Czech Republic

A series of machine learning methods described in Section 3.2.1 was used to learn behavioural patterns associated with the presence and absence of a school sports ground in the HBSC data collected in the Czech Republic in 2018. The accuracy of the methods, corresponding to their ability to discover distinctive behavioural patterns, is summarized in table 1. The decision trees algorithm (DT) providing the best performance to accuracy ratio, was further used to find the minimum set of variables that were, in reality, needed to learn the behavioural patterns of all target groups in all regions of the Czech Republic. The seven identified variables were used to create visual fingerprints of discovered behaviour of target groups in the presence and absence of a school sports ground in all regions of the Czech Republic. The mean values of the variables for the whole Czech Republic and selected regions, indicating an *average* behaviour in the population of school-aged children on country-wide and regional levels, are shown in Table 2.

The mean level of physical activity in the past seven days (Physact60) of an average child in the Czech Republic in the presence of a school sports ground is in the range [3.53*,* 4.48], depending on its sex and age. The mean level of Physact60 of average children in the absence of a school sports ground falls within the range [3.66*,* 4.41] (see Table 2). It means that typical Czech adolescents aged 11–15 reach the limit of 60 min of physical activity only three days every week. The amount of physical activity significantly decreases with the age and reaches the lowest levels in the groups of 15-year-old girls. The average decrease of Physact60 in boys with age is by 0.47 in the presence of school sports ground and by 0.32 in its absence. The average decrease of Physact60 in girls with age is larger and equals 0.87 in the presence of school sports grounds and 0.7 in its absence.

In the Czech Republic as a whole (region R0), mostly no statistically significant effects of the presence and absence of school sports ground on mean Physact60 levels in the target groups were found. The only exception was the group of 13-year-old boys where the difference in mean Physact60 in the presence of school sports ground (4.41) and in its absence (4.39) is according to the chi-squared test statistically significant with p-value = 0.048.

There are clear differences in the level of physical activity in the target groups in the presence and absence of school sports ground in some regions, as summarized in Table 2. The table shows the differences in the mean values of the variables in the whole Czech Republic (R0) and in regions R4, R10, and R12, respectively. The regions were selected because they very well illustrate regional differences in behavioural patterns and trends associated with the presence and absence of school sports ground in the target groups.

It demonstrates that children in these regions respond to the presence and absence of a school sports ground by different physical activity patterns. Region R4 is also illustrated by visual fingerprints in Fig. 2. However, it should be noted that the visual differences in Physact60 are not statistically significant. A statistically significant (p-value = 0.029) difference in Physact60 of 13-year-old boys in the presence and absence of school sports ground was identified in region R10. In this case, the presence of a school sports ground has a positive impact on the level of physical activity. In this region, it has also a positive impact on the time spent watching TV (PA1) and using the computer (PA4), which is reduced.

4.2. Pattern visualization for information communication

The results of the computational analysis are graphically represented by the fingerprints in Fig. 3. The figure illustrates both, the statistically significant and insignificant differences in the behaviour of children in the presence and absence of a school sports ground and underpins the usefulness of information visualization for effective communication. However, the circular

representation can be used to illustrate the results in more than one way. Few examples of their use are provided in this section.

Fig. 2 highlights the computational findings by visual fingerprints in a single region. It clearly illustrates that in the region R4, there are several groups of children, e.g., 11-year-old boys and 13-year-old girls that have mean PA values (Physact60) higher when the school sports ground is present. These differences are not statistically significant at the level of significance 0.05 but advocate the positive impact of the presence of a school sports ground on the physical activity of school-aged children in this region of the Czech Republic.

The fingerprint representation can be also used to graphically illustrate and conveniently communicate the differences in the behaviour of the target groups in one or more regions. Fig. 4 shows how can the fingerprints of the two groups from Fig. 3 be aggregated into a single plot that illustrates quantity (behaviour in each group), quality (difference in behaviour between the groups), and context (relationship of groups' behaviour to population average) at the same time.

