Czech Technical University in Prague
Faculty of Architecture

Department of Architectural Modelling (MOLAB)

Disertační práce
Ph.D. Thesis

MOBILE-BASED SENSING – SMARTPHONE APPLICATION FOR LONG-TERM URBAN LIFESTYLE AND MOBILITY SENSING

Author of the Thesis: Ing. arch. Ladislava Fialka Sobková

Supervisor: prof. Dr. Henri Hubertus Achten
Branch: Architecture - Theory and Design

2022

Prohlášení:

Prohlašuji, že jsem dizertační práci napsal samostatně s využitím pouze uvedených a řádně citovaných pramenů a literatury a že práce nebyla využita vrámci jiného vysokoškolského studia či k získání jiného nebo stejného titulu.

Ing. arch. Ladislava Fialka Sobková
V Praze dne 10. ledna 2022

CONTENT

ABSTRACT

The increasing demand for data and smart solutions is one of the fastest growing sectors of human development. This trend is also noticeable in the fields of architecture and urban planning. Data on city processes are necessary indicators for the precise assessment of their current state and can be identifiers for evaluating changes.
Cities and the people living in them are constantly producing large amounts of data through sensors. Combining these data layers can reveal much about the way we use cities and how cities affect their inhabitants.

The mobility of individuals can be mapped through a simple mobile application that records the movement of users. The sensors contained in smartphones are a low-cost yet long-term source of information that, if properly interpreted, can be a dynamic indicator of city life.
I propose the structure and user interface of a smartphone application that uses the fundamental sensors of smartphones to capture data on the mobility of the application's users. The sensors in a simple sport-tester trace the time, type and route of movement around the city, which they report to a database. Based on additional data that users are willing to provide through the application, a stable source of information about users' lifestyles is established. The app for calculating users' caloric expenditure requires information about their age, height, weight and gender. The collected data can be used for developing a long-term understanding of urban life. This paper presents practical applications of this particular dataset that are potentially capable of providing data-driven arguments for strategic decision-making on urban and settlement development. This theoretical part of the thesis can then be applied to other datasets of a similar structure.

I demonstrate the possibilities of working with these data through a case study of urban mobility in Prague and its influencing factors. Data from a multimodal agent-based model of urban mobility in Prague and the Central Bohemia Region are used for demonstration. Data from the agent-based model replaces the data collected from a smartphone application, the programming of which was outside the scope of the research.
The case study using data from the agent-based multimodal urban mobility model of Prague and the Central Bohemia Region focuses on the determinants that influence the pedestrian movement of residents. The study showed low pedestrian physical activity of Prague residents. For a selected segment of individuals between 21-65 years of age who commute daily to work by walking or by public transport, the average daily walking distance was found to be 3 106 m[1]. Of this, 85.4% consists of routine routes - i.e., from home to work and back. Only 14.7% of daily walking activity is linked to non-routine activities. There are gender differences in the walking activity of Prague residents - women's walking activity is 4.8% lower than the daily cumulative walking activity of men. Only 2% of women meet the WHO daily recommendations for walking activity. For men, the number of active individuals is higher - 2.7%. With each year over the age of 40, the average daily walking activity decreases by 3.87m for men and 4.7m for women.

Data from the agent-based model provides more categories than the data from the smartphone app. The analysis of the effect on walking activity was also done for the categories "marital status", "highest education attained", "financial income per household member", which could not be obtained through the app. On the other hand, it was not possible to conduct an analysis of the effect of BMI on the walking activity of the population using the data from the agent-based model.
Unlike the data provided by the users of the app, the agent model data only provides insight into one typical day. Therefore, it is not possible to read from them the long-term evolution of the walking phenomenon and the influence of the urban fabric, which could be tracked through the dataset from the smartphone app.

Through this case study, it was achieved to confirm the thesis that indicates the smartphone app data as a source of information needed for projects and strategies for the development of healthy cities with a high quality of social life.

Keywords: *physical activity, walking, smartphone, app application, data acquisition, active mobility, smart cities*

[1] *World Health Organization recommends walking aktivity of 10 000 steps a day (aproximately 6,6 km).*

ABSTRAKT

Zvyšující se poptávka po datech a chytrých řešeních je jedním z nejrychleji rostoucích odvětví vývoje lidské činnosti. Tato tendence je znatelná také v oblasti architektury a městského plánování. Data o procesech ve městě jsou potřebným ukazatelem pro přesné hodnocení jejich stávajícího stavu a dokáží být identifikátorem pro hodnocení změn.
Města a lidé v nich produkují prostřednictvím sensorů neustále velké množství dat. Kombinací těchto datových vrstev můžeme odhalit mnohé o způsobu, jakým města využíváme a jak města na své obyvatele působí.

Mobilitu jednotlivců je možné mapovat prostřednictvím jednoduché mobilní aplikace, která zaznamenává pohyb uživatelů. Sensory obsažené ve smartphonech jsou nízkonákladovým a zároveň dlouhodobým zdrojem informací, které při správné interpretaci mohou být dynamickým indikátorem života ve městě.
Navrhuji strukturu a uživatelské rozhraní aplikace pro smartphony, která využívá základní sensory smartphonů k získávání dat o mobilitě uživatelů aplikace. Sensory v jednoduchém sport-testeru mapují čas, způsob a trasu pohybu po městě, kterou zaznamenávají do databáze. Na základě dalších údajů, které uživatel je prostřednictvím aplikace ochoten poskytnout, vzniká stabilní zdroj informací o životním stylu uživatelů. Aplikace pro výpočet kalorické spotřeby od uživatele vyžaduje informace o jeho věku, výšce, váze a genderu. Získaná data lze využít pro dlouhodobé poznávání městského života. Práce prezentuje praktické možnosti využití této konkrétní datové sady, které jsou schopny poskytovat daty podložené argumenty pro strategická rozhodování o rozvoji měst a sídel. Tato teoretická část práce může být následně aplikována na další sady dat o stejné struktuře.

Možnosti práce s daty demonstrujeme na případové studii městské mobility v Praze a jejích vlivových faktorů. Pro demonstraci jsou použita data z multimodálního agentového modelu městské mobility v Praze a Středočeském kraji. Data z agentového modelu nahrazují masivně získávaná data ze smartphone aplikace, jejíž programovací část není součástí výzkumu.
Případová studie za použití dat z agentového modelu multimodální mobility Prahy a Středočeského kraje se zaměřuje na vlivové faktory, které ovlivňují pěší pohyb obyvatel. Studie prokázala nízkou pěší fyzickou aktivitu Pražanů. U vybraného segmentu jedinců mezi 21-65 lety, kteří denně dojíždějí do práce městskou hromadnou dopravou, bylo zjištěno průměrné denní penzum chůze 3 106 m[2]. Z toho 85,4% tvoří trasy rutinní – tedy z domova do místa výkonu práce a zpět. Jen 14,7% denní pěší aktivity je svázáno s aktivitami nerutinními. V pěší aktivitě Pražanů se projevily také genderové rozdíly – pěší aktivita žen je 4,8% nižší, než denní souhrn chůze mužů. Jen 2% žen splňuje denní doporučení WHO stran pěší aktivity. U mužů je počet aktivních jedinců vyšší – 2,7%. S věkem se od 40-ti let se s každým rokem snižuje denní průměrná pěší aktivita u mužů o 3,87 m, u žen o 4,7m.

Data z agentového modelu poskytují vice kategorií, než data ze smartphone aplikace. Analýza vlivu na pěší aktivitu byla provedena i u kategorií "rodinný stav", "nejvyšší dosažené vzdělání", "finanční příjem na člena domácnosti", které by prostřednictvím aplikace nebylo možné získat. Naopak na datech z agentového modelu nebylo možné provést analýzu vlivu BMI na pěší aktivitu obyvatelstva.
Na rozdíl od dat, poskytovaných uživateli aplikace, data z agentového modelu poskytují vhled jen do jednoho typického dne. Není z nich tedy možné vyčíst dlouhodobý vývoj fenoménu chůze a vlivu městské struktury, který by bylo možno sledovat prostřednictvím datasetu ze smartphone aplikace.

Prostřednictvím případové studie se podařilo potvrdit tezi, která indikuje data ze smartphone aplikace jako zdroj informací, potřebných k projektům a strategiím pro rozvoj zdravých měst s vysokou kvalitou společenského života.

Klíčová slova: *fyzická aktivita, chůze, smartphone, aplikace, získávání dat, aktivní mobilita, chytrá města.*

[2] *World Health Organization doporučuje denní pěší pohybovou aktivitu 10 000 kroků, tedy cca. 6,6 km.*

ACKNOWLEDGEMENTS

This thesis is dedicated to my husband Vladimír, my children Klára and František, and both of their grandmothers.
I am forever grateful to them for being so supportive and endlessly patient.
Thank you to my supervisor, Henri Achten, for his expert guidance and to the MOLAB institute, especially to Dana Matejovska.

1. CHARACTERISTICS OF THE DISSERTATION

1.1. Research questions and goals

The research presented in this dissertation starts with the notion that contemporary urban planning can benefit from bottom-up data acquisition such as the data obtained from the ubiquitous use of smartphone devices. Such data, as well as it's processing, provides valuable insights not available through traditional top-down approaches. Increasing demands on big data and smart solutions are visible in most branches of human activity. This movement is also present in the field of architecture and urban design. To build proper tools and information structures, which deliver the required information to architects and urban designers, the further use of big data is necessary.
The aim of this work is to prove the usability of the mobility data made available by smartphone applications for data-supported decisions in the field of urban development.
The first step is the design of the data acquisition source which can provide the mobility data. The proposed smartphone application – a simple sport-tester – collects and organises the requested data. For the successful long-term data aggregation using the smartphone application it is crucial to solve both the technical issues of the software and question of how to motivate users to install the application and make the data accessible for further processing.
The proposal of the possible usage of the data for urban purposes, is the foundational property of the designed database in the second step. The proposed combination of data layers and their outputs are described in the main principle.
The third step – case study – is elaborated in more detail in the selection proposal of processing the data to confirm its feasibility. I focused on the walking activity in the daily movement pattern of inhabitants of Prague. For the analysis I used data obtained by the agent-based model of multimodal mobility of Prague. The output of the case study confirmed the hypothesis of the thesis.

1.1.1. Data acquisition

The smartphone application with the working title "UrbanFit" is designed as a long-term data source providing mobility data for the Czech Republic.
UrbanFit comes with innovative technology that monitors daily movement and caloric usage of individuals through smartphone sensors without the need to purchase a sports tester. The proposed smartphone application is, from the users-perspective, a tool for of obtaining information about the user's daily calorie expenditure and daily physical activity patterns. To obtain the information it is necessary to input basic information about user: users are required to fill in their age, height, weight and gender. The mode of the movement type is detected via readings from the smartphone chip data.
The output of the first step is a manual for UrbanFit, which contains a functional and graphical solution of the application. In the manual the required organisation structure of the data is also described. Programming aspects of the app are outside the scope of this dissertation.
The acquired database can then be used for smart city planning, as well as commercial and marketing purposes depending on user consent.

1.1.2. Data interpretation

Applications and sensors provide "hard" data to be interpreted – an unbiased reflection of the city's functioning in a well-defined segment. Without a deeper connection, they provide only very narrow profile information about the monitored area. Through the observation and comparison of physical activity in different urban contexts (topography, size of settlement, density of population, density of infrastructure, quality of public spaces, location, etc.), new alternatives are developed and better knowledge about how the above-mentioned factors influence the life in cities is obtained. This work describes data layer combinations that bring novel insights into the connection of physical activity and urban contexts by using data mining technology based on smartphone applications. The proposals are based on previous state of the art reviews.
The theoretical framework can be subsequently applied to various datasets with certain properties.

1.1.3. Case study

The case study of urban mobility and influence factors is based on the dataset of daily activity schedules of urban citizens extracted from the agent-based simulation model of multimodal mobility of Prague. The selected sample is constituted by inhabitants represented by agents who commute to work and back daily. In the case study we observed the sample from diverse perspectives, looking for influence factors in daily pedestrian activity.

2. INTRODUCTION TO RESEARCH QUESTION AND TERMINOLOGY

2.1. Summary of the research question

Cities continuously produce large amounts of information [1]. The validity of some of the information is only very short. However, by using this volatile information, we can monitor and document the processes which are going on in a city. By combining these fragile and unstable "maps" and city plans, as we know them today, we can achieve a more comprehensive imaging and modelling of a city.
Information about ongoing events and processes in the city is easier to obtain, but the full potential of the data from mobile technologies for spatial planning and crisis management has not yet been fully recognised in the field of city management.
The data can be gained automatically by many different sensors [2], which are a part of the public space and its facilities, or the data can be produced by the users of the city – its inhabitants [3].
72,6% of the population in the Czech Republic have a smartphone. In the age group of 16-24 years the share is 97,9% (see Tab.1) [4]. An average user of a smartphone has 80 apps installed on their phone and uses almost 40 of them each month [5]. The big data of mobile network operators is not a publicly available source – the data is provided by the companies on a commercial basis which makes their availability for research difficult [6]. The smartphone application is an alternative for massive and long-term data acquisition.
The proposed smartphone application collects the mobility data of its users. By establishing the data lake of the mobility data the strong and long-term data source for further urban research is created. This thesis presents possibilities of data sample processing and shows the ways to work with the specific data focusing on urban planning and urban design.
The proceedings of the proposed data analysis aims to be incorporated into the design decision-making process. The feasibility of the proposed data analysis methods is validated by the case study: the selected data sample processing provides data on pedestrian activity of Prague residents, who commute to work and back daily by walking or by a combination of public transport use and walking.

	Mobile phone total		Smartphone		Phone without an operating systém		Internet on mobile phone		
	in th.	%1)	in th.	%1)	in th.	%1)	in th.	%1)	%2)
Total 16+	**8 681,4**	**98,8**	**6 379,1**	**72,6**	**2 509,1**	**28,6**	**5 932,0**	**67,5**	**68,3**
Gender									
Men 16+	4 220,9	98,7	3 134,8	73,3	1 198,9	28,0	2 928,9	68,5	69,4
Women 16+	4 460,6	98,9	3 244,4	71,9	1 310,2	29,0	3 003,1	66,6	67,3
Age group									
16–24 years	850,9	99,0	840,9	97,9	31,0	3,6	829,3	96,5	97,5
25–34 years	1 339,6	99,3	1 307,3	96,9	72,8	5,4	1 275,3	94,5	95,2
35–44 years	1 657,0	99,8	1 553,2	93,5	158,4	9,5	1 497,6	90,2	90,4
45–54 years	1 528,5	99,5	1 341,5	87,3	222,6	14,5	1 242,9	80,9	81,3
55–64 years	1 289,2	99,3	848,9	65,4	469,8	36,2	746,8	57,5	57,9
65–74 years	1 262,4	99,1	417,2	32,7	867,4	68,1	299,2	23,5	23,7
75+	753,9	93,0	70,1	8,6	687,3	84,8	40,9	5,0	5,4
Education (25-64 years)									
Basic	311,5	95,0	203,2	62,0	114,2	34,8	171,0	52,1	54,9
Secondary without FE	2 028,8	99,6	1 629,9	80,0	448,8	22,0	1 481,3	72,7	73,0
Secondary with final exam	2 139,8	99,8	1 961,7	91,5	243,5	11,4	1 867,5	87,1	87,3
University	1 334,1	99,9	1 256,2	94,1	116,9	8,8	1 242,8	93,1	93,2

1) Percentage of the total number of people in a given socio-demographic group
2) Percentage of the total number of people in a given socio-demographic group who use a mobile phone

Table 1: Persons in the Czech Republic using a mobile phone (source: Czech Statistical Office, 2020)

2.2. Hypothesis

The mobility of people can be monitored using a simple smartphone application that maps their movement. Sensors in smartphones are a low-cost source of information that can be interpreted and used as a dynamic indicator of urban life. We can gain access to data by offering attractive and gripping benefits. Using this widespread and accessible tool, we can collect data about the lifestyle in urban structures. However, it is necessary to develop an appropriate marketing strategy for the successful acquisition of the data.
The design of the application contains also the backend development – the database structure in which the application will store data. The database of the application, that aggregates the users' data in the longer term can become the data lake for further research on the fields of urban planning, urban design and city development. The interpretation of the collected dataset can provide useful information for decision making or become a measure for urban and mobility strategies.

2.3. Methodology

The goal of the research is the design of a tool for mobility data aggregation via smartphone. This thesis proves the ability of the outcoming dataset to become a source of information for urban planning and management, heading towards healthier and social responsible cities.
The research comprised four main phases:

- State of the art – Urban lifestyle studies
- Design of the data source
- Defining the possibilities for the use of the data obtained from the designed application
- Case study

The bases for the design of the research was formed by the book by Jan Gehl – How to study public life [7]. The book describes the method of observing public spaces to indicate the weak points and potentials of the locality before the strategy for the urban planning and design is set. From the, methods described in the book, I looked for those where the physical observation of the place can be replaced by sensor data provided by the smartphone chips. Therefore, the research focuses on the key issue of urban life studies and human movement around the city.
After studying the previous works in the field of smartphone sensor applications, the UrbanFit application was designed. The UrbanFit application collects user data into a database for further research. An application programming manual has been developed, including a graphical user interface designed in Auxure Pro. The proposal was preceded by a search of the mobile applications market. The aim was the uniqueness of the application in the Czech environment, and thus also gaining motivation for users. The application market turned out to be volatile and dynamic, not just in the content of the applications, but also in development of legal conditions.
In the available literature, I searched for research in which data with the same or very similar categories as the proposed application database were used. However, these data were obtained in another way (crowdsourcing, questionnaire survey, respondent reported). The output is an overview of ways of processing the dataset from the mobile application.
To confirm the hypothesis, the case study of the mobility and their influencing factors of the Prague population was chosen. The smartphone application remained in the manual stage, so I used alternative data from the agent model of multimodal mobility in Prague for analysis. Data were extracted from the model and subsequently processed in Excel and R + programmes using standard statistical methods.
The above-mentioned research of English-language scientific literature was performed primarily by searching Web of Science, Scopus, Elsevier, IEEE, Google Scholar and ResearchGate. The search was limited to items published between 1975 and January 2022 and the keywords included "smartphone", "fitness", "lifestyle", "physical activity", "walkability", "mobility", "biking", "urban", "smart city". We searched the results for articles related to the topic of this study. We then selected studies that could be repeated or conducted by using smartphone application data.
The bibliographies of the selected articles were examined for further relevant articles. Links found on websites where these articles were published were also searched for pertinent information.
Based on the literature review, thematically specific categories of data use in the urban sphere were created. Furthermore, the necessary input data for these individual categories were determined.

2.4. Terminology

As the project bridges on the edge of urbanism, social sciences and information technologies, it appeared necessary to specify and clarify the used terminology. Moreover, the definitions of the terms slightly differ across the literature, so I specify the meaning in which I use them in the context of the dissertation.
Mobility data – wide collection geolocated data [1] which describe the trajectory of the movement of individuals. The mobility data can also contain information about the mode of transport (car, tram, bike, walking, etc.) and a time stamp [2].

Database – a collection of data. The database is created by a data layers (see Fig.1, Fig.2).

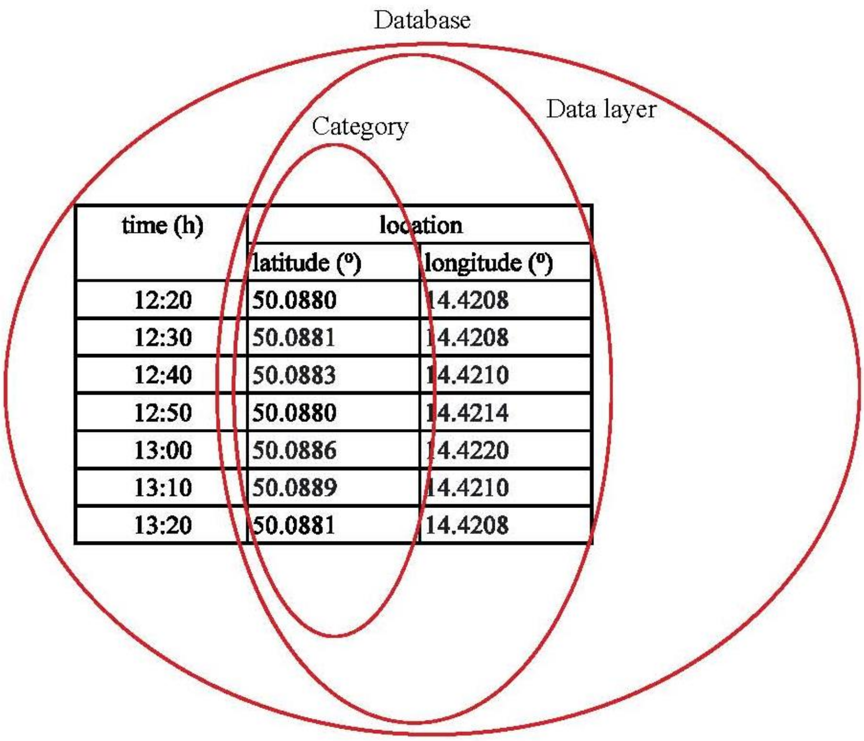
Data layer – a set of data obtained from a single source describing one aspect of the observed phenomenon (eg location, acceleration, etc.).

Data lake – storage for any kind of data in high volumes that are gained from multiple sources. The data stored in the data lake could be in their unprocessed raw data format. The data lake is supposed to supply data to other entities for further use, such as data analyses [8] [9].

Agent – an independent component that can range from primitive reactions to various stimuli to complex behaviour and intelligence [10].
Defining features of an agent:

1. Autonomy: agents are self-governing individuals that make decisions and act without centralised influence.
2. Heterogeneity: agents are diverse individuals that are distinguished by differences in their characteristics (e.g., age, gender, height)
3. Active: agents percept and affect their environment, including other agents, to achieve their goals. [11]

Agent-based model – An agent-based model is a system of autonomous processes characterised by sets of individual and collective goals which upon execution typically result in complex emergent behaviour [12].



time (h)	location	
	latitude (°)	longitude (°)
12:20	50.0880	14.4208
12:30	50.0881	14.4208
12:40	50.0883	14.4210
12:50	50.0880	14.4214
13:00	50.0886	14.4220
13:10	50.0889	14.4210
13:20	50.0881	14.4208

Figure 1 - Scheme of data management

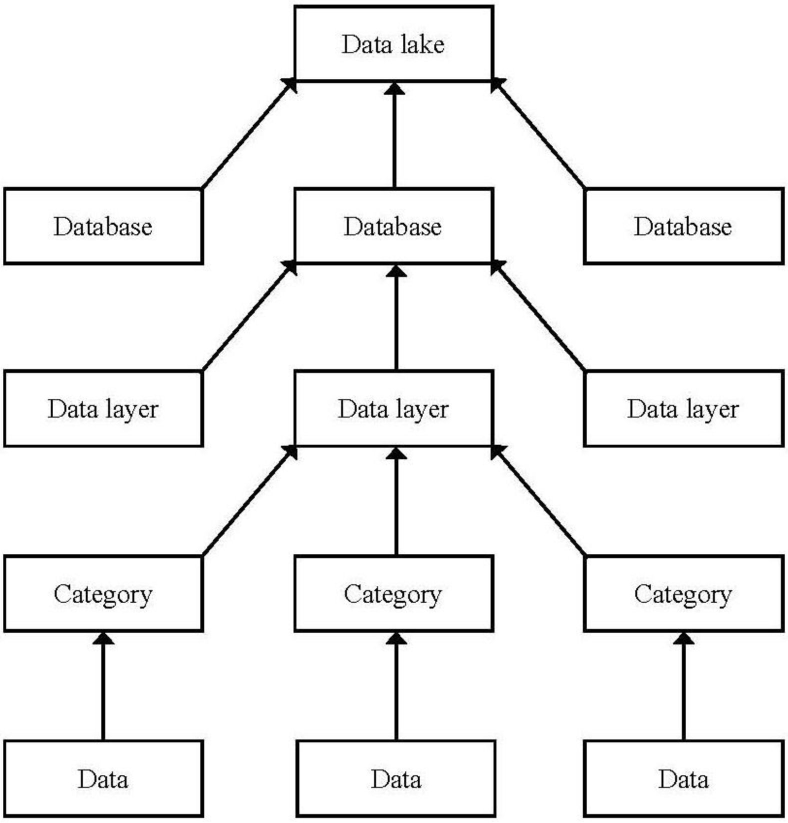


Figure 2 - Hierarchy of the entities

Smart city – a system that strengthens human and social capital by continuously capturing data from the urban environment and autonomously contributing to the improvement of the quality of life of citizens in various branches of human activity (health, transportation, utilities, entertainment and government services) through innovative technological solutions [13] [14]. The performance of the technological solutions, as well as decision-making in diverse branches of human activity, should be based on forecasts and analyses of the acquired data [15].

Body Mass Index (BMI) – a measure for indicating nutritional status in adults [16]. It is defined as:

$$BMI = \frac{weight[kg]}{height^2[m]}$$

WHO – World Health Organisation, WHO's primary role is to direct international health within the United Nations' system and to lead the states in global health responses. WHO coordinates the world's response to health emergencies [17].

NCD – Non communicable diseases, also known as chronic diseases. They tend to be of long duration and are the result of a combination of genetic, physiological, environmental and behavioural factors. The rise of NCDs is conditional on risk factors: tobacco use, physical inactivity, high consumption of alcohol and unhealthy diets. The main types of NCD are cardiovascular diseases, diabetes, cancer, and chronic respiratory diseases (such as chronic obstructive pulmonary disease and asthma). The NCDs are the cause of almost 70% of all deaths worldwide [18].

DALYs – disability-adjusted life years. The aim is to measure both morbidity and mortality. Morbidity is measured by assigning disability weights (DWs) to health conditions, where 0 represents the absence of disability, $0 \leq DW \leq 1$ quantifies the burden that a particular health condition incurs and 1 is the highest possible DW, defined as equivalent for death. After a condition is assigned a DW, years lived on disability (YLDs) are calculated as the product of the duration of the condition (Y_i) and its DW, which take into account morbidity. Years of life lost (YLLs), relative to the reference life expectancy, take into account mortality [19].

$$DALY = YLL + DW * Y_i$$

MET (Metabolic Equivalent of Task) is the methodology for expressing the energy cost of physical activities as a multiple of the resting metabolic rate. For sitting phase is the MET equal of 3.5 ml O_2 per kg body weight x min. The energy cost of an activity can be determined by dividing the relative oxygen cost of the activity (ml O2/kg/min) x by 3.5 [20].

Wireframe - the layout of the content of each page of the website into a model in which it should be clearly visible what content will be on a given page, what priority it will have, how it will be laid out and what the relationships between the different parts of the content will be [21].

2.5. History of work, gradually achieved results

2.5.1. Workflow

First step of the work was development of the application for smartphone for data acquisition of mobility habits of their users. Subsequently – after the mining will aggregate sufficient amount of data – one case study (the test of usage of the data in urban context) should be done.
However, successful entry into the competitive market of mobile applications includes, in addition to the coding part, also application marketing. The full version of the application and the further PR work to aggregate bigger amount of data turned out to be more expensive than was originally expected. For the case study has been replaced the smartphone applications data has been replaced by the data from agent-based model of multimodal mobility of Prague, developed by a scientific team from Department of Computer Science, FEL, CTU.
The data from the agent-based model has been organised to be of a similar structure to the proposed database. The system of the work with the agent-based model data can also be used for the work with the data aggregated by smartphone application.

2.5.2. Application programming

The biggest problem turned out to be the coding and maintenance of the application. This is an interdisciplinary project and although DCGI FEL CTU, represented by the team of Ing. Miroslav Macík, Ph.D., participated in the acquisition of the graphics and structure of the application, I was unable to run in its full version. The private commercial sector was also approached for cooperation, but the estimated expenditure proved to be unrealistic. Two SGS grant applications were submitted for application processing, and although compliance with the long-term focus of the Faculty and interdisciplinary cooperation was stated, the project was not granted due to a lack of financial resources.

The purchase and operation is interdisciplinary work on the edge of IT and architecture. The programming part is beyond the scope of an architect. A development of professional software requires hiring professional programmers to the team. The dissertation contains a manual for the application developers, including the design of the UI[3] and UX[4]. Coding was, from the beginning of the work, considered to be an outsourced service.
The placing of the application was consulted with Adikt mobile s. r.o..

The proposal represented by the manual for UrbanFit was evaluated as feasible; it was proposed to split the experiment into 2 steps:

1. Application source code development according to the manual

- UI and UX development according to the designed proposal
- Development of data acquisition and storage from accelerometer + GPS
- Analytical part
- Signal filtering
- API connection, periodic sending of server data
- Backend development – database schema and REST API
- User testing on selected phones[5], feedback processing

The amount required by the commercial company Adikt mobile s. r.o. for this step is about 300 000 CZK, VAT not included.[6]

---

[3] *User Interface*
[4] *User Experience*
[5] *Sony Xperia, Android version 4.3 and higher*
[6] *price offer was issued in 2016*

2. Adapting the application to a wider range of devices

The required amount depends on the group of devices to which the application will be adapted.

Maintenance and operating costs:

Operating costs for hosting the server is around 500 CZK/month for long-term[7] bindings and 1000 CZK/month for short-term bindings. This flat rate assumes an average load. If this load is exceeded, it would be necessary to install a dedicated server on the provider, which is required to be paid at additional costs. Time spent on upgrading and maintaining the server is charged at hourly rates.

