Minimizing the influence of coronavirus in a built environment

MICROBE

O3. Development, testing and improvement of the MICROBE System

Project No: 2020-1-LT01-KA203-078100

CONTENT

1. O3/A1: Formulation of the Research Problem

1.1. Affective Internet of Things

Affective Internet of Things is applicable in various areas (Fig. 1). For example, wearable emotion sensors are widely used by psychologists and therapists, in clinics, hospitals, etc. IoT is implementing emotional ingredients in the wristbands too. Their sensor technology also allows for gathering data on heart rate, blood pressure and temperature to define an individual's emotional states. Such emotion sensors are relatively low-cost, easy to use, and have a wide variety of utilization.

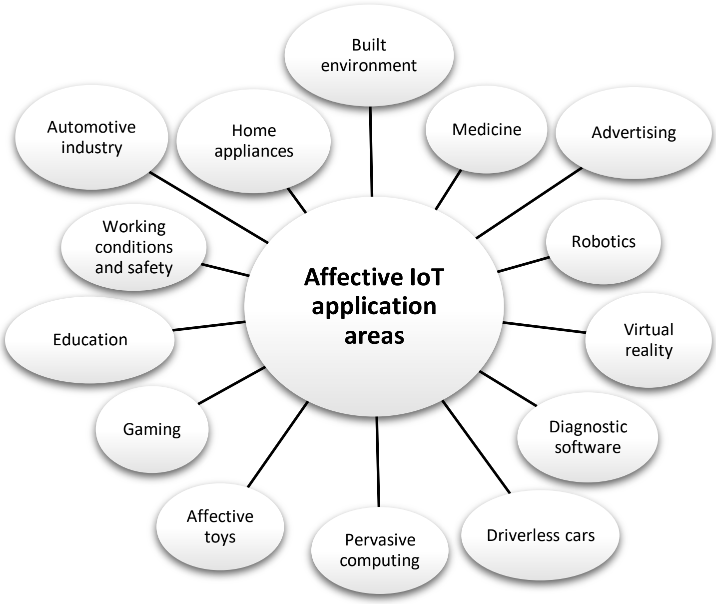


Figure 1. Affective IoT application areas.

Smart watches and health wearables create a foundation for technology that helps coordinate daily habits while avoiding potential health issues and other problems. With a modern smart device, the user can track and evaluate their physical condition and how they react to stress-inducing situations, as well as learn to manage stress and anxiety better. The device might instruct them to practice a mind controlling technique or to do breathing exercises to calm down, or turn on relaxing music [1]. There are many advantages to using anthropomorphic approaches when designing things. Anthropomorphic techniques that use human language and symbolism, and devices such as virtual assistants and chatbots, can promote natural interaction, trust, learning and empathy between artificial intelligence (AI) software/models and humans. That's not to say that a strong anthropomorphic approach is always best. In sensitive situations (such as a robot providing medical advice to a user) overly anthropomorphic approaches could make patients uncomfortable and prevent them from disclosing essential information. Anthropomorphization also offers another opportunity. This is the notion of obtaining digital customer/worker/citizen feedback from the "voice of the thing" (VoT). Humanizing a connected thing creates the opportunity to obtain feedback from it in the same way we would from a human being, complementing existing human feedback. Another key consideration is determining whether a thing has a "voice." It's important to distinguish between simple reporting of operational Internet of Things data and what would be considered the VoT. The key distinction is that VoT requires some form of intelligence that drives thing opinion. The VoT doesn't just report facts. It enriches them, contextualizes, them and provides a rationale for the feedback. While the baseline for thing feedback is simply factual and event-based reporting, the VoT should be associated with something more — encompassing opinions, beliefs, contextual enrichment of narratives and exposition of rationales around balancing short- and long-term goals. That's the difference between operational reporting and the VoT for the various types of feedback — whether direct, indirect and inferred. Another potential stumbling block is that the anthropomorphization of things will likely span multiple departments including CRM, digital workplace, innovation, IT, marketing and multiple other business units. The ensuing cultural, political and technical hurdles could all complicate progress. As things become more autonomous — and are better able to take actions independent of humans — the ability for things to provide feedback to other things will help accelerate their learning and subsequent performance [2].

New emotion-sensing technologies and software fueled by artificial emotional intelligence can read and analyze not only skin conductance, breathing and heart rate, but also eye movements, facial expressions, changes in voice, etc. And they don't necessarily require installing expensive hardware, but rather just some recognition software or additional code for computers or smartphones. For example, even slow or uneven cursor movements may reflect distraction or negative emotions of the user. New emotion detection technologies could help employees make better decisions, improve their focus and performance in the workplace, manage stress, and adopt healthier and more productive work styles. Traders are a good example. They tend to overpay for assets and downplay risk in what they call a 'bidding frenzy'. To address this problem, Philips and ABN AMRO developed the Rationalizer bracelet back in 2009. While the bracelet measured emotions via electrodermal activity, a display was reflecting the user's heightened emotional states. The display thus signaled the need to pause and rethink financial decisions. Some of the world's elite coaches, teams, and individual athletes have used headsets produced by San Francisco-based SenseLabs Inc. Their Versus gear connects to an iPhone or iPad via bluetooth and has dry sensors for assessing brain performance. This makes it possible to identify strengths and weaknesses in problem-solving, multitasking, resource management, decision-making, and sleep tendencies. Versus then provides customized exercise protocols to improve mental acuity, concentration, and sleep management. Aggregated data from such devices can help companies understand how internal and external environmental factors impact employees and groups. As a result, they might redesign processes accordingly to help keep personnel better engaged and productive [1].

Emotion AI, also known as affective computing, enables everyday objects to detect, analyze, process and respond to people's emotional states and moods — from happiness and love to fear and shame. This technology can be used to create more personalized user experiences, such as a smart fridge that interprets how you feel and then suggests food to match those feelings. In the future, more and more smart devices will be able to capture human emotions and moods in relation to certain data and facts, and to analyze situations accordingly. Although emotion AI capabilities exist, they are not yet widespread. A natural place for them to gain traction is in conversation systems — technology used to converse with humans — due to the popularity of virtual personal assistants (VPAs) such as Apple's Siri, Microsoft's Cortana and Google Assistant. Today VPAs use natural-language processing and natural-language understanding to process verbal commands and questions. But they lack the contextual information needed to understand and respond to users' emotional states. Adding emotion-sensing capabilities will enable VPAs to analyze data points from facial expressions, voice intonation and behavioral patterns, significantly enhancing the user experience and creating more comfortable and natural user interactions. Prototypes and commercial products already exist — for example, Beyond Verbal's voice recognition app and the connected home VPA Hubble [3].

Speech-based emotion analysis in real time opens up more business opportunities. This and other emotion-sensing technologies can enable companies to establish deeper emotional connections with their consumers through virtual assistants. Popular VPA like Siri, Cortana, and Google Assistant use natural-language processing and natural-language understanding to process verbal commands and questions. Adding emotion sensing capabilities will enable them to create more comfortable and natural user interactions. Call centers are another potential customer group. Voice-based emotion sensing can enable automated customer service agents to recognize callers' emotional states and adapt to them. It will also help management analyze stress levels of human workers. In the future, more and more smart devices will be able to capture emotional reactions to certain data and facts, analyze situations accordingly, and come up with appropriate recommendations. Currently, the healthcare and automotive industries are among the most eager to adopt emotion-sensing features. Car manufacturers are exploring the implementation of in-car emotion detection systems to improve road safety by managing the driver's drowsiness, irritation, and anxiety. For instance, Panasonic Corporation's new sensing technology can detect a person's emotions and sense of being hot or cold in a contactless manner. This information can be used for predicting a driver's drowsiness to help keep them awake. The technology measures a driver's blinking features and facial expressions captured by an in-vehicle camera and processes these signals using AI. Further, using the data on heat loss from the driver and in-vehicle illuminance, it predicts transitions in the driver's drowsiness level. Combining this thermal sensation monitoring function, the system helps the driver to stay comfortably awake while driving. When the drowsiness level is high, it issues a sound alarm or a command to rest [1].

Personal assistant robots (PARs) are also prime candidates for developing emotion AI. Many already contain some human characteristics, which can be expanded upon to create PARs that can adapt to different emotional contexts and people. The more interactions a PAR has with a specific person, the more it will develop a personality. Some of this work is currently underway. Vendors such as IBM and startups such as Emoshape are developing techniques to add human-like qualities to robotic systems. Qihan Technology's Sanbot and SoftBank Robotics' Pepper train their PARs to distinguish between, and react to, humans' varying emotional states. If, for example, a PAR detects disappointment in an interaction, it will respond apologetically. The promise of emotional AI is not too far into the future for other frequently used consumer devices and technology, including educational and diagnostic software, video games and the autonomous car. Each is currently under development or in a pilot phase. The video game Nevermind, for example, uses emotion-based biofeedback technology from Affectiva to detect a player's mood and adjusts game levels and difficulty accordingly. The more frightened the player, the harder the game becomes. Conversely, the more relaxed a player, the more forgiving the game. There are also in-car systems able to adapt to the responsiveness of a car's brakes based on the driver's perceived level of anxiety. In both cases, visual sensors and AI-based, emotion-tracking software are used to enable real-time emotion analysis. These systems will detect the driver's moods and be aware of their emotions, which in return, could improve road safety by managing the driver's anger, frustration, drowsiness and anxiety [3].

With the help of mood sensor technology, children or elderly family members in need of care will be able to receive timely assistance and support from their families or caregivers. Emotion-sensing wearables will help monitor the state of mind of persons with mental and other health conditions 24/7. When necessary, they will alert doctors and caregivers and inform about upcoming changes in the person's mood and behaviour. Remote emotions detection is possible as well. One of the devices created at MIT's Computer Science and Artificial Intelligence Laboratory emits radio signals that reflect off a person's front and back body. By measuring heartbeat and breathing, the device can accurately detect emotional reactions. Such remote sensing technologies could be used to diagnose or track conditions such as depression and anxiety, as well as for non-invasive health monitoring and diagnosis of heart conditions. Technology that deduces human emotion based on audio-visual cues may enable businesses to detect consumers' positive and negative moods to better understand their preferences, analyze customers' choices to utilize in marketing, and detect users' annoyances to improve product usability, etc. For instance, a fridge with a built-in emotion sensor may interpret a person's mood and suggest a more suitable food. Emotion-sensing smart home devices could provide entertainment (music, videos, TV shows or imagery) which matches the user's current state of mind. Video games might use emotion-based biofeedback technology to adjust game levels and difficulty according to the player's emotional states. MIT Media Lab spinoff Affectiva has been analyzing people's facial expressions and non-verbal cues for applications in advertising, marketing, and video games for years. But their vision is to build a multimodal emotion AI platform that senses and measures emotions the way humans do. In September 2017, Affectiva announced the release of cloud-based software that identifies the speaker's gender and observes changes in speech paralinguistics, tone, volume, speed, and voice quality to distinguish anger, laughter, or arousal.

IBM along with numerous startups are developing techniques to add human-like qualities to robotic systems. The development of emotional AI will lead to creating more effective personal assistant robots. They will be able to distinguish between, and react to, different people and their emotional states. For example, when a robot detects disappointment on the human's part, it will respond apologetically in a modulated voice. Interacting with a specific person, it will gradually learn emotional awareness. Since emotions remain a fundamental need for humans, emotion-sensing technology should start teaching intelligent objects how to interact with humans as soon as possible [1].

1.2. IoT, Smart Homes, Ambient Intelligence and Affective Computing

Humans deeply modified their relationships to their housing over the past centuries. Once a shelter where humans could find protection and rest, their living place became the center of the family – the expression of their culture. Nowadays, it is a more self-centered place, where individuals develop their own personal aspirations and can express their social position. Electricity was the first technology to enter the home environment, followed by communication technologies to make a human, 'a motionless nomad,' connected with others in any place at any time. A new living place is being invented, the 'witness' of our existence, perceiving the inhabitants' rhythms of activities, habits, tastes, and wishes. Among all the services a living place can bring to inhabitants, we find comfort, security, wellness, and health services. The information and communication technologies in homes can now help extend our longevity (Noury 2014).

The world population is ageing rapidly with the percentage of older adults increasing to 24% by 2030 from 10% in 2000. Therefore cost of providing aged care has been growing, especially in countries such as Japan, the USA and Australia. Robotic technology has been identified as being able to help older adults to live independently, and is emerging as an innovative approach to assist older adults directly, for example, robotic wheelchairs and indirectly for instance providing support to stakeholders, including caregivers. A systematic literature review of peer-reviewed literature published in Medline, ScienceDirect, ProQuest, PubMed, Scopus and SpringerLINK, from 1 January 2000 to mid-July 2015 was undertaken. An initial set of 8533 studies was refined to 58 studies. Nine robot types were identified in addressing aged care problems, including companion, manipulator service, telepresence, rehabilitation, health monitoring, reminder, entertainment, domestic, and fall detection/prevention robots. These robot types have been applied to eight key problem areas in aged care, namely social isolation, dependent living, physical or cognitive impairment, mobility problems, poor health monitoring, lack of recreation, memory problems and fall problems. The frequency of research into each robot type was analysed, with the finding some robotic technologies have received more attention (e.g., companion) while other types that can assist older adults with independent living (e.g., cooking and bathing) were not as comprehensively researched [4].

The elderly population is increasing and the response of the society was to provide them with services directed to them to cope with their needs. One of the oldest solutions is the retirement home, providing housing and permanent assistance for the elderly. Furthermore, most of the retirement homes are inhabited by multiple elderly people, thus creating a community of people who are somewhat related in age and medical issues. The ambient assisted living (AAL) area tries to solve some of the elderly issues by producing technological products, some of them dedicated to elderly homes. One of the identified problem is that elderly people are sometimes discontent about the activities that consume most of their day promoted by the retirement home social workers [5]. Costa et al. [5] attempt to improve how these activities are scheduled taking into account the elderlies' emotional response to these activities. The aim is to maximize the group happiness by promoting the activities the group likes, minding if they are bored due to activities repetition. In this sense, this paper presents an extension of the Cognitive Life Assistant platform incorporating a social emotional model. The proposed system has been modelled as a free time activity manager which is in charge of suggesting activities to the social workers [5].

Wilson et al. [6] describe an integration of robots into smart environments to provide more interactive support of individuals with functional limitations. Robot Activity Support (RAS) system, partners smart environment sensing, object detection and mapping, and robot interaction to detect and assist with activity errors that may occur in everyday settings. Wilson et al. [6] describe the components of the Robot Activity Support system and demonstrate its use in a smart home testbed. To evaluate the usability of RAS, Robot Activity Support also collected and analyzed feedback from participants who received assistance from Robot Activity Support system in a smart home setting as they performed routine activities [6].