Two more examples of a graphical comparison of the two groups is shown in Fig. 5. It provides a convenient side–by–side comparison of

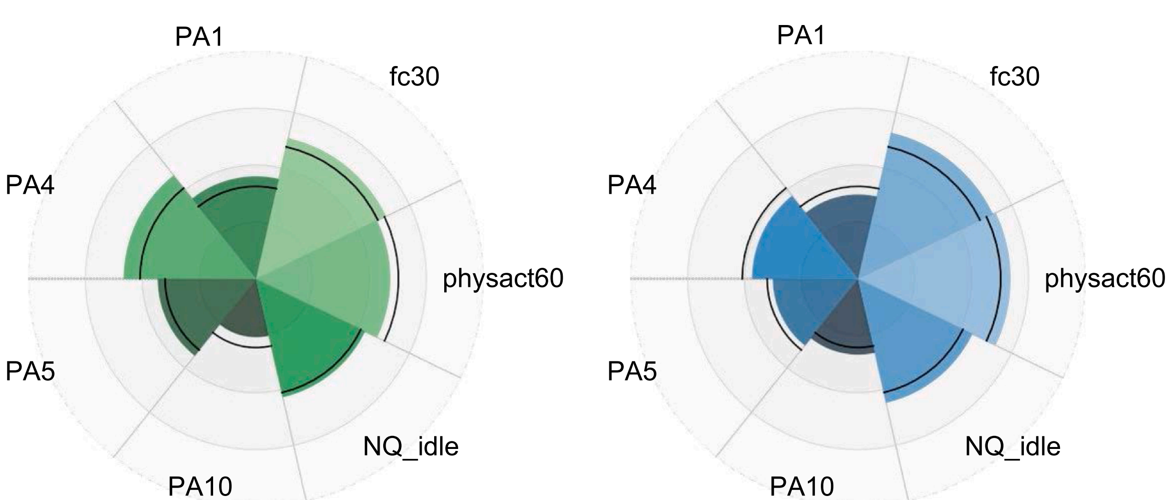


Fig. 3. The fingerprints of region R12. Comparison of the behaviour of 13-year-old boys in the presence and absence of a school sports ground in region R12. From the fingerprints, it is obvious, that the boys with the presence of the school sports ground have fc30, NQ idle, PA5, PA4, and PA1 greater than the country mean and physact60 and PA10 lower than the country mean. The boys with the absence of the school sports ground have fc30, physact60, NQ idle, and PA10 greater than the country mean and PA5, PA4, and PA1 lower than the country mean. The differences in physact60 and PA10 are statistically significant (see table 2).

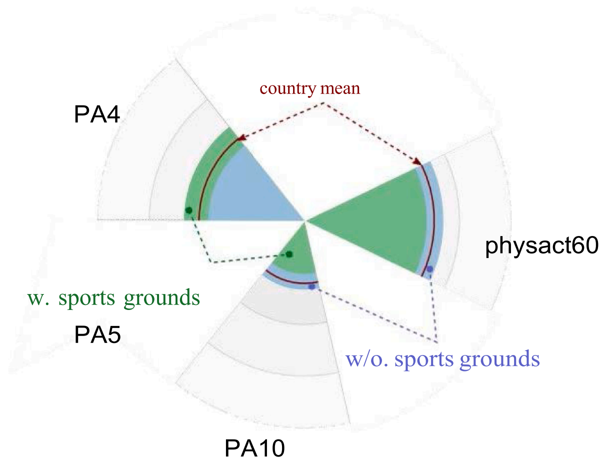


Fig. 4. Focus and compare. The fingerprints from Fig. 3 (boys aged 13 in region R12 in the presence and absence of a school sports grounds) with the focus on three features and explanatory information inside the plot. Information about two groups has been merged into a single plot that highlights their mutual differences as well as their relationship to the average behaviour. Red arcs represent country means. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

group's behaviour and enables a visual illustration of their change (trends) associated with the presence and absence of a school sports grounds.