The annual operating costs of the application would be in excess of CZK 6,000.

2.5.3. Database replacement

The result of the programming part required finding an alternative data source. At this point it was necessary to find an alternative data source, which provides a database with properties which are similar to the dataset from Urbanfit.

In 2018, The General Data Protection Regulation entered into legal force [22], the comprehensive set of data protection rules for collecting or processing the personal data of Europeans. This precluded the possibility of cooperation in the field of data acquisition with another private sport-tester application.

Following this, we established a cooperation with the team from the Department of Computer Science of the Faculty of Electrical Engineering, led by RNDr. Michal Čertický, PhD. They were recently working on the agent-based model of multimodal mobility in Prague. Through this cooperation we extracted from the model-space the dataset similar to the requested one. The model provides a representation of mobility during one average day in Prague in 2017. As such, the possibility of observing the development of the city over time was lost.

During the cooperation with the Department of Computer Science we also cooperated with the Prague Institute of Planning and Development, where we implemented the report from the agent-based model to the process of design decision-making in two case studies – projects for the reconstruction of the public space on the streets Revoluční and Klárov [23]. From this experiment, the need for mediation between the computer scientist and urban designers in the field of content and format of the purchased information became evident.

2.5.4. Case study acquisition

Active mobility and its influencing factors were analysed using data from the agent-based model. We deliberately chose a narrower segment of the population to demonstrate that the data can be manipulated at different levels. For example, respondents with a specific mobility pattern can be selected from the data lake. The analysis provided data on pedestrian movement in Prague that was previously unavailable from other sources. This data work demonstrated that a database acquired through an app will provide valid and unique information about urban lifestyle.

[7] *minimum period of six months*

3. STATE OF THE ART

3.1. Public life mediated by smart phone chips

Approaches to city development have changed significantly during the last century [7]. Functional cities with strictly divided zones for work, housing and leisure time, defined by Athens charter in the 1940s [24], were questioned by Jane Jacobs in the early 1970s [25]. She started to introduce sociological concepts such as "eyes on the street" and "social capital” to urban development. This shifted the focus of urban planners from the machine functionality of the city to the human level – on pedestrians and their movement. The ability of places for public life is the requirement of contemporary society.
From around 2000, research on the integration of pedestrians has become increasingly important with the rapidly growing volume of motorised traffic. The aim of architects and urban planners is to balance the cycle, pedestrian and motorised traffic to provide decent conditions for all kinds of participating individuals. This indisputable measurement in the field of public life studies can serve as convincing argument for public space renewal projects. The theoretical framework of methods for monitoring public spaces and their public life are described by the nestors of public life studies Jan Gehl & Birgitte Svare in the book *How to study public life* as analogue [7], but it is apparent that some of mentioned method of observation can be mediated also by smartphone chips. The above mentioned eyes on the streets could be replaced by smartphone chips on the streets, who are already present there. The data could be gained from a large number of individuals, without the need for human resources on a daily basis.
The possibility of technological solutions is also developed in the methodology. The mediation of the individuals’ activities require observational neutrality and a systematical approach [26], which are the basic properties of technological solutions. The observers should not be a part of the activities. The work of the observer in its sensitivity is so far indispensable. In the manual, Gehl admits the employment of tracking devices but emphasises the role of human registration and common sense for understanding the ongoing situation. The monitoring of individuals’ movement via smartphone offers one more benefit: to obtain data over a long period of time.

Gehl compares the study of public life to biological research of animal species: the observation focused on its activities, velocity and manner of movement. We count its occurrence in varied places. For lifestyle monitoring in a settlement structure, three factors seem to be traceable through a smartphone:

- How many people are using the monitored area in certain space?
- Who are the people, what do we know about them?
- Where are they and what are they doing?

The interaction between life and space is an ephemeral phenomenon. That’s why Gehl considers it useful to ask repetitively the basic questions about the pedestrian flow and stationary activity.
The quantitative question in the larger scale can be answered by analysing the residual data of mobile operators, but the quality criteria (who are the people and what they do) is easier to follow through smartphone applications. Smartphone applications can collect data more efficiently and with more precise temporal information than traditional observation methods. However, the data can be captured only for some categories – observation tools (see Tab.2) . Using a smartphone is a regular daily activity and thus does not disturb the users (respondents) in any way [27].

3.1.1. Integration of smartphone applications in previous research

Smartphones collect data in a passive manner and create low-burden protocols over a long period of time [28]. This advantage has been used, for example, in a study of urban vitality conditions conducted in Barcelona [29], which utilised the Moves© application to aggregate data on the mode and trajectory of the participants ’movement [30]. The data obtained were used to compare the activity of pedestrians in pedestrian activity spaces and in residential buffers.
The INTERACT study monitored the physical activity of its participants in 4 Canadian cities; the data were aggregated using the Ethica© application, which was developed specifically for the purposes of scientific research studies [31]. When designing a study, the researchers can select which activities and which sensor-based data will be monitored. The participants can join the study by downloading the application and signing in through a registration link. The data from the participants ’application are available for analysis in real time [32]. The INTERACT study aims at collecting a database of 100TB of data which will also be made available for analysis by other research teams [31].

observation tools	observed activities	result	repetition (yes/no)	purpose
counting	count of persons walking staying grouping talking to cell phones count of greenery count of equipment of the space	integer	yes	evaluation of initiatives analysis of density analysis of change in time
mapping	indicate staying indicate sitting indicate activities: talking to phone web-browsing playing, sports, etc. indicate of equipment of the space	plan	yes	evaluation of initiatives analysis of density analysis of change in time
tracing	movements: walking sequence choice of direction flow use of entrances to the space	plan	yes	analysis of flow evaluation of initiatives analysis of change in time analysis of density
tracking	movements: walking speed mapping activities: standing turning head stopping making unexpected detours	plan footage	yes	analysis of flow evaluation of initiatives analysis of change in time
looking for traces	traces footprints, paths in grass, etc.	plan text note	yes	analysis of space
photographing	freezing of picture time lapse	picture film	yes	document analysis of change in time
weather diary	weather humidity temperature precipitation	text note number	yes	relational note
keeping a diary	change with diverse conditions	diary layers	yes	analysis of change in time evaluation of initiatives
test walks	walking time waiting time possible hindrances diversions on the way	plan footage	yes	analysis of time evaluation of time analysis of route

suitable for digital data collection
suitable for smartphone data collection

Table 2: Compatibility of the observation methods with digital data collection

3.2. Impact of urban life on human health

From the beginning of the 20th century, the incidence of lifestyle diseases has been on the rise [7]. Their causes include office work, stress, air-conditioning, inappropriate diet and the lack of physical movement on a daily basis [33]. The need to commute to work by car minimises the natural opportunities for other forms of physical movement – walking, cycling, etc.

It has been proven that the proximity of high-quality outdoor areas and the accessibility of physical activities has a positive effect on movement habits [34] [35]. Establishing the connection between health, social life and spatial structure [36] makes smartphone sensors, due to their ability to detect information about an individual's life and environment, powerful tools for both urban, sociological and medical research [37].

3.2.1. The pandemic of physical inactivity

The physical activity of individuals is the blood circulating in veins of the city. In recent years the volume of daily physical activity (PHA) exhibited a decreasing tendency [33]. In 1960, nearly half of private sector jobs required at least a moderate level of physical activity. With the advent of digitalisation and the automation of production, the demands for physical activity at work also decreased, and occupations that required sedentary activity increased. As a result, both the average energy expenditure and metabolic equivalent of tasks (MET) decreased by 20% by 2010. This trend is also matched by an increase in the average weight of both men and women [38] (see Fig.3).

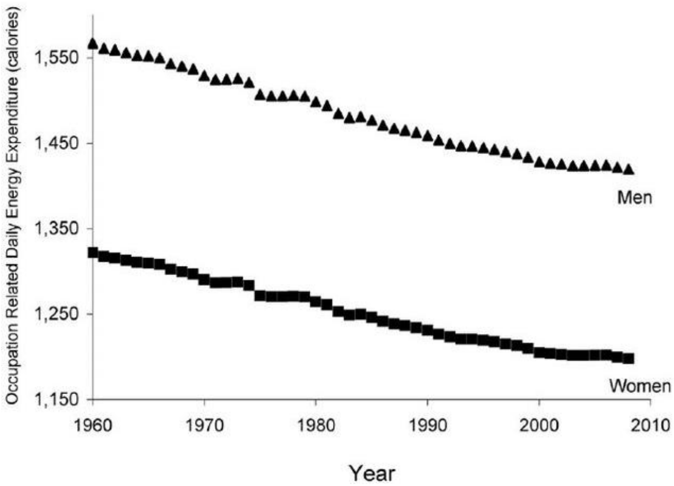


Figure 3 - The mean occupational daily energy expenditure in men and women since 1960

(source T. S. Church et.al, 2011).

In order to fulfil WHO guidelines, a physically active individual should do at least 150-300 minutes of moderate-intensity aerobic physical activity or at least 75-150 minutes of vigorous-intensity aerobic physical activity [17]. An alternative criterion for achieving the required physical activity level is reaching the 10,000 steps per day recommendation [39]. In 2009, 17% of the global population was not meeting the daily PA requirements. Three years later, 31% of the global population was physically inactive.

Even though the Czech population is relatively more physically active than other nations[8] [40], 44% of the population physically inactive. The outlook for active lifestyles seems to be even darker when looking at behaviour of children and adolescents: 80% of the children aged 6-17 years in Czech Republic does not meet the WHO physical activity guidelines [41]. The trend of inactive behaviour is confirmed by studies of transport to and from school. Active modes of transportation (cycling, walking) for the main part of the trip to school and back was the choice of 53.4% of children aged 9-17 years in 2014. This represents a significant decrease from 74.3% recorded in 2006. Although the lack of active commuting among the youth population has also been reported in other high-income countries such as Canada and the United States, this trend in the Czech Republic was greater than in other countries [42]. The choice of commuting mode took parental concerns and time constraints into consideration. The organisation of the traffic in front of the school and the perceived safety of the travel mode are primary factors influencing parental decisions. The weight of the economic factor of commuting to school is minimal [43].

[8] *In 2008, 29% of the population in the Czech Republic was physically inactive, whereas globally, the share was 31%.*

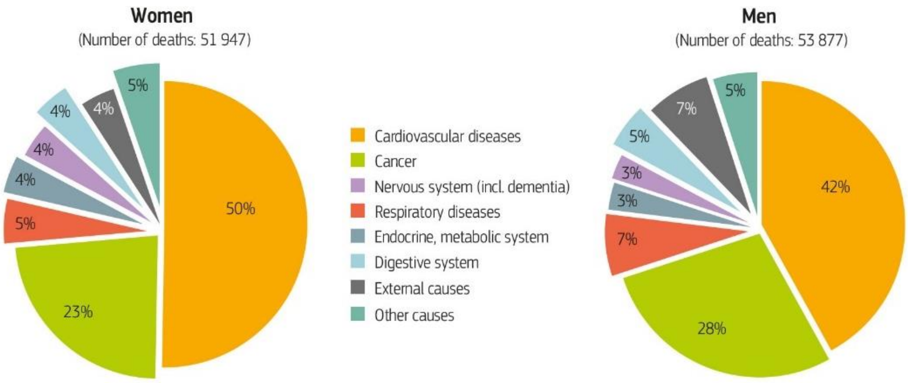


Figure 4 – Mortality graph, source: : Eurostat Database 2014 (source: European Comission, 2017)

The research on the adolescent population in the Czech Republic also illustrates significantly higher pedestrian activity in safe environments – in the safest neighbourhood the average activity was 11 024 steps/day, whereas in the least safe environment the average activity was only 9686 steps/day. The difference was even bigger among girls [44]. The research also shows the connection between leisure time activity and commuting: individuals, who tend to be inactive in their free time prefer passive behaviour while commuting.

3.2.2. The health impact of passive behaviour

In 2007, cardiovascular disease (CVD) accounted for 50% of deaths among women and 42% of deaths among men in the Czech Republic (see Fig.4). The European Commission has identified reduced levels of physical activity and increased obesity as major risk factors for public health in the Czech Republic. The graph below shows that the number of obese individuals among the adult population in the Czech Republic is significantly higher than the European average (see Fig. 5).

Reduced daily physical activity together with inappropriate dietary habits lead to obesity. The prevalence of obesity in the Czech population is increasing rapidly. Between 2002 and 2014, its prevalence increased by more than 25%. As expected, the trend of obesity among adolescents follows the trend of physical inactivity. The proportion of overweight 15-year-olds doubled from 2002 to 2014 [45].

The physical framework of the cities has an impact on the physical activity of its population. Research underlines the strong association between land-use mix and obesity, with each quartile increase being associated with a 12.2% reduction in the likelihood of obesity. Sedentary jobs, along with commuting, take up a large part of the day. Thus, even though the number of completely physically inactive individuals in the population is declining (the number decreased by 15% in the US between 1997 and 2018), the overall balance of energy expenditure is not trending towards an overall increase in physical activity [38], [46].

Easy accessibility in terms of walking distances and the variety of services offered in the area, which can be influenced through urban planning, play a crucial role in the physical activity of residents. In contrast, an increase in commuting time is a risk factor for obesity. Every additional hour spent in a car increases the likelihood of obesity by approximately 6% [47].

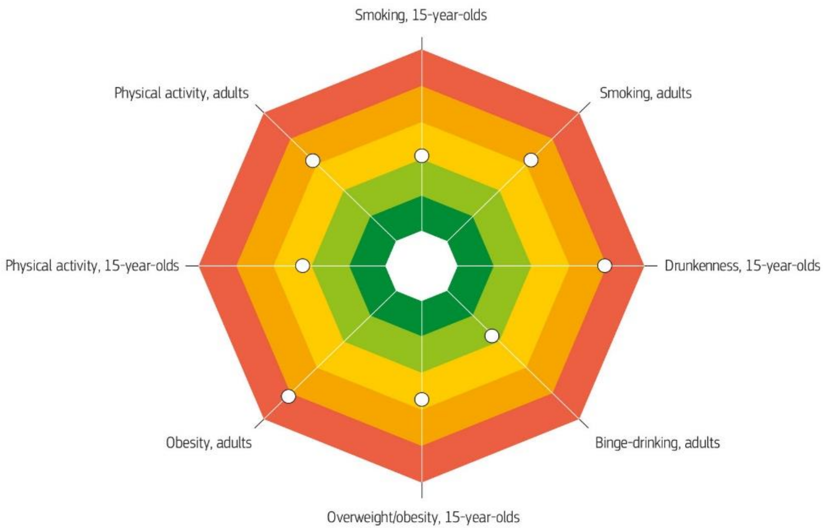


Figure 5 - Behavioural risk factors in the Czech Republic compared with other EU countries (source: European Commission, 2017)

Physical activity illustrates the opposite influence: each kilometre of walking per day is associated with a 4.8% decrease in the likelihood of obesity [47]. Active transport has a small but still significant effect on BMI and blood cholesterol levels. The effect of the reduction was experienced mainly by those who had not been actively moving until the start of the study, and therefore changed their exercise pattern. However, this clear correlation between active transportation and health does not necessarily mean that active transportation causes good health. When there are endogeneity concerns about measures of active transportation, there is less reason to believe that encouraging cycling and walking for transportation will improve the health of a population.
The health impact of inactive behaviour can also be quantified using economic indicators. Physically inactive individuals represent a greater burden on the health system. They spend 38% more time in hospital than patients who were physically active before admission [48]. Czech health insurers' expenditure on the treatment of the consequences of physical inactivity represents 0.4% of their total expenditure, which in 2018 represented an investment of 700 million CZK. Inactive behaviour were responsible for 1.2% of all disability-adjusted life years (DALYs[9]) in 2004 [41].

3.2.3. Public space as social equilibrity tool

A study of adults and children in Geneva proved a relation of spatial dependence of BMI. In both groups BMI was clearly not distributed randomly – the clusters of higher BMI in adults and children are located in close, yet different, areas of the state. An area's income level was associated with children's BMI clusters [30].
In population groups with lower socio-economic status and/or lower education, behavioural risk factors are more common. For example, those with the lowest levels of education are almost twice as likely to be obese as those with the highest levels of education [45]. Children from socially disadvantaged families usually have a lower proportion of lifelong needs for physical activity [49]. Only five percent of children from high social status families play no sports at all; in contrast, a quarter of children from low socio-economical status are completely physically passive [50].
Public space from its definition is accessible and free to use for everybody. Access to attractive, large public spaces is associated with higher levels of physical activity [36]. The physical activity of low-income residents has been shown to be related to modifiable aspects of the built environment. Individuals with greater access to multiple sources of physical activity with few barriers are more likely to be physically active [34].
It is therefore important to integrate the above mentioned facts into the urban planning and perceive public space as a tool that enables the physical enjoyment of vulnerable groups and motivates them to include free activity in their daily routine.

3.2.4. Influence factors of public space affecting physical activity.

The structure of the settlement and the density of the street network play a role in transport mode selection – greater street connectivity promotes active traffic behaviour [47]. The availability and variety of functions in the locality, together with the quality of public space and availability of public transport, are important factors influencing the willingness to choose to be active. The physical activity of humans tend to be useful, thus the targets and points of interest should be located close at hand, within walking accessible distance [51]. In a more interconnected street network, with a high density of intersecting

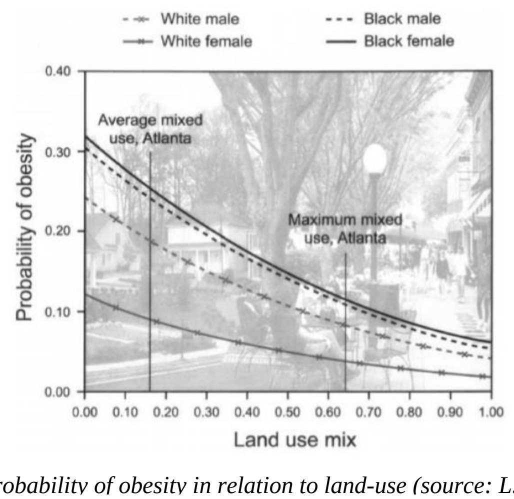


Figure 6 – Probability of obesity in relation to land-use (source: L.D. Frank et al., 2004)

9 DALYs is an indicator of the summary burden of disease on society, see chapter 2.4

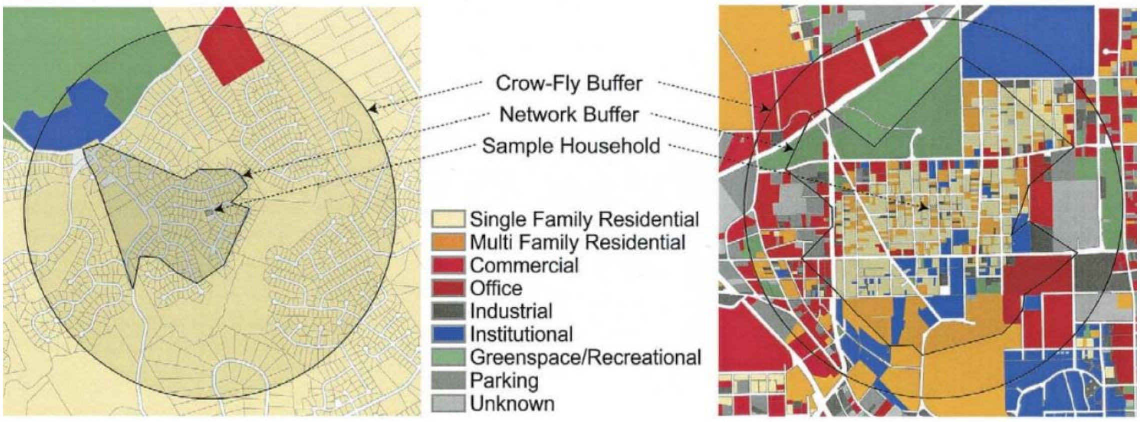


Figure 7 - Connected and disconnected neighbourhood (source: L.D. Frank et al., 2004)

streets, it is easier to develop intuitive and meaningful movement. Conversely, long streets with a minimum of intersections are one of the hallmarks of urban sprawl and mono-functional residential zones (see Fig. 6 and Fig.7).
A mixture of points of interests is essential for social life in the area. The vibrancy and liveability of the streets are determined by the mix of uses of the public space – if the public space is lined with leisure, commercial, educational, public administration and residential functions, the space is expected to serve different functions at different times and the space will live in its own dynamics throughout the entire day and even during night hours. If the area is mono-functional – just housing or just an office district, the utilisation of public space will have significant peaks and troughs. This setup is also replicated by the traffic pattern of the day – the beginning and end of normal working hours tend to be accompanied by traffic jams. The mixture should appear not just in the land mix policy. The diversity of the age group and individuals with varying socio-economic status create vibrant urban life and a balanced society.
People tend to be action-oriented in an area with a varied functional mix, where they also experience security in terms of both traffic and crime. Eyes on the streets and social control of inhabited areas gives the walker the feeling of safety. The perception of safety during movement is also a crucial question when deciding between active or passive modes of transport. An important factor in the choice of transport mode is the feeling of safety experienced by the user of the public space when moving around in it, not just the measure. The objective quality of traffic measures is not always able to be realistically assessed [51].
The quality of the public space reflects the liveability of the space in terms of amenities. Public space is a place predestined for social interaction. The liveliness of public space means that different people do different things within it at the same time. They can observe each other, influence each other, stay together. This forms the basis for creating community. By creating a mix of opportunities, lively zones are created, pulsating places in the environment of the city. When designing such spaces, the importance in the city structure (local, citywide) the population density of the catchment area and the accessibility of the site must be taken into account. The dimensions and potential of the space should correspond to each other.
A public space that encourages citizens to the most basic physical activity, walking, should be comfortable for children, disabled people and the elderly: it should offer barrier-free access, easy intuitive orientation in space, quality surfaces and furnishings for eventual resting.
Rome regularly tops Lonely Planet's list of top-rated cities for pedestrians. While it often fails to meet the aforementioned prerequisites for walkability (pavements are not in good condition, pedestrian movement is not very safe), in Rome this discomfort is balanced by the grandeur of the city and its liveability. Indeed, The Czech capitol, Prague, also has the highest concentration of pedestrians within the Prague 1 district, where the historic core of Prague is located [52]. The streets in the centre of Prague are lined with historic buildings that define the street profile with their unique facades that are rich in detail. Both the genius loci of Prague and grandeur of Rome can only be experienced and absorbed while walking. Other modes of movement are too fast to allow for a clear perception of the details and overall atmosphere of the place.

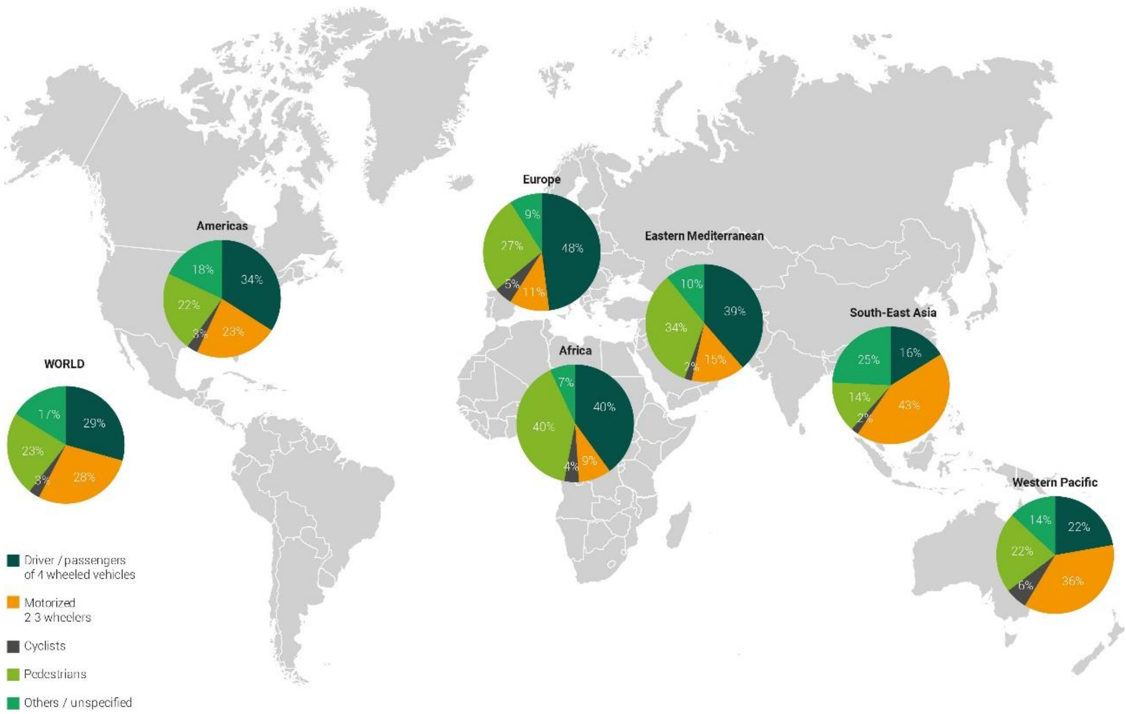


Figure 8 - Distribution of deaths by road user type by region, 2018 (source: WHO, 2011)

3.2.5. Passive behaviour in commuting – consequences and solutions

The passive mode of transport (i.e., commuting by car) also contains risks associated with car use, the consequences of which are passed on to society as a whole. Those who are not involved in production (pedestrians and cyclists) are globally even more affected by the consequences of car use (see Fig. 8).

Internal combustion engines are a producer of greenhouse gases. In addition to greenhouse gases and particulate matter, exhaust gases contain carcinogens (toluene, formaldehyde) and carbon monoxide, which blocks the ability of haemoglobin to carry oxygen from the lungs to the tissues. Exhaust gas inhalation is the source of 3% of DALYs [53].

The preference for car transport brings with it an increased risk of traffic accidents. The consequences of traffic accidents are the eighth most frequent cause of DALYs. In Europe, pedestrians and cyclists represent 36% of all deaths, while car occupants make up 48% of all deaths (see Fig. 8). The safety policies applied in Europe together with the high technological standard of vehicles including critical components such as helmets and child restraints, and public healthcare are reducing traffic based deaths and injuries [54].

The risk factors connected with car use, such as lower physical activity, higher BMI and air pollution, are among the leading global attributable DALYs (see Fig. 9).

Redirecting traffic in favour of active movement can be achieved by changing the organisation of transport: reducing speeds in cities to 30km/hour and installing traffic lights can protect vulnerable road users. Pollution reduction can also be achieved by introducing tolls to enter exposed parts of the city, and defining a standard for car traffic: only allow cars with a certain emission standard to enter the city (excluding diesel cars, allowing only electric cars, etc.). Car traffic into the city centre should be replaced by a combination of increased parking capacity outside of the centre (park and rides) and easily accessible public transport bringing commuters to the central areas. Access to public transport can be widened by offering alternative modes (bikeparking, bikesharing, car and ride sharing) [55].

Reducing the number of cars in the urban transport network also helps reduce the number of parking spots. The freed-up parking capacities in stable street profiles can be used to promote active types of movement – i.e., the establishment of safe and comfortable cycle and pedestrian paths. Measures to increase active mobility in terms of encouraging people to walk and cycle, despite the proven positive impact on population health, is not what people unconditionally want. Restricting parking spaces or limiting entry is often met with disapproval from residents and business owners who operate a business in the restriction affected area.