A home is not only a technical space according to each individual's role but also a social space where family members interact with each other. However, the number of single-person households has recently shown an exponential increase. At the same time, the smart home technology has been growing in order to provide at-home rest to individuals. In this situation, a home's role as a social space is diluted, and many people cannot receive the social support they need at home [7]. Lee et al. [7] introduce the concept of social connectedness for the interaction between users and smart home devices. It can be divided into two types. One is the Inner Social Connectedness (ISC) that is generated through connections between the user and the devices in their smart home. The other is the Outer Social Connectedness (OSC) that is generated through connections between the user and the smart home devices in other people's houses. Lee et al. [7] also introduce two types of interaction. One is the unmediated interaction, in which users interact with each device and the individual device reveals its presence. The other one is the mediated interaction, in which users interact with a single agent that represents various smart home devices. In order to investigate the impact of both inner/outer social connectedness and mediated/unmediated interaction types, Lee et al. [7] conducted a controlled experiment using a prototype smart home system.

Currently, there is an increasing number of patients that are treated in-home, mainly in countries such as Japan, USA and Europe. As well as this, the number of elderly people has increased significantly in the last 15 years and these people are often treated in-home and at times enter into a critical situation that may require help (e.g. when facing an accident, or becoming depressed). Advances in ubiquitous computing and the Internet of Things (IoT) have provided efficient and cheap equipments that include wireless communication and cameras, such as smartphones or embedded devices like Raspberry Pi. Embedded computing enables the deployment of Health Smart Homes (HSH) that can enhance in-home medical treatment. The use of camera and image processing on IoT is still an application that has not been fully explored in the literature, especially in the context of HSH. Although use of images has been widely exploited to address issues such as safety and surveillance in the house, they have been little employed to assist patients and/or elderly people as part of the home-care systems [8]. In Mano et al. [8] view, these images can help nurses or caregivers to assist patients in need of timely help, and the implementation of this application can be extremely easy and cheap when aided by IoT technologies. This article discusses the use of patient images and emotional detection to assist patients and elderly people within an in-home healthcare context. Mano et al. [8] discuss few studies that take into account the patient’s emotional state, which is crucial for them to be able to recover from a disease.

Smart home technology (SHT) has been identified as a promising means of helping seniors to remain independent and maintain their quality of life (QoL) while containing spiralling care costs for older people. Despite official pilot schemes in many countries to promote SHT in seniors housing, there is limited understanding of the forms that such SHT interventions should take [9]. Wong et al. [9] research builds on the analytical model of intelligent building control systems; the aim is to provide a systematic approach to understanding the key intelligent attributes of smart-home devices. A qualitative participatory evaluation approach involving focus groups was adopted to investigate the needs of seniors and their SHT preferences [9].

Pieroni et al. [10] introduce the concept of Affective Internet of Things (AIoT) where smart objects are empowered with affective capability in terms of abstraction of their emotional state. Moreover each smart object can be associated with a specific `personality'. This approach, already used in the field of social robotics, mainly exploits robots' appearance (i.e. anthropomorphism or zoomorphism). The research aims at extending such a paradigm to everyday-life objects in order to `warm-up' the empathic connections that humans generally establish with `cold' gadgets and devices. A new framework for the Affective IoT has been developed: EMPATI (EMPATI Mimics Personalities on Affective Things on Internet). It provides models and functions to simulate different personality for affective objects living in both virtual and real world. Finally, a set of experiments has been conceived to assess the key aspects of the framework in terms of capability to simulate emotional responses depending on the object interaction with the environment and the affective stimuli [10].

1.3. BIM, Smart and Interactive Buildings

Building Information Modeling (BIM) is a powerful technology that is used to support decision-making about a building during its life-cycle. The article shows that traditional BIM solutions, due to its static nature, don't cover all needs of "smart" buildings technology. Dynamic extension of Building Information Model is proposed to cover gaps of traditional BIM in the design and operational stages of "smart" buildings life-cycle.An exploratory model on the usability of a prototyping-process for designing of Smart Building Envelopes [11].

Application of nD BIM Integrated Knowledge-based Building Management System (BIM-IKBMS) for inspecting post-construction energy efficiency [12]. Tracking Users' Behaviors through Real-time Information in BIMs [13]. An intelligent building supports the needs of its occupants by data analytics. Nowadays, buildings are evolving from being products to become effective service providers for end-users: thus, occupancy topics become crucial. Implementation of Building Management Systems (BMS) into a Building Information Modeling (BIM) environment, connecting real-time information collected by sensors to a BIM database [13].

The IoT application domains empower the vision of a built environment pervaded by sensors and actuators in which homes do not waste energy, where interactive walls display useful information, as well as pictures of art or videos of friends. Even more potentialities could be exploited through data collection, considering that the connected devices have an annual growth more than 10%, and over 500 billion connected devices are expected worldwide by 2025 [14]. Nowadays, several buildings are built from the ground up with nearly one IoT-enabled sensor per square meter monitoring temperature, humidity, the weight in the trash cans, how many people are in a room, and on and on [13].

It has been estimated that users waste 30% of energy in buildings because of their behavior [15]. Anyway, the occupant variable and the behavior tracking are crucial to define an operational rational use and tailored services on the real needs of users, avoiding wastes of energy [16, 17] in a lean vision of the buildings management [18]. To analyze how the information collected during the operational stage could enlighten end-users about the behavior of both buildings and occupants. Therefore, advantages in tracking the behavior of occupants and in satisfying the needs of users should be derived through the availability of real-time information (e.g., data collected by sensors measuring and reporting outdoor conditions, indoor comfort parameters, system efficiency factors). Later, predictive buildings anticipated the occupancy needs and set themselves to face environmental and behavioral inputs using Information and Communications Technology (ICT) to support managers and operators. Nowadays, cognitive buildings learn from the user behavior and traduce the data coming from the outdoor, the indoor and the social environment using an IoT approach. In this way, the responsiveness is reset in time, making the building autonomous to react in some situation [13].

Within this scenario, user behavior could be tracked in order to define customized operations in which the building measures the number of people inside and adjusts heating and lighting accordingly, turning an empty building off, as a computer goes into standby mode. Moreover, it is possible to localize the heating and cooling systems, providing a detailed, individual climate for each user by means of arrays of responsive infrared heating elements that are guided by sophisticated motion tracking providing thermal "clouds", following people through spaces and ensuring pervasive comfort whereas improving overall energy efficiency. By adequately processing these data, it is possible to assess building performances, to evaluate user levels of satisfaction, to estimate occupant preferences or to track user behaviors [13].

The research aims to define a workflow to populate BIM models using data gathered through remote sensors, driving parameters in BIM models, changing parameters in digital models to provide input and possibly modifying physical models. In this way, users become aware of their behavior and should interact with buildings, i.e., through online dashboards or apps, improving their behavior and increasing their awareness. Moreover, designers benefit of an improvement of the building process not only collecting and filtering feedback of users in operation, but also checking and verifying instantaneous and historical values of defined parameters. Finally, facility managers are instantly informed about failures or damages and the process can support rapid fault detection [13].

Through ad-hoc apps, it is possible to access sensors data, retrieved from the BMS or directly from the sensors through the Z-wave gateways and to provide feedbacks of the students on comfort level in the classrooms, interacting with the building. In this way, it should be possible to develop strategies such that buildings could adapt their behavior depending on the user needs, communicated via app. The bi-directional interaction through the app embodies the introduction of the human factor into the IoT structure to enable the cognitive building to learn from behaviors providing data in real-time with the capability to process them into adaptive and predictive strategies for improved comfort and servitization. The scenarios are created with data gathered through sensors installed into the building. As an example, in the scenario of the school, when a sensor gives feedback that the air quality in the classroom is getting worse, ventilation will be triggered and the room will improve its air quality. Cognitive buildings are also highly feasible [19] as most modern buildings have already a series of sensors implemented in them when they are finished [20, 21]. The idea is to introduce the user in the loop of information and connect the body of knowledge about the building. Objective data coming from sensors and subjective data coming from students and visitors can be collected directly, i.e., by the user definition of the comfort conditions, and indirectly, i.e. through the sentiment analysis [22]. As an example, data could be gathered through sensors, could be encoded in language (e.g., textbooks, formulas, conversation) or could be captured in sight, sound and motion [23]. By adequately processing these data, it is possible to assess building performances, to evaluate user levels of satisfaction, to estimate occupant preferences or to track user behaviors. Through BIM models, it is possible to transform collected data in usable information to gain deeper insights on how buildings perform throughout their life cycle. In this way, users become aware of their behavior and should interact with buildings, i.e., through online dashboards or apps, improving their behavior and increasing their awareness [13].

Distributed, networked, electronically tagged, interactive devices are increasingly incorporated into the physical environment blurring progressively the boundary between physical and virtual space. This changing relationship between physical and virtual implies not only a change in the operation and use of buildings but also a change in their physical configuration, and therefore, their design and production. Interactive building addresses, therefore both the building defined as physically built environment and the building process implying on the one hand the changing role of architecture with respect to incorporation of interactivity and the resulting multiple and varied use of built environments in reduced timeframes. On the other hand, it is implying the changing role of the architect with respect to the use of networks connecting digital databases and parametric models with customizable design and production tools allowing for linking design to production and use [24].

In order to raise awareness of the role of building information modeling (BIM) in improving energy efficiency and comfort conditions, the work introduces a strategy of combining building simulation tools and optimization methods. Furthermore, it emphasizes the fact that a combination of these strategies with BIM can improve not only the construction process but also enable exploration of alternative approaches. The work discusses the potential application of data integration methodology for an office environment and focuses on the review of the potential performance of integrated systems. It also explains how BIM can help facilitate review of results and methods for improving building performance in terms of energy efficiency and indoor environmental quality [25, 26].

Most BIM (Building Information Modelling) systems serve designers well up until now but will have to evolve toward a more user-centered design, focusing on interactive spaces rather than focusing on digital representation. They are lack of information needed in order to create a virtual environment which can interact with users. Such problems will become more prominent in the case of smart spaces where the environment reacts to users' activity. There are no sufficient tools to design and represent real usage of smart space. A task-based interaction is proposed to apply Smart BIM in a design process. Smart Design systems help end users to experience their daily activity in a virtual environment and understand the space reactions. It can be used as a toolset to improve communications among users and designers in design processes especially in the design of smart environments. Eventually, it is expected that Smart-BIM will lead to match smart technology usability with users' demands. Hence, the prototype gives the opportunity of evaluating users' attitude and expressions toward an interactive and responsive BIM [27].

Intelligent management systems (IMSs) have significant potential for energy savings, but they have not been fully used in buildings and cities. Smart sensor systems based on user behavior will improve indoor environmental quality (IEQ) and user comfort. This work aims to reduce energy consumption and provide comfort conditions by learning user behavior. In order to improve energy efficiency and comfort conditions, smart sensor systems and digital simulation tools play a crucial role in finding optimal solutions to optimization problems [28].

CoSMoS: A BIM and wireless sensor based integrated solution for worker safety in confined spaces [29].

This work explores the application of a real-time monitoring system to achieve optimal indoor environmental quality (IEQ). ICT-related applications have drawn attention from smart buildings as potential means of providing correlations between users and building systems to improve energy efficiency and comfort. In order to investigate whether users can take advantage of natural environmental factors during occupied hours in office buildings, daylight and energy performance simulations were carried out. This work explores users as the primary factors to improve indoor environmental quality (IEQ) and energy efficiency. The results support the use of real-time monitoring systems in office buildings. It seems, however, that there is a need for individual user control of thermal, ventilation, and lighting [28].

This research presents the architecture of a technology platform capable of integrating different types of data from building sensors and providing an interface to manage and operate facility devices, which is supported by advanced optimization algorithms. This interface is potentiated by a BIM-based interface presenting real-time data of the building. The solution, called 3i buildings - Intelligent, Interactive, and Immersive Buildings, is a tool to monitor and manage smart buildings, as well as optimize users experience, energy consumptions and environment quality. This is achieved by a grid of sensors and devices that continuously gather information (structural conditions of the building, occupancy, comfort of occupants, energy consumptions and CO2, COV's and Humidity levels, etc.), which is processed by predictive models able to learn over time. The 3D representation of the models allows managers to take advantage of the virtual environment, by augmenting the facility model and including information about the facility, making it easier and perceptible to users and owners, helping them to make better decisions. These types of systems might help reducing energy consumptions as well as increasing comfort and satisfaction of occupants, maintaining a constant concentration of CO2 and humidity within the facility. The optimized algorithms will allow the system to learn, predicting and reacting to different conditions, giving a more reliable and smooth response to occupants needs [30].

Current urban water research involves intelligent sensing, systems integration, proactive users and data-driven management through advanced analytics. Such research would pave the way for demand-side management, active consumers, and demand-optimized networks, through interoperability and a system of systems approach. The web service integrates state of the art sensing, data analytics and middleware components. We propose an ontology for the domain which describes smart homes, smart metering, telemetry, and geographic information systems, alongside social concepts. This integrates previously isolated systems as well as supply and demand-side interventions, to improve system performance [31].

Building energy management systems (BEMS) are integrated building automation and energy management systems, utilizing IT or ICT, intelligent and interoperable digital communication technologies promoting a holistic approach to controls and providing adaptive operational optimization. The system may have multiple levels from individual sensors and actuators to users' interface, to facilitate data collection, analysis, diagnose, trend finding, and decision-making. BEMS dynamically control indoor climate in a cost-effective manner and ensures the comfort, safety, and wellbeing of the occupants in buildings [32].

The ability to process large amounts of data and to extract useful insights from data has revolutionised society. This phenomenon—dubbed as Big Data—has applications for a wide assortment of industries, including the construction industry. The construction industry already deals with large volumes of heterogeneous data; which is expected to increase exponentially as technologies such as sensor networks and the Internet of Things are commoditised. In this paper, we present a detailed survey of the literature, investigating the application of Big Data techniques in the construction industry. We reviewed related works published in the databases of American Association of Civil Engineers (ASCE), Institute of Electrical and Electronics Engineers (IEEE), Association of Computing Machinery (ACM), and Elsevier Science Direct Digital Library. While the application of data analytics in the construction industry is not new, the adoption of Big Data technologies in this industry remains at a nascent stage and lags the broad uptake of these technologies in other fields. This paper fills the void and presents a wide-ranging interdisciplinary review of literature of fields such as statistics, data mining and warehousing, machine learning, and Big Data Analytics in the context of the construction industry [33].

Buildings are key players when looking at end-use energy demand. It is for this reason that during the last few years, the Internet of Things (IoT) has been considered as a tool that could bring great opportunities for energy reduction via the accurate monitoring and control of a large variety of energy-related agents in buildings. However, there is a lack of IoT platforms specifically oriented towards the proper processing, management and analysis of such large and diverse data. In this context, we put forward in this paper the IoT Energy Platform (IoTEP) which attempts to provide the first holistic solution for the management of IoT energy data. The platform support for data analytics. As part of this work, we have tested the platform IoTEP with a real use case that includes data and information from three buildings totalizing hundreds of sensors [34].