A final example of a more complex graphical illustration of behavioural patterns associated with the presence/absence of a school sports grounds in two regions is shown in Fig. 6. It provides a direct comparison of the behaviour in groups organized according to one primary (access to school sports grounds) and one secondary (region) criterion. A visual assessment of the plot can reveal whether the trends in the behaviour are in both regions the same (sectors in both rows face the same direction) and different (sectors in both rows face opposite directions). This article contains two types of results. The first result of this study verifies the applicability of our proposed method on suitable data. The important part of this result is the visualization of analyzed data. Another output of our work is to highlight the heterogeneity of the behavior of selected subgroups of adolescents in Czech Republic. From this point of view, the article can

5. Conclusion

In this work, we study the behavioural patterns related to the physical activity and inactivity of school-aged children in the Czech Republic. The patterns are extracted from data, analyzed, and graphically illustrated. The main contributions of the research include the discovery of novel knowledge about the links between the physical activity and inactivity of adolescents and the presence and absence of sports grounds in their schools, the design and application of a semi-

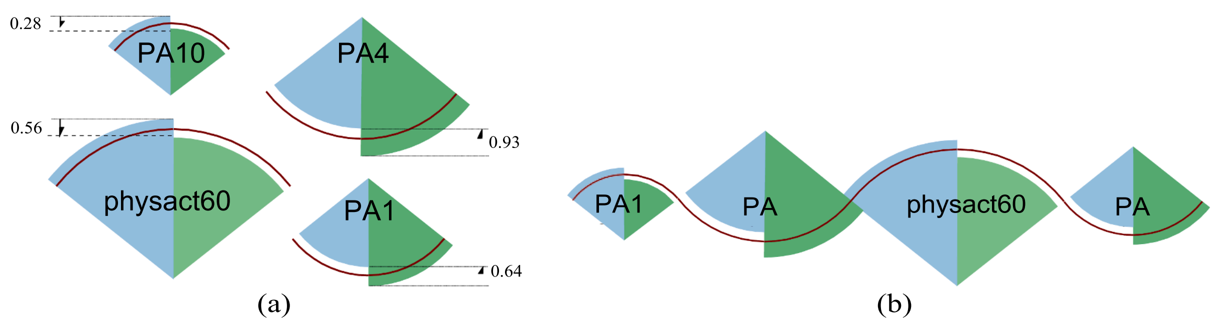


Fig. 5. A side–side comparison with trends organized as a grid (a) or as a sequence (b). The plots illustrate the differences in the behaviour of the groups in the presence (green) and absence (blue) of school sports grounds by the distance between sector rims. The relationship of the behaviour of both groups to the country mean is illustrated by the distance of sector rims to the red line (country mean). The information whether the presence of school sports grounds is associated with an increase or a decrease in the intensity of the behaviour is illustrated by the up or downward orientation of the sectors, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