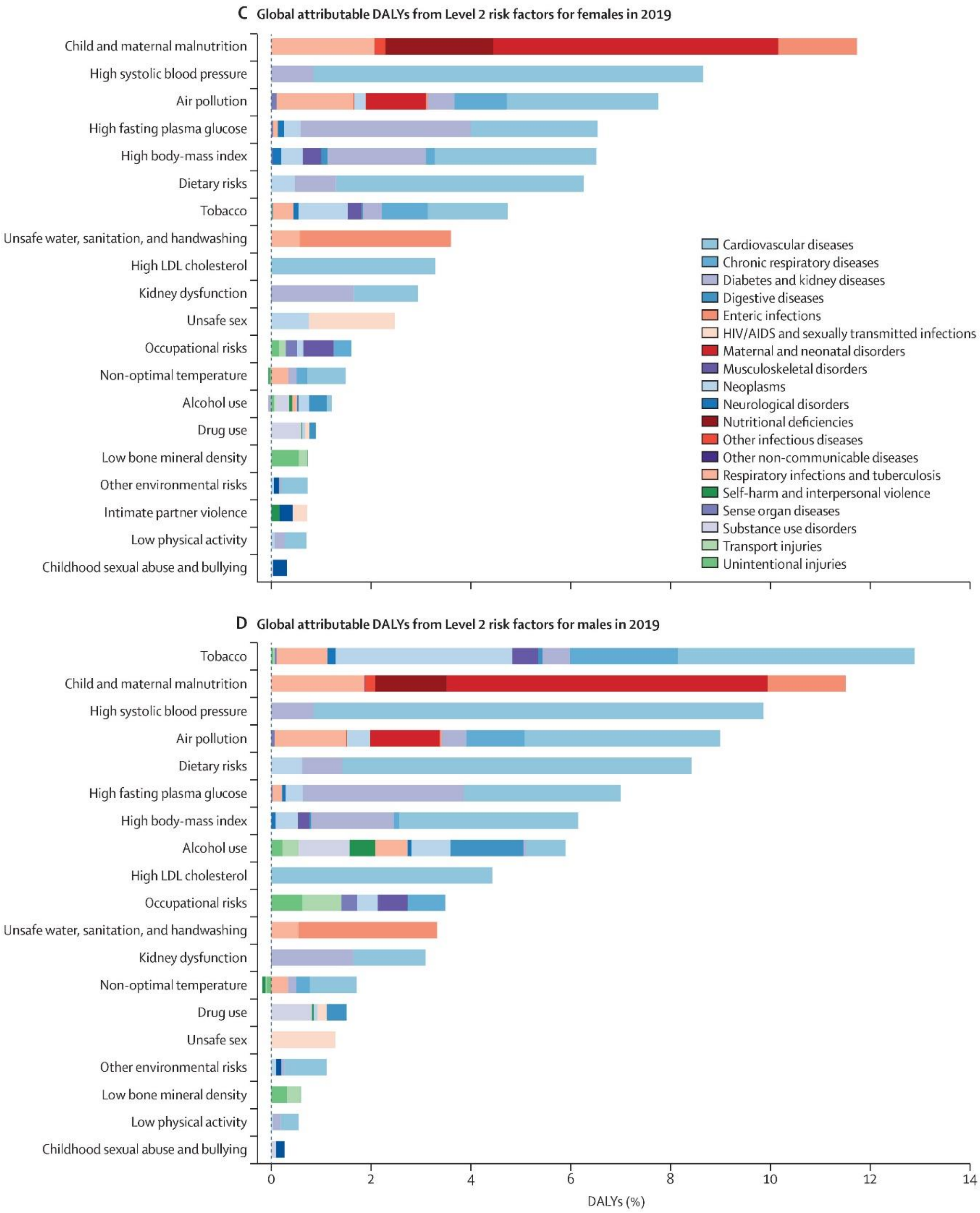


Figure 9 - Global number of deaths and percentage of DALYs attributable to risk factors, by cause and sex, 2019 (source: Murray, C. J. L. et al.,2020)

Another benefit of reducing car traffic is a reduction in traffic noise. Traffic is the most significant source of ambient noise exposure worldwide. Long-term exposure to noise can result in sleep disorders, chronic stress disorders , as well as hypertension and CVDs [56].

An interesting factor, which is connected with the daily commute by private car is the loss of social contact [36]. Walking and using public transportation is a rich source of social interaction, which is not necessary active. However, the option of contact or observation of urban life may lead to an increase in social cohesion.

3.3. Economy of physical activity

The benefits of pedestrian and cycling activity are not just in the categories of public health, ecology and transport lightening. All these categories have consequences that can be viewed through an economic prism. In the discussion about the implementation of measures to promote physical activity, a common argument is the financial aspect – the amount of investment in policies and/or in the adaptation of the physical environment. The intricacy of the return on investment in public space lies in the fact that its effect is multifaceted, and the benefits of investment will appear in other departments than those that provide the payment. There is not yet a single generally accepted methodology that can capture and map the impact of these investments. Some of the aspects like social contributions or better feelings in the renovated areas or an improvement of the medial image of the city are hard to measure and even harder to transform the measure into an economic indicator [57] [58]. This chapter will discuss cases where there where observed impacts of projects and policies to support physical activity in urban landscapes and where there were efforts to monitor their economic effect.

3.3.1. Property values and the real estate market

The walkability of an area can be expressed by walkability indexes. The impact of the walkability index is reflected on the real estate market. Walk Score is a US based web application which calculated the walkability of a specific neighbourhood using a very basic method; the area’s proximity to daily destinations. The tool measures how far an area is from amenity categories such as shopping, dining, cafes, parks, and schools. The algorithm doesn’t cover many aspects of walkability like safety, mixed land use or size of the blocks in the neighbourhood. The Walk Score within a range of 0-100 evaluates the addresses and ranks them into 5 categories: from “car depend” to “walkers paradise” (those areas which reached a score of 90 or more points). A positive correlation was found in 15 of the 17 US markets evaluated [59]. The case study in Omaha, Nebraska also proved a relationship between Walk Score and sale prices of commercial properties in the local market: Commercial properties with a Walk Score of 60 were sold at a premium of 11% to 49%, when compared to properties with a Walk Score of 10, dependent on property type [60].

Findings from metropolitan Washington proved a positive relation of a neighbourhood’s Walk Score to several key economic indicators. Higher Walk Scores [10] are related to higher economic performances and local household incomes. One level increase (20 points at the range of 94 points) translates into a $8.88 value premium in office rents, a $6.92 premium in retail rents, an 80% increase in retail sales, a $301.76/square foot premium in residential rents, and a $81.54/square foot premium in residential housing values. Walkable urban places benefit from their proximity to other walkable urban places. Isolated areas with good levels of walkability performed worse economically than places situated in clusters. The research also demonstrated a correlation between the walkability of an urban area and residents’ transportation costs. The residents have higher transit access. The disadvantage of living in area with high walkability, however, is the higher price of housing and higher housing costs. Residents of more walkable neighbourhoods in metropolitan Washington generally spend approximately 12% of their income on transportation and 30% on housing. Residents of places with fewer environmental features that encourage walkability spend around 15% on transportation and 18% on housing [61]. This calculation is tightly linked to the price of fuel. Findings of a study from Clark County, Nevada illustrate that a ten percent increase in gasoline prices can shift relative home values by roughly 2.5 percentage points. Real estate prices in different neighbourhoods performed differently, however [62]. The change of the prices in the above-mentioned studies is connected with walkability, but not necessary with walking in the sense of physical activity. Both tools include the evaluation of conditions which are associated with higher walkability. Yet, the research did not measure the actual pedestrian movement in the site. The shift seen in the prices of commercial properties may also be connected with other indicators: the central position of site, the liveability of area or the perceived safety.

Integrating biking infrastructure into a city's transportation system can be beneficial for property owners and bring revenue to the municipal treasury[11]. After the bike sharing system was introduced in Pittsburgh, the housing prices and rents in proximity to the bike sharing stations increased [63].

---

[10] *As measured by a place’s Irvine Minnesota Inventory (IMI) – a tool that collects objective data on built environment characteristics hypothesised to be related to physical activity.*

[11] *Depends on the property tax collection system and its subsequent redistribution.*

3.3.2.Support of local economy

The turnover in middle European and Scandinavian city centres increased in 60% and remained constant in 25% after being pedestrianised [64]. Pedestrians make twice as many visits to local centres (on average 16 times a month) than people arriving by car. Cyclists visit a local centre on average 8 times a month [65].

Local surveys that have examined visitor behaviour in the Vaňkovka shopping centre, which is centrally located within the city of Brno, show that visitors choosing an environmentally friendly means of transport (i.e., walking, cycling, scooter or public transport, etc) have a higher visiting probability [66]. The study of shoppers travel modal split in shopping boulevards, Grafton Street and Henry Streets in Dublin's historic core, also shows that traffic behaviour differs from shopkeepers' expectations. Contrary to retailers' expectations, customers are significantly more likely to arrive by public transport or to walk. The number of pedestrians was underestimated by merchants by more than 10%. Conversely, the estimate of the number of customers arriving in the centre by car would be overestimated by retailers [67] (see Fig.10).

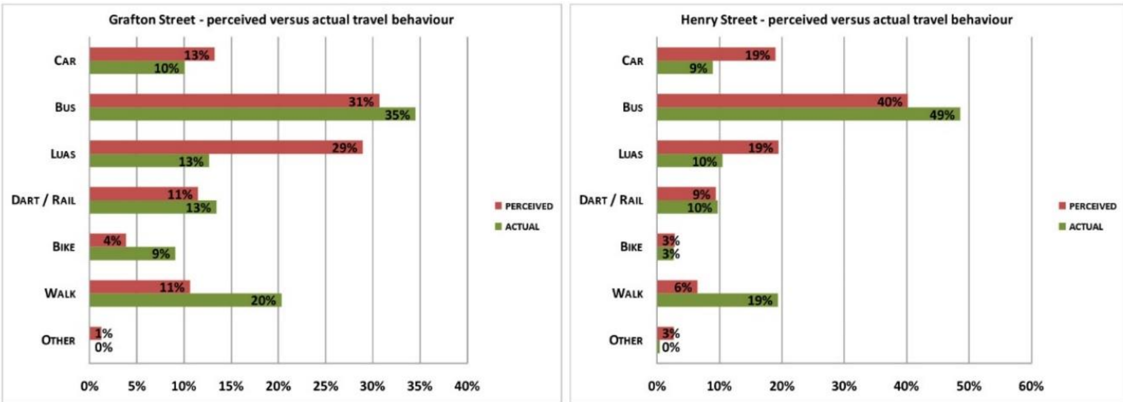


Figure 10 - Perceived versus Actual Travel Behaviour in Dublin Centre (source: O'Connor, D., 2021)

Choosing a physically active mode of transport generates opportunities in the local economy. When these modes of movement are prioritised, more money stays in the region, while services related to motoring are often provided by business chains or multinationals (petrol stations, oil companies, toll gates, etc). Pedestrians and cyclist use more local services in the proximity of their residences and workplaces. Foot traffic accounts for 40% more spending in shops than people driving by [68]. Walkers also spend more than motorists in bars and cafes (see Fig.11) [69].

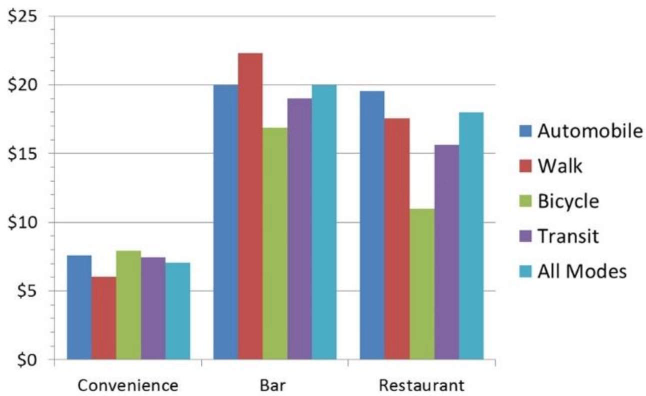


Figure 11 - Average Consumer expenditures per Trip (source: Clifton, K., 2012)

Austrian research shows cyclists account for 6.6% of shopping receipts. This share is increasing by 1% year-on-year, with spending in small local shops increasing by 1.2%. The data shows that 80% of car trips for shopping take place within a 5 km radius, a distance well feasible by bicycle. The average bike shopper takes a 1.5km route to the store. The annual value of cyclists' purchases is worth 111 billion EUR. However, it should be noted that cyclists spend about 20 EUR per purchase, whereas the average purchase by a customer with a car is double the value. Cyclists are limited in their purchases by transport capacity and the weight of the baggage[12] [70]. Active modes of movement, especially cycling, do not only contribute with their spending power. The use and operation of a bicycle and services related to cycling, such as maintenance, rental, and cycle tourism, generate employment opportunities in the regions. Compared to car transport, cycling generates more jobs per euro invested. These jobs are often low-skilled and therefore suitable as inclusive employment opportunities [71] [72].

By 2025, 1 in 4 employees in London will be a millennial [73]. They will demographically represent a bubble in 40 years [51]. The millennial generation perceives different qualities and has a different value ladder from their parents. 64% of college-educated millennials first choose the place where they want to live and then look for employment [74]. Ecology is important to millennials. They are watching their carbon footprint – 77% of them plan live in urban cores [75]. They also gravitate towards carsharing and bikesharing services.

75% of employers in London say that in order to attract and retain employees and clients that it is important for the workplace to be surrounded by a healthy and vibrant public space that offers a comfortable space for walking and cycling [76]. Active commuting is beneficial also from the employer's perspective: employees who actively commute by bike take 1.3 fewer sick days per year than their inactive colleagues [77]. For the national economy, this represents a savings of 128 million GBP per year [78]. If every Londoner spent 20 minutes a day walking or cycling, it would save the national economy 1.7 billion GBP over 25 years.

The Department for Transport in London reports that the Benefit Cost Ratio for projects directly supporting walking or cycling is 13:1, where one pound invested in walking or cycling infrastructure has a return of 13 GBP in two years [79].

Savings on active travel also affect individuals and households. The cost of walking is zero and the cost of cycling is significantly lower than buying and maintaining a car.

3.3.3. Economic evaluation of travel behaviour change

Evaluating the economic benefits of infrastructure investments that change the population’s travel modal split is not yet a frequently used argument in debates about the feasibility of projects. Economic evaluations of the benefits associated with active modes of transport are not a common part of the comparison of revenues and expenditures. There continues to be a lack of a uniform and generally accepted methodology for calculating the economic impact of changing citizens' transport behaviour. In order to calculate the economic impact, it is necessary to obtain an appropriate set of data on the initial state and the target state. The target state can be anticipated on the basis of a reference to similar business cases and evidence from similar interventions elsewhere [79] by extracting data from a model or by additional data measurements after the project has been implemented and put into normal operation.

The risks associated with the health impact of changing a population's active travel mode habits are frequently measured and quantified by the Health Economic Assessment Tool methodology (HEAT) [72] [79], which is published and updated by the WHO as a web-based tool and is widely accepted. The tool evaluates the impact of changes in the field of physical activity, air pollution, injuries and carbon impact assessments [80]. HEAT calculates the answer to the following question: if x people cycle or walk y distance in given timeframe[13], what is the economic value of above-mentioned rate improvements? HEAT works in a European context and with local data for each country.

Cost benefit analysis (hereinafter, CBA) of infrastructure investments in Seville established the social and economical contribution of a project and its realisation. The economic benefit calculation analysed two main effects of the implementation of a bicycle lane network in the city of Seville: modal split change and savings in journey times. From the modal split change a growing preference for biking is evident. The cost benefit analysis included an economic evaluation of travel time savings, vehicle use, infrastructure maintenance, health effects, travel accident reductions, and air pollution. All the mentioned factors were considered for cyclist as private persons and also for the city population as a whole in the sense of the society. The CBA evinced economic benefit of cycling 557 million EUR and an internal rate of return over 130%[14].

The EU methodology for the external cost of transport covers the calculation of costs caused by different modes of transport. However, this methodology does not include walking or cycling among the transport modes monitored (see Fig. 12). Its use is limited by the fact that it can only calculate the change in transport behaviour that reflects the use of non-active modes. For example, an increase of pedestrian activity can be observed as an increase in the use of public transport and a decrease in the use of private car transport, but the direct calculation is not possible using this methodology [81].

---

[12] *The average weight of a cyclist's purchase is 5kg.*

[13] *In years*

[14] *From 2006 to 25 years afterwards*

The methodology covers all of the main externalities of transport:
— accidents;
— air pollution;
— climate change;
— noise;
— congestion;
— well-to-tank emissions;
— habitat damage; and,
— other external cost categories (e.g., soil and water pollution).

	Passenger Transport								
	Road						Rail		
	Pass car - petrol	Pass car - diesel	Pass car - total	Bus	Coach	MC	High-speed Train	Electric pax convent (non high speed)	Diesel tot pax
Cost category	**bn €/a**	**bn €/a**	**bn €/a**	**bn €/a**	**bn €/a**	**bn €/a**	**bn €/a**	**bn €/a**	**bn €/a**
Accidents	210.2			5.3		21.0	0.06	2.0	
Air Pollution	8.6	24.8	33.4	1.4	2.7	1.8	0.002	0.03	0.52
Climate	32.0	23.5	55.6	0.8	1.6	1.5	0.00	0.00	0.22
Noise	13.8	12.4	26.2	0.8	0.9	14.8	0.4	2.6	0.9
Congestion *	196.1			4.5					
Well-to-Tank	10.4	7.7	18.1	0.3	0.5	0.8	0.3	2.7	0.1
Habitat damage	14.1	11.8	25.9	0.2	0.4	0.5	0.7	1.4	0.5
Total			**565.4**	**19.3**		**40.5**	**1.4**	**11.0**	
Total per mode	**625.2**						**12.5**		
Total as % of EU28 GDP	**4.2%**						**0.1%**		
Total passenger transport	**637.7**								

* Congestion in terms of delay cost generated by the various vehicle categories.

Figure 12 - Total external costs 2016 for EU28 passenger transport by cost category and transport mode

(source: European Commission, 2019

3.4. Mobility Sensing

Worldwide mobile-phone penetration is increasingly turning the mobile network into a gigantic, ubiquitous sensing platform [82] [83]. In big picture, the quantitative question can also be answered by using mobile phone distribution analysis. The trajectories of individuals in the scale of public space (street, square) can hardly be tracked by the mobile phone network data, because it is difficult to recognise the exact path and way of movement due to the long period of registering devices and low location precision [84].

3.4.1. Mobile phone traces

The first studies of population mobility monitored through mobile operator network data were published in 2005-2006 [85]. The visualisation of datasets collected via mobile phone traces was a part of the Venice Biennale in 2006 [83]. The research on this topic was conducted in the Czech Republic by the Department of Social Geography and Regional Development [84], [86]. Thanks to the massive use of mobile phones, data from mobile operator networks provide a comprehensive picture of population mobility. Residual mobile phone data are used in the urban context for socio-economic and demographic analysis [87], [88], but they are also applicable in transportation modelling for future scenarios, where they form a data source for activity-based models and agent-based simulations [89], [90].

The basic transmitter station system (hereinafter, BTS) is the part of the GSM network responsible for transmitting and receiving radio signals from mobile phones. Based on the signal reception, the BTS is able to determine the location of the phone. In a dense network of stations, the system can determine the location accurately to tens of metres (even inside buildings and underground garages), but in a sparse network of stations (e.g., in a unpopulated landscape) the error can be on the order of kilometres. The mobile transmitter network is formed by individual cells in the mobile network, with the
mobile phone reporting to the nearest transmitter (see Fig.13). Cell global identity (CGI) is the simplest and easiest way to obtain and use mobile phone location data. Specifically in the case of Prague, the accuracy of location by mobile phone ranges from 150-350 m in the city centre and inner city, about 600 m in the outer city and about 1000 m on the outskirts of Prague [91].

Mobile phones report to the nearest BTS if there is activity on the device (receiving or sending SMS, making a phone call or using the Internet), but even beyond that the identity of the respective transmitter is detected about once every 5-30 minutes. This provides operators with the data on the distribution of devices in time and space. For detecting the type of user movement this time span is excessive.

Residual data from mobile operators are not, however, freely available sources. They are provided by individual companies for a fee, which makes them difficult to access for research purposes. According to Czech legislation, the mobile network logs can only be kept for 2 months.

Further use of residual data from mobile operators is evidenced by the Prague Institute of Planning and Development (IPR) intention to use residual operator data analysis in spatial planning and development. IPR acquired the analysis of mobility of the City of Prague in 2016 [92]. However, the cost for a two-month analysis (10/2015-12/2015) is in the millions of crowns, which is out of reach for university research. Czech operators currently do not provide the raw data, only analyses of these data can be purchased [93].

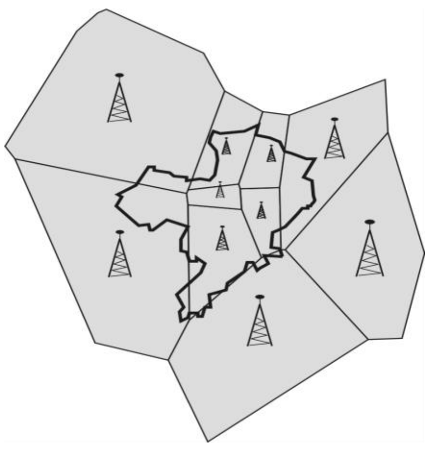


Figure 13 - Outline of a Czech town of about 15,000 inhabitants with cells of BTS (source: J. Novák, 2010)

3.4.2. Sensor based activity recognition

Smartphones and mobile internet use can give us a more holistic view of urban use. Obtaining data from smartphones is a non-obstructive way of getting data from respondents (in this case application users) without the need for time-consuming questionnaires, interviews and/or shading. The clear advantage of data captured via smartphone use is its quantity and regular repetition of data capture. The data can be categorised as it is being retrieved.

The smartphone device can provide detailed information about its location and environment. Smartphones include hardware and software sensors that record, for example, air humidity, acceleration, or rotation of a smartphone (see Table 3) [94].

Sensor	Type	Description
Accelorometer	Hardware	Measures the acceleration force in m/s^2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity.
Ambient temperature	Hardware	Measures the ambient room temperature in degrees Celsius (°C).
Gravity	Software Hardware	Measures the force of gravity in m/s^2 that is applied to a device on all three physical axes (x, y, z).
Gyroscope	Hardware	Measures a device's rate of rotation in rad/s around each of the three physical axes (x, y, and z).
Light	Hardware	Measures the ambient light level (illumination) in lx.
Linear Accelerator	Software Hardware	Measures the acceleration force in m/s^2 that is applied to a device on all three physical axes (x, y, and z), excluding the force of gravity.
Magnetic Field	Hardware	Measures the ambient geomagnetic field for all three physical axes (x, y, z) in µT.
Orientation	Software	Measures degrees of rotation that a device makes around all three physical axes (x, y, z)..
Pressure	Hardware	Measures the ambient air pressure in hPa or mbar.
Proximity	Hardware	Measures the proximity of an object in cm relative to the view screen of a device. This sensor is typically used to determine whether a handset is being held up to a person's ear.
Relative humidity	Hardware	Measures the relative ambient humidity in percent (%).
Rotation vector	Software Hardware	Measures the orientation of a device by providing the three elements of the device's rotation vector.
Temperature	Hardware	Measures the temperature of the device in degrees Celsius (°C).

selected for further use by proposed smartphone application

Table 3: Sensor types supported by the Android platform

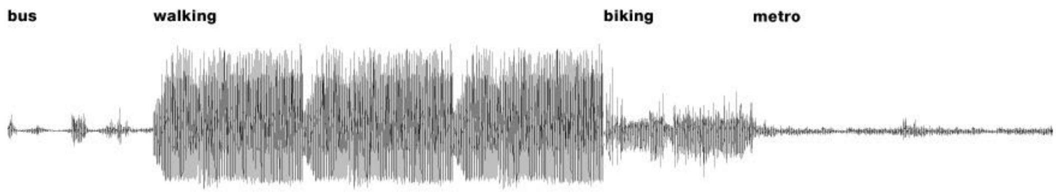


Figure 14 - Graph of acceleration curve in varying transportation modes (source: http://senseable.mit.edu/co2go)

Senseable City Lab MIT developed a smartphone application "CO2Go!" that tracks the user's trajectory and mode of transport. The next step suggests in real time an alternative route and mean of transport that is more environmentally friendly and leaves a lower carbon footprint. The application acquires users trajectory by GPS and, through segmentation of the acceleration curve obtained from the accelerometer chip, recognises the mode of transport (walking, bus, train, etc.) [95]. The topic of transport detection has also been developed by research made by Future Cities Laboratory from ETH Zürich. Their application called "CITYing" differs from the previous version by offering improvements to the travel detection mode and location sensing [96]. The acceleration curve is classified robustly and allows the adaptability of the sampling window and lowers battery consumption [97]. Additionally, a more battery efficient method for the location determination is used; the network based location sensing [98]. The aim of the application is the collection of data about users' transportation mode, which allows for this less accurate location method.

Avoiding high power consumption is an important factor for smartphone application development. Intensive battery drainage while using a smartphone application is annoying for users, and they will reject having the application installed for longer periods. The application CITYing collects data about users movement pattern for urban planning by using crowdsourcing [99]. The application was developed only for one type of smartphone devices (Samsung Galaxy), so the use of the application is very limited. In the experiment they collected data from 78 volunteer users.

Motion detection is based on reading smartphone accelerometer data. Every mode of transport evinced the typical waveform of the acceleration curve. The shape of acceleration graph is used to recognise the transportation mode (walking, car, train, tram, bus, bicycle) of smartphone user. The acceleration of smartphone device is measured by the chip in 1s intervals in 3 axes: x,y,z. Based on the measured data, the acceleration value is calculated as the Euclidean length of the 3D acceleration vector:

$$A_{tot} = \sqrt{(x^2 + y^2 + z^2) - g^2}$$

where g is gravity as 9.8 m/s^2

Walking is characterised by a very typical variable acceleration curve (see Fig.14). The average acceleration value of walking (12.4m/s^2) is typically about 27 times higher than that of the other activities (0 to 0.9 m/s^2). Minimum average walking acceleration was set to 7 m/s^2. Based on the data from acceleration sensor, walking and running can be detected with great accuracy.

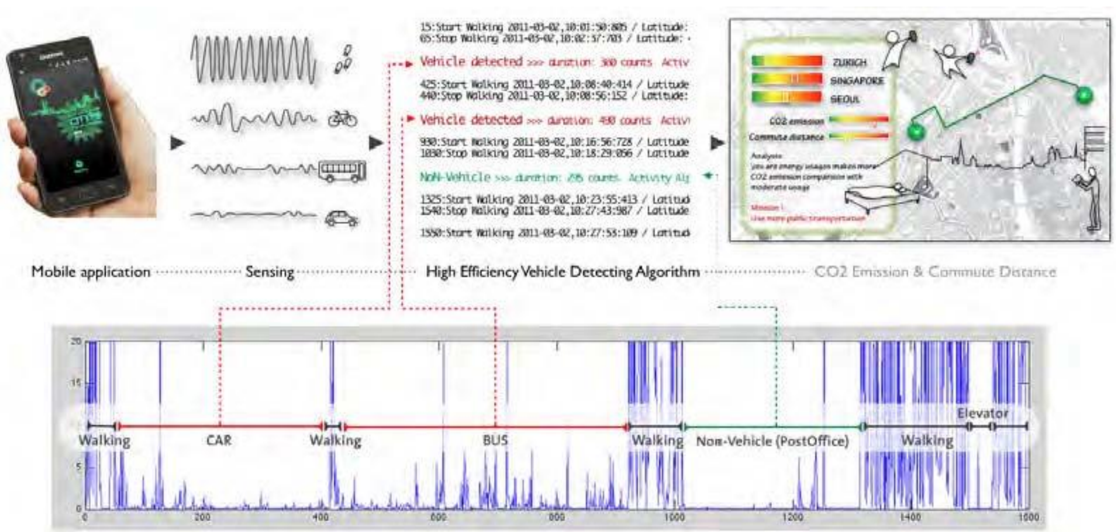


Figure 15 - Segmentation of the transportation model (source: Shin,et al. 2015)

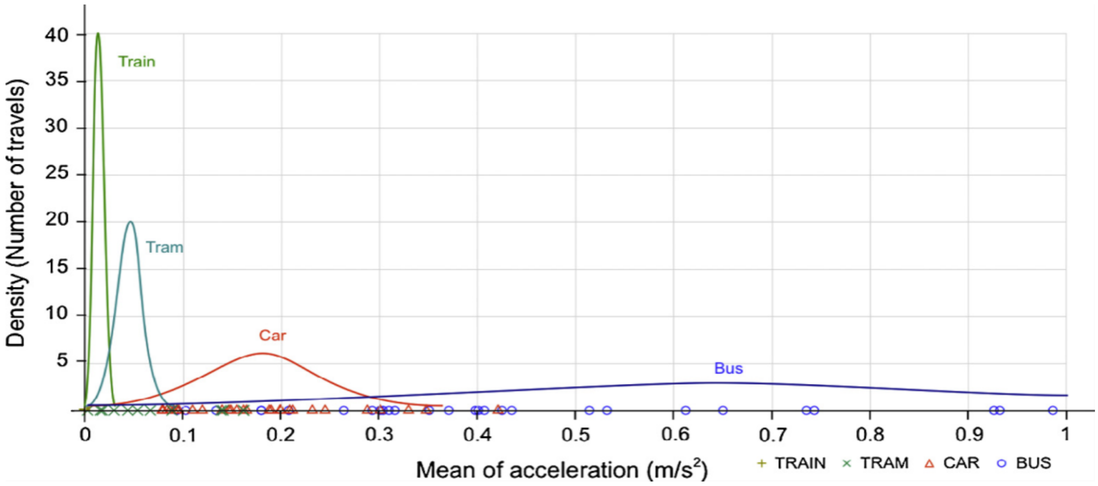


Figure 16 - Acceleration distribution on different vehicles. - distribution of each vehicle's mean acceleration value (source: Shin,et al. 2015).

When a motion mode is detected, an error caused by an abnormal motion (e.g., checking the smartphone display or receiving a call) is considered. Therefore the pedestrian activity is captured as valid, when it has a minimum duration of 10 seconds. The difference between two kinds of un-wheeled movement is in the intensity of movement. The movement of the device along the Y axis and in the X-Z surface evinced higher standard deviation of acceleration [100]. Every non-pedestrian activity is always surrounded by a walking activity. This fact allows the adaptability of the sampling window during the classification of the transportation mode (See Fig.15). First, the walking segments are detected and then serve as dividing elements between other modes of transportation or motionless phases. A motionless phase is recognised as a segment in time during which the user remains in the same location — i.e., it does not exhibit distance or acceleration in time.

Vehicle-riding activity limits were determined based on the Gaussian distribution curve of the average acceleration for each traffic segment (see Fig.16). Based on the results of the experiment, the average acceleration intervals were determined (m/s^2):

- train/tram = [0, 0.072]
- car = [0.072, 0.290]
- bus =[0.290, 1.0].