Due to the complexity and increasing decentralisation of the energy infrastructure, as well as growing penetration of renewable generation and proliferation of energy prosumers, the way in which energy consumption in buildings is managed must change. Buildings need to be considered as active participants in a complex and wider district-level energy landscape. To achieve this, the authors argue the need for a new generation of energy control systems capable of adapting to near real-time environmental conditions while maximising the use of renewables and minimising energy demand within a district environment. They could provide energy management and cost savings for adaptable users, while meeting energy and CO2 reduction targets [35].

1.4. Modern Office Smart Systems

Some researchers have proposed asking officemates to basically vote on what the temperature should be. Using a phone app or website, building occupants say whether they're too hot or too cold, and what would make them more comfortable. An algorithm then analyzes the groups' answer and calculates a temperature estimated to be most acceptable to most people. In previous research, our group placed multiple temperature sensors around an office, and combined their data with information from wristbands that sensed occupants' skin temperature and heart rates and apps that polled workers about how they felt. We found that adding the data about how people's bodies were reacting made the algorithm more accurate at calculating the room temperature at which people occupying a given space would feel most comfortable. Our current project, seeks to make things even easier and less intrusive for people, eliminating the wristbands and apps, and only using remote sensing of people's skin temperature to measure how comfortable they are. We developed a method using regular cameras, thermal imaging and distance sensors to detect occupants' presence in a space, focus on their faces and measure their skin temperature. From that data, our algorithm calculates whether – and how – to change the temperature in the room regardless of the number of occupants in the space. When we tested it in an office occupied by seven people, they complained less about feeling uncomfortably cold or warm [36].

Smart HVAC technology reduces energy costs, lessens the workload on facilities staff, and provides better comfort conditions for employees. Occupancy sensors. Occupancy sensors are useful for office environments (like most) that don't have uniform usage all the time. Increasingly mobile workers are leaving desks and conference rooms empty as much as 50 to 60 percent of the time. Meanwhile, you're heating and cooling space for people who are not there. Occupancy sensors detect the presence of people (typically by detecting motion) currently using individual spaces within an office. That data can be used to adjust temperatures based on real-time utilization, saving you money on energy consumption. While your HVAC system consumes anywhere from 40 to 70 percent of your building's energy usage, electricity for lighting is also a huge expense. That figure can be 25 percent or more. In addition to controlling a smart HVAC system, occupancy sensors also control lighting to further reduce lighting costs. Thermal sensors. Strategically-placed thermal sensors can detect the differences in conditions in each zone of your space. For example, a crowded conference room can get warm in a hurry, while an open office area with high ceilings can get chilly (since warm air rises and people are closer to the floor). A smart HVAC system uses that data to adjust to changing conditions throughout the day or week. CO2 sensors. CO2 sensors can detect the levels of CO2 gas in a space, which can increase to undesirable levels as occupancy increases. When the threshold is reached, a smart HVAC system can increase levels of fresh air supplied to the space. This technology can have a significant impact on workforce wellbeing [37].

The smart sensors, including mobile phone, wearable device and other sensors, are introduced. They are the key elements to determine human intentions. Wearable devices, such as watches or bracelets, may be adopted for detecting the human sleeping state as the feedback signals of the sleeping function. It can collect human motion information, and feedback to the smart air conditioner for further control. Smart control, based on the information collected by the use of mobile phones and wearable devices, intensifies the interaction with occupants and carries out the intention causing control [38]:

(1) Mobile phones with GPS and personal schedules, for detecting the occupants' position and intentions, could foresee the occupants' intention of entering the enclosed space. At this moment, the compressor, which is off in the general situation, could turn on in the full power. Before entering, the circulating fan turns on at the highest speed, and the air deflector swings for 10 min to enhance the air circulation. Therefore, smart control may enable the enclosed space could be cooled down rapidly after the occupant enters.

(2) The bracelet with the accelerator could detect the movement of occupants while the sleeping. After the occupant falls into a deep sleep, the air conditioner would lift the indoor temperature flexibly to avoid energy consumption. The smart air conditioner could adjust the compressor output actively according to the occupants' active intention (going home) and passive one (falling into a deep sleep) for the goals of human comfort and energy conservation.

One such system, Comfy, integrates with an office's heating, ventilation and air conditioning (HVAC) system. It allows employees to make requests from their smartphone or Web browser to have the office space warmed or cooled. The system also makes employee requests visible to everyone else in their heating and cooling "zone"—which subtly encourages compromise and communication between employees who might not see eye-to-eye. With this type of technology, employees get the instant gratification of having their voice heard. Over time, the software analyzes usage habits for each occupant and "learns" workday patterns (for example, when employees arrive and leave for the day). The system then begins to automatically tailor heating and cooling flows accordingly, while optimizing them to be as efficient as possible—resulting in less dramatic fluctuations in office temperature, which can help companies save money. One interesting note that might explain many office squabbles: Women like it hot; men like it Hoth. The median preferred temperature for men is 70F, compared to 72F for women. Among 18- to 25-year-olds and 26- to 35-year-olds, only 32 and 34 percent, respectively, express frequent dissatisfaction (several times a week or more) with their office's temperature. Compare that to dissatisfaction rates among the 46- to 55-year-old bracket, where 69 percent are frequently dissatisfied.

SOLUTION: Provide different temperature "zones" throughout the office—perhaps in the form of a digital "heat" map—and allow employees to work where they are most comfortable [39].

This system enables users to determine the minimum and maximum conditions for ensuring the best estimated indoor air quality (IAQ) while a building under examination is in the design stage. With the simulator, a user can have detailed information by clicking links for the rooms of the graphical output. Some important information about a classroom is presented at the graphical interface, such as open/closed windows, door status, instant temperature, humidity, current student number, predicted CO2 and O2 ppm values, minimum outdoor air ventilation requirement, and calendar information. To improve the prediction capability, besides their quantity the characteristics of the occupants are also added to the model, such as their physical activity, body weight and height, and time spent in a classroom. For example, CO2 estimations calculated by the model and the number of students in the classroom/corridor that comes from the real course schedule of the department can be seen as a function of time. The statuses of the door/windows (open/closed) are also considered in the model [40].

Sensor and actuator technologies based on ubiquitous computing and wireless sensor networks (WSN) have been employed in attempts to implement responsive environments. The office at Xerox PARC is one of the examples of such responsive environments, where electric outlets, HVAC systems, and lightings were automatically controlled in response to the occupants' preferences [41]. Pan et al. developed an intelligent light control system based on WSN in indoor environments [42]. They showed the proposed system can determine the proper illuminations of devices to achieve the desired optimization goals depending on the illumination requirement according to the user activities and profiles. Much effort has been also devoted to developing smart heating systems using smart thermostat and occupant behaviors. Gao and Whitehouse [43] claimed large potential energy savings would be possible without sacrificing the occupant's comfort only if setback schedules are defined correctly. They introduced a self-programming thermostat that automatically create an optimal setback schedule by sensing the occupancy statistics of a home, but also allow the occupants to select. The experimental results show that the method can reduce heating and cooling demand by up to 15% over the default setback schedule recommended by EnergyStar [44].

However, researchers at Concordia University may have found a solution to this problem: A system that automates the control of indoor environmental conditions and optimizes both individual workers' productivity and energy consumption. The system optimizes indoor environmental conditions including air quality, temperature and lighting based on the preferences of each office worker. The researchers created a mathematical model of the preferences of each office worker to simulate worker preferred indoor temperatures, ventilation rates, natural light and artificial lighting based on sensors places throughout the office [45].

The optimization uses the personal satisfaction curves for all occupants to determine the temperature settings in each office. This optimized “Have-It-Your-Way” (HIYW) system improves occupant’s comfort while reducing energy consumption. Since occupants remain thermally comfortable within a certain temperature tolerance that varies from one individual to another, the results of this approach, which takes advantage of the varying thermal comfort tolerances of the occupants, are quite encouraging. The “Have-It-Your-Way” (HIYW) approach would use all the sensor network connectivity in the building [46].

1.5. Analysis of patents and systems

Many scientists have also done researches in the field of individual thermal comfort and indoor air quality [47-57]. An overview of patent and systems analysis is provided in Fig. 2. Some of them are briefly described below.

Kim et al. [47] employ machine learning to predict individuals' thermal preference. Kim et al. [47] claim that personal comfort models based on occupants' heating and cooling behavior can effectively predict individuals' thermal preference and can therefore be used in everyday comfort management to improve occupant satisfaction and energy use in buildings.

Liu et al. [49] developed a neural network evaluation model for individual thermal comfort based on the back propagation algorithm. Compared with the experimental data from the human thermal comfort survey, the evaluation results showed a good match with the subject's real thermal sensation, which indicated this model can be used to evaluate individual's thermal comfort, rightly [49].

Wang et al. [50] evaluated a novel approach to personal comfort systems that leverages the time-dependence of human thermal perception. A 6.25 cm2 wearable device, Embr Wave, delivers dynamic waveforms of cooling or warming to the inner wrist. The results indicate that this low-power, wearable device improves whole-body thermal sensation, comfort, and pleasantness [50].

Jung and Jazizadeh [53] have investigated the impact of personal thermal comfort sensitivities – distinct individual reactions to temperature variations– on collective conditioning. They proposed an agent-based control mechanism to simulate the multi-occupancy space, controlled by an HVAC agent to provide air conditioning for multiple human agents using three operational strategies to compare conventional strategies with proposed approach. Researchers' investigations demonstrated that thermal comfort sensitivity plays a statistically significant role in collective conditioning as it resulted in changes of temperature setpoint in 86% of cases and a higher probability of achieving collective comfort [53].

ComfortSense aimed at decoupling energy demand from indoor comfort [55]. Cottafava et al. [55] approach - which was multidisciplinary and included the contribution of sociologists, physicists and computer scientists - was based on Internet of Things technologies, on a Living Lab design and testing process and on a Crowdsensing approach. With ComfortSense, users send a feedback about thermal comfort. If the negative feedback is received and, due to other negative feedback previously received, plans to reduce the temperature by 1°C, increasing the comfort and reducing the energy consumption. Cottafava et al. [55] also developed three Direct Virtual Sensors (DVS) to predict: (1) the global, (2) the thermo-hygrometric and (3) the air quality comfort. Each DVS was designed to predict future users' feedback from a few environmental objective measurements as described by the following equation, $y(t+1) = f\left(\overline{u(t)}\right)$, where $y(t+1)$ is the output (i.e. the comfort feedback) at time t+1, f is a non-linear function and $\overline{u(t)}$ is the array of the average values of the environmental variables (input) at time t. More precisely, each DVS needs the following variables as input: (1) temperature, relative humidity and CO2 (global comfort), (2) temperature and relative humidity (thermo-hygrometric comfort), and (3) temperature, humidity and CO2 (air quality comfort). Thus, for instance, the general comfort DVS equation is described by $y(t+1) = f\left(u_1(t), u_2(t), u_3(t)\right)$ where ui represents the average value of temperature (u1), relative humidity (u2) and CO2 concentration (u3) at time t [55].

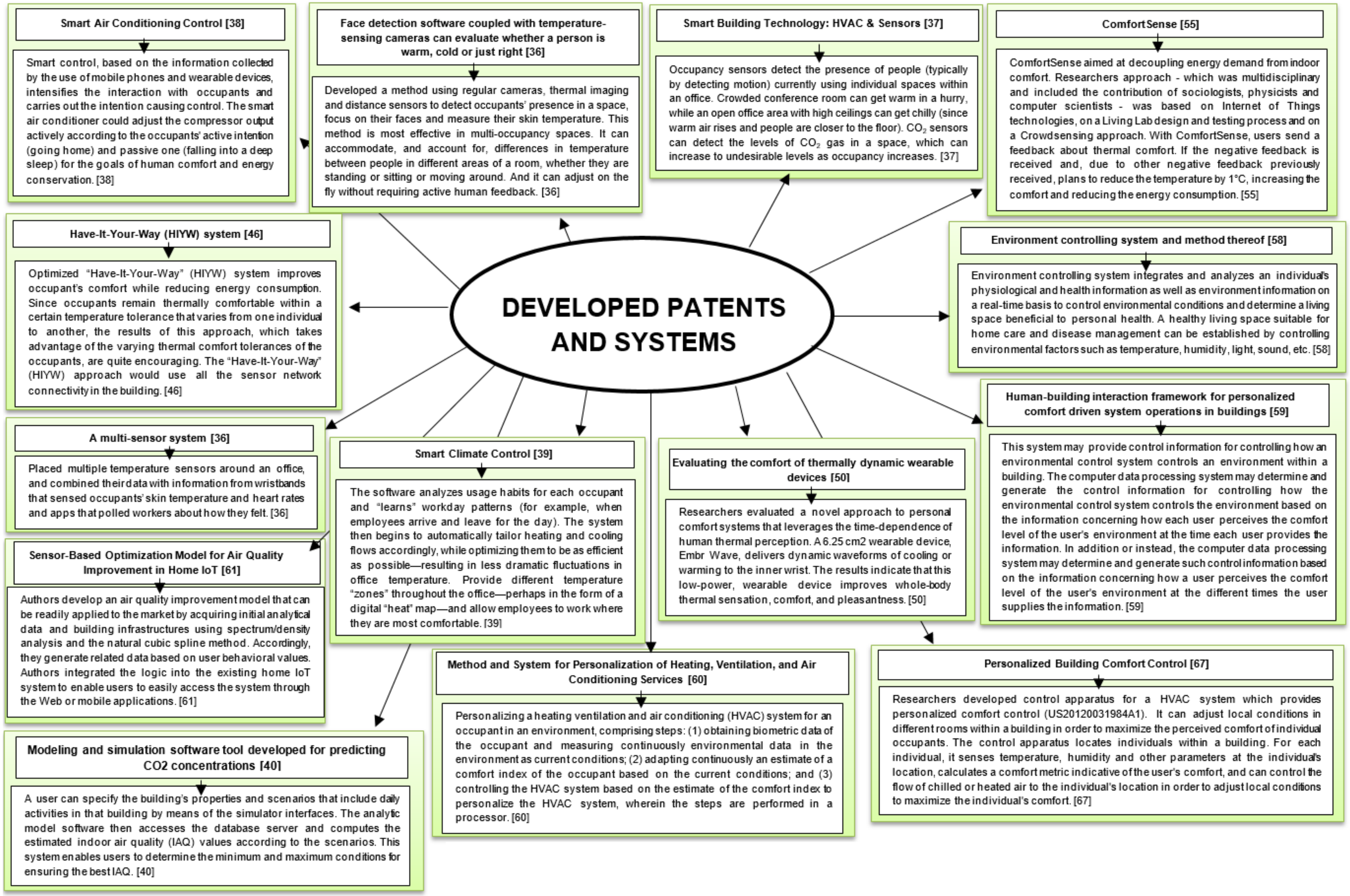


Figure 2. An overview of patent and systems analysis

Lu et al. [57] develop a thermal comfort model with RP 884 of three major climate zones based on k-nearest neighbor (KNN), random forest (RF) and support vector machine (SVM). During the experiment, the researchers also changed the temperature at 1°C by analyzing a thermal comfort model. The results have shown that the best recall of the statistical thermal comfort model is 49.3%, which outperforms that of PMV being 43% based on 7-point thermal sensation scale. In addition, the Q-learning based temperature control can indeed reach the comfortable temperature ranges for occupants with whatever initial temperature set-point [57].