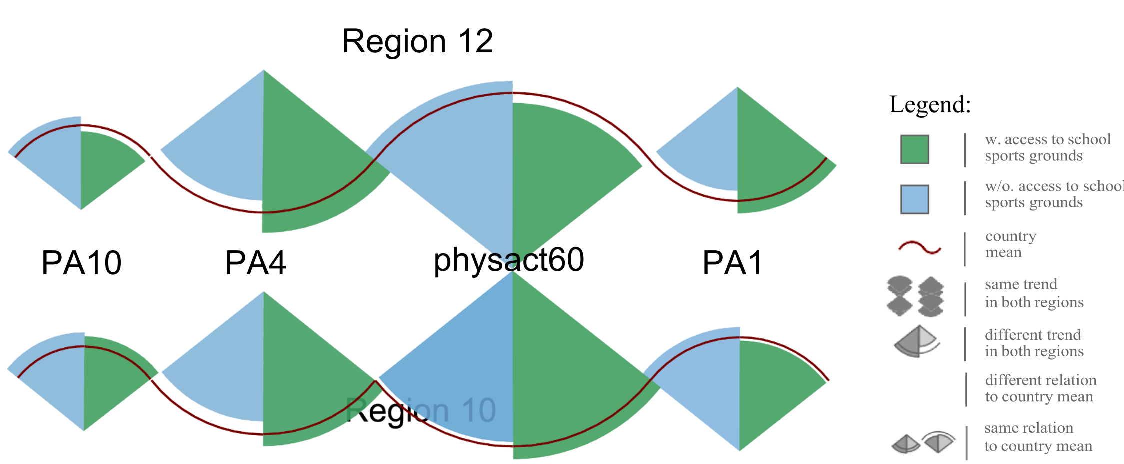


Fig. 6. A side–by–side comparison with trends in two regions. Behaviour is encoded by the horizontal location of the sectors (*columns*), primary group selection criterion (presence of a school sports ground) is encoded by *colors*, secondary grouping criterion (region) is encoded by the vertical location of the sectors (*row*). A detailed description of all graphical elements is provided inside the figure.

automated pipeline of advanced algorithms for the extraction of domain-specific information from large data sets, and the proposal of new graphical methods for an intuitive and accessible visual communication of the outcomes of computational data analyses. The top-level goal of the work is to support evidence-based policy making in sports management, planning, and development with impacts on the health behaviour of children.

The data used in this work comes from two sources: the 2018 HBSC survey on the health behaviour of school-aged children in the Czech Republic (a part of the international HBSC study) and orthophoto images of the schools in which the survey took part. The aerial images of school facilities, obtained from public online map services, were analyzed and the information about the presence or absence of sports ground in each school was added to the HBSC data set. The data was further processed and a set of 17 variables relevant for the physical activity and inactivity were selected by experts. Then, machine learning (in particular, the decision tree algorithm) was applied to reduce the manually selected set of variables to the ones that are in reality needed to learn models of behaviour of groups associated with the presence and absence of school sports grounds in all regions of the Czech Republic. This procedure led to the identification of 7 variables needed to characterize the physical activity of the target groups in every region of the Czech Republic.

The selected variables were studied in order to obtain novel insights into the physical activity and inactivity of adolescents in the Czech Republic. The result of the analysis suggests that there indeed are behavioural patterns that can be associated with the presence and absence of school sports grounds in the Czech Republic. However, the patterns differ between age and sex groups and across regions of the Czech Republic. This is an important result that suggests that the impact of the same activities in one region might not be similar in other regions and interventions (e.g., organized sports and leisure time activities, sports ground development) need to be studied and planned in the local context. Nevertheless, the methods and algorithms introduced in this work can be used for the identification of regions and locations where similar behavioural patterns can be found and the experience from sport development, planning, and policy making can be, potentially, shared.

In order to support an efficient communication of the information found by rigorous statistical and computational analyses towards non-experts, the behavioural patterns of different target groups in different regions have been graphically illustrated by visual fingerprints in the form of circular plots. Several ways how such visual representations can be used to characterize the between-group variability, the relation of local and global behavioural patterns, and to compare the patterns in the context of one or more regions have been proposed and demonstrated. Such a visual communication is useful, in particular, to support objective and evidence-based decisions in policy making which needs to find a balance between the interests of particular stakeholders (actors) and transform it into long-term, sustainable, and consensual policies.

Last but not least, the proposed pipeline of manual, machine learning, and information visualization steps is data and domain independent and can be applied to arbitrary data sets, different regions and sub-regions, and in the context of any focus area. In the future, we will use the same approach to study physical activity in children in the context of their residence (city vs. village) and to study physical activity and social behaviour in adults on the basis of other data set, e.g., the European Social Survey. We used data only from the Czech Republic, although the HBSC study is international. In future work, we want to focus on applying the proposed methodology to data from multiple countries.

Declaration of Competing Interest

The author declare that there is no conflict of interest.

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