The minimum interval of the duration other transportation modes is 55 continuous seconds, which matches the minimal distance of public transportation stops in Zürich.

The CITYings 5-step transportation-mode classification (see Fig.17, Fig.18) shows 95% accuracy.

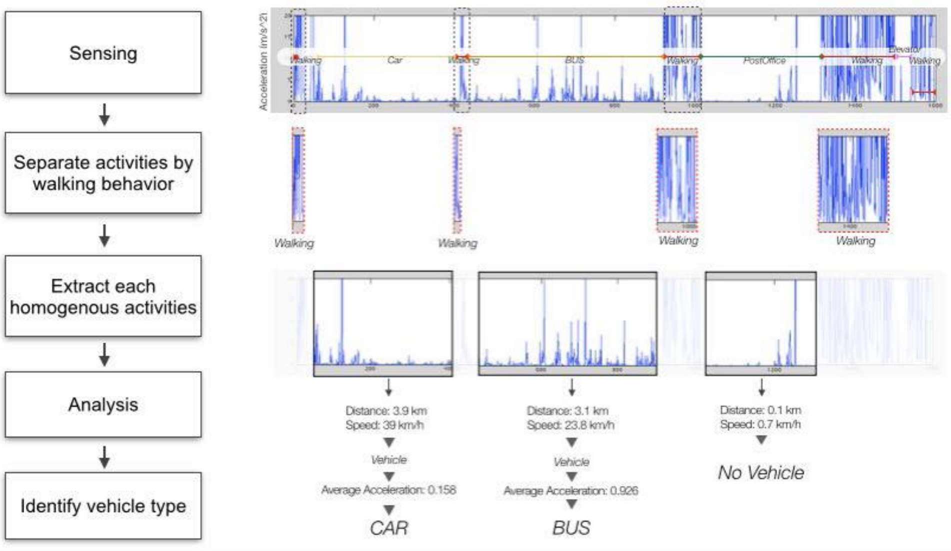


Figure 17 - Hierarchical transportation-mode detection process (source: Shin, 2015)

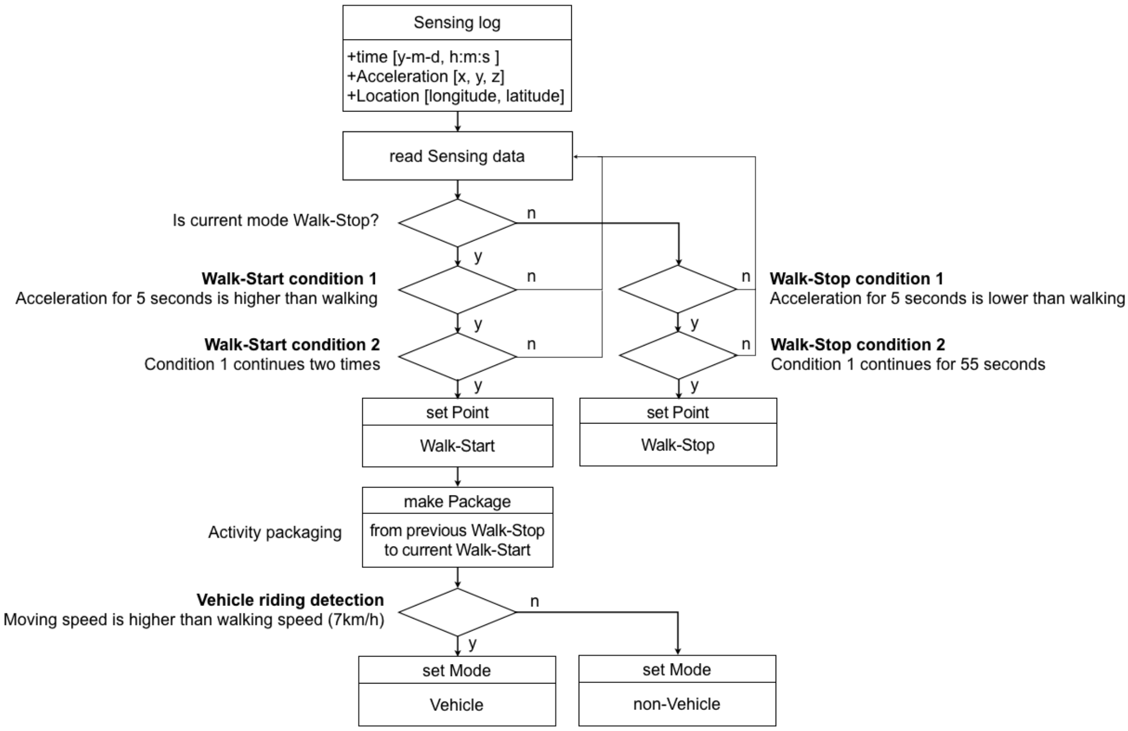


Figure 18 - Diagram of transportation-mode detection process (source: Shin, 2015)

3.4.3. GPS (Global Positioning System) based transportation mode detection.

Based on the received time stamps from each satellite and its position, the GPS receiver's latitude, longitude and altitude can be calculated [101]. The task of the GPS receiver is to locate four or more satellites, find the distance to each of them and calculate its position using the information obtained. This whole operation is based on a simple mathematical principle called trilateration. The disadvantage of GPS is the need for direct visibility to the sky. If external influences are neglected, an accuracy in the order of centimetres can be achieved.

Sometimes GPS data can become inaccurate and unavailable because of multipath propagation and satellite signal blackout, caused by urban canyons, tunnels, forests, and so on. The accuracy also decreases in indoor spaces and even outdoors during poor weather situations. Acquiring data via smartphone is battery draining, but it depends on the frequency of the capture of GPS logs [102]. The above-mentioned application, CO2Go!, has a fixed high sensing frequency — 50 times per second [95]. By reducing the GPS data capture frequency, battery consumption can be decreased.

For travel mode recognition, the trajectory was achieved by GPS logs which were divided into segments. Features, such was velocity, acceleration, heading change range, etc., were then calculated for each segment [103], [104], [105].

3.4.4. Implementation of GIS information

The accuracy of the vehicle-reading activity could be improved by enhancing the GIS data layers in the travel mode detection. User location and the velocity of the transportation could be compared to the timetable: overlap with bus routes; and, whether the trajectory is along expressway sections (in this case walking and cycling can be excluded). Cars and bus can also be excluded when the trajectory goes in the wrong direction on any one-way road [106]. For example: If the start-point and the endpoint of the trip corresponds to the location of the specific means of public transport stops and the time-spatial data of the trip match the timetable information of the identical means of public transport, the trip can be detected as public transport use, and it can also be specified the type of transport vehicle [106]. The proximity of public transport stations are also contained in the POI (points of interest), which is accessible even in offline mode [101] (see Fig.19).

Using GIS layers in the transportation recognition process provide highly accurate inference results. However, they usually lead to a reliance on large amounts of GIS data and complex calculations, which make them difficult to use in fully automatic processing mode. The GIS data could be cropped and divided into spatial segments, to achieve the offline functionality of the application. By implementing GIS features in the algorithm, the accuracy increased by 4% for bus mode and 18.5% for subway mode [101].

Figure 19 - Bus and subway GPS trajectory (source: Li, J., Pei, X. et al., 2021)

3.4.5. Machine learning

Progress in the field of machine learning increases the accuracy of the travel detection methods described above. Machine learning is a branch of artificial intelligence that deals with algorithms and techniques that allow a computer system to 'learn'. By learning, we mean changing the internal state of a system in such a way that it becomes more capable of adapting to changes in the environment. Machine learning makes it more efficient to compute and set thresholds on individual variables that are indicators of single movement modes, based on statistical feature extraction.
Travel mode recognition (TMR) is considered as a multiclass classification problem [105]. Using Support vector machine and Bayes Net learning model for the smartphone sensors data analysis improved the recognition of the wheeled vs. un-wheeled movement mode to 100%; recognition of the walking, jogging, bicycling, car driving, tram and bus riding reaches average accuracy of 97.1%. This type of calculation can also be performed via smartphone and in an offline environment [100]. Accuracy of automatic recognition of the raw GPS data Deep Neural Networks reached 98.6% [107].

3.4.6. The commercial sector

Commercial applications provide a benefit to their users that users must consider as pleasant or necessary. Specifically, applications that monitor transportation modes are demanding on battery consumption, so there is a need to develop a benefit that balances this handicap. User mobility data can also be collected through crowdsourcing, but here the assumption is that the collection will only be temporary and the app will then be uninstalled, as these apps provide required data for a third party. The intention to build an application that is competitive on the market thus required a search of existing offerings.
In commercial applications that monitor users’ movement patterns, users usually have to select the activity manually, or the application uses the acceleration data obtained from a gyroscope and an accelerometer via the above-mentioned method. This thesis is focused on lifestyle monitoring. Its key factor is the most natural human movement – walking. There are also applications on the market that track the users’ behaviour during special activity (e.g., navigation during driving, activity at social network services), but do not include walking in their functionalities or track users’ movement only at certain times of the day. These applications do not provide the required information on daily movement patterns and are therefore excluded from the research.

Applications providing a comprehensive picture of users’ lifestyles can be found in 3 groups:

- Fitness trackers

Fitness tracking applications and pedometers (Google Fit©, Endomondo©, Apple Health©, Moves©, MiFit©, etc.) are primarily used to obtain information about users’ daily movement pattern, sports performance and calorie consumption. To find out their calorie consumption, users must enter certain basic factors influencing their metabolism, i.e., their age, weight, height and sex. The application software uses the above-mentioned methods to identify the type of movement. The application can use geo-location data as additional information. Fitness tracking applications installed on smartphones can be often linked with further wearable devices which provide additional, more precise information on the user’s activity – e.g., fitness bands, smartwatches, smart clothing with wearable technologies etc. [108].

- Environmental impact monitoring applications

The relation to the environmental impact of transportation behaviour is the motivation for application users. The distance and the choice of the transportation mode are, next to food and energy consumption, the key factors of greenhouse gas conscious lifestyles. Applications such as Greenly© or Capture© provide insights to the users' habits [109] [110]. Calculation of the emissions caused can lead users to adjust habits regarding low emission solutions.

- Healthcare applications

Tracking and activity monitoring applications are also often used in healthcare, in particular by patients with cardiovascular diseases. In combination with up-to-date information from the patients' wearable monitoring devices, such applications can be used to develop tailor-made motivation programmes for the patients. As the devices monitor users' pulse and location as well, they can be crucial in providing patients with quick help in case of health problems [111]. Movement tracking can also increase the safety of patients with neurological diseases (such as Alzheimer's), especially when they become disoriented or get lost [112].

3.5. Conclusion of the State of the art

In order to understand the life of the city, it is crucial to capture the activity of its inhabitants. Urban life can be monitored by a physical observer, but the mobile technology already implemented in society allows us to track the activity of the urban population over a long duration and without the physical presence of an observer.

Research shows that the physical activity of (not only) the Czech population has been following a decreasing trend. WHO refers to a pandemic of inactivity. Architects and urban planners can influence the shape of the physical environment of the city to encourage walking and other modes of physically active movement. Creating an urban environment that is friendly to active modes of transport (i.e., that not only enables but also encourages them) will have an impact that is extends beyond public health. Increasing the share of active modes of transport at the expense of private car transport also has environmental and economic implications. In order to evaluate these consequences and monitor the state of active movement in the Czech population, it is necessary to obtain data on the physical activity of the population, especially in terms of walking.

Smartphones are currently owned by more than 70% of the Czech population. Through acceleration sensors and location functions, time-spatial data and the information about traffic modes can be obtained non-invasively of the phone, and hence of the user. Detection of the movement mode is achieved by analysing the acceleration graph, where each transport mode has its own typical curve. The determination of the transport mode can be refined by comparing the trajectory over time with data from public transport timetables. GPS location has high battery requirements, which is inconvenient for the user, but it can be replaced by network based sensing.

The commercial offer includes types of applications that already provide geolocation information supplemented by activity monitoring. However, GDPR does not allow the data of these applications to be used without the explicit consent of the user. In this dissertation, I therefore propose a novel mobile application, through which it would be possible to collect data on users' active mobility over a long duration, as an important indicator of city liveability.

4. SMARTPHONE APPLICATION PROPOSAL

4.1. Aims of the application

In relation to the collection of data from smartphones, the key element is the motivation of users to provide the data. It is essential to offer them an attractive benefit which will turn the information they provide into a form they need.
The proposed smartphone application called "UrbanFit" focuses on gaining data about transportation mode and trajectory from the broadest range of users possible, aiming at the collection of mobile data from urban units of different sizes and from different topographic profiles, while still maintaining a representative sample of the population. Unlike crowdsourcing-based data mining, which relies on a positive perception of the project goals, UrbanFit offers a benefit focusing on a broader range of users (see Fig. 20).
The application will be collecting data on a long-term basis, enabling us to monitor changes in the mobility patterns of the respective samples of the population in variable timeframes.

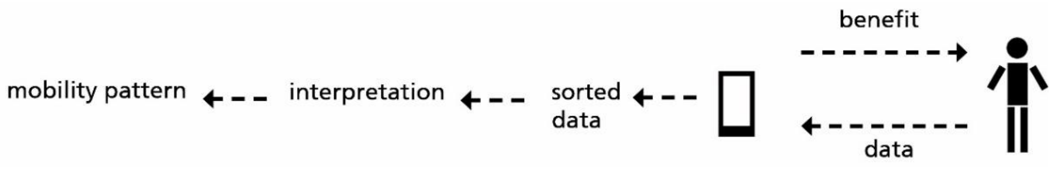


Figure 20 - Scheme of data mining

4.2. Focus on Health

The mode and duration of people's movements observed over a longer period of time reveal a lot about their physical condition and lifestyle [113]. The application monitors the mode and routes of their movement including time data (i.e., the same kind of data which is monitored by sport testers). The data about the user's movement, combined with information about their age, sex, height and weight can be interpreted as their daily calorie consumption caused by their ordinary movement. The application is able to distinguish physical activity such as running, cycling and walking; however, it will not record other sports activities (see Fig. 21).
The aggregated database will serve as a data lake for further research in a raw format, for increasing data processing options. For example, it will be possible to compare the mobility habits of different age groups, men and women, or overweight individuals and those with an average BMI.

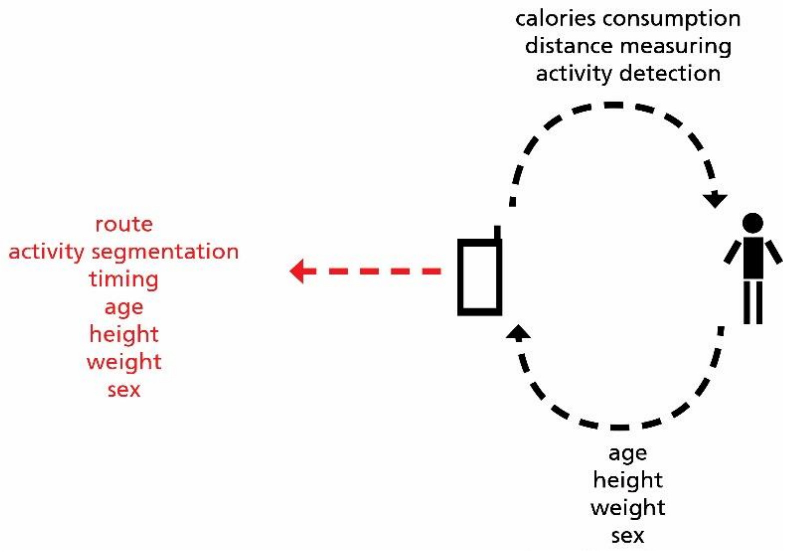


Figure 21 - Applications benefits

4.3. Marketing strategy

According to Google Play, sport testers are a popular and wide-spread software for smartphones in the field of health and fitness (see Fig.22). This means that it will not only be necessary to provide marketing support for the application and to launch it in the Czech language, but that it will also be essential to offer another benefit which will be particular to the application.

Calorie consumption – as a piece of information gained through the application – becomes relevant for the analysis of lifestyle quality only when combined with the information about the individual's calorie intake. For this reason, the application is designed to be compatible with the most downloaded smartphone application monitoring the calorie intake available on the Czech market – "Calorie Charts"[15]. In 2017, "Calorie Charts" did not include a daily calorie consumption function; we therefore expect that UrbanFit could be a practical supplement to "Calorie Charts". "Calorie Charts" enables users to fill in their sports activities and it is therefore not necessary to add this function to UrbanFit.

Food and eating patterns significantly influence people's health and thus also the quality of their lives. At the same time, food and eating patterns are often specific in individual countries. The market is becoming global, but still the food and its brands are often local, as we often see especially in branches of staple foods, dairy and bakery products.

The "Calorie Charts" app stores all the foods users eat during the day and provide a detailed overview of the nutritional values of users' menus. The application covers typical Czech dishes. This is why the combination of UrbanFit and "Calorie Charts" offers an advantage in comparison to commercial and international applications such as Strava (https://www.strava.com/), Endomondo (https://www.endomondo.com/), and others.

The "Calorie Charts" mobile app was released in 2011. As of August 8, 2021, it had over 5,000,000 downloads and 50,000 reviews on Google Play, where it also earned a relatively high rating — 4.5 stars out of a maximum of 5 [114]. Linking the apps has the potential to increase the reach of UrbanFit. After installing UrbanFit, users of "Calorie Charts" can take advantage of the functionality to measure calories burned through active movement so they are motivated to install UrbanFit app (see Fig.23).

UrbanFit's user interface has been developed with an emphasis on a clear graphic structure and an easy app design. Application UrbanFit should be advertised in professional environments as well as in the media dealing with nutrition, health, lifestyle, sports and medicine.

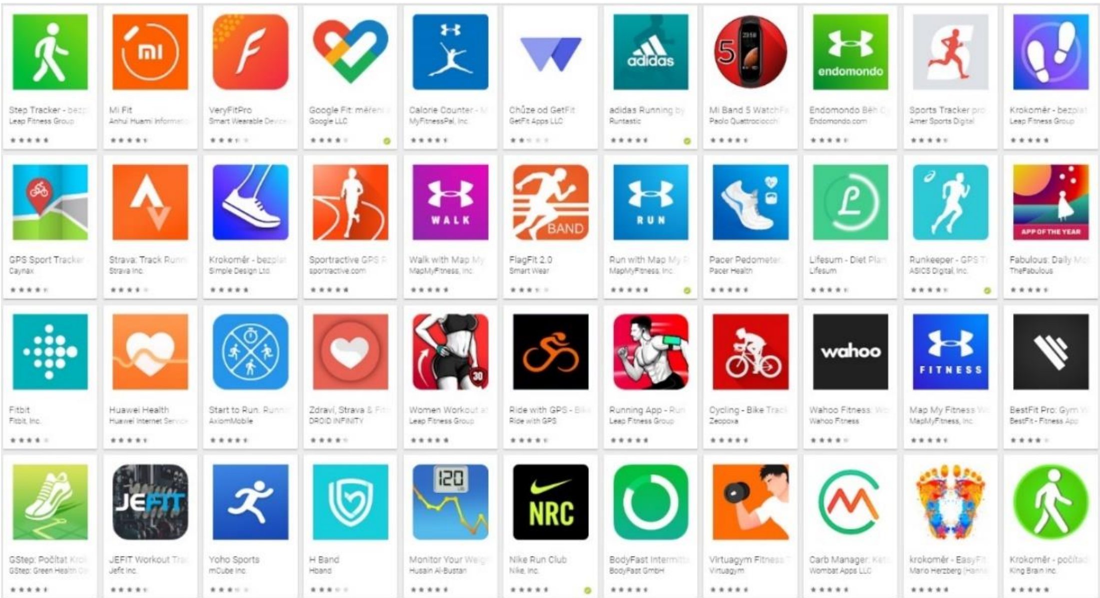


Figure 22 - Offer on the Android based application market in category "Health+Fitness"

[15] *Original Czech name "Kalorické tabulky", http://www.kalorickétabulky.cz/*

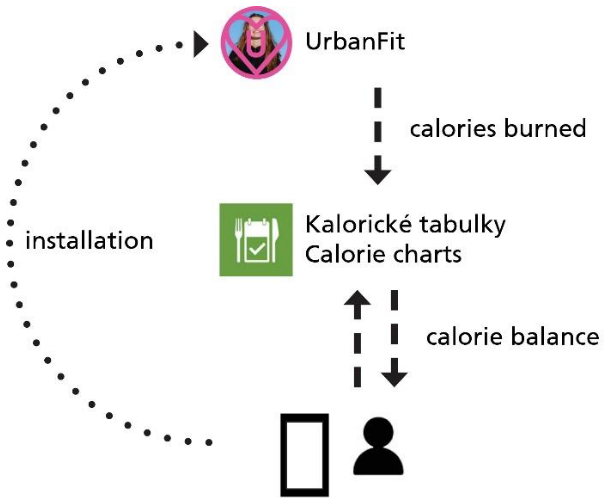


Figure 23 - Linking the applications

4.4. Method of data acquisition

The method of collecting data from smartphone sensors is based on accelerometer data, which are detected in the timeframe of 5s. The acceleration curve is classified and the mode of motion is detected according to its waveform. The differentiation of the traffic mode between car transport and means of public transport will use online timetables to evaluate the match in the movement of the user and the means of public transport.

value	date	time	latitude	longitude	x-value - acceleration	y - value - acceleration	z-value - acceleration
unit	year-month-day	h:m:s:ms	degree (0.6)	degree (0.6)	ms-2 (0.6)	ms-2 (0.6)	ms-2 (0.6)

Table 4: Sample of the text log

The application will track users' location via GPS if the GPS feature is turned on and enabled for the application in the phone. If the GPS is switched off, the localisation will read data from network-based location sensor. The precision of this method, however, may be poor outside of urban areas with a lower density of Wi-Fi networks. Data is temporarily stored locally on the phone, logged to a text field with a sampling period of 5s (see Tab.4). When connected to the network, the data is stored on the server at intervals of 1 hour.
The application will aggregate the time-spatial information connected with the users' ID enriched by transport mode information (see Fig. 24).

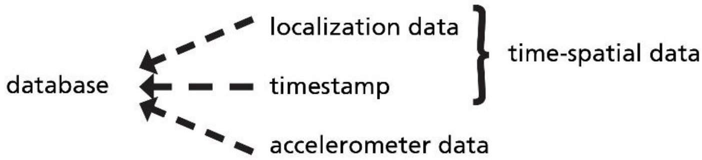


Figure 24 - Structure of the acquired data

4.5. Classification of the application's outputs

The database will store trajectories, divided into segments by transportation modes, as well as the starting and finishing time of the respective movements. The individual categories are: car, train/tram, bus, cycling, walking, running and the resting phase. The method of distinguishing traffic modes is described in more detail in Section 3.4.2 Sensor Based Activity Recognition. The minimal duration of each type of movement is set for minimum 10s. The information will be stored with a specific ID generated and assigned to individual application users. Information about the users' age, weight, sex and height, as entered into the system, will be attached to each ID (see Fig. 25). Further information entered by users, such as nickname, will not be stored in the database.

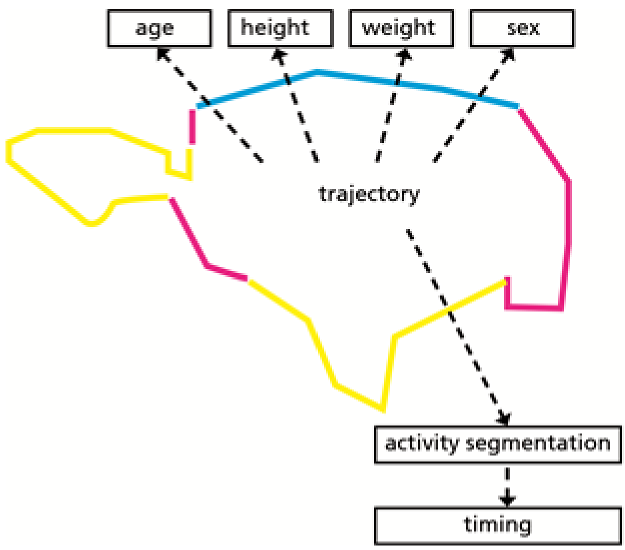


Figure 25 - Scheme of sorting data

UrbanFit will provide users a schematic visualisation of the trajectories travelled throughout the day, with the individual transportation modes graphically distinguished. The visual presentation of daily statistics, including the numeric values measured and the actual energy consumption, will be available online. In the history section, users will also be able to look back at individual days from the past. The application will also retrieve the information about passive transportation modes as the use of public transport or car rides. Using the app can thus motivate users to reduce passive transport behaviour in favour of physical activity.

4.6. Design of the application

First, a wireframe of the application was created (i.e., a sketch of the application, where the logic of interconnection and placement of individual functionalities of the application is solved). Next, this design was developed in the graphic programme Axure Pro into a user interface (UI) with the complete graphic design of the application, using Adobe Photoshop and Adobe Illustrator.
The aim of application design was providing information to users in a simple and easily readable interface. First, it is necessary to fill in a login form (see Fig.27a) or go to the profile registration (see Fig.27b), where the application asks for information about height, weight, gender, year of birth. It is possible to upload a profile picture to the profile section. After entering and confirming the profile information, users are taken to the main page with a pie chart showing daily physical activity (see Fig.27c). Already registered users can continue here seamlessly after log in. The application menu offers a transition to the profile section, a map view of the movement, a graph of the physical activity trend, a return to the main page or a transition to the help section (see Fig.26). The menu is displayed the same design in all UI layouts — the menu bar avoids in offer section which is currently displayed.
On the main page there is a visualisation of the users' physical activity in mobility segments: walking, running, biking, car ride, public transport (bus, tram, metro) and resting phase without evinced activity (see Fig.27c). Below the pie chart is an alignment of the segments in the timeline with the nodal points labeled.
In profile screen, users can modify their weight and profile picture; however, the height and the year of birth stays constant (see Fig.27d). The daily energy consumption is displayed here in kilojoules and calories. The activity modes are plotted in the form of a bubble chart, where the individual bubbles show the duration of the activity.
Evolution of daily movement over a longer period of time displays the weekly score of activity duration per day. In the calendar, it is possible for users to select a date and the algorithm of the application will show the evolution of each activity for a given calendar week (see Fig.27e).
Movement map per day displays the users' route and traffic mode on a map that can be scaled.
The map displays the current day by default, but it's possible choose to display the map for other past days in the calendar bar. Below the map of the movement trajectory, there is a timeline of activities with nodal points which carry information about the time and location of the movement mode change (see Fig.27f).