Patent analysis of methods [58, 60, 62-67] and systems [58-60, 62, 63, 65-70] has also been performed. The patented methods are briefly described below.

Huang [58] environment controlling method provide a central processing equipment, obtaine physiological and environmental information by means of said personal physiological measurement equipment and said environment measurement equipment, decide an optimum environmental condition on the basis of said physiological, environmental and health information, transmitte regulation information, and regulate environmental conditions by environment controlling equipment [58].

Nikovski [60] patented a method for personalizing a heating ventilation and air conditioning (HVAC) system for an occupant in an environment, comprising steps: (1) obtaining biometric data of the occupant and measuring continuously environmental data in the environment as current conditions; (2) adapting continuously an estimate of a comfort index of the occupant based on the current conditions; and (3) controlling the HVAC system based on the estimate of the comfort index to personalize the HVAC system, wherein the steps are performed in a processor [60].

Lee et al. [63] patented a method for controlling temperature and humidity by a temperature and humidity control device includes acquiring at least one piece of environmental information and user biometric information, determining, based on the acquired at least one piece of the environmental information and the user biometric information, control information that determines statistical information to be within a certain range, and controlling an HVAC system based on the determined control information [63].

CN107120782A [64] invention provides a heating and ventilating system control method based on multiple-user thermal comfort data. The method comprises the steps that user thermal comfort data are obtained according to current season information fed back by users, the current user movement states and thermal comfort preference; corresponding user thermal comfort preference curves are obtained according to the user thermal comfort data; the thermal comfort probability distribution curves of cold, hot and comfort are obtained according to the user thermal comfort preference curves; a multiple-user thermal comfort probability distribution curve at different indoor environment temperature is obtained according to the thermal comfort probability distribution curves of all users; and the comfort temperature interval of the multiple-user thermal comfort probability distribution curve is used as a selection interval of temperature set values, and the optimal temperature set value of a controlled thermal space is obtained according to the corresponding relation of the air supply volume and the temperature set value. Scientists provided a curve for thermal comfort probability distribution for the user (equation 1) [64]:

$$Prob_{agg}(T_{in}) = \frac{\sum_{j=1}^{n} Prob_j(T_{in}|S_{th} = C, \beta)}{max \sum_{j=1}^{n} Prob(T_{in}|S_{th} = C, \beta)} \tag{1}$$

where, [eta] represents a number of users of the hot space, C represents each person in the room cool, partial thermal comfort three kinds of comfort model "comfort" category corresponding to the model, indicating that the beta] parameter model of comfort, Sth representation, Tin represents the indoor temperature, Probagg output name, j denotes the number of person in the room [64].

CN108413588A [65] method based on thermal imaging and BP neural network, is characterized including following Steps: (1) by the regular typing of user and more new individual essential information, and carry out the Real-time Feedback of hot comfort, institute's typing information is used In the corresponding evaluation index such as calculating BMI and infrared thermal imaging data is instructed to acquire; (2) infrared thermal imaging module carry out thermal imaging data acquisition; (3) carries out the conversion of Infrared Thermogram and temperature field data; (4)is directed to the temperature data points of different user by the extraction of temperature field data according to user's typing information; (5) carries out BP neural network training using user as unit to input layer data; (6) obtains the control strategy of air-conditioning system by data analysis; (7) air-conditioning system automatic controller receive the control signal for coming from message processing module, and to air-conditioning system end End equipment carries out automatically controlling [65].

Laftchiev and Natarajan [66] developed method for controlling an operation of a set of devices for an occupant which use input devices to accept inputs from a plurality of humans, sensors to take sensor measurements, the sensor measurements including measurements of temperature, processor and actuator to cause, in accordance with the control signals, mechanical motion of one or more objects to alter air flow.

Huang [58] environment controlling system integrates and analyzes an individual's physiological and health information as well as environment information on a real-time basis to control environmental conditions and determine a living space beneficial to personal health. A healthy living space suitable for home care and disease management can be established by controlling environmental factors such as temperature, humidity, light, sound, etc. [58].

Karimi et al. [59] developed human-building interaction framework for personalized comfort driven system operations in buildings. This system may provide control information for controlling how an environmental control system controls an environment within a building. The computer data processing system may receive and store reports from multiple users and/or may receive and store reports at different times from a user. Each report may provide information concerning how the user perceives the comfort level of the user's environment at the time the user supplies the information. The computer data processing system may determine and generate the control information for controlling how the environmental control system controls the environment based on the information concerning how each user perceives the comfort level of the user's environment at the time each user provides the information. In addition or instead, the computer data processing system may determine and generate such control information based on the information concerning how a user perceives the comfort level of the user's environment at the different times the user supplies the information [59].

The system proposed by Nikovski [60] consists of a wearable device (configured to obtain biometric data and a comfort level of the occupant and measuring continuously environmental data in the environment as current conditions), a processor (configured to adapt continuously an estimate of a comfort index of the occupant based on the current conditions), and a HVAC system that is controlled according to the estimate of the comfort index [60].

Feldmeier [62] developed control apparatus for a HVAC system which provides personalized comfort control. It can adjust local conditions in different rooms within a building in order to maximize the perceived comfort of individual occupants. The control apparatus locates individuals within a building. For each individual, it senses temperature, humidity and other parameters at the individual's location, calculates a comfort metric indicative of the user's comfort, and can control the flow of chilled or heated air to the individual's location in order to adjust local conditions to maximize the individual's comfort [62].

Lee et al. [63] patented device for controlling room temperature and humidity. It is possible to provide a comfortable environment to a user and save energy while maintaining comfort. The present disclosure relates to a sensor network, Machine Type Communication (MTC), Machine-to-Machine (M2M) communication, and technology for Internet of Things (IoT). The present disclosure may be applied to intelligent services based on the above technologies, such as smart home, smart building, smart city, smart car, connected car, health care, digital education, smart retail, security and safety services [63].

CN108413588A [65] patented personalized air-conditioner control system based on thermal imaging and BP neural network. System includes human-computer interaction module, thermal imaging module, message processing module and passes through BP nerves network technique, which is calculated, optimizes air-condition system control parameter, airconditioning control module for receiving transmission signal and realizing to air-conditioning [65].

Levy and Betz [67] invention involves the personal air conditioning of individual workstations in an open office space layout. The individual workstation's air is supplied by a major air plenum located under a horizontal surface of the workstation. The conditioned air is directed by a smaller self-contained air terminal located under a floor representing a larger major air plenum or chamber. The conditioned air is supplied to the individual workstations at or near the atmospheric pressure. The multiple of smaller air terminals are the movers of the conditioned air by way of driving fans installed therein and activated as the need arises. The conditioned air is moved from the smaller air terminals by flexible air tubes to the air plenum mounted under the desk surface. A person situated at the workstation can control the direction of air emanating from the front of the personalized air outlet plenum toward the person in multiple directions. Further, the person can also control the volume of the personal air by being able to divert some of the air away from the person through a wall in the desk or through a wall of a room partition to an adjoining space. The person at the workstation has the option of dividing the main air stream either to a frontal outlet directed at the person or to an outlet away from the person to enter the general atmosphere of the work space [67].

Levy and Betz [68] object of the invention is to present a system for distributing conditioned air throughout an office layout in a most efficient way. In a building whether large or small, different people have different levels of metabolism and therefore different comfort needs. Personalized air conditioning/displacement ventilation system incorporated in a stand-alone unit, said system is installed on a floor having an air plenum below said floor but above a concrete slab, a supply of conditioned air is located in said plenum and is moving air into a flexible air duct, said stand-alone unit consists of an upstanding chamber being connected to said flexible air duct, said chamber having various controls therein to control a flow of air either to a front of said chamber or to a lateral side of said chamber into the ambient atmosphere surrounding said chamber [68].

CN103062871B [69] invention relates to an air conditioning control system based on the measured skin temperature, including infrared thermometer, the rotating bed, telescopically foldable stand, the orientation controller infrared thermometer, air-conditioning controller Temp, rubber hoses and gaskets, infrared thermometer orientation of the controller are connected with an infrared thermometer, base, air-conditioning controller Temp, infrared thermometer mounted on the base, the bracket fixed to the wall above the bed or table mounted on the desk, rubber a gasket mounted between the base and the bracket, respectively, air-conditioning controller Temp infrared thermometer, infrared thermometer orientation controller, room air conditioner or air conditioning personalized connected [69].

CN105258308A [70] invention discloses a personalized ventilation control system suitable for civil buildings and vehicles. The personalized ventilation control system comprises an air conditioner air supply opening arranged in a peripheral region of a seat. By means of the personalized ventilation control system, the energy utilization efficiency of personalized ventilation can be improved, the heat comfort of the human body is met, energy saving of the air conditioner system is achieved, and meanwhile the requirement for comfort of users is met, and the energy saving function is achieved [70].

1.6. References

[1] M. Slesar Emotion-Sensing Technology in the Internet of Things. (2018) https://onix-systems.com/blog/emotion-sensing-technology-in-the-internet-of-things (accessed November 08, 2019).

[2] J. Davies, L. Goasduff. How to Listen to the Voice of “Things” in the IoT. (2017) https://www.gartner.com/smarterwithgartner/how-to-listen-to-the-voice-of-things-in-the-IoT/(accessed November 08, 2019).

[3] A. Zimmermann, L. Goasduff. How artificial intelligence is being used to capture, interpret and respond to human emotions and moods. (2018) https://www.gartner.com/smarterwithgartner/emotion-ai-will-personalize-interactions/(accessed November 08, 2019).

[4] M. Shishehgar, D. Kerr, J. Blake. A systematic review of research into how robotic technology can help older people. Smart Health. 7 (2018) 1-18. https://doi.org/10.1016/j.smhl.2018.03.002

[5] A. Costa, J. A. Rincon, C. Carrascosa, P. Novais, V. Julian, V. Activities suggestion based on emotions in AAL environments. Artificial intelligence in medicine. 86 (2018) 9-19. https://doi.org/10.1016/j.artmed.2018.01.002

[6] G. Wilson, C. Pereyda, N. Raghunath, G. de la Cruz, S. Goel, S. Nesaei, B. Minor, M. Schmitter-Edgecombe, M. E. Taylor, D. J. Cook. Robot-enabled support of daily activities in smart home environments. Cognitive Systems Research. 54 (2019) 258-272. https://doi.org/10.1016/j.cogsys.2018.10.032

[7] B. Lee, O. Kwon, I. Lee, J. Kim. Companionship with smart home devices: The impact of social connectedness and interaction types on perceived social support and companionship in smart homes. Computers in Human Behavior. 75 (2017) 922-934. https://doi.org/10.1016/j.chb.2017.06.031

[8] L. Y. Mano, B. S. Faiçal, L. H. Nakamura, P. H. Gomes, G. L. Libralon, R. I. Meneguete, G. P. R. Filho, G. T. Giancristofaro, G. Pessin, B. Krishnamachari, J. Ueyama. Exploiting IoT technologies for enhancing Health Smart Homes through patient identification and emotion recognition. Computer Communications. 89 (2016) 178-190. https://doi.org/10.1016/j.comcom.2016.03.010

[9] J. K. W. Wong, J. Leung, M. Skitmore, L. Buys. Technical requirements of age-friendly smart home technologies in high-rise residential buildings: A system intelligence analytical approach. Automation in Construction. 73 (2017) 12-19. https://doi.org/10.1016/j.autcon.2016.10.007

[10] M. Pieroni, L. Rizzello, N. Rosini, G. Fantoni, D. De Rossi, D. Mazzei, D. Affective Internet of Things: Mimicking human-like personality in designing smart-objects. In 2015 IEEE 2nd World Forum on Internet of Things (WF-IoT), (2015), pp. 400-405. https://doi.org/10.1109/WF-IoT.2015.7389088

[11] A. A. Volkov, E. I. Batov. Dynamic Extension of Building Information Model for “Smart” Buildings. Procedia Engineering.111 (2015) 849-852. https://doi.org/10.1016/j.proeng.2015.07.157

[12] A. G. Hoseini, T. Zhang, O. Nwadigo, A. G. Hoseini, K. Raahemifar. Application of nD BIM Integrated Knowledge-based Building Management System (BIM-IKBMS) for inspecting post-construction energy efficiency. Renewable and Sustainable Energy Reviews. 72 (2017) 935-949. https://doi.org/10.1016/j.rser.2016.12.061

[13] A.L.C. Ciribini, D. Pasini, L. C. Tagliabue, M. Manfren, E. De Angelis. Tracking Users’ Behaviors through Real-time Information in BIMs: Workflow for Interconnection in the Brescia Smart Campus Demonstrator. Procedia Engineering. 180 (2017) 1484-1494. https://doi.org/10.1016/j.proeng.2017.04.311

[14] Cisco Systems. Inc. Annual Report 2013. (2013) http://goo.gl/8zqjl5 (accessed June 30, 2016)

[15] N. Brown, R. Bull, F. Faruk, T.Ekwevugbe. Novel instrumentation for monitoring after-hours electricity consumption of electrical equipment, and some potential savings from a switch-off campaign. Energy and Buildings. 47(2012) 74-83. https://doi.org/10.1016/j.enbuild.2011.11.023

[16] European Commission. Scoping study to identify potential circular economy actions, priority sectors, material flows and value chains. Funded under DG Environment’s Framework contract for economic analysis ENV.F.1/FRA/2010/0044 Publications Office of the European Union (2014).

[17] European Commission. Circular Economy Package communications on sustainable buildings. (2014).