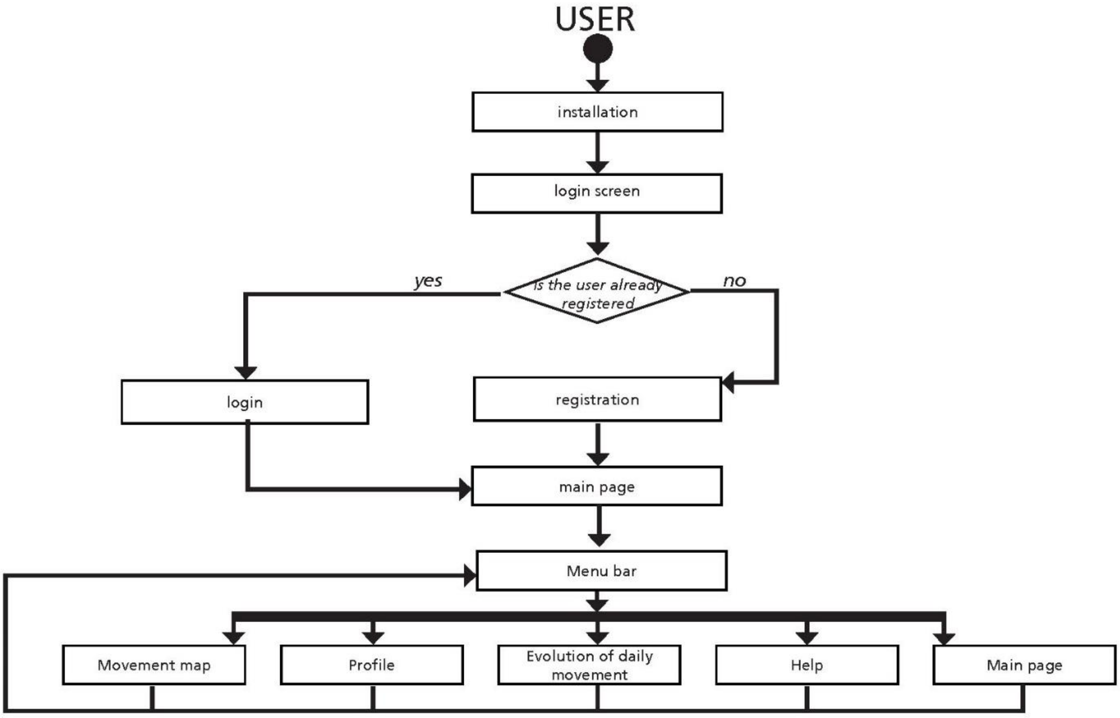
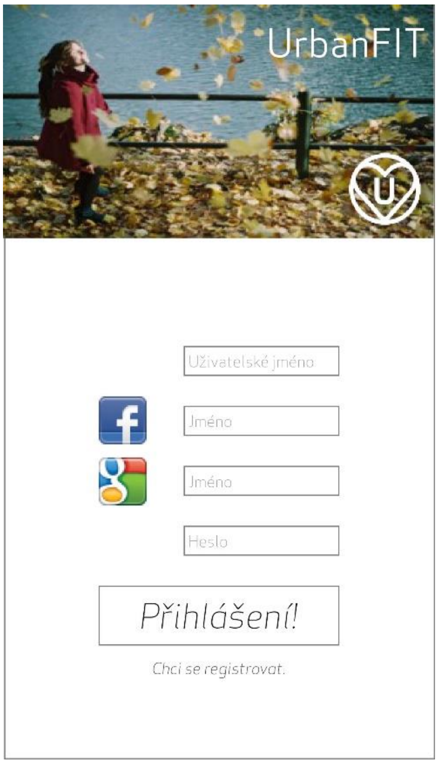
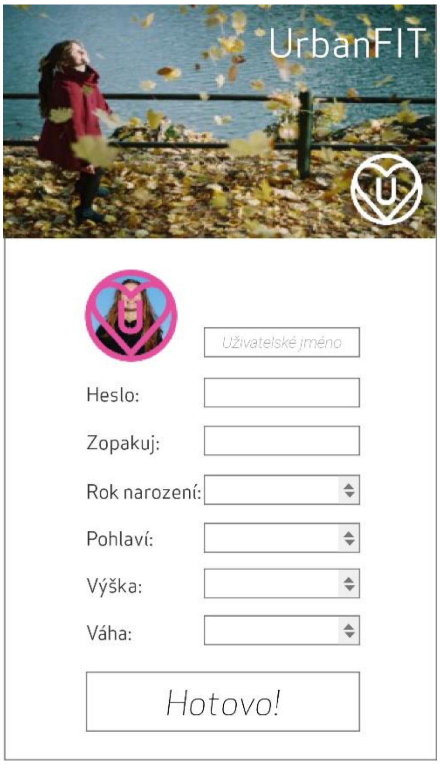


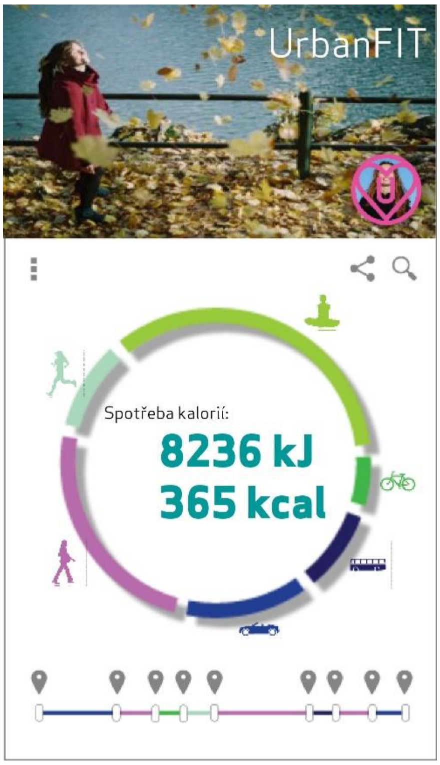
Figure 26 - Scheme of the application



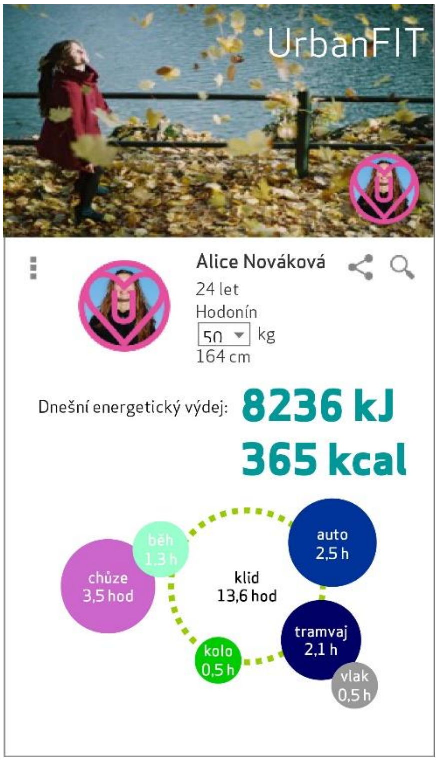
(a) Login



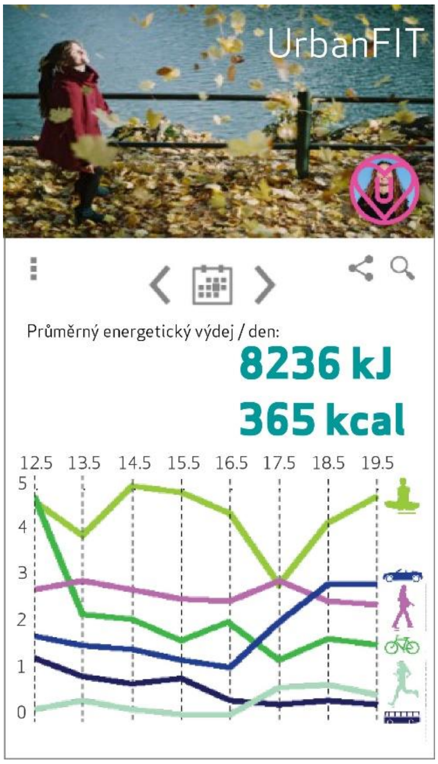
(b) Registration



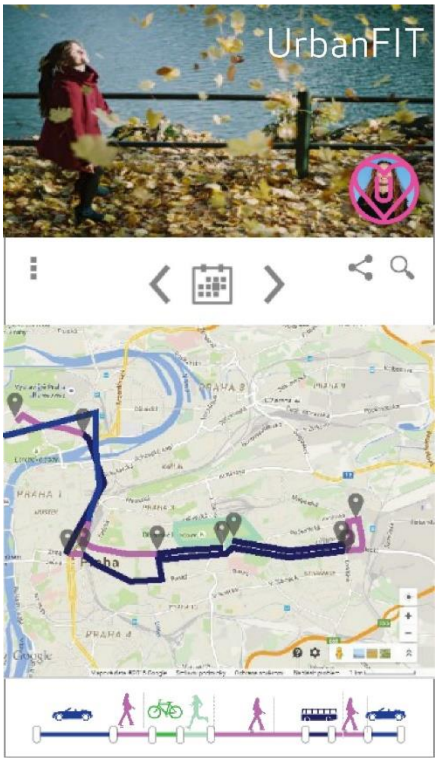
(c) Main page - Daily movement schedule



(d) Profile



(e) Evolution of daily movement over a longer period of time



(f) Movement map per day

Figure 27 – Application screens

4.6.1. Data collected by UrbanFit

For each ID set of logs will be collected (see Tab.4). The log consists of:
- Date
- Time
- Coordinates (latitude, longitude)
- Acceleration values in 3 axes x,y,z.

The set of logs will be stored in a database in dataset for each ID.

information about IDs age, gender, weight and height, which are attached to each ID and are based on information provided by the user during registration will be stored in a parallel dataset.
The next step is the recognition of transportation mode, where the logs are divided according to travel mode segments (see Tab. 5a). This functionality will be provide by the application because this information will be retrieved for users in the graphical interface of UrbanFit.
As the main function of UrbanFit is retrieving the caloric consumption value computed on the bases of daily basic physical activity (represented here by walking, running and biking), it is crucial for the function of the application to calculate the sum of each type of activity per day. The result is presented on the screens both in time [h:min] and through the distance covered by a specific movement mode [km] (see Tab 5).

The data files will be stored on a server under password protection.
The user identity data are anonymised in two ways: we store users in the database under an ID that does not contain any information about their identity. We further split the database into two files:
- a set of aggregated logs assigned to each ID.
- a set of user properties (age, gender, height, weight)

The files will be divided for security reasons: GDPR restricts aggregating personal data in a single file if the data would provide sensitive personal information. If the other information in the document clearly refers to a specific person, or to a very small set of specific people, the document cannot be considered anonymised. Anonymised personal data are data that do not even indirectly help identify a person and are therefore not in any way associated with that person. For example, by analysing the location of the ID at night it is possible to determine which urban unit is most likely the user's place of permanent residence [86], by following a regular routine, a place of work can be found. In the case of the UrbanFit database, the mobility data and information about users are stored in separate files.
The GDPR pays special attention to the processing of particular categories of personal data, inter alia on health. Personal data on health should cover all health-related data that are indicative of a person's physical or mental health, which may include data on physical activity. Also, the categories of weight and height can be considered as health data.
Conversely, anonymised data that are not of a commercial or institutional nature are excluded from the scope of the GDPR. Anonymised personal data are data that do not even indirectly help identify a person and are therefore not in any way associated with that person. The GDPR states that the anonymity of a dataset must therefore be assessed on a case-by-case basis [22].

Before completing the registration to the UrbanFit application, the user is informed by means of an introductory text about the scope and purpose of the data to be collected by the application. The text will state that the data will be stored in anonymised form and used for research purposes in the field of architecture and urban planning. The user's consent is conditional upon completion of registration and continued use of the UrbanFit application.

ID

date	startpoint			endpoint			transportation mode	trajectory length	duration
	latitude	longitude	time	latitude	longitude	time			
*[y:m:d]**	*[degree]*	*[degree]*	*[h:min:sec]*	*[degree]*	*[degree]*	*[h:min:sec]*	*[mode]*	*[km]*	*[h:min:sec]*

age	gender	weight	height
[y]	*[M/F]*	*[kg]*	*[m]*

(a)

ID - daily report

∑ walking		∑ running		∑ biking		∑ car ride		∑ public transport		∑resting phase
time *[h:min:sec]*	distance *[km]*	time *[h:min:sec]*	distance *[km]*	time *[h:min:sec]*	distance *[km]*	time *[h:min:sec]*	distance *[km]*	time *[h:min:sec]*	distance *[km]*	time *[h:min:sec]*

(b)

Table 5: Table of data collected by UrbanFit

(a) raw data for each ID

(b) processed data – daily report for each ID

5. POSSIBILITIES OF DATA UTILISATION

The database which is aggregated by the above-mentioned method can be used as a data source for the long-term monitoring of physical activity (PHA) and a choice of transportation modes (TM). In relation to municipal and urban spaces, PHA and TM can be monitored and analysed in various contexts. The proposed analyses aim to expand our knowledge of urban environments and enabling studies that will serve as a conclusive information base for the designs created by urban planners and for the decision making of municipalities.

The readiness to rely on one's own physical activity (such as cycling or walking) as a means of transport is essential in any city. Cycling has become an integral part of the identity of cities such as Copenhagen and Berlin. The acceptance of physical activity is not permanent, it changes over time: the motion patterns of inhabitants will differ in winter and summer as well as under exceptional conditions (such as the Covid-19 epidemic or restricted operation of public transport). Regular physical activity does not only affect the individual by contributing to the prevention of diseases of affluence and by supporting mental well-being [7] [115], it also affects the liveliness and the economy of cities. It is therefore in the interest of municipal administrations to regard the physical activity of the users of public spaces as a relevant issue and to use it as a basis when introducing new measures (pedestrianisation, creating a barrier-free environment and installing street furniture in public spaces, promoting the construction of bike paths).
Databases containing the data categories indicated in Table 6 can provide data to examine the influence of sex, age and BMI on ordinary daily physical activity of the population.

5.1. Walkability research

5.1.1. Walkable distance

Walkable distance is defined as a referential value or normative value of the greatest distance people are willing to walk from a residential house to facilities providing essential services or to public transport stations [116]. This value should be adjusted over time, as it is influenced by the readiness of the residents to reach their destination without using any other mode of transport other than walking. Long-term tendencies can be observed in the PHA data obtained from smartphone applications users of which replace the role of respondents of traditional questionnaires.
In terms of walkable distance, various factors can have an influence on users' decisions about daily mobility. Potential influencing factors include:

- Total commuting time
- Carpooling possibilities
- Time loss in case of alternative means of transport (e.g., bicycle, walking, public transport)
- Cost reduction in case of alternative means of transport
- Increased physical activity required for alternative modes of transport

5.1.2. Walkability index

The walkability of the area covers not only the suitability of the space for walking as a physical activity, but it also reflects the liveliness of the place. The walkability index is a methodology which is designed to describe the walkability of the area. The most commonly used indexes nowadays are the Global Walkability Index and the Asia index, but a whole range of alternative methods of measuring walkability have been developed [117].
The walkability index can be combined with the data from the UrbanFit database including the categories listed in Table 6 to assess a given locality and to examine the relation between the walkability index and the physical activity in the area. It will be possible to compare the results of each methodology with the activity reported by UrbanFit users in the monitored area. Observing the relation between the individual variables can be used to update or localise the formulas for the calculation of the walkability index.

5.2. Physical activity research

Using the data from the created database we can observe and compare PHA in different groups (based on age, gender, BMI, mobility pattern, and place of residence). We can observe the physical activity separately, in selected transportation modes: walking, running and biking. This is further elaborated in chapter 6.
As the data are collected over a long period of time, it is possible to observe and measure the relation between the mobility behaviour of the users of public spaces in the given locality before and after the locality has been adjusted.

5.2.1. Research on the influence of topography on PHA

In connection with the introduction of measures aimed at supporting cycling as a means of transport in Prague, one dissenting and unsubstantiated argument was mentioned in many discussions: Prague's topography (moderately undulating terrain) is not favourable for the development of cycling, the investment in this direction is therefore pointless [118]. However, with the advent of electromobility, this argument is losing ground. Moreover, there have been no studies in culturally comparable cities which would provide real data from different topographies and confirm or refute the aforementioned statement. Data from UrbanFit seem to be a suitable basis to examine the hypothesis that hilly areas have a lower share of bicycle traffic and to establish a relation between cycling and local topography. When analysing such data (similar to analysing the influence of topography on walking), it is necessary to consider the fact that topography is one of the influencing factors. Further major influencing factors are the density, quality and safety of bike paths in a given area [119] [120].

5.2.2. Research on the influence of the size and character of a settlement on PHA

Data from the mobile application UrbanFit can be used to measure the influence of lifestyle on the physical activity in various types of settlements, and to verify the results over time. An interesting way of using such data could be to compare the physical activity during the Covid-19 pandemic in settlements that are different in size and whose population is currently affected by the virus to varying extents [121]. The individual settlements can be sorted by the type and character of the buildings (historical vs. industrial buildings), their density, number of inhabitants as well as the quality and density of the services and facilities available, which also includes accessibility and elements of green infrastructure

5.3. A comparison of the spatial dependence of Body Mass Index (BMI)

Various studies have proven a connection between neighbourhood supportiveness for physical activity and BMI [122] [123]. There are also case studies that have examined the spatial dependence of BMI in certain localities [35]. We propose to use data from UrbanFit as a source data for examining the influence of urban factors on BMI.
Previous research has shown multiple interrelationships when examining BMI spatial dependence (social, individual and environmental – which are necessary to distinguish). This paper focuses on environmental factors because they can be influenced by changes in the development of public space, land use and transportation [124]. However, environmental factors can also be linked to gender and/or age groups which evince a higher rate of BMI relation to locality.

5.4. Economic Assessment

The HEAT methodology, developed by the World Health Organisation / Europe, which is described in further detail in chapter 3.3.3., uses the input data to calculate the economic impact of the health effects caused by a change in the way public and other spaces are used. Where data from traffic surveys are not available or accessible, data from the application UrbanFit can be used when recalculated in an appropriate manner to determine an approximate financial impact of change of the traffic behaviour.
The suitability of streets for physical activity does not only bring benefits to the field of public health, it is also proven that pedestrianisation of public spaces in city centres has a positive economic effect [64]. After an examination of the relation between the rental rates and the intensity of the use of public spaces in a given locality, it will be possible to assess the effects of the adjustment of the public space on the income from properties adjacent to the respective public spaces in the given locality. Mobility data reached by UrbanFit can be used to recalculate the economic effects of investments in public space from the point of view of the owners of local properties.

Usage of the data	gender	age	height	weight	GPS	mode	additional information
Walking	**x**	**x**			**x**	**x**	
Research of walkable distance							
Total commuting time	x	x			x	x	
Possibility of carpooling	x	x			x	x	
Time loss	x	x			x	x	public transport timetable
Cost reduction	x	x			x	x	cost of fuel+ public transport
Advantage in the field of PA	x	x			x	x	
Research of walkability index	**x**	**x**			**x**	**x**	using Walkability Index influence factors
A comparison of the spatial dependence of BMI	**x**	**x**	**x**	**x**	**x**	**x**	
Physical activity (PA) research	**x**	**x**	**x**	**x**	**x**	**x**	
Dependency PA/sex and age	x	x			x	x	
Dependency PA/sex and BMI	x		x	x	x	x	
Dependency PA/age and BMI		x	x	x	x	x	
PA - overview in time	x	x	x	x	x	x	timeframe
Research of influence of topography at PA	**x**	**x**	**x**	**x**	**x**	**x**	
BMI in different topographies			x	x	x	x	
Biking in different topographies	x	x			x	x	plan of bicycle paths
Walking in different topographies	x	x			x	x	plan of pedestrian paths
Research influence of character of settlement at PA	**x**	**x**	**x**	**x**	**x**	**x**	
Influence of density/quality of infrastructure	x	x	x	x	x	x	plan of infrastructure
Influence of green infrastructure	x	x	x	x	x	x	plan of green infrastructure
Influence of public transport infrastructure	x	x	x	x	x	x	plan of public transport
Influence of security landscaping	x	x	x	x	x	x	plan + report of measures
A comparison of the spatial dependence of BMI	**x**	**x**	**x**	**x**	**x**	**x**	
In different age groups		x	x	x	x	x	
Influence of gender	x		x	x	x	x	
Overview in time	x	x	x	x	x	x	timeframe
Economic Assesment	**x**	**x**			**x**	**x**	overcount of the input data
Economic assesment for cycling	x	x			x	x	using HEAT
Economic assesment for walking	x	x			x	x	using HEAT
Economic assesment for carbon emissions production	x	x			x	x	level of air pollution
Property value and walkability correlation					x	x	cost of property value

Table 6: Table of database and data employment

5.5. Summary of the possibilities of using urban lifestyle data

The basis of research on urban life from the perspective of an architect and urban planner is to observe the movement of people and to study their motivations. People's lifestyles are defined by their priorities and opportunities, which determine their behaviour. Physical activity connects people's activities during the day. The trajectory of movement can be viewed through the prism of movement modes, but can also be read as a sequence of goals — points of interest. These are sites designed to perform a particular function, such as shopping in a department store or studying at school. Through the UrbanFit-accessible dataset, users' daily activity and lifestyle can be observed.

Urban lifestyle is a multidisciplinary conceptual framework, which contains environmental quality, quality of life and human well-being [125]. Physical activity and active forms of population transport run like a thread throughout all these concepts. Physical activity is closely related to health, which is a major variable in quality of life, and is also central to well-being. Health and liveability are defined as two separate dimensions of quality of life. The liveability of places is also tightly connected with active modes of transportation. Whether the concept of safety or the socio-cultural environment, which are also mentioned in the literature as indicators of quality of life, cannot be created without pedestrians (i.e., people in active transport mode) [126].

From the dataset obtained through the UrbanFit smartphone app, not only time-spatial information can be extracted, but also data about the user's person — age, gender, height and weight, making it qualitatively more valuable than, for example, data taken from sensors installed in the city. The data from smartphone apps aims to be more accurate than information obtained through standard ways (i.e., through questionnaires answered by respondents, who often work with their own estimates). They represent a full-fledged alternative in quantitative research, which are respondent friendly (In this case the user of the application).

The dataset from UrbanFit can be combined further with available data layers to provide the basis for strategic decisions in the field of urban mobility and/or public health. They can also serve as a basis for the economic evaluation of urban projects. The data are collected by the smartphone application over a longer durational horizon and therefore provide an overview of the development of the monitored issue over time. They can also be used to compare the situation before and after the implementation of various scenarios.

Using a smartphone app, the users' movements can be tracked, but the interpretation and use of the data is left to architects and researchers. The UrbanFit dataset provides data input for further use, what can motivate researchers to develop tools to evaluate urban environmental influence factors.

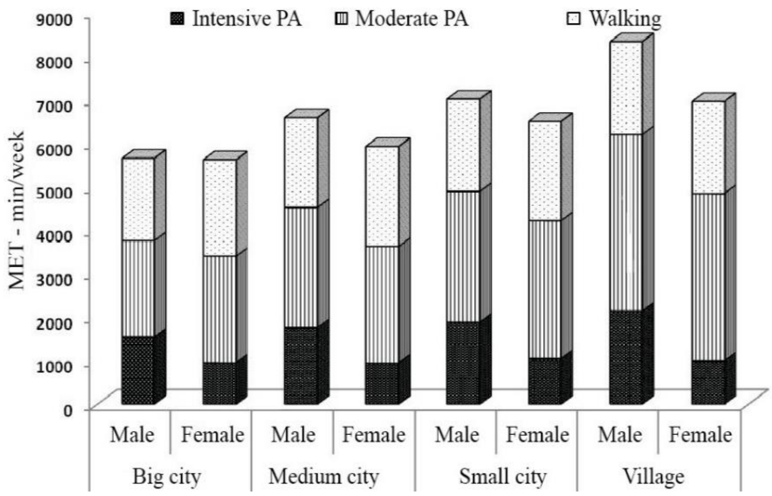
6. CASE STUDY

Walking is the most natural human movement. Yet, or perhaps because walking is often taken for granted, we do not have current data on the population's walking activity. Data show that individuals' physical activity is declining. It is very likely that this trend will spill over into walking. The lack of walking on a daily basis causes a number of lifestyle diseases including diabetes, obesity and cardiovascular diseases. These medical complications are increasingly widespread owing in part to urban lifestyles. The comfort of non-physical activity allowed by developed transportation systems leads to a pandemic of physical passivity.
The case study documents the current state of pedestrian movement in the population of the city of Prague. The obtained data on walking that can be seen as a report on the current health status of the local population, and can be used for further research as background data. The data can be compared to other data (e.g., from another period and/or from another environment) or can be used as a source data for HEAT analysis to estimate the economic impact of changes of a population’s transportation behaviour.

The lifestyle of Prague's residents could be explored through data obtained from UrbanFit. A draft of the application has been elaborated in previous chapter, but the acquisition of the programming is outside the scope this thesis. Therefore, to demonstrate how to use the data, alternative data were used which are similarly structured and their main categories are identical. For the analysis, the data from UrbanFit was replaced with data from the agent-based model of multimodal mobility of Prague and the Central Bohemian Region developed at the Department of Computing of the Faculty of Electrical Engineering CTU by Michal Čertický's team.
This case study is based on the dataset of daily activity schedules of 89 948 urban citizens extracted from agent-based simulation model of multimodal mobility in Prague. The schedules contain the exact routes, transport modes and durations of all trips made by public transport users. The case study tracks the walking activity of agents who commute to work by public transport or on foot. For all individuals, the walking distance and the distance of the routine route (to and from work) are measured.

6.1. Local conditions

Data on walking in the Czech population are only available in the form of temporal values of total physical activity or transport modal split [55] [127] [128] [129] [130]. These surveys are mostly based on questionnaires[16], which tend to be inaccurate because they are based on respondents' estimates, rather than exact measurements made by tracking [129] [130]. Previous research has reported that there were no differences in pedestrian activity between women and men in terms of size of residence (see Fig. 28). However, the research was carried out only in the regions, not in Prague [130] .



Large city - a settlement with more than 100 000 inhabitants

Medium city - a settlement with 30,000 - 100,000 inhabitants

Small town - a settlement with 1 000 - 30 000 inhabitants

Village - settlement with less than 1 000 inhabitants

Figure 28 - Structure of physical activity in men (n=3678) and women (n=4578) of the Czech Republic by place of residence (source: Mitáš, 2011)

[16] *International Physical Activity Questionnaire - IPAQ*

6.1.1. Prague transportation system

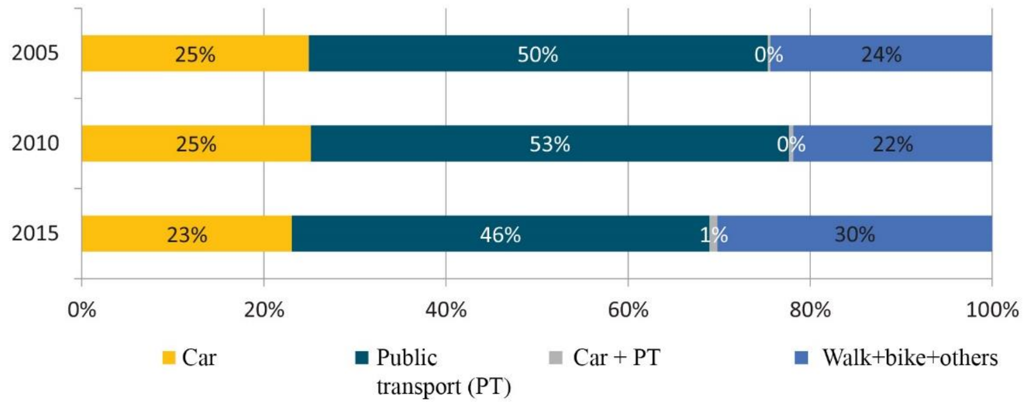


Figure 29 - development of the modal split - all journeys of the inhabitants of Prague (source: Plán udržitelné mobility Prahy a okolí - Analýza)

Prague has developed a dense system of public transport. This density is for sure comfortable for the citizens. However, it does not encourage regular physical activity. Approximately one quarter (26%) of all journeys are made by foot alone. The largest number of walking trips are made in the central area of the city, especially in the territory of Prague 1 [52]. The transport behaviour of residents differs from that of visitors to the city in its modal split — while Prague residents most often choose public transport (46%), walking (29%) and car transport (23%) (see Fig. 29), visitors to the Prague area mainly come by car (45%) and only then by public transport (36%) [55]. The calculation of pedestrian activity includes all trips that take more than 5 minutes, including walking to a means of transport. The number of journeys per inhabitant of Prague is steadily increasing, currently averaging 3.57 journeys per day. Prague residents exceed the European average with a high degree of motorisation (584 vehicles per 1000 inhabitants) [131] .

Data on the movement of the inhabitants of Prague are obtained through sample surveys. Initially, the surveys were conducted through face-to-face interviews. However, the above-mentioned method is currently on the decline due to the reluctance of the public to participate in this type of survey. Current surveys use web-based interviewing (CAWI), supplemented by telephone interviewing (CATI) [131].

In the area of active transport, Prague city representatives admit that they does not have much "hard data" to evaluate it in official documents [131]. In 2020, the City of Prague started to aggregate data on pedestrian movement via the project "Pedestrian traffic intensity in public space". Surveying the number of pedestrians in selected locations will be carried out using wifi sensors, PIR sensors and advanced video analysis providing motion detection. Statistical anonymised data will be transmitted to the data platform of the headquarters called “Golemio”, where they will be stored for further processing. The data will be further used for spatial planning, infrastructure modification, pedestrian traffic modelling, tourism development and security enhancement. The data were not yet accessible during the processing of this thesis [52].

The data from the above-mentioned technologies will provide the quantified data on pedestrian movement for specific location – they will count an amount of passing persons within a locality. But they are not able to bring the overview of transportation behaviour of the Prague population. The sensors pick up passing units, but do not provide other data that could be further worked with in statistics, such as age, gender or income group.

6.2. Method of the research

For this study, we decided to use the data from agent-based simulation model of mobility, which represents a typical day in Prague in 2017. This allowed us to analyse the behaviour of almost 90 000 residents — much higher number than alternative studies, which typically rely on on-site surveys with hundreds of participants. We studied multiple properties of the model output in order to reveal which factors are relevant for the daily pedestrian activity patterns. Statistical computation in R+ was done in collaboration with Mgr. Martin Dungl, collaborator of Institute of Information Theory and Automation, part of the Czech Academy of Sciences.

6.2.1. Replacement of the data

The data from the agent-based model does not contain all of the categories of data that could be obtained through the UrbanFit app. The dataset lacks height and weight categories, which are the basic information for calculating BMI. In contrast, the data from the model contain information that would be impossible to see through the app: information on marital status, highest level of education attained, and income per individual in the household (see Tab.7). These data are also relevant for insight into the topic of walking in the city, so they are processed in this case study, even if we could not obtain them using the application UrbanFit.

Category	**UrbanFit**	**Model**	**Concurrence**
Location	x	x	x
Travel mode	x	x	x
Gender	x	x	x
Age	x	x	x
BMI (height + weight)	x	-	-
Income	-	x	-
Marital status	-	x	-
Level of education	-	x	-

Table 7: Table of categories of data obtained

6.2.2. Model description

The database of daily schedules and trips of synthetic Prague residents that was used for our analysis was generated by the multi-agent activity-based simulation model of Prague and the Central Bohemian Region [132].In contrast to traditional four-step models of transport demand [133], which use trips as the fundamental modelling unit, activity-based models employ so-called activities (e.g., work, shop, sleep) and their sequences to represent transport-related behaviour of the population. Travel is then a derived demand occurring due to the necessity of the residents (agents) to satisfy their needs through activities performed at different places and at different times. These activities are arranged in time and space into sequential (daily) schedules and are interconnected by trips, each consisting of one or multiple legs with specific modes of transport, route and timing. Trip origins, destinations and times are endogenous outcomes of activity scheduling. The activity-based approach considers individual trips in context and therefore produces more realistic trip chains.