[18] C. Miller, A. Schlueter. Applicability of lean production principles to performance analysis across the life cycle phases of buildings. CLIMA 2013: 11thREHVA Congress and 8thInternational Conference on IAQVEC, Prague, Czech Republic (2013).
[19] D. Grünkranz. Towards a Phenomenology of Responsive Architecture: Intelligent Technologies and Their Influence on the Experience of Space. University of Applied Arts Vienna, Architecture. Vienna: University Publishing, (2007).
[20] E. Curry, S. Hasan, S. O'Riain. Enterprise energy management using a linked dataspace for Energy Intelligence. Proceeding of Sustainable Internet and ICT for Sustainability Conference, Pisa (2012).
[21] A. Khan, K. Hornbæk. Big Data from the Built Environment. Proceeding of 13th International Conference on Ubiquitous Computing, Beijing (2011).
[22] A. Montoyo, P.MartíNez-Barco, A. Balahur. Subjectivity and sentiment analysis: An overview of the current state of the area and envisaged developments. Decision Support Systems 53(4) (2012) 675-679. https://doi.org/10.1016/j.dss.2012.05.022
[23] E. Keinan. Five Ways To Build A Cognitive Business. (2015) http://goo.gl/YHrNLq (accessed June 30, 2016).
[24] H. Bier. Interactive building. Advances in Internet of Things. 2(04) (2012) 86. https://doi.org/10.4236/ait.2012.24011
[25] S. Habibi. The promise of BIM for improving building performance. Energy and Buildings. 153 (2017a) 525-548. https://doi.org/10.1016/j.enbuild.2017.08.009
[26] S. Habibi. Micro-climatization and real-time digitalization effects on energy efficiency based on user behaviour. Building and Environment. 114 (2017b) 410-428. https://doi.org/10.1016/j.buildenv.2016.12.039
[27] M. Heidari, E. Allameh, B. de Vries, H. Timmermans, F. Mozaffar. Smart-BIM virtual prototype implementation. Automation in Construction. 39 (2014) 134-144. https://doi.org/10.1016/j.autcon.2013.07.004
[28] S. Habibi. Smart innovation systems for indoor environmental quality (IEQ). Journal of Building Engineering. 8 (2016) 1-13. https://doi.org/10.1016/j.jobe.2016.08.006
[29] Z. Riaz, M. Arslan, A. K. Kiani, S. Azhar. CoSMoS: A BIM and wireless sensor based integrated solution for worker safety in confined spaces. Automation in Construction. 45 (2014) 96-106. https://doi.org/10.1016/j.autcon.2014.05.010
[30] A. A. Costa, P. M. Lopes, A. Antunes, I. Cabral, F. M. Rodrigues. 3I Buildings: Intelligent, Interactive and Immersive Buildings. Procedia Engineering. 123 (2015) 7-14. https://doi.org/10.1016/j.proeng.2015.10.051
[31] S. Howell, Y. Rezgui, T. Beach. Integrating building and urban semantics to empower smart water solutions. Automation in Construction. 81 (2017) 434-448. https://doi.org/10.1016/j.autcon.2017.02.004
[32] T. Yang, D. Clements-Croome, M. Marson. Building Energy Management Systems. Encyclopedia of Sustainable Technologies. (2017) 291-309.
[33] M. Bilal, L. O. Oyedele, J. Qadir, K. Munir, M. Pasha. Big Data in the construction industry: A review of present status, opportunities, and future trends. Advanced Engineering Informatics. 30(3) (2016) 500-521. https://doi.org/10.1016/j.aei.2016.07.001
[34] F. Terroso-Saenz, A. González-Vidal, A. P. Ramallo-González, A. F. Skarmeta. An open IoT platform for the management and analysis of energy data. Future Generation Computer Systems. 92 (2019) 1066-1079. https://doi.org/10.1016/j.future.2017.08.046
[35] J. Reynolds, Y. Rezgui, J.-L. Hippolyte. Upscaling energy control from building to districts: Current limitations and future perspectives. Sustainable Cities and Society. 35 (2017) 816-829. https://doi.org/10.1016/j.scs.2017.05.012
[36] C. Menassa, D. Li, V. Kamat. Offices are too hot or too cold – is there a better way to control room temperature? (2019) https://theconversation.com/offices-are-too-hot-or-too-cold-is-there-a-better-way-to-control-room-temperature-108982 (accessed November 08, 2019).
[37] I. Morley. Learn how smart HVAC technology is designed to modernize your workplace. (2019) https://serraview.com/smart-hvac-sensor-technology-smart-buildings/ (accessed November 08, 2019).
[38] C. C. Cheng, D. Lee, D. Smart sensors enable smart air conditioning control. Sensors (Basel, Switzerland). 14(6) (2014) 11179-203. https://doi.org/10.3390/s140611179.
[39] F. Burnson. How to Improve Employee Morale and Productivity Through Smart Climate Control. (2015) https://www.softwareadvice.com/resources/improve-employee-productivity-with-climate-control/ (accessed November 08, 2019).
[40] N. Yalcin, D. Balta, A. Ozmen. A modeling and simulation study about CO2 amount with web-based indoor air quality monitoring. Turkish Journal of Electrical Engineering & Computer Sciences. 26(3) (2018) 1390 – 1402. https://doi.org/10.3906/elk-1612-57
[41] S. Elrod, G. Hall, R. Costanza, M. Dixon, J.D. Rivi`eres. Responsive office environments. Communications of the ACM. 36 (1993) 84–85.
Pan, M.-S.; Yeh, L.-W.; Chen, Y.-A.; Lin, Y.-H.; Tseng, Y.-C. A WSN-based intelligent light
control system considering user activities and profiles. IEEE Sens. J. 2011, 8, 1710–1721
[42] M.-S. Pan, L.-W. Yeh, Y.-A. Chen, Y.-H. Lin, Y.-C. Tseng. A WSN-based intelligent light control system considering user activities and profiles. IEEE Sensors Journal. 8 (2011) 1710–1721. https://doi.org/10.1109/JSEN.2008.2004294

Gao, G.; Whitehouse, K. The Self-Programming Thermostat: Optimizing Setback Schedules Based on Home Occupancy Patterns. In Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings (BuildSys ’09), Berkeley, CA, USA, 4–6 November 2009; pp. 67–7
[43] G. Gao, K. Whitehouse. The Self-Programming Thermostat: Optimizing Setback Schedules Basedon Home Occupancy Patterns. In Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings (BuildSys ’09), Berkeley, CA, USA, (2009), pp. 67–7. https://doi.org/10.1145/1810279.1810294
[44] J. Yun, K. H. Won. Building environment analysis based on temperature and humidity for smart energy systems. Sensors. 12(10) (2012) 13458-70. https://doi.org/10.3390/s121013458.
[45] C. Borkhataria. The algorithm that could end office thermostat wars: Researchers claim new software can find the best temperature for everyone. (2017) https://www.dailymail.co.uk/sciencetech/article-4979148/The-algorithm-end-office-thermostat-war.html (accessed November 08, 2019).
[46] S. Ari, I. A. Cosden, H. E. Khalifa, J. F. Dannenhoffer, P. Wilcoxen, C. Isik. Constrained Fuzzy Logic Approximation for Indoor Comfort and Energy Optimization. NAFIPS 2005 - 2005 Annual Meeting of the North American Fuzzy Information Processing Society, (2005), pp. 500-504. https://doi.org/10.1109/NAFIPS.2005.1548586
[47] J. Kim, Y. Zhou, S. Schiavon, P. Raftery, G. Brager, G. Personal comfort models: predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning. Building and Environment. 129 (2018) 96-106. https://doi.org/10.1016/j.buildenv.2017.12.011
[48] J. Li, J. Niu, C. M. Mak, T. Huang, Y. Xie. Assessment of outdoor thermal comfort in Hong Kong based on the individual desirability and acceptability of sun and wind conditions. Building and Environment. 145 (2018) 50-61. https://doi.org/10.1016/j.buildenv.2018.08.059
[49] W. Liu, Z. Lian, B. Zhao. A neural network evaluation model for individual thermal comfort. Energy and Buildings. 39(10) (2007) 1115-1122. https://doi.org/10.1016/j.enbuild.2006.12.005
[50] Z. Wang, K. Warren, M. Luo, X. He, H. Zhang, E. Arens, W. Chen, Y. He, Y.Hu, L. Jin, S. Liu, D. Cohen-Tanugi, M. J.Smith. Evaluating the comfort of thermally dynamic wearable devices. Building and Environment. 167 (2020) 106443. https://doi.org/10.1016/j.buildenv.2019.106443
[51] B. Cao, Y. Zhu, M. Li, Q. Ouyang. Individual and district heating: A comparison of residential heating modes with an analysis of adaptive thermal comfort. Energy and Buildings. 78 (2014) 17-24. https://doi.org/10.1016/j.enbuild.2014.03.063
[52] H. Zhang, E. Arens, C. Huizenga, T. Han. Thermal sensation and comfort models for non-uniform and transient environments, part II: Local comfort of individual body parts. Building and Environment. 45(2) (2010) 389-398. https://doi.org/10.1016/j.buildenv.2009.06.015
[53] W. Jung, F. Jazizadeh, F. Comparative assessment of HVAC control strategies using personal thermal comfort and sensitivity models. Building and Environment. 158 (2019) 104-119. https://doi.org/10.1016/j.buildenv.2019.04.043
[54] Z. Li, D. Loveday, P. Demian. Feedback messaging, thermal comfort and usage of office-based personal comfort systems. Energy and Buildings. 205 (2019) 109514. https://doi.org/10.1016/j.enbuild.2019.109514
[55] D. Cottafava, S. Magariello, R. Ariano, O. Arrobbio, M. Baricco, V. M. Barthelmes, G. Baruzzo, M. Bonansone, L. Console, L. Contin, S. P. Corgnati, S. Dotta, V. Fabi, P. Gambino, I. Gerlero, A. Giovannoli, P. Grillo, G. Guaschino, P. Landolfo, M. Malano, D. Mana, A. Matassa, L. Monterzino, S. Mosca, M. Nuciari, E. Olivetta, D. Padovan, E. Pantó, A. Rapp, M. Sanseverino, A. Sciullo, S. Sella, R. Simeoni, A. Tartaglino, F. Vernero. Crowdsensing for a sustainable comfort and for energy saving. Energy and Buildings. 186 (2019) 208-220. https://doi.org/10.1016/j.enbuild.2019.01.007
[56] Y. Zhai, F. Miao, L. Yang, S. Zhao, H. Zhang, E. Arens. Using personally controlled air movement to improve comfort after simulated summer commute. Building and Environment. 165 (2019) 106329. https://doi.org/10.1016/j.buildenv.2019.106329
[57] S. Lu, W. Wang, C. Lin, E. C. Hameen, E. C. Data-driven simulation of a thermal comfort-based temperature set-point control with ASHRAE RP884. Building and Environment. 156 (2019) 137-146. https://doi.org/10.1016/j.buildenv.2019.03.010
[58] T. L. Huang. Environment controlling system and method thereof. US20070057077A1 U.S. Patent No. 7,764,180. Washington, DC: U.S. Patent and Trademark Office. (2010).
[59] F. J. Karimi, B. Becerik-Gerber, M. D. Orosz, T. Kichkaylo, A. Ghahramani. Human-building interaction framework for personalized comfort driven system operations in buildings. US20140277765A1. U.S. Patent Application No. 14/213,475. (2014).
[60] D. N. Nikovski. Method and System for Personalization of Heating, Ventilation, and Air Conditioning Services. US20160320081A1. U.S. Patent Application No. 14/697,943. (2016).
[61] J. Kim, H. Hwangbo. Sensor-Based Optimization Model for Air Quality Improvement in Home IoT. Sensors (Basel). 18(4) (2018) E959. https://doi.org/10.3390/s18040959.

[62] M. Feldmeier, J. Personalized Building Comfort Control. US20120031984A1 Paradiso. U.S. Patent Application No. 13/197,375. (2012).
[63] D. S. Lee, S. O. N. G. Sunggeun, P. A. R. K. Gunhyuk, S. E. O. Sungmok, S. O. N. G. Kwanwoo, C. H. O. Hyejung. Method and device for controlling room temperature and humidity. WO2016036062A1. U.S. Patent Application No. 14/829,065. (2016).
[64] CN107120782A. Heating and ventilating system control method based on multiple-user thermal comfort data. (2017) https://patents.google.com/patent/CN107120782A/en?oq=CN107120782A (accessed November 08, 2019).
[65] CN108413588A. A kind of personalized air-conditioner control system and method based on thermal imaging and BP neural network. (2018) https://patents.google.com/patent/CN108413588A/en?oq=CN108413588A (accessed November 08, 2019).
[66] E. Laftchiev, A. Methods and Systems for Personalized Heating, Ventilation, and Air Conditioning. US20190242608A1. Natarajan. U.S. Patent Application No. 15/888,172. (2019).
[67] H. F. Levy, P. G. Betz. Personalized air conditioned system. US6318113B1 U.S. Patent No. 6,318,113. Washington, DC: U.S. Patent and Trademark Office. (2001).
[68] H. Levy, P. Betz. Personalized air conditioning/ displacement ventilation system. US20060211362A1. U.S. Patent Application No. 11/415,638. (2006).
[69] CN103062871B. Air conditioning control system on basis of skin temperatures of human bodies. (2013) https://patents.google.com/patent/CN103062871B/en?oq=CN103062871B+ (accessed November 08, 2019).
[70] CN105258308A. Personalized ventilation control system suitable for civil buildings and vehicles. (2015) https://patents.google.com/patent/CN105258308A/en?oq=CN105258308A (accessed November 08, 2019).

2. O3/A2: Literature Review

Research in the areas of large-scale screening, diagnostics, monitoring, analysis and COVID-19-based categorizations of people by symptoms have wrought much honor and recognition to numerous scientists and practitioners for their achievements. Their applications for accomplishing such work includes wearable technologies, early warning systems, biometric monitoring technologies, IoT based systems, Internet of Medical Things and other tools pertinent to the COVID-19 pandemic.

Modern healthcare methods and systems have suffered a never before experienced crisis by the emergence of the COVID-19 pandemic. Remote monitoring became a primary means of healthcare provision for safeguarding millions of Americans as a result of the resource constraints, when this pandemic hit its first peak (Hollander and Carr, 2020).

Symptomatic people, as researchers have discovered, often indicate a drop in heart rate variability, although their resting heart rate and breathing rate rise. So long as measurements could capture such changes in a person, health can be treated as much as a week prior to a potential reporting of such disturbing symptoms. As many as 72% of the people suffering from COVID-19 most often report feeling fatigue. The other symptoms frequently reported by patients were headaches by 65%, body aches by 63%, a loss of taste and smell sensations by 60% and coughing by 59%. Researchers have discovered that as few as 55% of people ailing with COVID-19 reported having a fever, which is alarming, because merely temperature screening may be insufficient to denote such an infection (Terry, 2020).

Clinical care as well as the research in this field are bound to adopt remote monitoring permanently. The needs for convenience and security have opened opportunities for greater use of Telehealth and remote real-time monitoring of vital signs. Measurements of vital signs can be taken safely and conveniently within people's homes by employing biometric monitoring technologies (BioMeTs). BioMeTs can serve a number of clinical requirements for adequate responses to the COVID-19 pandemic. It can be applied for assisting initial physical evaluations of people, contributing to the triage of patients indicating COVID-19 symptoms and even for monitoring patients after their discharges from a hospital to lessen the risk of readmission. BioMeTs currently come in numerous versions for remote collections of vital signs for many days. The signs collected include body temperature, heart rate, BP, blood oxygen saturation (SpO2) and respiratory rate. These are needed for the overall care of people suffering from COVID-19. A number of research studies employ wearables like WHOOP, Oura Ring and smartwatches. These are in appropriate positions to undertake investigations regarding the use of BioMeTs measurements, not only for early detection of the illness but also as a means for predicting the possible severity of it (Manta et al., 2020).