The computational model used in this work covers a typical work day in Prague and the Central Bohemian Region. The population of over 1.3 million is modelled by the same number of autonomous, self-interested agents, whose behaviour is influenced by demographic attributes, current needs, context and cooperation.

Agent decisions are implemented using artificial intelligence and machine learning methods (e.g., neural networks, genetic algorithms or decision trees) and trained beforehand using multiple real-world datasets, including census data and/or travel diaries and similar transportation-related surveys (see Fig. 30)

Planned activity schedules are subsequently simulated and calibrated on a supercomputer, and finally, their temporal, spatial and structural properties are validated against additional historic real-world data (origin-destination matrices and surveys) using the six-step validation framework VALFRAM [134].

The model generates over 1.3 million daily schedules containing over 3 million trips per one 24-hour scenario.

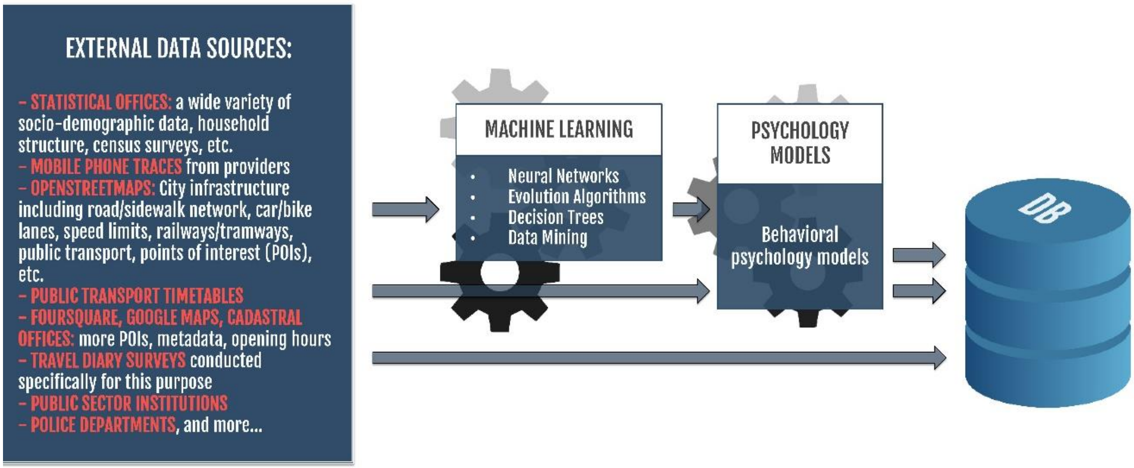


Figure 30 - Scheme of the multi-agent activity-based simulation model (source: M. Čertický, 2017)

6.2.3. The sample description

A sample of 89 949 agents with a specific mobility pattern was chosen from the agent-based mobility model of Prague. The agents regularly walk to work or commute using public transport. The agents who don't commute to work (home-office workers, unemployed) or who commute by car were not included in this study. We also excluded all the student agents (younger than 21 years of age) and retired agents who are likely older than 65 years of age (see Figure 31). The number of suitable agents was finally reduced to 88 547. The study focused on the daily pedestrian routine "residence – work" and its influence on the overall walking activity per day. We focused on the relationship between the necessary and voluntary physical activity on a daily basis. From the mobility model, we retrieved the distance walked to public transport stops, the distance walked from different stops to the workplace, total distance walked during the day, the GPS coordinates of the residence, the financial income of the agent, the marital status, gender of the agent and the highest reached education degree. Financial income[17] of agents is specified as a net monthly money income of the household divided uniformly among all household members.

6.2.4. Observed factors

Pedestrian activity of a selected category of agents for a single day is an average value of all agents who belong to the selected category. The value is calculated as

$$\frac{\sum_{i=1}^{n_{sel}} d_{sel}}{n_{sel}} \ (1)$$

where
d_{sel} is a length of the trajectory walked for a single day by an agent in the selected group, and
n_{sel} is the number of agents in the selected group
The equation was also used for pedestrian activity constituted by walking from the residence to the workplace and back.
The percentage of the walking activity recommendations (WAR) fulfilling agents in the selected group was calculated as

$$\frac{n_{actsel}}{n_{sel}} \times 100 \ (2)$$

where
$n_{act\,sel}$ is the number of walking activity recommendations fulfilling agents in selected group, and n_{sel} is the number of agents in the selected group.

[17] *The amount of income is converted by exchange rate 1 EUR = 26.11 CZK.*

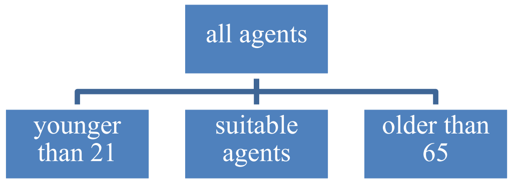


Figure 31 - Structure of the sample, age separation

6.3.Results of the case study

6.3.1. Daily pedestrian activity

Average pedestrian activity (PA) of Prague resident represented by an agent, is 3 106 m per day. This constitutes only 47% of the walking activity recommendations of 10 000 steps for a day (6 600 m) — less than half of the recommended pedestrian activity. Only 2.4% of the agents met this public health recommendation. Using a linear regression model we proved on a 5% level of significance that the percentage of active subject decreases by increasing age. On average it decreases very slightly by 0.01 % for each year of age.
We found a certain correlation between the average pedestrian activity and the activity constituted by walking from the residence to the workplace and back. This daily routine trajectory accounts for 85.4% of daily PA on average. Only 14.6% of walking activity for a day was not connected to the daily commuting routine (see Fig. 32).
Using a two sample Welch t-test is was proven on a 0.05% level of significance that the true ratio of residence-workplace walking doesn't differ from the observed mean by more than 0.25%. Using the t-test for the significance of a parameter in a linear regression model we proved on all significance levels that daily walking distance decreases with increasing age. On average it decreases by 3.96 meters for each year of age. This is a slight decrease and we can prove it only because we worked with quite a large dataset. However, no linear dependance of resident-workplace walking and the age of the subject has been proved (p-value of the test of significance of the regression parameter was almost 0.3).

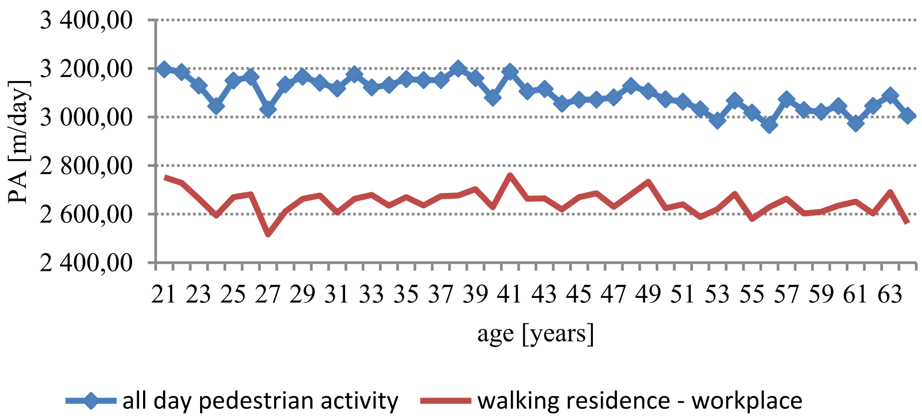


Figure 32 - Average daily PA according age

6.3.2. PA according to age

The difference between the daily pedestrian activity was not apparently connected to the agent's age. The average numbers were slightly lower with increasing age after 40 years, but the difference is small and irregularly distributed (see Fig. 33). Pedestrian activity would be possibly lower with higher age, but the participant agents are limited by the age of retirement. The WAR is met in 2.16-2.62% of the agent population.

Using a two sample Welch t-test we proved on all levels of significance that men walk more than women — 95% confidence interval for the difference between true means of the covered daily distances equals (132m, 172m). However, there are no gender differences between residence-workplace covered distances (similarly to the fact that this distance doesn't even depend on age). For both genders we can prove decreasing activity with increasing age, by 3.87m/day for each year of age among the male population and by 4.07 m/day for each year of age among the female population.

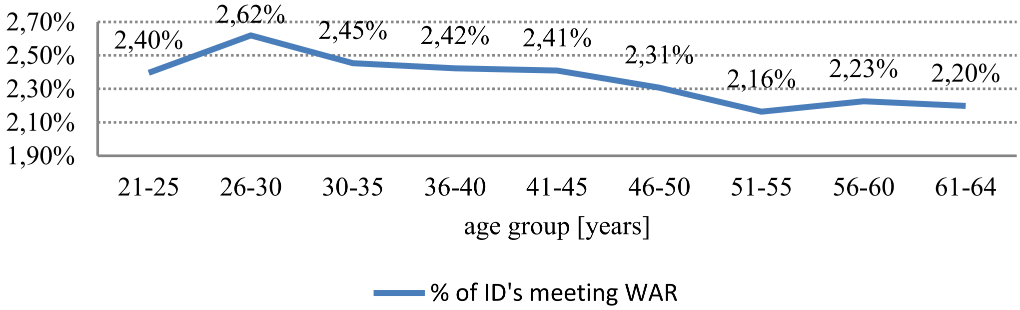


Figure 33 - Active population according to age

6.3.3. Relation between PA and gender

The difference in pedestrian activity between male and female agents was noticeable. Female agents walked 3 021m per day on average, compared to the average of 3 172m walked by males. The female average pedestrian activity is therefore approximately 4.8% lower (see Fig. 34). Only 2% of female agents met the WAR, while the percentage in the male population higher - approximately 2.7%.

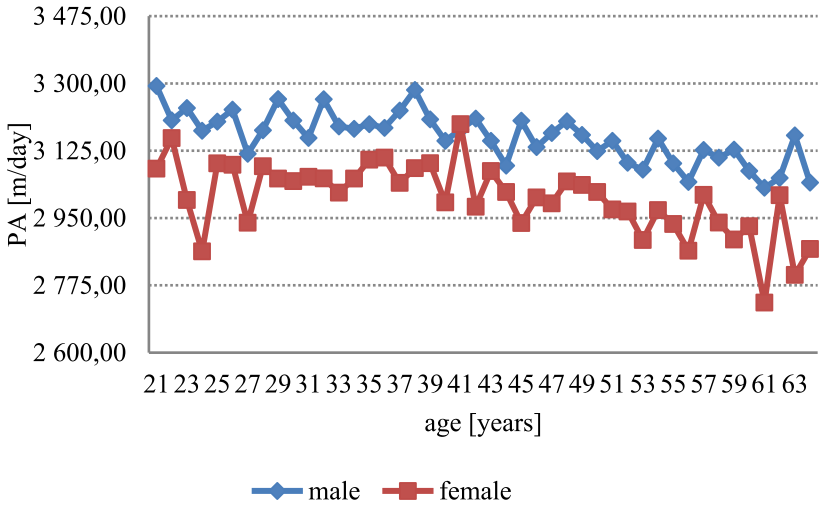


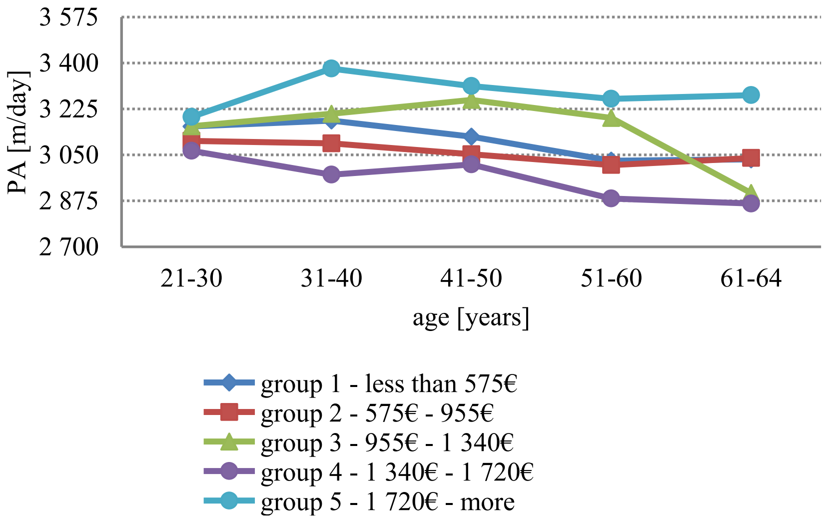
Figure 34 - PA according gender and age

6.3.4. Relation between PA and financial income

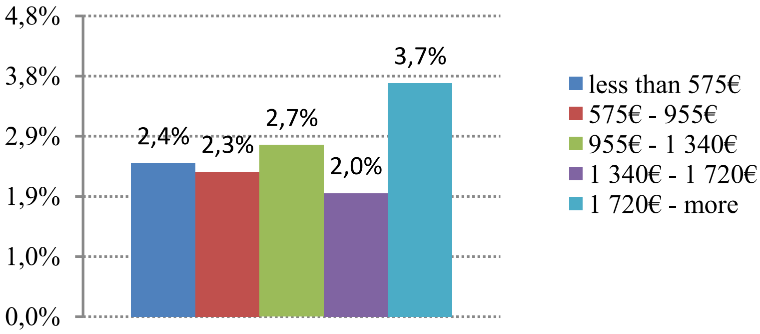
For this analysis the agents were divided into five groups according to their financial income. The income groups were calculated in CZK and converted to EUR. The difference between the group with the lowest and highest PA was 10% (see Fig. 35). Surprisingly, the lowest PA was found in the group with the income of 1 340-1 720 EUR and the highest PA in the group with the income of 1 720 EUR and more. The difference between other income groups was not significant (See Fig. 35(a)).

The highest income group (1 720 EUR and more) also contains the highest percentage of active agents. Specifically, 3.7% of the agents in this income group fulfil the WAR. The percentage of agents meeting the WAR (see Fig. 35(b)) is similar in remaining income groups.

By using a Welch anova test we proved on all significance levels the difference between pedestrian activity and income group. Searching for the groups which caused the overall difference, only the difference between the activity of the income group 3 and the income group 5 has been proven, all other groups are significantly differently active. If we order groups by average income, they are mixed (5, 3, 1, 2, 4 by descending order) so no global conclusion about the influence of higher income groups on the activity is obvious. However, if income as a number is considered (instead of the income group) as the independent variable and focus on dependence of it on the daily activity, it turned to be statistically relevant using a linear regression model. In this case activity decreases on average by 3.21m.



(a)



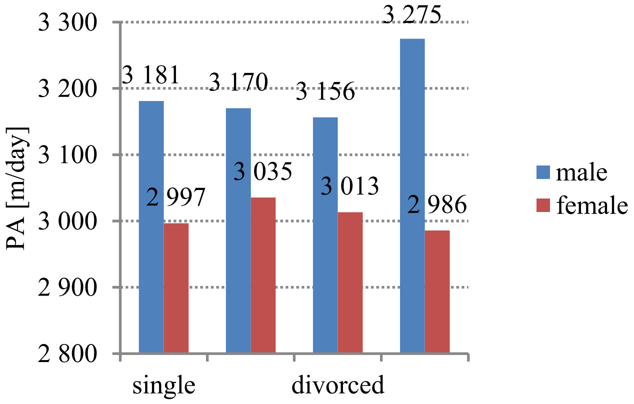
(b)

Figure 35 - (a) PA according income group and age;

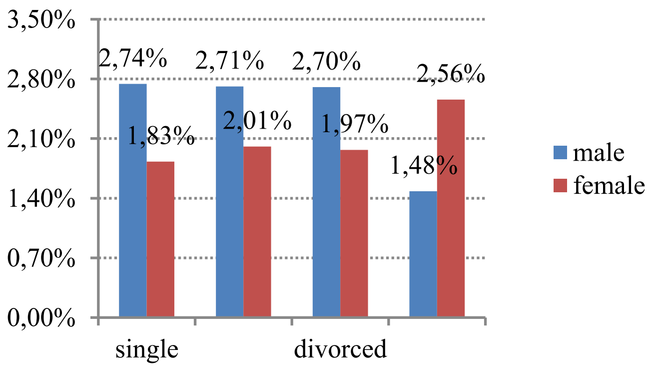
(b) percentage of WAR fulfilling agents according income group

6.3.5. Relation between PA and marital status

Next, I analysed the agents in the following categories: single, married, divorced, widowed.
First, we analysed the significance of the influence of gender on the pedestrian activity, among all four categories of marital statuses. We used a two sample Welch t-test. The statistical significance of the difference on the significance level 5% has been proved for all four categories.
I then analysed the significance of the influence of gender on the percentage of active subjects. It can be concluded that it is statistically significant except widowed subjects where no statistically significant result can be stated.
Then, the influence of the marital status on pedestrian activity and on the percentage of active subjects was analysed using a Welch Anova test. No differences of the pedestrian activity influenced by the marital status were proven as statistically relevant. Also, no differences of the percentage of active subjects were discovered. These results remain consistent even if we analyse the male and female populations separately.



(a)



(b)

Figure 36 - (a) PA according to marital status; (b) percentage of WAR fulfilling agents by marital status

6.3.6. Relation between PA and education

The highest achieved degree of education seems to have a limited influence on PA (see Fig. 37). We analysed the significance of the influence of gender on PA among all five categories of educational attainment. A two sample Welch t-test was used. A statistically significant difference has been proven for all five categories, on all levels of significance.

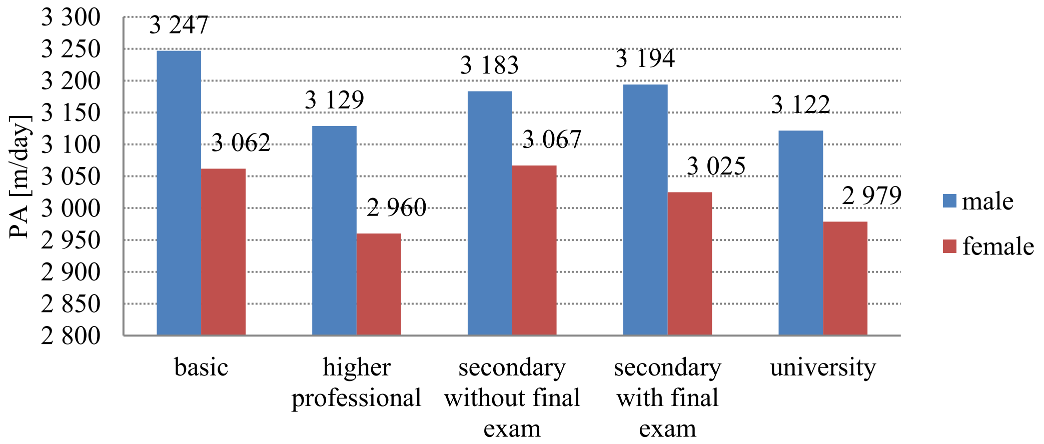
I conclude that the differences between the average pedestrian activity by educational attainment is significant on all levels of significance. It was proven that higher education is connected with lower pedestrian activity. Searching for the groups causing the overall difference, are three clusters of education levels were found:

The first group is composed of subjects with secondary education without final exam and with basic education. The second group is composed of persons with secondary education with final exams. The third cluster is composed of the remaining groups of higher professionals and university graduates. The clusters differ significantly from one another, while the groups within one cluster don't.

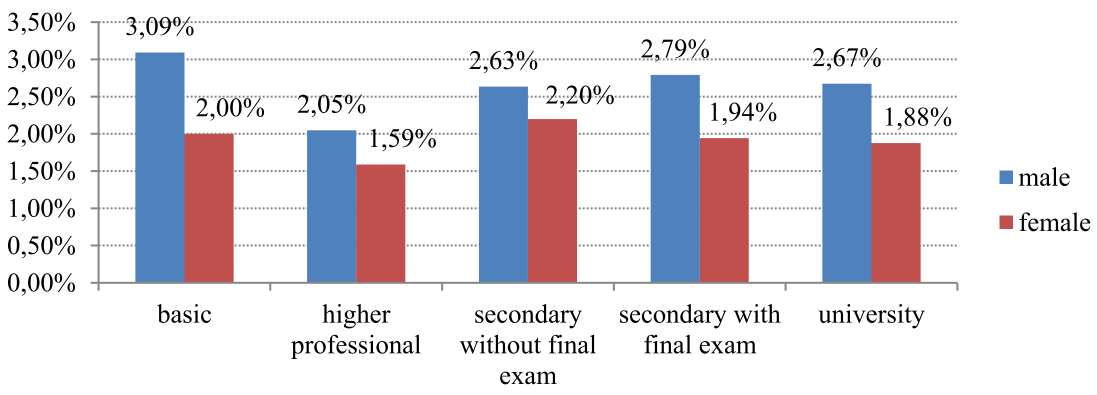
Among the male population there is also significant difference between PA by level of educational attainment. Higher education corresponds to lower pedestrian activity, as in the overall case. Even the pedestrian activity of the female population witnessed significant deviation by education. There are two clusters of groups causing the difference. First of them is composed of the groups with basic and secondary education. The second one is composed of groups of higher professionals and university graduates.

The analysis also illustrates the significance of the influence of education on the percentage of active subjects. It can be concluded that it is statistically significant except for the group of higher professionals where no statistically significant result can be stated, due to the law of small numbers.

The influence of education on the percentage of active subjects was then analysed using a Welch Anova test. No differences in the percentage of active subject given by educational attainment were proven as statistically relevant. This result remains consistent even if the male and female population are analysed separately.



(a)



(b)

Figure 37 - (a) PA according educational degree; (b) percentage of WAR fulfilling agents educational degree

6.4. Discussion of the case study

6.4.1. Limitations of the case study

Pedestrian activity among the residents of Prague represented by modelled agents is low. Only 2.16-2.66% of the population meets the WAR and can be considered as physically active. However, this study did not consider additional physical activities the agents may have undertaken, such as sports, physical activity in the workplace and other means of transport demanding physical activity (cycling). The multi-agent activity-based simulation model of Prague – just as the UrbanFit application – follows only transportation mode and location. The information about complementary physical activity is not traceable using this tool.

Walking activity apart from the PA related to the daily commute is only 14.7% of the daily PA. Modelled agents tend to choose the shortest way to their destination. In reality, there are additional factors that influence the choice of the pedestrian route, such as quality of public space and pedestrian roads [135] [136], presence of the green vegetation, pollution along the frequented highways or the presence of a shade in the summer [137]. This can be addressed by using the exact trajectories from tracking using wearable devices or smartphone applications.

The baseline data from the study provides insight into a typical day in Prague and the Central Bohemian Region in 2017. Therefore, from the data at our disposal provided by the model, it is not possible to observe changes in agent/occupant behaviour over time and their reactions to emergent conditions (change in weather, lockdown, traffic constraints). The data from UrbanFit, which was originally intended as the data source for this case study, is designed as a long-term mobility data source in contrast to the data from the agent-based model.

It would be possible to update the model with input data from a different timeframe. Since its key input data includes residual data from mobile operators, which can only be stored unprocessed for two months retrospectively according to Czech legislation, it is not possible to choose the timeframe at will. In addition to the time limit, the acquisition of residual data from mobile operators also contains a financial limit – it would probably be more expensive than the acquisition of the UrbanFit application. The model is also based on POIs defined on opensource platforms, which also cannot be accessed backwards in time.
The work on the TAČR grant, which supported the development of the agent-based model of multimodal mobility in Prague and the Central Bohemian Region, has been completed. It is therefore unlikely that the data will be collected again.

6.4.2. Influence factors

The difference in PA seen in the highest income group (1 720 EUR and more) could be caused by the location of their residence. The highest income group usually lives in residential quarters with low urban density, where public transport stops have longer spacing. The second highest income group (1 340 EUR - 1720 EUR) could be located closer to public transport stations in more dense urban structures, because the prices of the apartments and rents are higher than in the parts farther away from public transport.
Marital status seems to have a negligible influence on PA. It is surprising (and even slightly suspicious) that widowed males seemingly show bigger pedestrian activity with lower percentage of active subjects, in comparison to widowed females. This discrepancy, however, results from the law of small numbers – there are only 280 widowed males in the dataset.

6.5. Conclusion of the case study

This study demonstrates a stable relationship between general daily pedestrian activity and the PA related specifically to commuting to the workplace on a sample of 88,547 working-age agents who walk to work daily or choose a combination of walking and public transport. The findings are based on the dataset extracted from the multi-agent activity-based simulation model of Prague and the Central Bohemian Region.

The average daily walking activity of Prague residents who meet the above transport behaviour pattern is 3106 m, which corresponds to 47% of the daily recommended walking distance according to WHO. The average daily walking distance decreases with age — by 4m per year for individuals over 40 years of age.
PA connected to necessary daily routine constitutes 85.4% of total PA, while non-routine PA accounts for only 14.6%. This ratio is slightly influenced by the age of the population – non-routine PA decreases with age, but PA related to commuting to workplace remains.
The walking activity recommendation is fulfilled by only 2.16-2.62% of the agent population. The accurate number depends on the age group.
The case study shows a difference in PA among male and female residents. PA of females was approximately 4.8% lower than PA of males, which makes the difference in walked distance 151 m/day. Similarly, the ratio of females meeting WAR was lower.

Overall a global conclusion about the influence of higher income group on the daily average pedestrian activity was not found. However, we detected a certain impact of financial income on PA in various income groups: The group with the highest income evinced the highest average PA, while PA values of the group with the second highest income were lowest.
A noticeable impact of educational attainment was found. The difference between agents with different education were statistically relevant in groups. However, it was not able to prove agent PA is coherently increasing or decreasing with the level educational degree.
Statistical significance of the difference on the significance level 5% has been proven for all four categories of marital status, but the divergence of the group is very small.

7. DISCUSSION

The UrbanFit application was not implemented due to the financial demands of programming on the project. Rather this study.used a substitute dataset from an agent-based model that contains identical data categories. Both approaches contain certain limitation resulting from the properties of the datasets.

7.1. Data distortion

Unlike data from a mobile app, data from an agent-based model is not biased by users' motivations to install the app. It is assumed that users who pay attention to their health and exercise regime, are more interested in an app that monitors physical activity conducted during the normal daily routine. It is safe to assume users are probably interested in their body and healthy lifestyle. It is also possible that the data measured by UrbanFit would motivate users to incorporate more physical activity into their daily routine. While this is certainly beneficial for users' health, the results of population physical activity monitoring may be biased by this phenomenon.

The UrbanFit data is also unlikely to be uniformly dense in space or in population representation. Smartphone use is higher among younger age groups, so we assume that even among UrbanFit users there would be more younger people than would correspond to the percentage of the population. The spread of the app among users is influenced by the marketing of the app, which we see as necessary in supporting the propagation of the app on the market. It is likely that more use will be made of the app in frequented locations, whereas in less populated locations the data will be completely absent.

The UrbanFit dataset is therefore more suitable for investigating the selected phenomenon in different structures (social, urban) than for assessing its presence in a specific location. To work with a particular location it is unlikely to achieve an indicative density of users. The density of data for research on a particular phenomenon will always need to be verified before the project begins.

7.2. Comparison with current datasets

The intention of aggregating user data for scientific research has certain similarities with the GeoLife dataset — a project carried out by the Microsoft Research Asia team between 2007 and 2011. During the acquisition of the GeoLife dataset, 178 users shared time-stamped information about their location (longitude, latitude, altitude) over a period of 4 years. This dataset contains 17 261 trajectories with a total distance of 1 251 654 km over 48 203 hours. The trajectory points were obtained through different GPS loggers and phones and the instruments had different sampling rates [138] [139] [140]. For the UrbanFit dataset, we also assume that the acceleration sensing will be performed on different smartphones. The sampling rate is defined by the application, so it will be identical for all devices.

GeoLife, similar to the UrbanFit dataset, can be used in many research fields, such as mobility pattern mining, user activity recognition, location-based social networks, location privacy, and location recommendation [141].

The GeoLife dataset is freely available for download on the Microsoft website. Research on urban mobility and machine learning has been carried out using this dataset. The UrbanFit dataset contains more categories than the GeoLife dataset described above. In addition to time-stamped localisation, the set also contains acceleration data and personal information about the user. While the informational value of the dataset is higher, the presence of personal information makes it a non-public, inferential resource without the ability to publish the dataset openly.

The GeoLife dataset contains data from Asian countries that are culturally different from the Czech Republic. Therefore, it is not able to describe Czech local specifics and habits. To have local data was the aim of the development of the UrbanFit application.

GeoLife data was collected as part of a survey where respondents/users of the tracking devices gave consent for their routes to be published. The data was collected directly for the purpose of publishing the tracks within the GeoLife dataset and was taken by the respondents with this intention. This is ethically different from the (albeit also informed) consent that conditions the use of the UrbanFit app. For app usage, I assume the main purpose is for users to get information about their own lifestyles. Providing data is a secondary and, for some users, superfluous issue.

Work on the GeoLife dataset was completed in 2011, so the data does not correspond to the current trend.

7.3. Personal data protection

By registering, the user consents to the use of the data for research purposes. The data will be anonymised by separating the time-spatial data file and the file with the user's personal data — age, gender, height, weight. Pairing information will be possible through ID matching. Data would be stored in separate files, secured by passwords.
Even so, it remains unclear whether the data anonymisation requirements will be met. This is a problem for all geolocation data with a time trace provided by the user. If the user lives in a sparsely populated area (for example, in a house in a secluded area on the edge of a forest), the geolocation data indicate a narrow group of inhabitants based on their regular presence in that area.
According to the GDPR, the collected data can only be used for limited purposes, specified in the text of the user consent. Here the data would be used for urban research purposes and for the actual operation of the application that would be implemented by the founding institution of the UrbanFit app.
However, it would not be possible to publish the dataset from the agent-based model or even from UrbanFit as free-to-use material. The use will be regulated — restricted to the members of research teams of the Czech technical university, who will be assigned a password for personal access. The log of accesses to the dataset will be monitored.

7.4. Discussion regarding the case study

7.4.1. Comparing the data sources

The data obtained from the agent-based model does not offer a 100% correlation to the range of data obtained from the mobile app — it does not include height and weight categories. Therefore, the case study could not capture the dependency of PA and WAR on user/agent BMI. In contrast to the dataset obtainable from UrbanFit, the data from the agent-based model contains the categories "marital status" and "education degree", which were also included in the analysis of PA and WAR.

The data provided by the agent-based model of multimodal mobility of Prague and the Central Bohemian region has not been verified. We do not have another data source that would be able to verify the accuracy of the data through cross-reference. However, the model has been published in prestigious peer-reviewed publications. It was developed by a team of experts with high scientific credibility.

7.4.2. Time anchoring of the data

The data from the agent-based model provides a picture of a typical day in Prague and the Central Bohemian Region in 2017. Therefore, the model data cannot be used to track long-term trends in physical activity over time, unless the whole range of updated input data would be provided. Even then, the agent-based model provides an image of an average day over a longer period of time. Therefore, the data extracted from the agent-based model cannot be used to track changes in agent behaviour over time and their reactions to short-term conditions such as weather changes, traffic restrictions, pandemics or lockdowns. In contrast, the dataset from the UrbanFit app would allow for long-term monitoring of the daily activities and at the same time provide a picture of single day.

It would be possible to update the model with input data from a different timeframe. Since its key input dataset includes residual data from mobile operators, which can only be obtained for the preceding 2 months, the timeframe cannot be chosen arbitrarily. The agent-based model is based on POIs defined on opensource platforms such as OpenStreetMaps, which cannot be accessed retroactively.
Acquiring residual data from mobile operators is also a costly operation. The work on the grant that provided the development and maintenance of the agent-based model of multimodal mobility in Prague and the Central Bohemian Region ended in 2018. Therefore, it is unlikely that an update to the model will be obtained within the timeframe of choice.

7.5. Future work

Data about active urban mobility are still lacking as the authorities confirmed. Pedestrian movement is a key variable for urban life, but we do not yet have comprehensive data for Prague or other regions. Continuous data on how people choose transport around the city is important for many sectors as described in sections 3.2 and 3.3 of this thesis. However, data focused at the active mobility should be of particular interest to public health administrators.
Several dozen surveys of active transport behaviour have been carried out in the Czech Republic so far, most recently in the framework of the preparation of Sustainable Urban Mobility Plans (e.g., Pardubice in 2013 and 2017, Uherské Hradiště in 2013, South Moravian Region 2013, Olomouc 2016, Litoměřice 2017 and many others) [142]. Designing strategies of active, smart and sustainable mobility requires knowledge of the current state of mobility. Otherwise, it will not be possible to set a target state and thus evaluate the usefulness of the strategy document. We therefore anticipate a higher demand for data on active population movements. The proposed UrbanFit app maps the overall physical activity of users - the active mobility section includes cycling, walking and running, while passive mobility includes public transport and car use.

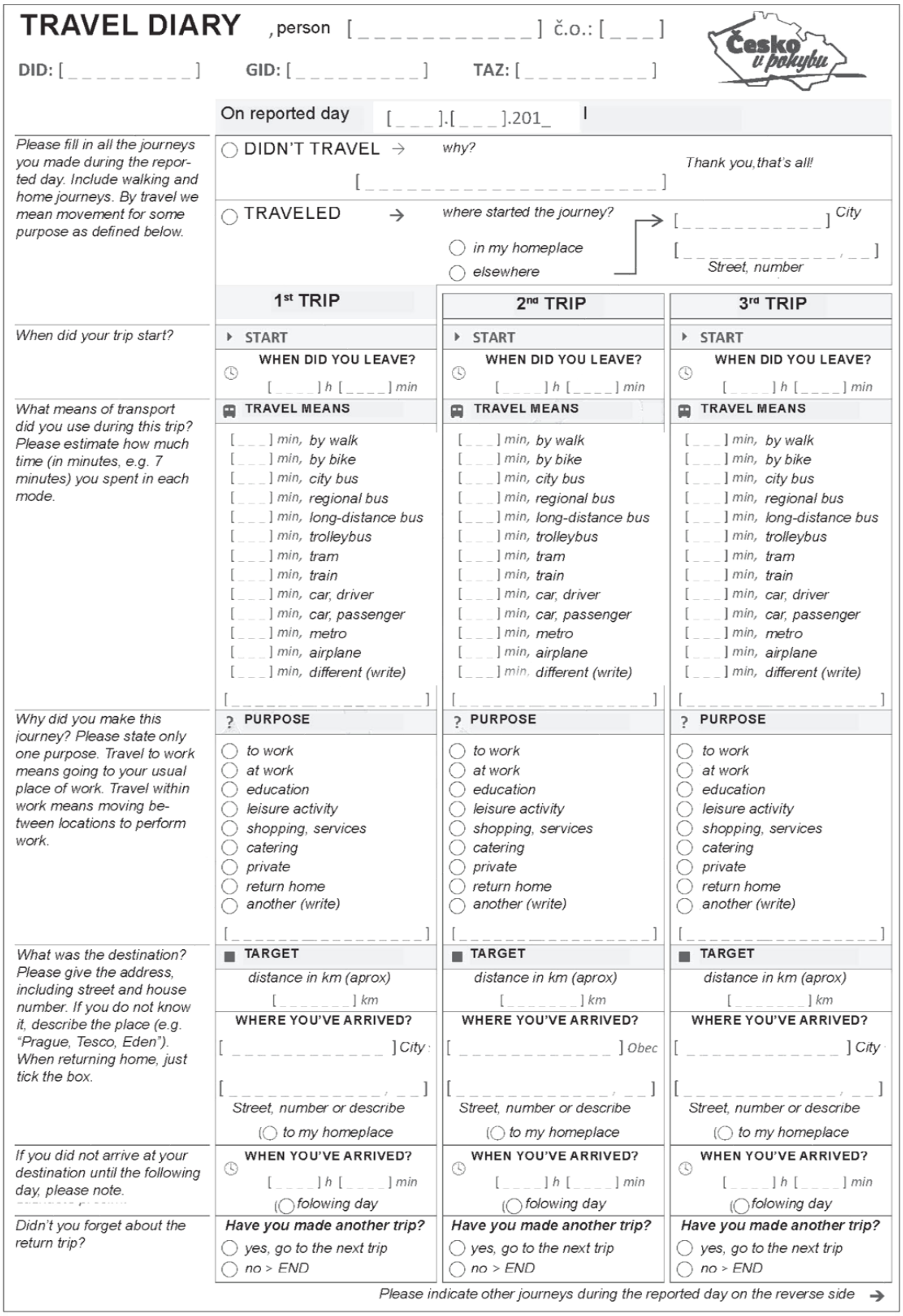
7.5.1. Widening of samples

A random, albeit large, sample of agents with a specific mobility structure was chosen for the case study. The sample chosen for the conducted case study includes only agents who commute daily by public transportation combined with walking or who walk to work.
It would be interesting to replicate the study on a sample that is not subject to mobility pattern restrictions, but still contributes insights on the resolution of the transport modes to the dataset. From this data, it would be possible to observe the average values of the Prague population's pedestrian activity compared to other subgroups defined by mobility routines — car commuters, P+R parkers, cyclists, and our study subjects; the population who walk to work or combine walking with public transport. Here we could observe the choice of transport mode as well as other influencing factors that are observed in the conducted case study: the dependence of PA on age, gender, income, education and BMI.
If we knew the background of transport choices for urban mobility, it would be possible to understand it better and then target measures more effectively to promote healthy lifestyles and active modes of movement. Data analysis of the mobility patterns can highlight the sensitive interface where the willingness to be active breaks down and where measures on the field of city planning, urban design or urbanism can be used to motivate people to be physically active.

7.5.2. Questionnaire survey sources for pedestrian activity

The case study was conducted on data from an agent-based model of multimodal mobility of Prague and the Central Bohemian region, replacing data collected through a mobile application UrbanFit. However, these data sources can also be replaced by other sources. Although the data from different sources are qualitatively and quantitatively different, they can, in principle, be handled in the same way. This is, using the same methods and observing the relationships between variables.
An option for obtaining data for analysis is to integrate to the research a questionnaire survey. The survey would have to include a sufficient number of respondents in all groups surveyed. If we were to repeat the case study, we would have to include a sufficient number of respondents in all of the observed categories (age, gender, income groups, highest educational attainment and marital status), including their subgroups.
The classic questionnaire survey of traffic behaviour is demanding to implement and post-produce. In addition to engaging respondents, data must be collected through trained interviewers. The data is then processed by coders who geocode the data into matrices. The Centre for Transport Research (here and then CDV), which carries out major transport surveys for the Department for Transport, normally uses paper forms for interviewing, with the help of interviewers. Fig.38 shows the form used by CDV for the "Czech in Motion" project. However, this format is intended for one-day trip monitoring. Completing questionnaires over a longer research timeframe appears to be burdensome for respondents.
It is also possible to use data that have been collected in other transport mobility studies. The aforementioned project "Czech in Motion" aggregated data from 2017-2019 on the daily mobility of households and their members. The survey assembled data from 10 391 households. This is the first national survey of traffic behaviour in the Czech Republic. It reflects both active and passive mobility and provides an overview of the mobility choices of the Czech population. Household members over 5 years of age were monitored on the selected day and their mobility was tracked through questionnaires. In this way, 40 861

trips were obtained. The data is freely available for further analysis on the web "Czech in Motion" [142]. However, it was published after the case study was completed. Data for traffic research would also be possible in the future through an app, as I propose in this thesis. This would allow the elimination of the interviewer, and would allow for the partial automation of the geocoding of the matrices. Automated data collection would also allow data to be collected over a longer timeframe than a single decision day, as the application is not burdensome to the respondent. According to the authors of the survey, seniors who do not own a smartphone would have a particular problem with using the app.



TRAVEL DIARY , person [_ _ _ _ _ _ _ _ _ _ _ _] č.o.: [_ _ _]

DID: [_ _ _ _ _ _ _ _ _ _] GID: [_ _ _ _ _ _ _ _ _ _] TAZ: [_ _ _ _ _ _ _ _ _ _]

Česko v pohybu

On reported day [_ _ _].[_ _ _].201_

Please fill in all the journeys you made during the reported day. Include walking and home journeys. By travel we mean movement for some purpose as defined below.

◯ DIDN'T TRAVEL → why? [_] Thank you, that's all!

◯ TRAVELED → where started the journey? ◯ in my homeplace ◯ elsewhere → [_ _ _ _ _ _ _ _ _ _ _] City [_ _ _ _ _ _ _ _ _ _ _ _ , _ _] Street, number

	1st TRIP	2nd TRIP	3rd TRIP
When did your trip start?	START WHEN DID YOU LEAVE? [_ _ _] h [_ _ _] min	START WHEN DID YOU LEAVE? [_ _ _] h [_ _ _] min	START WHEN DID YOU LEAVE? [_ _ _] h [_ _ _] min
What means of transport did you use during this trip? Please estimate how much time (in minutes, e.g. 7 minutes) you spent in each mode.	TRAVEL MEANS [_ _] min, by walk [_ _] min, by bike [_ _] min, city bus [_ _] min, regional bus [_ _] min, long-distance bus [_ _] min, trolleybus [_ _] min, tram [_ _] min, train [_ _] min, car, driver [_ _] min, car, passenger [_ _] min, metro [_ _] min, airplane [_ _] min, different (write) [_ _ _ _ _ _ _ _ _ _ _ _]	TRAVEL MEANS [_ _] min, by walk [_ _] min, by bike [_ _] min, city bus [_ _] min, regional bus [_ _] min, long-distance bus [_ _] min, trolleybus [_ _] min, tram [_ _] min, train [_ _] min, car, driver [_ _] min, car, passenger [_ _] min, metro [_ _] min, airplane [_ _] min, different (write) [_ _ _ _ _ _ _ _ _ _ _ _]	TRAVEL MEANS [_ _] min, by walk [_ _] min, by bike [_ _] min, city bus [_ _] min, regional bus [_ _] min, long-distance bus [_ _] min, trolleybus [_ _] min, tram [_ _] min, train [_ _] min, car, driver [_ _] min, car, passenger [_ _] min, metro [_ _] min, airplane [_ _] min, different (write) [_ _ _ _ _ _ _ _ _ _ _ _]
Why did you make this journey? Please state only one purpose. Travel to work means going to your usual place of work. Travel within work means moving between locations to perform work.	? PURPOSE ◯ to work ◯ at work ◯ education ◯ leisure activity ◯ shopping, services ◯ catering ◯ private ◯ return home ◯ another (write) [_ _ _ _ _ _ _ _ _ _ _ _]	? PURPOSE ◯ to work ◯ at work ◯ education ◯ leisure activity ◯ shopping, services ◯ catering ◯ private ◯ return home ◯ another (write) [_ _ _ _ _ _ _ _ _ _ _ _]	? PURPOSE ◯ to work ◯ at work ◯ education ◯ leisure activity ◯ shopping, services ◯ catering ◯ private ◯ return home ◯ another (write) [_ _ _ _ _ _ _ _ _ _ _ _]
What was the destination? Please give the address, including street and house number. If you do not know it, describe the place (e.g. "Prague, Tesco, Eden"). When returning home, just tick the box.	TARGET distance in km (aprox) [_ _ _ _ _] km WHERE YOU'VE ARRIVED? [_ _ _ _ _ _ _ _ _ _] City [_ _ _ _ _ _ _ _ _ , _ _] Street, number or describe (◯ to my homeplace	TARGET distance in km (aprox) [_ _ _ _ _] km WHERE YOU'VE ARRIVED? [_ _ _ _ _ _ _ _ _ _] Obec [_ _ _ _ _ _ _ _ _ , _ _] Street, number or describe (◯ to my homeplace	TARGET distance in km (aprox) [_ _ _ _ _] km WHERE YOU'VE ARRIVED? [_ _ _ _ _ _ _ _ _ _] City [_ _ _ _ _ _ _ _ _ , _ _] Street, number or describe (◯ to my homeplace
If you did not arrive at your destination until the following day, please note.	WHEN YOU'VE ARRIVED? [_ _ _] h [_ _ _] min (◯ folowing day	WHEN YOU'VE ARRIVED? [_ _ _] h [_ _ _] min (◯ folowing day	WHEN YOU'VE ARRIVED? [_ _ _] h [_ _ _] min (◯ folowing day
Didn't you forget about the return trip?	**Have you made another trip?** ◯ yes, go to the next trip ◯ no > END	**Have you made another trip?** ◯ yes, go to the next trip ◯ no > END	**Have you made another trip?** ◯ yes, go to the next trip ◯ no > END

Please indicate other journeys during the reported day on the reverse side →

Figure 38 - The sample of questionnaire for the project "Czech in Motion" (source: CVD, 2019 – translated)

7.5.3. Alternative smartphone application aggregation tools

Data for further research can also be obtained using smartphone apps which are already on the market. Data on the pedestrian activity of the population can be obtained through the applications mentioned in section 3.4.6. Most of the applications are focused on health factors, so they reveal only active types of mobility (biking, running and walking).

The most suitable tool for the mobility pattern recognition is the Ethica© app. This smartphone application was developed within a research project conducted at the University of Saskatchewan. The predecessor of Ethica, the iEpi app, was originally designed to use sensors for tracking the spread of the H1N1 virus in 2009. The Ethica© app is specifically designed for research in the field of health and well-being. The Ethica© app has been developed to enable the aggregation of mobility data and offers sensor-based quantitative behaviour measurement. Ethica© can continuously record location data via GPS, with minimum battery usage (~10% per day). The application provides access to the collected raw data as well as processed output in real-time, and can utilise programme conditions to trigger actions, such as prompting an experience sampling, or notifying a researcher. The app is available for both iOS and Android phones and also selected wearable devices. The Ethica© app configures experience sampling or cognitive tasks to be prompted when sensors detect a certain condition [32].

The Ethica© app aggregates data of cooperating respondents who voluntarily provide predetermined data within a precisely defined timeframe. The participation of research respondents works on the principle of crowdsourcing, where participation is not based on a personal benefit as in the proposed UrbanFit app. The motivation then is the reward for participating in the research or the good feeling of voluntary participation. Collecting a representative sample of the population necessitates the targeting of respondents or the collection of a big sample of respondents. This problematises the motivation of survey participants - without the element of selfish motivation we are likely to get fewer respondents than if we were providing a benefit to the user.

Before participating in the study, the respondent confirms their consent to what data is provided, for how long and for what purpose. The app user can withdraw from the study, stop data collection, delete some or all of their data collected by the app at any time [32].

8. CONCLUSION

Active movement is the blood in the veins of the physical city. Understanding urban life through the prism of the architect and urbanist, as defined by Jan Gehl, means observing the movement and actions of humans and understanding their motivations and goals. Collecting data on active mobility, which forms an important foundation for social connections and local economy, is emission-free, environmentally friendly, and is also a key factor for public health in the prevention of lifestyle diseases, is of interest to municipal and state institutions as well as organisations dealing with urbanism, public space or public health. Based on this measured 'hard data', the impact of sustainable mobility projects can be assessed.

This work focuses on monitoring the active movement of the population. The movement activity of an individual, through the prevalence of smartphones and the ubiquity of internet connectivity, can be monitored through a simple smartphone application. Traditional methods of collecting population mobility data, such as traffic surveys, are being replaced by digital measurements.

This section has 2 chapters. Chapter 8.1 consists of the design of the smartphone application, its operating principle and marketing strategy for the local market. In this chapter, a wireframe of the application is developed and a database structure is proposed. The database would start to emerge and expand once the application is extended. Chapter 8.2 focuses on processing data from a database; a confirmation of the hypothesis. The research outcomes measure and evaluate the length of the walking trajectory of the Prague population with specific traffic behaviour and examine its influencing factors. Thus, it demonstrates that the dataset obtained through the application can be used as background information for mobility studies and the implementation of urban design concepts.

8.1. UrbanFit application design

The UrbanFit smartphone app was designed. UrbanFit provides its users a daily report of their routes and caloric expenditure in a simple graphical environment, as well as an overview of the time and route taken by the user in each movement mode over a longer timeframe in calendar mode. The application collects time-spatial stamps and accelerometer logs into its database at regular intervals. The combination of these data layers allows the detection of individual modes of movement based on the acceleration progression curve: walking, running, cycling, driving, train or public transport. It also monitors the resting phase. UrbanFit also uses data entered by the user and associated with their ID to calculate calorie expenditure: age, weight, height and gender. A wireframe structure, UI and UX of the app, a method for detecting the mode of movement, as well as a marketing strategy were designed for UrbanFit. The data processed by the app is being stored with the users' consent in its raw form in a database that will be preserved for research purposes in the fields of architecture and urbanism.
Data acquisition through the smartphone application is highly non-obstructive to the respondent/user. On the contrary, it provides a benefit to users in the form of information about their daily physical activity and caloric expenditure. Users are also motivated to participate in the research by personal gain, so we assume that we will be able to obtain data from a longer timeframe than would be the case with standard traffic surveys.

Sensing the transportation mode via the UrbanFit app also has its limits:

- Engaging users according to interest

The app is likely to be used primarily by individuals who are interested in a healthy lifestyle and active movement. Information about their caloric expenditure and small amount of active movement may motivate them to change their typical mobility mode.

- Data density

The smartphone application will be freely available for download on the web. The data is unlikely to have the same density in space. On the contrary, a higher data density in larger cities can be predicted. The assumption is that the spread of the app will replicate the spread of smartphone ownership in the population. A sufficient number of respondents/users moving in the addressed area will need to be checked before the data can be used. We do not expect to be able to use this data to address small units (streets, squares) where we will probably not achieve the desired density.

- The data will be subject to GDPR.

The database and related data will be for internal use only: they will be stored in a special mode and password protected.

The use of the aggregated data will be possible in the fields of architecture and urban planning. The main potential for using the data in upcoming research are in the branches of:
- Walkability research
- Physical activity research
- A comparison of the spatial dependence of Body Mass Index (BMI)
- Economic assessment of walking

The possibilities of using the data for public health and related urban planning purposes is demonstrated in the case study. The programming aspect of the smartphone application was not part of this dissertation as financial funding was unfortunately not available. As such, the application could not be launched and the data could not be realistically collected. Therefore, the validation of this thesis on the use of data from the smartphone app was carried out on a replacement dataset with similar characteristics.

8.2. Urban mobility and influence factors - Case study Prague

The case study provides insight into the movement and transport habits of the population of Prague and the Central Bohemian region. The study focuses on a segment of active mobility: walking and its influencing factors. Walking has been chosen as a key factor of urban life, the positive impact of which on social interaction, the local economy, environment and public health has been demonstrated by previous research. In the case study, the unavailable data from the smartphone app was replaced with data from an agent-based multimodal mobility model of Prague and the Central Bohemian Region, which have similar structure and categories.

For the analysis, a demographic segment with a specific mobility pattern was selected from the model: agents who walk to and from the workplace daily or use public transport in combination with walking. A sample of 88 547 agents aged 21-65 years was selected. For each agent, the routes associated with routine movement (i.e., the walking route from home to workplace and back) were extracted from the model, and the total walking distance per day was measured. The dataset from the agent-based model contained extra categories compared to the dataset from the app: the financial income of the agent, as well as their marital status and highest achieved education degree. Conversely, the model dataset lacked the weight and height categories that are required to determine BMI.

The average walking activity of Prague residents, represented in the model by agents with the above transport routine, is 3 106 m, which corresponds to 47% of the daily recommended walking activity according to WHO. This distance decreases by 4 m per year of age for the population over 40 years of age. Only 2.16-2.62% of Prague residents, depending on age group, complete the recommended daily walking distance (10,000 steps). Of the total daily walking route, 85.4% is comprised of routine trajectories — from home to work and back. Only 14.6% of the walking distance is associated with non-routine activities. It is both likely and cautionary that the segment of the population that drives to work daily and/or has a home office is missing out on a significant amount of daily walking activity.

Research has indicated differences in walking activity by gender, with the walking trajectory of women being 4.8% shorter than the average daily walking summary for men. Only 2% of women meet the WHO daily walking recommendations. Among men, the number of active individuals is higher — 2.7%. A difference was noted in the decrease in daily average walking activity — for men over 40 years of age it decreases by 3.87m/year of age, for women by 4.7m/year of age.

The case study also processed data from other categories that could not be obtained from the proposed UrbanFit application: financial income of the household member, the marital status of the agent and highest achieved education degree.

No association was found between income group and walking activity, although the differences between groups were statistically significant. The highest income group with an income of 1720 EUR or more per household member reported the highest walking activity, while the second highest income group with an income per household member of 1340 EUR - 1720 EUR showed the lowest walking activity. Similarly, the highest number of persons meeting WAR requirements was among the highest income group and the lowest number of physically active persons was in the second highest group.

Differences in walking activity between agents with different marital status are minimal, although statistically significant due to the sample size. Analysis was performed in the following groups: single, married, divorced, widowed. There were no statistically significant differences between groups when looking at the number of individuals meeting WAR.
Educational attainment has an effect on the walking activity of respondents. Higher education has been shown to be associated with lower walking activity. In looking for groups that cause the overall difference, we concluded that there are three groups of education levels. The first is made up of subjects with no high school diploma and those with primary education, the second is made up of only subjects with high school diploma and the third cluster is made up of the remaining groups of senior professionals and university graduates. The clusters differ significantly from one another, but the groups within a cluster do not differ.

According to the indicators of physical activity development presented in chapter 3.2, the physical activity of the Czech population is likely to decline in the long-term. The author of the dissertation considers it appropriate to develop and implement urban concepts together with mobility strategies that would help reverse this trend [143].
The impact of unpredictable events such as natural disasters, epidemics or lockdowns on the active mobility of the population can also be viewed through the prism of 'hard data'. Through the data collected from the proposed smartphone app UrbanFit, it would be possible to track the impact of implemented projects on urban mobility in a before/after scenario, and to monitor the adaptation process, whether it is a modification of the public space or a broader concept.

BIBLIOGRAPHY

1. Batty, M., Big data, smart cities and city planning, *Dialogues in Human Geography*, **3**(3), pp. 274–279, 2013.
2. Batty, M., *The New Science of Cities*, The MIT Press: Cambridge, Massachusetts, London, England, pp. 15-18, 2017.
3. Goodchild, M. F., Citizens as sensors: the world of volunteered geography, *GeoJournal*, pp. 211–221, 2007
4. Individuals using mobile phone in the Czech Republic, 2020, Czech Statistical Office (CZSO), https://www.czso.cz/csu/czso/3-pouzivani-internetu-jednotlivci, Accessed on: 18. July 2021
5. Monthly Average Number of Apps Used and Installed – Smartphone Users in Selected Markets, 2017, App Annie, www.appannie.com/en/insights/market-data/apps-used-2017/ , Accessed on: 18. July 2019
6. Novobilsky, J. (2015, December 12). Personal interview
7. Gehl, J. &Svarre, B., *How to Study Public Life*, Island Press: Washington D. C., 2013.
8. Giebler, C., Gr¨oger, C., Hoos, E., Schwarz, H., Mitschang, B., Lever-aging the Data Lake - Current State and Challenges., *Proceedings of the21st International Conference on Big Data Analytics and Knowledge Dis-covery (DaWaK 2019),* 2019, doi:10.1007/978-3-030-27520-4_13
9. Fang, H.., Managing Data Lakes in Big Data Era: What's a Data Lakeand Why Has It Became Popular in Data Management Ecosystem, *IEEE International Conference on Cyber Technology in Automation,Control, and Intelligent Systems (CYBER*), pp. 820–824, 2015
10. Bonabeau, E., Dorigo, M., Theraulaz, G., Swarm Intelligence: From Natural to Artificial Systems, Oxford University Press, pp.7-16, 1999
11. Heppenstall A., Crooks A., See L., Batty M., *Agent-Based Models of Geographical Systems*, Springer, Dordrecht, pp 85-105, 2011, https://doi.org/10.1007/978-90-481-8927-4_5
12. Clark, A. G., Walkinshaw, N., Hierons, R. M., Test case generation for agent-based models: A systematic literature review, *Information and Software Technology*, 135, 2021
13. Fernandez-Anez, V., Stakeholders Approach to Smart Cities: A Survey on Smart City Definitions, *Transactions on Computational Science XXXVIII* , pp. 157–167, 2 016
14. Gharaibeh, A., Salahuddin, M. A., Hussini, S. J., Khreishah, A., Khalil, I., Guizani, M., Al-Fuqaha, A., Smart Cities: A Survey on Data Management, Security, and Enabling Technologies, *IEEE Communications Surveys & Tutorials*, **4**(19), pp. 2456–2501, 2017
15. Mapping The Smart Cities in the EU, https://op.europa.eu/s/oZUg, Accessed on: 22. April 2021
16. WHO/Europe - Body mass index – BMI, https://www.euro.who.int/en/health-topics/disease-prevention/nutrition/a-healthy-lifestyle/body-mass-index-bmi, Accessed on: 20 July 020
17. World Health Organization, https://www.who.int/about, Accessed on: 20 July 2020
18. WHO – Noncommunicable diseases, https://www.who.int/health-topics/noncommunicable-diseases , Accessed on: 18 June 2021
19. Solberg, C. T., Sørheim, P., Müller, K. E., Gamlund, E., Norheim, O. F., Barra, M., The Devils in the DALY: Prevailing Evaluative Assumption, *Public Health Ethics*, 13(3), pp. 259–274, 2020
20. Jetté, M., Sidney, K., Blümchen, G., *Metabolic equivalents (METS) in exercise testing, exercise prescription, and evaluation of functional capacity*, Clin Cardiol, 13(8), pp. 555-565, 1990
21. Řezáč, J., *Web ostrý jako břitva*, Baroque partners, 2014
22. General Data Protection Regulation, https://gdpr-info.eu/, Accessed on: 12. April 2021
23. Sobková, L. F.., Čertický, M., Jiráček, Š., Application of transportation big data to support decision-making for architecture teams: processes and experiences from two case studies, *WIT Transactions on Ecology and the Environment*, 238, pp. 639-651, 2019
24. CIAM's "The Athens Charter" (1933). Modernist architecture. [Online] https://modernistarchitecture.wordpress.com/2010/11/03/ciam%E2%80%99s-%E2%80%9Cthe-athens-charter%E2%80%9D-1933/. Accessed 6. Jun. 2017.
25. Jacobs, J., Life and Death of Great American Cities, Random House: New York, 1993.
26. Perec, G., Sturrock. J., *Species of Spaces and Other Pieces*, London, England: Penguin Books, 1997
27. Clarke, A., Steele, R., How personal fitness data can be re-used by smart cities. *2011 Seventh International Conference on Intelligent Sensors, Sensor Networks and Information Processing*, pp. 395-400, 2011
28. Perchoux, C., Chaix, B., Kestens, Y., Activity spaces in place and health research: Novel exposure measures, data collection tools, and designs. *Health & Place*, **58**, 2019