While people are isolated during this pandemic, there is the potential of discretely applying Doppler radar for data on breathing-related information. This adapted, battlefield radar for biomedical purposes has the ability to view people's bodies beneath their clothing in order to record their breathing frequency rates, heart rates, tidal volume and pulse pressure. The aim of such testing is finding ways to ease lockdowns meant to restrict coronavirus infections. Furthermore such technology for sensing respiration in an inconspicuous manner is capable of monitoring pulse, heart rate variability and respiratory rates. Thereby early-stage symptoms of COVID-19 can be easily captured (Islam et al., 2020).

The spread of coronavirus infections can also be greatly curtailed by the use of wearable technology. This technology can gather numerous sorts of data including heart rate, blood pressure, body temperature, ECG, lung sound, levels of blood oxygen saturation (SpO2) and the like (Ding et al., 2020).

The physiological stress on the body caused by the COVID-19 virus rises. This generally causes a rise in heart rate as well. Wearable remote monitoring systems, once upgraded, could offer healthcare solutions that are cost-effective and timely. Furthermore these offer an entire range of help over the course of managing COVID-19 illnesses for patients, covering early warning systems for preventative purposes, diagnosis, treatment and, finally, rehabilitation (Islam et al., 2020).

Health monitoring must track the primary metrics of people. The IoT based system has been recommended by Tamilselvi et al. (2020) for this purpose. The system is fully capable of tracking body temperature, heart rate, eye movement and percentage of oxygen saturation. Furthermore this system offers integrated heartbeat, SpO2, temperature and eye blink sensors to handle the gathering of data. The Arduino-UNO has also been recommended as a processing device.

Physicians must identify clinically meaningful changes in vital signs when they monitor for COVID-19 or any other changes in health status. Various technologies are potentially able to assist in such efforts to denote health deviances from their normal variations. Deviances can be due to biological variability, time of day, food and drink, age, a person's exercise or underlying physiological conditions (Li et al., 2017, Izmailova et al., 2019, Buekers et al., 2019).

The accuracy of a wearable is not the only consideration involving the product. People are not likely to use a product if wearing it is uncomfortable. To name two examples, sticky adhesives and bulky smart clothing will simply never be adopted by all people, whether they are patients or not (Manta et al., 2020).

Management of the medical and logistical aspects of the COVID-19 crisis evidently required a real-time, command and control tool for hospitals. The requirement for maximizing the efficiency of hospitals is a system capable of integrating clinical data on patients, medical staff status, inventories of critical clinical resources and asset allocations into one dashboard. The development of the CoView™ System addressed such a goal. It was able to join together defense concepts, big data analytics and health care protocols. Decision-makers can use this system to respond efficiently and optimally, because this system provides needed evidence pertinent to the status of all COVID-19 patients at all hospitals and admission facilities. The system is capable of analyzing aggregated data from patient monitors and electronic charts by employing artificial intelligence algorithms. It then permits appropriately alerting medical staffs regarding a worsening health among certain patients on an individual basis or analyzing treatment procedures at specific hospitals. High-level experts acting as professional advisors are able to monitor every hospital for its current situation along with its schedules of treatments and their effectiveness. Thereby such experts can assist hospital staffs everywhere in the country as required. Hospital occupancy, patient conditions, logistics and other similar factors must enter into a centralized, real-time review to establish the status of hospitals. Effective decision-making and resource allocations fundamentally rely on this sort of overview (Abbo et al., 2020).

One monitoring technology used for measuring breathing and heart rates involves thermal imaging techniques (Hu et al., 2018). Others include breathing dynamics (Pereira et al., 2015) and respiration rate (Lewis et al., 2011). A recommendation offered by Jiang et al. (2020) involves use of a portable non-contact method. It is meant to screen the health conditions of people by analyzing respiratory characteristics even while people are wearing their face masks. This is possible with the application of a device mainly consisting of a FLIR one thermal camera and an Android phone. Its use includes monitoring possible COVID-19 patients by inspecting them in practical scenarios such as in hospitals or for pre-inspections at schools. Health screenings were performed by Jiang et al. (2020) by virtue of combining the RGB and thermal videos, which they acquired from the dual-mode camera and from deep learning architecture. A respiratory data capture technique was first accomplished by Jiang et al. (2020) on people wearing face masks by employing facial recognition.

Next, they applied a bidirectional GRU neural network with an attention mechanism to the respiratory data to arrive at a final health screening result. Respiratory health status can be recognized to an 83.7% accuracy rate on the real-world dataset, as the results of validation experiments indicate regarding the Jiang et al. (2020) model.

When it comes to predicting respiratory symptoms over the course of COVID-19 progression, Dhanapal et al. (2020) recommend a Pervasive computational model with wearable devices system. Breathing rate, inhale–exhale rate, temperature ratio and shortness of breath the focus of the information examined. Deep-learning computational models depict and process the difference between normal and abnormal breathing conditions. This recommended approach gathers data on how far away people are from the sensory devices, regardless of the cloth used to construct the facemask, the angles of measurement and other information, which is appropriate for classification purposes. The results of the recommended system are at a 94% rate of accuracy. Their precision, rate of recall and F1-measure display as averages in the performed experiments. Automatic encoders obtain possible traits by virtue of the machine-learning algorithms. These are possible due to the simplicity of large-scale screening and monitoring as well as their being requirements (Dhanapal et al., 2020).

The three levels of severity of the COVID-19 viral infection, according to the categorizations by the latest clinical research, are mild, moderate and severe. Different respiratory symptoms are observable at each level, ranging from, e.g., the dry cough occurring in mild infections, to shortness of breath in moderate illnesses and onward to the severe dyspnea and respiratory distress, when the respiratory frequency > 30 breaths/min, which is also known as tachypnea, in cases of severe illness (Cascella et al., 2020). Despite the three categories, actually, all such breathing deviations progress to abnormal articulation variations. Subsequently, the employment of automatic speech and voice analysis for assistance in diagnosing COVID-19 are expected to have great interest, since these are non-invasive and inexpensive (Han et al., 2020). Cases of intelligent speech analysis relevant for COVID-19 diagnosis among patients have been the focus of Han et al. (2020) for developing potential, future use. Currently Han et al. (2020) have already built audio-only based models from an analysis of patient speech recordings for automatic categorization of patient health states by four aspects: illness severity, sleep quality, fatigue and anxiety. Such experimentation by Han et al. (2020) indicate a 69 percent average rate of accuracy relevant to the severity of illness, derived from the number of hospitalization days.

The class of CIoT that is specific for the medical industry is the Cognitive Internet of Medical Things (CIoMT). It holds a key position in smart healthcare. The availability of remote data on patients in real time to medical personnel include physiological data like body temperature, blood pressure, heart rate, glucose level, EEG, ECG, oxygen level and such as well as psychological data like speech, expression, and such. The IoMT delivers such data remotely (Yang et al., 2020). Real-time communications of medical data are possible via Internet, and all hospital units caring for COVID-19 patients have extensive interconnections with Internet, making information transmittals both cost and time efficient. Real-time clinical parameters are available due to the assistance from CIoMT sensors, including the Electroencephalogram (EEG) sensor, Electrocardiogram (ECG) sensor, Blood pressure sensor, Pulse Oximeter, Electromyography (EMG) sensor and others. Such data is useful when assessing the severity an illness and when employing predictive analysis. Thereby, by monitoring feedback on patients, it becomes possible to prescribe effective treatments of the disease (Swayamsiddha and Mohanty, 2020).

Next, the COVID-19 time series can be forecast a hybrid intelligent approach, as Castillo and Melin (2020) explain, by a combination of fractal theory and fuzzy logic. The complexity of dynamics in the time series of countries around the world can be measured by the mathematical concept of fractal dimension. Castillo and Melin (2020) provide a key contribution by proposing the hybrid approach, which combines the fractal dimension and fuzzy logic, that then facilitates fast and precise COVID-19 time series forecasting. Use of the information in a short window assists decision-makers in taking immediate actions needed in the fight against the pandemic according to this proposed approach. Meanwhile this same approach is also beneficial in the use of the longer window, such as the 30-day one, for long-term decisions, as per the study by Castillo and Melin (2020). Self-organizing maps were applied by Melin et al. (2020) for their analysis of the spatial evolution of the global coronavirus pandemic. The clustering abilities of these self-organizing maps served as the basis in this Melin et al. (2020) analysis to spatially group countries. Such groupings form in terms of similarities relevant to their coronavirus cases. These have enabled the use of similar strategies to benefit similarly behaving countries in managing the virus and curtailing its contagion.

The central objective for the study by Dansana et al. (2020) was a classification of X-ray images in three categories — those of people ill with pneumonia, ill with COVID-19 and healthy people. The two algorithms used were convolution neural networks and decision tree classification. Dansana et al. (2020) were able to infer highly satisfactory performances by the fine-tuned version of the VGG-19, Inception_V2 and decision tree model. These indicated a 91% rate of increase in training and validation accuracy compared to that of the Inception_V2 (78%) and the decision tree (60%) models.

Clinical trials applying marketable wearables for identifying and screening COVID-19 have been enacted recently by an entire array of universities like, e.g., Stanford University, Florida Atlantic University, McMaster University, Central Queensland University and University of California San Francisco; scientific research institutes like, e.g., Scripps Research Institute; hospitals like, e.g., Cleveland Clinic and companies like, e.g., AVA Sensors and NEC XON. These studies examined different physiological parameters of people like, e.g., temperature, heart and respiratory rates, heart rate variability, activity and sleep levels, oxygen saturation, sleep measures, galvanic skin response, electrodermal activity, electrocardiogram, blood pressure and others.

Some of the health metrics that consumer devices can measure quite easily include, e.g., respiration rate, heart rate and heart rate variability. These are notable for their ability to foresee early symptoms of potential illnesses. An additional feature is the ability of mobile applications accompanying wearable devices to gather data on related, self-reported symptoms and demographics. Such consumer devices can play valuable roles in the battle against the COVID-19 pandemic (Natarajan et al., 2020). Two approaches for assessing COVID-19 were considered by Natarajan et al. (2020). These were a symptom-based approach and a physiological signs-based technique. Illness usually raises the respiration rate and heart rate; whereas, heart rate variability generally drops. An early diagnosis of this condition is possible by recording a history of such measurements. Such a history aids in tracking the progress of the illness as well (Natarajan et al., 2020). The digital infrastructure for remote patient monitoring has come into prominence during the recent COVID-19 pandemic. The clear-cut need is for harnessing and leveraging it. Tests and related vaccines are implemented slowly, making clear the deficiencies in disease detection and in the monitoring of health at both the individual level and for the entire population. The assistance for accomplishing these tasks can come from wearable sensors. Numerous physiological parameters can be accurately measured remotely due to the developed, integrated sensor technology. Such measurements have proven beneficial for tracking the progress of a viral disease. This technology has a wide range of impact. For example, a person who is under quarantine at home may suddenly require better care, and this technology can be brought into play. Another example might involve an entire community under threat of an oncoming outbreak of illness that vitally needs immediate intervention (Seshadri et al., 2020).

Physiological metrics have been correlated with daily living and human performance pertinent to the functionality of this technology. Nonetheless, this technology must translate into predictions of COVID-19 cases. People wearing devices that are joined to predictive platforms could receive alerts regarding changes in their metrics whenever they correspond with possible COVID-19 symptoms. Depersonalized data gathered on the basis of neighborhoods or zip codes, especially during a second wave, could prove valuable for public health officials and researchers for tracing and alleviating the spread of this virus. Once certain persons are identified with a COVID-19 diagnosis, others with whom they have associated, such as families, coworkers and persons encountered in businesses and other facilities, can also be engaged into remote monitoring. Thereby very needed data regarding the speed of disease transmission and the beginning of its pertinent symptom manifestations can be detected (Seshadri et al., 2020).

The H2020 ROCK project conducted in Vilnius city during which the ROCK Video Neuroanalytics and related infrastructure were developed involved studies of passers-by at eight sites in the city (Kaklauskas et al., 2019). We analyzed the Vilnius Happiness Index (see https://api.vilnius.lt/happiness-index) with ROCK Video Neuroanalytics in real-time, also conducted different other activities (see https://Vilnius.lt/en/category/rock-project/). The ROCK Video Neuroanalytics consists of framework containing a Database Management Dystem, a Database, Sensor Network, a Model Database Management System, a Model Database and a User Interface. The kinds of states stored in the ROCK Video Neuroanalytics Database are emotional states (happy, sad, angry, surprised, scared, disgusted or a neutral state), affective states (boredom, interest and confusion) and physiological states (average crowd facial temperature, crowd composition by gender and age groups as well as heart and breathing rates), arousal and valence. These are the MAPS data assembled in the Sensor Network. The subsystems contained within the Model Database are the Data Mining Subsystem, Recommendations Model, Decision Support and Expert Subsystem and Correlation Subsystem. Meanwhile the Database consists of the developed Video Neuroanalytics as well as the Historical, Recommendations, Decision Support and Expert Subsystem Databases. Remote data generated from affective, emotional and physiological parameter measurement devices base the compilation of a Sensor Network. Such remote data consist of MAPS data, sex, age (as per FaceReader 8), temperature (as per Infrared Camera FLIR A35SC), breathing rate (as per Sensor X4M200) and numbers of passersby (as per the H.264 Indoor Mini Dome IP Camera).

A dependency was discovered in the pre-COVID-19 and post-COVID-19 periods in an entire array of studies, including the research by Speth et al. (2020), Karadaş et al. (2020), Nalleballe et al. (2020), Altable and de la Serna (2020), Groarke et al. (2020) and Mishra and Banerjea (2020). These two periods linked with neurological and neuropsychiatric manifestations like apathy, confusion, anxiety and mood disorders; neurological problems and symptoms that include stress and mood as well as anxiety levels indicating depression. Therefore, the research conducted by these same authors on potential COVID-19 infection includes supplemental analyses on emotional and affective states.

A study pertinent to elderly age by Speth et al. (2020) discovered baseline depressive mood and anxiety levels during the pre-COVID-19 period, which positively associated with more depressive moods and anxiety during the COVID-19 period. Headaches, stress, stroke, itch, cerebrovascular dysfunction and BBB disruption are all examples of COVID-19-caused symptoms stemming from numerous neurological problems (Kempuraj et al., 2020). A study involving 239 patients of which 133 were males and 106 were females, all with COVID-19 diagnoses, was performed by Karadaş et al. (2020). Of the 239 patients, 83, or 34.7% involved neurological findings. COVID-19 causes harm to the nerve and muscle systems. Typical neurological symptoms include headache, muscle pain, sleep disorder, impaired consciousness, smell and taste impairments, dizziness and cerebrovascular diseases (Karadaş et al., 2020).

Then, in 2020, a study was conducted by Nalleballe et al. (2020) on 40,469 COVID-19 positive patients. Its finding was that 22.5% of patients displayed neuropsychiatric symptoms associated with COVID-19. A handful of minor studies corresponded with this same finding. These had been performed by Mao et al. (2020) and Helms et al. (2020). There appears to be a potentially strong relationship between coronavirus infections and psychosis. COVID-19 patients display neuropsychiatric symptoms, which customarily include anxiety, mood disorders, headache, sleep disorders, encephalopathy, stroke, seizures and neuromuscular complications (Nalleballe et al., 2020). Neuropsychiatric symptoms appear from the start of a COVID-19 illness whether it is mild, moderate or severe. The kinds of neuropsychiatric symptoms include anxiety, panic attacks, depression, mental confusion, acute confusional syndrome, psychomotor excitement, psychosis and, possibly, suicidal inclinations. The importance of these symptoms appearing in COVID-19 cases is that patients suffer these in addition to the customary symptoms of fever, cough and dyspnea. The suffering of such an illness further causes apathy, anorexia and muscular pain (Altable and de la Serna, 2020).

Morbidity and mortality have outcropped significantly during the ongoing COVID-19 pandemic due to neurological complications. A large number of hospitalized patients indicate neurological symptoms in addition to a respiratory insufficiency. Such symptoms appear as a wide range of maladies from a headache and loss of smell, to confusion and disabling strokes (Groarke et al., 2020). Coronavirus-caused neurological maladies constitute clear-cut pathogenic symptoms. The damage caused by neurological impairments can extend from general, cognitive and motor dysfunctions up to a wide spectrum of CNS anomalies like anxiety and other kinds of audio-visual incapacities (Mishra and Banerjea, 2020).

2.1. References

Abbo, A. R., Miller, A., Gazit, T., Savir, Y., & Caspi, O. (2020). Technological Developments and strategic management for overcoming the COVID-19 challenge within the hospital setting in Israel. Rambam Maimonides Medical Journal, 11(3).

Altable, M., & de la Serna, J. M. (2020). Neuropsychiatry and COVID-19: An Overview. Qeios.

Buekers, J., Theunis, J., De Boever, P., Vaes, A. W., Koopman, M., Janssen, E. V., ... & Aerts, J. M. (2019). Wearable finger pulse oximetry for continuous oxygen saturation measurements during daily home routines of patients with chronic obstructive pulmonary disease (COPD) over one week: Observational study. JMIR mHealth and uHealth, 7(6), e12866.

Cascella, M., Rajnik, M., Aleem, A., Dulebohn, S., & Di Napoli, R. (2022). Features, evaluation, and treatment of coronavirus (COVID-19). StatPearls.

Castillo, O., & Melin, P. (2020). Forecasting of COVID-19 time series for countries in the world based on a hybrid approach combining the fractal dimension and fuzzy logic. Chaos, Solitons & Fractals, 140, 110242.

Dansana, D., Kumar, R., Bhattacharjee, A., Hemanth, D. J., Gupta, D., Khanna, A., & Castillo, O. (2020). Early diagnosis of COVID-19-affected patients based on X-ray and computed tomography images using deep learning algorithm. Soft Computing, 1-9.

Dhanapal, J., Narayanamurthy, B., Shanmugam, V., Gangadharan, A., & Magesh, S. (2020). Pervasive computational model and wearable devices for prediction of respiratory symptoms in progression of COVID-19. International Journal of Pervasive Computing and Communications.

Ding, X., Clifton, D., Ji, N., Lovell, N. H., Bonato, P., Chen, W., ... & Zhang, Y. T. (2020). Wearable sensing and telehealth technology with potential applications in the coronavirus pandemic. IEEE reviews in biomedical engineering, 14, 48-70.

Groarke, J. M., Berry, E., Graham-Wisener, L., McKenna-Plumley, P. E., McGlinchey, E., & Armour, C. (2020). Loneliness in the UK during the COVID-19 pandemic: Cross-sectional results from the COVID-19 Psychological Wellbeing Study. PloS one, 15(9), e0239698.

Han, J., Qian, K., Song, M., Yang, Z., Ren, Z., Liu, S., ... & Schuller, B. W. (2020). An early study on intelligent analysis of speech under COVID-19: Severity, sleep quality, fatigue, and anxiety. arXiv preprint arXiv:2005.00096.

Helms, J., Kremer, S., Merdji, H., Clere-Jehl, R., Schenck, M., Kummerlen, C., ... & Meziani, F. (2020). Neurologic features in severe SARS-CoV-2 infection. New England Journal of Medicine, 382(23), 2268-2270.

Hollander, J. E., & Carr, B. G. (2020). Virtually perfect? Telemedicine for COVID-19. New England Journal of Medicine, 382(18), 1679-1681.

Hu, M., Zhai, G., Li, D., Fan, Y., Duan, H., Zhu, W., & Yang, X. (2018). Combination of near-infrared and thermal imaging techniques for the remote and simultaneous measurements of breathing and heart rates under sleep situation. PloS one, 13(1), e0190466.

Islam, M., Mahmud, S., Muhammad, L. J., Nooruddin, S., & Ayon, S. I. (2020). Wearable technology to assist the patients infected with novel coronavirus (COVID-19). SN computer science, 1(6), 1-9.

Izmailova, E. S., McLean, I. L., Hather, G., Merberg, D., Homsy, J., Cantor, M., ... & Wagner, J. A. (2019). Continuous monitoring using a wearable device detects activity-induced heart rate changes after administration of amphetamine. Clinical and translational science, 12(6), 677-686.

Jiang, Z., Hu, M., Fan, L., Pan, Y., Tang, W., Zhai, G., & Lu, Y. (2020). Combining visible light and infrared imaging for efficient detection of respiratory infections such as COVID-19 on portable device. arXiv preprint arXiv:2004.06912.

Kaklauskas, A., Zavadskas, E. K., Bardauskiene, D., Cerkauskas, J., Ubarte, I., Seniut, M., ... & Velykorusova, A. (2019). An affect-based built environment video analytics. Automation in Construction, 106, 102888.

Karadaş, Ö., Öztürk, B., & Sonkaya, A. R. (2020). A prospective clinical study of detailed neurological manifestations in patients with COVID-19. Neurological Sciences, 41(8), 1991-1995.

Kempuraj, D., Selvakumar, G. P., Ahmed, M. E., Raikwar, S. P., Thangavel, R., Khan, A., ... & Zaheer, A. (2020). COVID-19, mast cells, cytokine storm, psychological stress, and neuroinflammation. The Neuroscientist, 26(5-6), 402-414.

Lewis, G. F., Gatto, R. G., & Porges, S. W. (2011). A novel method for extracting respiration rate and relative tidal volume from infrared thermography. Psychophysiology, 48(7), 877-887.

Li, X., Dunn, J., Salins, D., Zhou, G., Zhou, W., Schüssler-Fiorenza Rose, S. M., ... & Snyder, M. P. (2017). Digital health: tracking physiomes and activity using wearable biosensors reveals useful health-related information. PLoS biology, 15(1), e2001402.

Manta, C., Jain, S. S., Coravos, A., Mendelsohn, D., & Izmailova, E. S. (2020). An evaluation of biometric monitoring technologies for vital signs in the era of COVID-19. Clinical and translational science, 13(6), 1034-1044.

Mao, L., Wang, M., Chen, S., He, Q., Chang, J., Hong, C., ... & Hu, B. (2020). Neurological manifestations of hospitalized patients with COVID-19 in Wuhan, China: a retrospective case series study. MedRxiv.

Melin, P., Monica, J. C., Sanchez, D., & Castillo, O. (2020). Analysis of spatial spread relationships of coronavirus (COVID-19) pandemic in the world using self organizing maps. Chaos, Solitons & Fractals, 138, 109917.
Mishra, R., & Banerjea, A. C. (2020). Neurological damage by coronaviruses: a catastrophe in the queue!. Frontiers in immunology, 2204.
Nalleballe, K., Onteddu, S. R., Sharma, R., Dandu, V., Brown, A., Jasti, M., ... & Kovvuru, S. (2020). Spectrum of neuropsychiatric manifestations in COVID-19. Brain, behavior, and immunity, 88, 71-74.
Natarajan, A., Su, H. W., & Heneghan, C. (2020). Assessment of physiological signs associated with COVID-19 measured using wearable devices. NPJ digital medicine, 3(1), 1-8.
Pereira, C. B., Yu, X., Czaplik, M., Rossaint, R., Blazek, V., & Leonhardt, S. (2015). Remote monitoring of breathing dynamics using infrared thermography. Biomedical optics express, 6(11), 4378-4394.
Seshadri, D. R., Davies, E. V., Harlow, E. R., Hsu, J. J., Knighton, S. C., Walker, T. A., ... & Drummond, C. K. (2020). Wearable sensors for COVID-19: a call to action to harness our digital infrastructure for remote patient monitoring and virtual assessments. Frontiers in Digital Health, 8.
Speth, M. M., Singer-Cornelius, T., Oberle, M., Gengler, I., Brockmeier, S. J., & Sedaghat, A. R. (2020). Mood, anxiety and olfactory dysfunction in COVID-19: evidence of central nervous system involvement?. The Laryngoscope, 130(11), 2520-2525.
Swayamsiddha, S., & Mohanty, C. (2020). Application of cognitive Internet of Medical Things for COVID-19 pandemic. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 14(5), 911-915.
Tamilselvi, V., Sribalaji, S., Vigneshwaran, P., Vinu, P., & GeethaRamani, J. (2020, March). IoT based health monitoring system. In 2020 6th International conference on advanced computing and communication systems (ICACCS) (pp. 386-389). IEEE.
Terry M., (2020). Fitbit COVID-19 study suggests wearables can detect disease before symptoms arrive BioSpace. Available online: https://www.pharmalive.com/fitbit-covid-19-study-suggests-wearables-can-detect-disease-before-symptoms-arrive/
Yang, T., Gentile, M., Shen, C. F., & Cheng, C. M. (2020). Combining point-of-care diagnostics and internet of medical things (IoMT) to combat the COVID-19 pandemic. Diagnostics, 10(4), 224.

3. O3/A3: The Big Picture

The ‘big picture’ stage defines the reality of the built environment. This stage involves describing a human-centered built environment and establishing the demands of interested groups. The ‘big picture’ stage involves establishing a system of metrics that comprehensively describe a human-centered built environment. Each metric can be measured both at the individual level and at the public space level. This stage involved the gathering of eight quantitative and qualitative layers of data, and subsequently systematically evaluating them:

- 1st layer: emotional states (happy, sad, angry, surprised, scared, disgusted or neutral), and depression, valence, stress and arousal;
- 2nd layer: affective attitudes (boredom, interest, confusion);
- 3rd layer: biometrical states (average crowd facial temperature, crowd composition by gender and age groups, heart and breathing rates);
- 4th layer: neuro-surveys;
- 5th layer: circadian rhythm of Vilnius city inhabitants;

- 6th layer: weather conditions (air temperature, relative air humidity, average wind velocity, atmospheric pressure; the data will be obtained from the Vilnius Meteorology Station);
- 7th layer: pollution (particulates, nitrogen dioxide, noise, carbon monoxide, sulfur dioxide, magnetic storm; the data will be obtained from the Environmental Protection Agency and recalculated by Raimondas Grubliauskas);
- 8th layer: Vilnius built environment and municipal district data;

The Big Picture stage defines the reality of the smart, self-learning and adaptive built environment. This stage involves describing a human-centered, smart, self-learning and adaptive built environment establishing the demands of interested groups. In the opinion of Dubin (1978) the more exhaustive the explanation, the larger is the probability that the description will be valuable for developing the following method.

One of the most important stages in the life cycle of a smart, self-learning and adaptive built environment regards the establishment of the weights and significances of the criteria describing alternatives. The utility degrees and priorities of the variants under comparison are established by calculating the criteria weights and significances and applying methods for planning project variants and for a multicriteria analysis. This way an exhaustive picture of a smart, self-learning and adaptive built environment is drawn during this stage. The Big Picture stage involves establishing a system of metrics, which would exhaustively describe a human-centered smart, self-learning and adaptive built environment. Each metric can be measured at the individual and the built environment level.

According to developed MICROBE Method (O2), Stage 8 involves developing the big picture of the urban planning, calculating correlations, analyzing the data and establishing the trends. The definition of a city's reality appears on the stage of the big picture. A System of metrics is formed during this stage, which describes human-centered, urban areas and establishes interest group demands. The measurement of each metric includes both a personal and a urban area levels. Stakeholders can use the assistance of this novel set of additional, multifaceted data for their decision-making processes. A sustainable approach that centers around local residents, who tend to be the users of urban areas, fosters effective decision-making.

An emotions digital map of 8 Vilnius locales as well as correlations and trends in terms of the following parameters have been established:

- emotional states (happy, sad, angry, surprised, scared, disgusted or a neutral state), valence and arousal
- affective attitudes (boredom, interest and confusion)
- physiological states (crowd composition by gender and age groups, average crowd facial temperature, heart rate, breathing rate)
- circadian rhythms
- weather conditions (air temperature, air humidity, average wind velocity, atmospheric pressure, apparent temperature)
- pollution (Magnetic Storm, SO_2, $KD_{2.5}$, KD_{10}, NO_2, CO, O_3)

4. O3/A4: Scanning a Human-Centered Built Environment and Collecting Data

Performance of tests (human affective attitudes, emotional and physiological states, depression, valence, stress and arousal, human comfort in built environments (personal factors, health and wellbeing, thermal comfort, indoor air quality, pollution, visual comfort, noise nuisance, ergonomics, and so on)) will took place from the beginning of the project. The MICROBE system collected various layers of data in different formats, which must be processed, integrated and analyzed.

According to developed MICROBE Method (O2), Stage 7 involves collecting MAPS data upon conducting the scanning of human-centered urban areas. Anonymous passersby were administered biometric/emotional tests at ten defined sites in Vilnius city. By applying ASP, six layers of data were gathered in different formats requiring processing, integration and analysis. All measurements are performed under real time conditions. The ASP is usable in the evaluation of “in situ” urban planning. Over 0.5 billion items of data have been accumulated at this time. This number continues to increase.