29. Delclòs-Alió, X., Gutiérrez, A., Miralles-Guasch, C,. The urban vitality conditions of Jane Jacobs in Barcelona: Residential and smartphone-based tracking measurements of the built environment in a Mediterranean metropolis. *Cities*, **86**, pp. 220–228, 2019
30. Evenson, K.R., Furberg, R.D., Moves app: a digital diary to track physical activity and location, *British Journal of Sports Medicine*, **51**, pp.1169-1170, 2017
31. Kestens, Y., Winters, M., Fuller, D., Bell, S., Berscheid, J., Brondeel, R., et al.. INTERACT: A comprehensive approach to assess urban form interventions through natural experiments. *BMC Public Health*, 2019
32. Product – Ethica, https://ethicadata.com/product. Accessed on: 20 July 2020
33. Kohl, H. W., et al., The pandemic of physical inactivity: global action for public health. *Lancet*, 380, pp. 294–305, 2012
34. Heinrich, K. M., et al., Associations between the built environment and physical activity in public housing residents. *International Journal of Behavioral Nutrition and Physical Activity,* 4, 2007
35. Guessous, I., et al., A comparison of the spatial dependence of body mass index among adults and children in a Swiss general population. *Nutrition & Diabetes*, 4 (e111), 2014
36. Giles-Corti, B., et al., Increasing Walking - How Important Is Distance To, Attractiveness, and Size of Public Open Space? *American Journal of Preventive Medicine*, pp.169–176, 2005
37. Boulos, M., et al., How smartphones are changing the face of mobile and participatory healthcare: an overview, with example from eCAALYX., *BioMedical Engineering OnLine,* 2011
38. Church, T. S., et. al., *Trends over 5 Decades in U.S. Occupation-Related Physical Activity and Their Associations with Obesity*, PLOS ONE, 6(5), 2011
39. World Health Organization - Physical activity - https://www.who.int/news-room/fact-sheets/detail/physical-activity, Accessed on: 14 May 2021
40. World Health Organization - Framework for Accelerating the Communication of Physical Activity Guidelines, https://www.who.int/dietphysicalactivity/publications/pacific_pa_guidelines.pdf, Accessed on: 14 May 2021
41. Marešová, K., The Costs of Physical Inactivity in the Czech Republic in 2008, *Journal of Physical Activity and Health*, 11(3), pp. 489–494, 2013
42. World Health Organization - Czech Republic - Physical Activity Factsheet – 2018- https://www.euro.who.int/en/countries/czechia/data-and-statistics/czech-republic, Accessed on: 14 May 2021
43. Pavelka, J., Sigmundová, D., Hamřík, Z., Kalman, M., Sigmund, E., Mathisen, F., Trends in Active Commuting to School among Czech Schoolchildren from 2006 to 2014, *Central European Journal of Public Health*, 25(1), pp. 21–25, 2017
44. Rojas Lopez, M. C., Wong, Y. D., Children's active trips to school: a review and analysis, *International Journal of Urban Sustainable Development*, 9(1), pp. 79-95, 2017
45. European Commission – State of Health in the EU – Czech Republic_2017, https://ec.europa.eu/health/system/files/2017-12/chp_cs_english_0.pdf, Accessed on: 22. June 2021
46. Leisure-time Physical Activity Recodes - National Center for Health Statistics, U.S. Department of Health & Human Services, https://www.cdc.gov/nchs/nhis/physical_activity/pa_recodes.htm. Accessed on: 22. June 2021
47. Frank, L. D., Andresen, M. A., Schmid, T. L., Obesity relationships with community design, physical activity, and time spent in cars, *American Journal of Preventive Medicine*, 27(2), pp. 87–96, 2004
48. Sari, N., Physical inactivity and its impact on healthcare utilization, *Health Economics*, 18(8), pp. 885–901, 2009
49. Hastrmanová, Š., Houdek, L., Romské etnikum a sport: Percepce, přínosy a omezení, *Aktuální otázky sociologie sportu*, 2007
50. Vanreusel, B., Meulders, B., Sedentary lifestyles and physical (in)activity in youth, a social risk perspective, *Obesity in Europe*, Bern, Switzerland: Peter Lang D., pp. 119–133, 2007
51. Speck, J., *Walkable City: How Downtown Can Save America, One Step At a Time*, Farrar, Straus and Giroux: New York, 2012
52. TSK a.s. (Technical Road Administration) - Ročenka Dopravy Praha 2020 - https://www.tsk-praha.cz/static/udi-rocenka-2020-cz.pdf, Acessed on: 12. July 2021
53. Lim, S., et al. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990-2010: a systematic analysis for the Global Burden of Disease Study 2010, *Lancet*, 380, pp. 2224–2260, 2012
54. World Health Organization - Global status report on road safety 2018: summary, http://apps.who.int/iris/bitstream/handle/10665/277370/WHO-NMH-NVI-18.20-eng.pdf?ua=1, Accessed on : 22. June 2021

55. Polaď Prahu - Plán udržitelné mobility Prahy a okolí – Analýza, https://poladprahu.cz/wp-content/uploads/2019/10/PAnalyza_2017-08-10.pdf, Accessed on: 1. July 2021
56. Moudon, A.V., Real noise from the urban environment: how ambient community noise affects health and what can be done about it, *Am J Prev Med*, 37, pp. 167–171, 2009
57. Brey, R., Castillo-Manzano, J. I., Castro-Nuño, M., López-Valpuesta, L., Marchena-Gómez, M., & Sánchez-Braza, A., Is the widespread use of urban land for cycling promotion policies cost effective? A Cost-Benefit Analysis of the case of Seville, *Land Use Policy*, 63, pp. 130–139, 2017
58. Allam Z., Moreno C., Chabaud D., Pratlong F., Proximity-Based Planning and the "15-Minute City": A Sustainable Model for the City of the Future, In: Brinkmann R. (eds) *The Palgrave Handbook of Global Sustainability*, Palgrave Macmillan, Cham, pp. 1-20, 2022
59. Cortright, J., Walking the Walk: How Walkability Raises Home Values in U.S. Cities, *For CEOs for Cities,* pp. 20, 2009
60. Ivey, R., Bereitschaft, B., The Impact of Walkability on the Sales Price of Commercial Properties When Controlling for the Effects of Economic Recession: A Case Study of Omaha, Nebraska, *Journal of Real Estate Literature*, 2021
61. Leinberger, Ch. B., Alfonzo, M., Walk this Way: The Economic Promise of Walkable Places in Metropolitan Washington, D.C., Metropolitan Policy Program on Brookings, https://www.brookings.edu/research/walk-this-waythe-economic-promise-of-walkable-places-in-metropolitan-washington-d-c/, Accessed on: 16. July 2021
62. Morris, A., Neill, H.R., Do Gasoline Prices Affect Residential Property Values?, The Climate And Energy Economics Project, https://www.brookings.edu/research/do-gasoline-prices-affect-residential-property-values/, Accessed on: 20. July 2021
63. Pelechrinis, K., Zacharias, C., Kokkodis, M., Lappas, T., Economic impact and policy implications from urban shared transportation: The case of Pittsburgh's shared bike system, *PLOS ONE*, 12(8), 2017
64. Soni, N. & Soni, N., Benefits of pedestrianization and warrants to pedestrianize an area, *Land Use Policy*, 57, pp. 139–150, 2016
65. Transport for London: Town Centres 2014 / 2015, http://content.tfl.gov.uk/town-centres-report-2014-15.pdf , Acessed on: 24. July 2021
66. Kunc, J., Frantál, B., Szczyrba, Z., Tonev, Z., Toušek, V., Shopping Centres And Shopping Behaviour: Selected Relations And Socio-Geographical Implications (the Vaňkovka Gallery Brno, Czech Republic Example), *Acta Universitatis Palackianae Olomucensis – Geographica*, 42 (1), pp. 5-17, 2011
67. O'Connor, N., Bradshaw, S., Shopping Travel Behaviour in Dublin City Centre, Proceedings of the ITRN 2011, https://arrow.tudublin.ie/cgi/viewcontent.cgi?article=1010&context=comlinkoth Acessed on: 23. July 2021
68. Transport for London, Town Centres 2013, http://content.tfl.gov.uk/town-centres-report-13.pdf, Acessed on: 24. July 2021
69. Clifton, K., Currans, K. M., Muhs, C. D., Ritter, C., Morrissey, S., Roughton, C., Consumer behavior and travel choices: A focus on cyclists and pedestrians, 2012, National Association of City Transportation 2012. https://nacto.org/docs/usdg/consumer_behavior_and_travel_choices_clifton.pdf. Accessed on: 23. July 2021
70. Bundesministerium für Land- und Forstwirtschaft, Umwelt und Wasserwirtschaft, Studie Radfahren und Einkaufen: Potentiale des Fahrrads für den Einzelhandel in Österreich, https://www.bmk.gv.at/themen/mobilitaet/fuss_radverkehr/publikationen/radfahren_einkaufen.html, Accessed on: 23. July 2021
71. Blondiau, T., Van Zeebroeck, B., Haubold, H., Economic Benefits of Increased Cycling. *Transportation Research Procedia*, 14, pp. 2306–2313, 2016
72. Ferreira, J. P., Isidoro, C., Moura Sá, F., Baptista Da Mota, J. C., The economic value for cycling – a methodological assessment for Starter Cities, *Hábitat y Sociedad*, (13), 2020
73. Deloitte, Big demands and high expectations - The Deloitte Millennial Survey, 2014, https://www2.deloitte.com/content/dam/Deloitte/global/Documents/About-Deloitte/gx-dttl-2014-millennial-survey-report.pdf , Accessed on: 29. July 2021
74. The Segmentation Company, Attracting College-Educated,Young Adults to Cities, *CEOs for Cities,* https://1library.net/document/y8xw6vwq-attracting-college-educated-young-adults-to-cities.html , Accessed on: 29. July 2021
75. Doherty, P. C., Leinberger, Ch. B., The Next Real Estate Boom, https://www.brookings.edu/articles/the-next-real-estate-boom/, Accessed on: 29. July 2021
76. Aldred, R., Sharkey, M., Healthy Streets: a Business View, Report prepared by the University of Westminster as a commission from Transport for London, 2017, http://content.tfl.gov.uk/healthy-streets-a-business-view.pdf , Accessed on: 29. July 2021

77. Hendriksen IJ, Simons M, Garre FG, Hildebrandt VH. The association between commuter cycling and sickness absence. *Prev Med.*, 51(2), pp. 132-135, 2010
78. Grous, A., The British cycling economy: 'gross cycling product' report, *LSE Research Online Documents on Economics,* 2011
79. Department for Transportation – London, Investing in cycling and walking – The economic case for action, https://www.gov.uk/government/publications/cycling-and-walking-the-economic-case-for-action , Accessed on: 29. July 2021
80. World Health Organization – Health economic assessment tool (HEAT) for walking and for cycling. Methods and user guide on physical activity, air pollution, injuries and carbon impact assessments (2017), Https://www.euro.who.int/en/health-topics/environment-and-health/Transport-and-health/publications/2017/health-economic-assessment-tool-heat-for-walking-and-for-cycling.-methods-and-user-guide-on-physical-activity,-air-pollution,-injuries-and-carbon-impact-assessments-2017, Accessed on: 30. July 2021
81. European Comission - Handbook on the external costs of transport - Version 2019 – 1.1, https://op.europa.eu/cs/publication-detail/-/publication/9781f65f-8448-11ea-bf12-01aa75ed71a1, Acessed on: 11. August 2021
82. Hoteit, S., et al., Estimating human trajectories and hotspots through mobile phone data, *Computer Networks*, 64: p. 296–307, 2014
83. Calabrese F. et al., Real-Time Urban Monitoring Using Cell Phones: A Case Study in Rome, *IEEE Transactions Intelli-gent Transportation Systems*, **12** (1), pp. 141-151, 2011
84. Novák, J., Temelová, J., Everyday Life and Spatial Mobility of Young People in Prague: A Pilot Study Using Mo-bile Phone Location Data, *Czech Sociological Review*, **48** (5), pp. 911–938, 2012
85. Ahas, R., Mark, Ü., Location based services—new challenges for planning and public administration?, *Futures*, 37(6), pp. 547–561, 2005
86. Novák, J., Novobilský, J., Inovativní přístupy k zachycení přítomného obyvatelstva: Data mobilních operátorů. *Urbanismus a územní rozvoj,* 16, pp. 14-19, 2013
87. Cesare, N., Lee, H., McCormick, T., Spiro, E., & Zagheni, E., Promises and Pitfalls of Using Digital Traces for Demographic Research, *Demography*, **55(5)**, pp.1979-1999, 2018
88. Cottineau, C., & Vanhoof, M., Mobile Phone Indicators and Their Relation to the Organisation of Cities, *ISPRS International Journal of Geo-Information*, **8(1)**, 2019
89. Anda, C., Erath, A., & Fourie, P.J., Transport modelling in the age of big data, *International Journal of Urban Sciences*, pp. 19-42, 2017
90. Leng, Y., Noriega, A., Pentland, A.S., Winder, I., Lutz, N., & Alonso, L., Analysis of Tourism Dynamics and Special Events through Mobile Phone Metadata, *Proceedings of Data for Good Exchange (D4GX),* 2016
91. Novák, J., *Lokalizační data mobilních telefonů: Možnosti využití v geografickém výzkumu*, Charles University in Prague, Faculty of Science, Department of Social Geography and Regional Development, 2010
92. Čtyroký, J., Novotný, V., Soukup, M., Big data Praha: Využití lokalizačních dat mobilních operátorů v hl. M. Praze, GIS Ostrava 2016 conference
93. Čtyroky, J. – Head of Spatial Information Section, IPR Prague (2016, May 27). Personal interview
94. Android senzory, https://developer.android.com/reference/android/hardware/, Accessed on: 20 April 2020
95. CO2GO, SENSEable City Laboratory, http://senseable.mit.edu/co2go/, Acessed on: 30. May 2014
96. Shin, D., et al., A Crowdsourcing Urban Simulation Platform on Smartphone Technology – Strategies for urban data visualization and transportation mode detection, Human-Computer interaction, *Human-Computer Interaction – Proceedings of the 30th International Conference on Education and research in Computer Aided Architectural Design in Europe,* **2**, pp. 377-384, 2012¨
97. Shin, D., et. al, Urban sensing: Using smartphones for transportation mode classification, *Computers, Environment and Urban Systems*, 53, pp. 76–86, 2015.
98. Sayed, A. H., Tarighat, A., Khajehnouri, N., Network-Based Wireless Location - Challenges faced in developing techniques or accurate wireless location information, *IEEE Signal Processing Magazine*, pp. 24-40, 2005
99. Shin, D., Urban Sensing by Crowdsourcing: Analysing Urban Trip behaviour in Zurich, *Int J Urban Regional*, 40, pp. 1044-1060, 2016
100. Su, X., Caceres, H., Tong, H., He, Q. , Online Travel Mode Identification Using Smartphones With Battery Saving Considerations*, IEEE Transactions on Intelligent Transportation Systems*, 17(10), pp. 2921-2934, 2016
101. Li, J., Pei, X., Wang, X., Yao, D., Zhang, Y., Yue, Y., Transportation mode identification with GPS trajectory data and GIS information, *Tsinghua Science and Technology*, 26(4), pp. 403–416, 2021

102. Yao, Y., Su, X.., Tong, H., *Mobile Data Mining*., Springer, Cham, 2018
103. Zheng, Y., Liu, L., Wang, L., Xie, X., Learning Transportation Mode from Raw GPS Data for Geographic Applications on the Web, *WWW '08: Proceedings of the 17th international conference on World Wide Web,* pp.247–256, 2008
104. Zheng, Y., Chen, Y., Li, Q., Xie, X., Ma, W.Y., Understanding transportation modes based on GPS data for web applications*, ACM Transaction on the Web,* 4 (1), 2010
105. Wang, B., Wang, Y., Qin, K., Xia, Q., Detecting Transportation Modes Based On LightGBM Classifier From GPS Trajectory Data, *26th International Conference on Geoinformatics*, pp. 1-7, 2018
106. Chung, E.H., Shalaby, A., A Trip Reconstruction Tool for GPS-based Personal Travel Surveys, *Transportation Planning and Technology*, 28 (5), pp.381-401, 2005
107. Delli Priscoli, F., Giuseppi, A., Lisi, F., Automatic Transportation Mode Recognition on Smartphone Data Based on Deep Neural Networks, *Sensors*, 20 (24), pp. 7228, 2020
108. Higgins, J.P., 2016. Smartphone Applications for Patients' Health and Fitness. The American Journal of Medicine, 129(1), 2016
109. Greenly, https://en.greenly.earth/, Acessed on: 3.5.2021
110. Capture - Carbon Footprint & CO2 Tracker for Travel and Food, https://www.thecapture.club/, Accesed on: 3. May 2021
111. Dobrican, R.A., Zampunieris, D.A., Proactive Solution, using Wearable and Mobile Applications, for Closing the Gap between the Rehabilitation Team and Cardiac Patients. *2016 IEEE International Conference On Healthcare Informatics (ICHI)*, pp.146-155, 2016.
112. Armstrong, N., Nugent, C., Moore, G., Finlay, D., Using smartphones to address the needs of persons with Alzheimer's disease. *Annals of telecommunications - annales des télécommunications*, **65**, pp. 485–95, 2010
113. Brown, D.K., Barton, J.L., Pretty, J., Gladwell, V.F., Walks4Work: assessing the role of the natural environment in a workplace physical activity intervention, Scand J Work Environ Health, 40(4), pp. 390-9, 2014.
114. Google Play – Kalorické Tabulky, https://play.google.com/store/apps/details?id=cz.psc.android.kaloricketabulky&hl=cs&gl=US, Accessed on: 12 August 2021
115. Nakládalová, M., Sovová, E., Ivanová, K, Kaletová, M., Lukl, J. & Fialová, J., Risk factors for cardiovascular diseases in physicians, *Biomed Pap Med*, **149** (2), pp. 293-5, 2005.
116. Stavební slovník - Construction dictionary, www. stavebnikomunita.cz/page/stavebni-slovnik-d, Accessed on: 20 July. 2020
117. Stockton, J. C., et.al., Development of a novel walkability index for London, United Kingdom: cross-sectional application to the Whitehall II Study, *BMC Public Health*, **16**(1), 2016.
118. Auto*mat - Cyklistika v kopcovitých městech? Rozhodně ano!, https://auto-mat.cz/23959/cyklistika-v-kopcovitych-mestech-rozhodne-ano, Accessed on: 9 July. 2020.
119. Xing, Y., Volker, J., Handy, S., Why do people like bicycling? Modeling affect toward bicycling. *Transportation Research Part F Traffic Psychology and Behaviour*, **56**, pp. 22–32, 2018.
120. Wang, Y., Ao, Y., Zhang, Y., Liu, Y., Zhao, L., Chen, Y.,. Impact of the Built Environment and Bicycling Psychological Factors on the Acceptable Bicycling Distance of Rural Residents. *Sustainability*, **11** (4404), 2019.
121. Moreno, C., Allam, Z., Chabaud, D., Gall, C., Pratlong, F., Introducing the" 15-Minute City": Sustainability, Resilience and Place Identity in Future Post-Pandemic Cities. *Smart Cities,* **4**, pp. 93–111, 2021
122. Feng, J., Glass, T.A., Curriero, F.C., Stewart, W.F., Schwartz, B.S., The built environment and obesity: A systematic review of the epidemiologic evidence. *Health & Place*, **16**, pp. 175–90, 2010
123. Carlson, J.A., Remigio-Baker, R.A., Anderson, C.A.M., Adams, M.A., Norman, G.J., Kerr, J., et al.. Walking mediates associations between neighborhood activity supportiveness and BMI in the Women's Health Initiative San Diego cohort. *Health & Place*, **38**, pp. 48–53, 2016
124. James, P., Kioumourtzoglou, M.-A., Hart, J.E., Banay, R.F., Kloog, I., Laden, F., Interrelationships Between Walkability, Air Pollution, Greenness, and Body Mass Index. *Epidemiology*, **28**, pp. 780–788, 2017.
125. Van Kamp, I., Leidelmeijer, K., Marsman, G., De Hollander, A., Urban environmental quality and human well-being. *Landscape and Urban Planning*, **65**(1-2), pp. 5–18, 2003
126. Mitchell,.G., Namdeo, A., Kay, D., A new disease-burden method for estimating the impact of outdoor air quality on human health, *Sci Total Environ*, **246**(2-3), pp.153-63, 2000
127. Dygrýn, J., Medrano, M., Molina-Garcia, P., Rubín, L., Jakubec, L., Janda, D., Gába, A., Associations of novel 24-h accelerometer-derived metrics with adiposity in children and adolescents. *Environmental Health and Preventive Medicine*, **26**(1), 2021

128. Hamrik, Z., Sigmundová, D., Kalman, M., Pavelka, J., Sigmund, E., Physical activity and sedentary behaviour in Czech adults: Results from the GPAQ study. *European Journal of Sport Science*, **14**(2), pp. 193–198, 2014.
129. Pelclová, J., *Physical activity in the lifestyle of the adult and senior population in the Czech Republic*, First English Edition, Palacký University, Olomouc, pp. 51– 60, 2015
130. Mitáš, J., Frömel, K., Pohybová aktivita dospělé populace české republiky: Přehled základních ukazatelů za období 2005–2009, *Tělesná kultura*, **34**(1), pp.9–21, 2011
131. Polaď Prahu – Analýza, https://poladprahu.cz/wp-content/uploads/2019/10/PAnalyza_2017-08-10.pdf, Accessed on: 9. August 2021
132. Čertický, M., Drchal, M., Cuchý, M. & Jakob, M., Fully Agent-based Simulation Model of Multimodal Mobility in European Cities, *Models and Technologies for Intelligent Transportation Systems*, 2015.
133. McNally, M. G., "*The four-step model". Handbook of Transport Modelling: 2nd Edition*, Emerald Group Publishing Limited: West Yorkshire, pp. 35-53, 2007.
134. Drchal, J., Čertický, M. & Jakob, M., Data Driven Validation Framework for Multi-agent Activity-based Models, *Multi-Agent Based Simulation XVI. MABS 2015*, Springer International Publishing: Cham, 2015.
135. Mäki-Opas, T. E., et al., The contribution of travel-related urban zones, cycling and pedestrian networks and green space to commuting physical activity among adults – a cross-sectional population-based study using geographical information systems, *BMC Public Health*, BioMed Central: London, 2016.
136. Handy, S. L., Boarnet, M. G., Ewing, R. & Killingsworth, R., E., How the Built Environment Affects Physical Activity - Views from Urban Planning, *American Journal of Preventive Medicine*, **23** (2), pp. 64-73, 2002
137. Rahman, N. A., Shamsuddin, S. & Ghani, I., What Makes People Use the Street?: Towards a liveable urban environment in Kuala Lumpur city centre, *Procedia - Social and Behavioral Sciences*, 170, pp. 624-632, 2015
138. Zheng, Y., Zhang, L., Xie, X., Ma. W.-Y, Mining interesting locations and travel sequences from GPS t rajectories., *Proceedings of International conference on World Wild Web*, ACM Press, Madrid Spain, pp. 791-800, 2009
139. Zheng, Y., Li, Q., Chen, Y., Xie, X., Ma. W.-Y, Understanding Mobility Based on GPS Data, *Proceedings of ACM conference on Ubiquitous Computing*, ACM Press, Seoul, Korea, pp. 312-321, 2008
140. Zheng, Y., Xie, X., Ma, W.-Y, GeoLife: A Collaborative Social Networking Service among User, location and trajectory. *IEEE Data Engineering Bulletin*, **33**(2), pp. 32-40, 2010
141. Microsoft – GeoLife, https://www.microsoft.com/en-us/research/publication/geolife-gps-trajectory-dataset-user-guide/, Accessed on: 12 August 2021
142. The Transport Research Centre (Centrum Dopravního Výzkumu) - Czech Republic on the Move, https://www.ceskovpohybu.cz/zprava#sber-dat, Accessed on: 12 August 2021
143. Moreno, C., The 15 minutes-city: for a new chrono-urbanism!, http://www.moreno-web.net/the-15-minutes-city-for-a-new-chrono-urbanism-pr-carlos-moreno/. Accessed on 10 September 2021

GRANTS

This thesis was supported by:

Grant SGS - SGS20/077/OHK1/1T/15
In year: 2020;

Grant SGS - SGS19/075/OHK1/1T/15
In year: 2019;

Scholarship of the CTU - Stanislav Hanzl Foundation
In years: 2018, 2017 ;

Josef, Marie and Zdeňka Hlávka Endowment Foundation
In year: 2017

CURRICULUM VITAE

Ing. arch. Ladislava Fialka Sobková
Čechova 34, Prague 7
Tel.: +420 732 571 178
E-mail: sobkolad@fa.cvut.cz, ladi.sob@gmail.com
Date of birh: 9.7.1982
Place of birth: Uherské Hradistě

Education:

2013 - 2022	doctoral degree - FA, ČVUT
2006 – 2009	masters degree - FA, ČVUT
2002 – 2005	bachelor degree - FA, ČVUT
2006 – 2007	Erasmus – internship Escola Técnica Superior de Barcelona, Spain
1997 - 2001	Grammar school, Uherské Hradiště

Practice:

04. 2011- 2017 — Atelier 8000 spol. s r.o., Prague, CZ
senior architect

Execution:
Residential complex K Hájům / Jindrova

Projects:
Warehouse complex for flood protection parts, Mlazice - study, DUR
Císařská louka - urban planning study
Residential complex Lučištníků - DSP
Reconstruction of the BBC-C office building - study
Study of the Prague 5 waterfront
Urban planning of the development area - Čestlice - study
IGY 2 - shopping mall - interior study
Doosan Industrial Complex - study
Residential complex Řevnice - study

Competitions:
Revitalization of Perla 01 - Ústí nad Orlicí - 3rd place
Residence for Kuwaiti diplomats - 3rd place

02 - 04. 2011 — M1 architekti

12. – 02. 2011 — TheKey.to, International Event for green Fashion
architect of the fair-event

04. - 10. 2010 — J MAYER H , Berlin, Germany
internship

06. 2008 – 03. 2010 — MCA atelier, Prague, CZ
junior architect

03. 2006 – 09. 2006 — Despatx Bardon y Conrado , Barcelona, Spain
junior architect

03. 2004 – 09. 2005 — Atelier A – Prague, CZ
junior architect

PUBLICATIONS

Fialka Sobková, L.; Jiráček, Š. Čertický, M., Smartphone-Based Sensing: Lifestyle And Mobility Data Interpretation By Smart Cities¨
In: *WIT Transactions on Ecology and the Environment,* Cambridge: WIT Press, pp. 335-347, 2020
ISBN 978-1-78466-413-8.

Fialka Sobková, L., M. Čertický , Š. Jiráček., Application Of Transportation Big Data To Support Decision-Making For Architecture Teams: Processes And Experiences From Two Case-Studies.
In: Mambretti, S., Miralles I Garcia, J.L. eds., *WIT Transactions on Ecology and the Environment. Sustainable City 2019 - 13th International Conference on Urban Regeneration and Sustainability*, Southampton: WIT Press, Ashurst Lodge, pp. 639-651, 2019
ISSN 1743-3541.
ISBN 978-1-78466-355-1.
DOI 10.2495/SC190551
supported by a grant: SGS 19/075/OHK1/1T/15

Fialka Sobková, L., M. Čertický. Urban mobility and influence factors: A case study of Prague.
In*: WIT Transactions on the Built Environment. 23rd International Conference on Urban Transport and the Environment*, Cambridge: WIT Press, pp. 207-217, 2018
ISSN 1743-3509.
ISBN 978-1-78466-210-3.
DOI 10.2495/UT170181
supported by Stanislav Hanzl Foundation

Fialka Sobková, L., H. Achten., Smartphone Application for Long-term Urban Lifestyle and Mobility Monitoring.
In: DA COSTA, M.J.R.C. et al., eds. *Architectural Research Addressing Societal Challenges: Proceedings of the EAAE ARCC 10th International Conference (EAAE ARCC 2016)*, London: CRC Press, pp. 77-80, 2017
ISBN 978-1-138-02966-8.
DOI 10.1201/9781315226255-13
supported by Stanislav Hanzl foundation and “Endowment of Josef, Marie and Zdeňka Hlávka” Foundation

Sobková, L., How to Use Mobile-Based Sensing to Crowdsource - Smartphone. Application for Long-term Urban Lifestyle and Mobility Monitoring.
In: Saura, M., Muntanola, J.,eds. *Arquitectonics Network: Mind, Land and Society, Barcelona.* 2016.
http://pa.upc.edu/ca/Varis/altres/arqs/congresos/congresointernacional-arquitectonics-network-mente-territorio-y-sociedad/abstracts
ISBN 978-84-617-6829-5.
supported by Stanislav Hanzl foundation and “Endowment of Josef, Marie and Zdeňka Hlávka” Foundation

Sobková, L., - UrbanFIT - Od kalorií k chytrým městům, *TecniCall,* 23 (**1**), pp. 23, 2016
ISSN 1805-1030.