5. O3/A5: The Integrated MICROBE Method (nuoroda į Metodą)

The developed MICROBE Method is presented in the O2/A5 report: http://microbe-erasmus.vilniustech.lt/wp-content/uploads/2022/02/Developed-MICROBE-method-2.pdf.
MICROBE Method integrates coronaviruses and stress management techniques, Damasio’s somatic marker hypothesis (Damasio, 1994); Russell’s circumplex model of affect (Russell, 1980); emotional, affective, biometrics and the surrounding environment (pollution, noise, etc.) (pollution, noise, etc.) data; neuro-decision and neuro-correlation matrices; biometric and opinion mining methods; spatial analysis of categorical data by means of built environment analysis and multiplecriteria methods, for example, generation of human affective, emotional, biometrical states and the surrounding environment (pollution, noise, etc.) maps; neuro-questionnaire method; affective computing. It also involves statistical analysis (LOGIT, KNN, MBP, RBP), recommender technique and Web-based opinion analytics technique, as well as five methods for multiple-criteria analysis.

Research offers the original, Integrated MICROBE method for collecting data on inhabitants affective attitudes, emotional and physiological states and depression, valence, stress and arousal in a smart, self-learning and adaptive built environment, developing an innovative method by interconnecting and examining the above, and human comfort in built environments.

The Integrated MICROBE method captures affective attitudes, emotional and physiological states, depression, valence, stress and arousal from a human-centered built environment and correlates these data with human comfort in built environments and other data.

The Integrated MICROBE method collects and integrates data on affective attitudes, emotional and physiological states, depression, valence, stress and arousal, human comfort in built environments (personal factors, health and wellbeing, thermal comfort, indoor air quality, pollution, visual comfort, noise nuisance, ergonomics, and so on). Additionally, during this stage, there is an explanation of what has been developed earlier and what has been employed from earlier studies for this research.

Neuro and neurocorrelation matrices will be generated, which will permit comprehensively analyzing MICROBE problems by quantitative, qualitative, neuro and COVID-19 perspectives, compiling and analyzing thousands of alternative recommendations and selecting the most rational according to user needs. These will also permit establishing a market, investment, hedonic, emotional value on a built environment. No neuro and neurocorrelation matrices have yet been developed in the world for analyzing the MICROBE problems and quality of a built environment and submitting recommendations.

6. O3/A6: Development of the MICROBE system

The MICROBE System was developed during this stage based on the results from the first six stages:

1. Development of the MICROBE System.
2. Multiple-Criteria Analysis of Alternatives.
3. The MICROBE System Correlation Subsystem.
4. Real-time negative emotions and possible COVID-19 indices in Vilnius
5. Assessing the Accuracy of the MICROBE System through verification and validation.

The MICROBE System comprises the following four components:

1. Correlation Subsystem (see Stage 9)
2. Video Neuroanalytics
3. Web-based opinion analytics
4. Recommender System for the Protection against COVID-19 and Depression Reduction in Built Environment

Video Neuroanalytics analyses, rates and maps built environment according to risk on COVID-19 and negative emotions. During the H2020 ROCK project in Vilnius developed the ROCK Video Neuroanalytics and related infrastructure in Vilnius eight places. The Applicants determined in real-time the Vilnius Happiness Index (see https://api.vilnius.lt/happiness-index) with Video Neuroanalytics and performed various other activities (see https://vilnius.lt/en/category/rock-project/). During the MICROBE project, we adapted the ROCK Video Neuroanalytics for the negative emotions and potential coronavirus analysis in Vilnius and Bologna cities and develop real-time negative emotions and possible COVID-19 indices in Vilnius.

Web-based opinion analytics automatically detect in real-time opinions expressed in articles, reviews, surveys, comments, opinions, notices, papers, research, studies, blogs, online forums, Facebook, Twitter and other social media channels, thereby allowing visualisation of opinions citizens hold towards issues of built environment protection against COVID-19. The Applicants during the H2020 ROCK project developed the ROCK Web-based opinion analytics. During the MICROBE project, we will adapt the ROCK Web-based opinion analytics for the Google negative emotions and potential COVID-19 risks Web-based opinion analytics.

Recommender System for the Protection against COVID-19 and Depression Reduction in Built Environment gives recommendations to different stakeholders on ways to minimize the negative emotions and influence of COVID-19. Recommender System can assist in determining the level of negative stress and resolve the problem for lessening it. The system can help to manage current stressful situation and to minimise future stress by making the level of future need satisfaction more rational. The system facilitates individuals to make a real-time assessment of their stress level and, after they fill in a stress management questionnaire, to get rational tips for the reduction of current stress based on the MICROBE System global practice accumulated in the System. The multi-variant design and multiple criteria analysis methods are used for that purpose. The generation of recommendations and the selection of the most rational are based on criteria systems and on Maslow's Hierarchy of Needs.

We permitted distinguishing the following traits of innovation in the MICROBE System:

- The Web Opinion Mining will analyze the opinion, information and knowledge about MICROBE problems provided by the public media (articles, social networks, commentaries and the like). This will permit observing the opinions, outlooks, emotions and expectations of city residents and submitting recommendations in consideration of public opinion.
- Emotional, affective, physiological, pollution and COVID-19 perspectives maps will be

compiled and applied practically on a built environment.

- Neuro and neurocorrelation matrices will be generated, which will permit comprehensively analyzing MICROBE problems by quantitative, qualitative, neuro and COVID-19 perspectives, compiling and analyzing thousands of alternative recommendations and selecting the most rational according to user needs. These will also permit establishing a market, investment, hedonic, emotional value on a built environment. No neuro and neurocorrelation matrices have yet been developed in the world for analyzing the MICROBE problems and quality of a built environment and submitting recommendations.

7. O3/A7: Multiple Criteria Analysis of Alternatives

This method recommends an INVAR Method for a multiple criteria analysis (Degree of Project Utility and Investment Value Assessments along with Recommendation Provisions (Kaklauskas 2016)). Its use can be for a sustainable MICROBE alternatives assessment. The INVAR Method can additionally assist in determining various values (market, investment, user perceived, utilitarian, synergistic, hedonic and fair) of MICROBE alternatives under deliberation and provide digital recommendations for improving alternatives. Furthermore the INVAR Method can optimize the selected criterion seeking that the alternative under deliberation would be equally competitive in the market, as compared to the other alternatives under comparison. The INVAR Method is additionally able to calculate the value that the alternative under deliberation should be for this alternative to become the best among those under deliberation. The case studies presented in this research are for demonstrating this developed method.

The multiple criteria analysis is prepared about Kaziuko Fair. Kaziuko (Saint Casimir's) Fair is an annual, large-scale exhibition in Vilnius that displays folk arts and crafts, a tradition dating back to the early 17th century. The fair operates in the city center, and displays by hundreds of craftspeople stretch across Gedimino Prospect and into the side streets of äventaragio, B. Radvilaites, Maironio and Pilies. The fair takes place on the Sunday nearest to March 4, which commemorates St. Casimir. In Lithuanian, Kaziuko (or Kaziukas) is the diminutive form of the name Casimir (or Kazimieras in Lithuanian). Today, St. Casimir's Fair also involves music, dance and plays, attracting tens of thousands of visitors and craftspeople from all over Lithuania, as well as from neighboring countries such as Latvia, Russia and Poland. This fair has a unique atmosphere in which tradition and authenticity are particularly important. Kaziuko is not only the largest fair in Vilnius, but is also the oldest event of this type, and has been a tradition for over 400 years.

The items sold during the fair included handmade goods of national origin, folk arts, fine crafts, agricultural products and other types of goods made using old-fashioned methods and tools. The locations of the two sites of this fair chosen for this study were at 1 Pilies St. (site a_1) and Lukiskiu Square, at 35 Gedimino Pr. (site a_2). The locations consisted of booths (3 x 3 m) with a rental price of 69.66 for three days. The municipality charged the same price for booths in different locations, and the price was based only on the size of the booth. Thus, the objective of our work was to assess the rental fees for the market of these specific sites, taking into consideration physical, economic, social, environmental and emotional criteria. The designated weight for all of the first four sets of criteria (except for the rental value of a 3 x 3 m sales booth) was one, and this total was the same as the weight for the set of emotional criteria and the rental value of a 3 x 3 m sales booth. Sixteen fair experts in the field (advertisers, built environment experts, fair organizers, sellers) determined a weight factor (weight) of 0.25 for each of the physical, economic (except for the rental value of a

3 x 3 m sales booth), social and environmental criteria groups, reflecting sustainable principles of development and the primary importance of humans and their well-being during the event. They determined the same weight for the set of emotional criteria as for the total weight of previously mentioned four groups.

The location of sales site a_1 was one of the oldest streets in Vilnius, at 1 Pilies St. Vilnius Cathedral, the Palace of Lithuania's Grand Dukes and Bernardinai Garden are no more than a few hundred meters away from this site, and, a little farther away, visitors can find the Tower of Gediminas Castle and the Hill of Three Crosses.

Nearby sales site a_2 was located in Lukiskiu Square, at 35 Gedimino Pr. This has views of the Ministry of Foreign Affairs of the Republic of Lithuania, Lukiskiu Square, the Lithuanian Academy of Music and Theatre, Vilnius Regional Court, Lukiskiu Prison and Holy Apostles Philip and Jacob Church.

The following factors were considered in the set of physical criteria: the accessibility of the site; the number of visitors to this part of the fair; the widths of the street and sidewalk; the surroundings; eye-catching views of buildings with unique features (monuments, memorials, sculptures and other special or unique features, such as a bridge or bandstand); and hard landscaping (benches, bins, railings, paths, etc.).

The set of economic criteria included housing prices, the prices for renting commercial property, real estate tax rates and the attractiveness to small businesses. The housing prices, rental prices for commercial property and level of taxes on real estate are rather high at both sites a1 and a_2, since these are prestigious locations within Vilnius City where real estate prices are the highest. However, site a_1 is more highly valued, and the experts therefore assigned slightly higher points to this site.

The set of social criteria consisted of the popularity of the site as a meeting place for residents, its popularity among tourists, its popularity as a place for taking walks and the crime rate. Site a1 is more popular among both townspeople and tourists than site a_2. Thus, experts gave site a_1 a rating of 8, 9 and 9 points for these criteria, respectively, and gave 5, 6 and 5 points, respectively, for site a_2.

The items in the environmental criteria included levels of particulate matter (KD2.5, KD10), carbon monoxide (CO), nitrogen oxide (NO2), sulfur dioxide (SO2), visual contamination, noise levels, magnetic storms (Kp), atmospheric pressure and soft landscaping (trees, flower beds, meadows, lawns etc.). The indicators for the first four criteria were taken from the Environmental Protection Agency's 2018 data from tests of air quality (http://gamta.lt/cms/index?lang=en). The visual contamination and noise levels were lower at site a_1 than they were at site a_2.

Pilies St. (a_1) data for a multiple-criteria analysis of IEMR and MR alternatives (see Table 1) appear in graphic form in Fig. 3. This illustration also provides an emotional, biometrical and the surrounding environment (its physical, economic, social and environmental criteria) map relevant to the same area under study.

In the following, we describe the application of the INVAR method in carrying out the IEMR and MR values analysis for sales booths at two sites: Pilies St. (a_1) and Lukiskiu Square (a_2). The division of Table 1 is in two parts – the left side of the table shows IEMR data matrix divided into five groups of criteria: physical criteria, economic criteria, social criteria, environmental pollution criteria and emotional criteria. The right side shows MR data divided into four groups of criteria: physical criteria, economic criteria, social criteria and environmental pollution criteria. Criteria values and weights are equal, both on the right as well as on the left sides of the table. The IEMR and MR alternatives analysis results appear at the end of the table. Experts determined an equal weight of 0.25 for each of the first four groups to reflect the principles of sustainable development. They set the weight of the emotional criteria group as equal to the sum of the weights of the first four groups, since the most important issue at such an event was considered to be the people, their well-being and their positive emotions. All sets of criteria were broken down further, and the experts provided weights for each individual criterion.

Table 1. Decision matrix and assessment results of IEMR and MR alternatives from Kaziuko Fair (on March 2) using the COPRAS method

Criteria describing the alternatives	+/-	**Units of measurement**	**Weight**	**Integrated emotional market rental (IEMR) compared alternatives**		**Market rental (MR) compared alternatives**	
Empty Cell				**Pilies St. a_1**	**Lukiskiu Square a_2**	**Pilies St. a_1**	**Lukiskiu Square a_2**
Physical criteria						**Physical criteria**	
Accessibility of the location	+	Points	0.07	6 0.03	8 0.04	6 0.03	8 0.04
Number of visitors to the fair	+	Number of visitors	0.08	16410 0.0435	13750 0.0365	16410 0.0435	13750 0.0365
Widths of the street and sidewalk	+	m	0.03	28 0.0171	21 0.0129	28 0.0171	21 0.0129
Eye-catching views	+	Points	0.05	9 0.0321	5 0.0179	9 0.0321	5 0.0179
Hard landscaping	+	Points	0.02	6 0.0086	8 0.0114	6 0.0086	8 0.0114
Economic criteria						**Economic criteria**	
Rental value of a 3 x 3 m sales booth	–	Euros for three days	1	69.66 0.5	**69.66** 0.5	69.66 0.5	**69.66** 0.5
Housing prices	+	Points	0.06	9 0.0338	7 0.0262	9 0.0338	7 0.0262
Commercial property rental prices	+	Points	0.08	8 0.0427	7 0.0373	8 0.0427	7 0.0373
Real estate tax rates	+	Points	0.04	9 0.0212	8 0.0188	9 0.0212	8 0.0188
Attractiveness to small business enterprises	+	Points	0.07	8 0.0373	7 0.0327	8 0.0373	7 0.0327
Social criteria						**Social criteria**	
Popularity as a meeting place	+	Points	0.08	8 0.0492	5 0.0308	8 0.0492	5 0.0308
Popularity with tourists	+	Points	0.07	9 0.042	6 0.028	9 0.042	6 0.028
Popularity of the walkways	+	Points	0.05	9 0.0321	5 0.0179	9 0.0321	5 0.0179
Criminality	–	Points	0.05	9 0.0281	7 0.0219	9 0.0281	7 0.0219
Environmental pollution criteria						**Environmental pollution criteria**	
Particulate matter (KD_{10})	–	µg/m3	0.04	25.09 0.02	25.09 0.02	25.09 0.02	25.09 0.02
Carbon monoxide (CO)	–	mg/m3	0.03	0.52 0.015	0.52 0.015	0.52 0.015	0.52 0.015

Criteria describing the alternatives	**+/-**	**Units of measurement**	**Weight**	**Integrated emotional market rental (IEMR) compared alternatives**		**Market rental (MR) compared alternatives**	
Empty Cell				**Pilies St. a_1**	**Lukiskiu Square a_2**	**Pilies St. a_1**	**Lukiskiu Square a_2**
Nitric oxide (NO_2)	–	µg/m3	0.02	4.55 0.01	4.55 0.01	4.55 0.01	4.55 0.01
Sulfur dioxide (CO)	–	µg/m3	0.03	2.6 0.015	2.6 0.015	2.6 0.015	2.6 0.015
Visual pollution	–	Points	0.02	6 0.0086	8 0.0114	6 0.0086	8 0.0114
Noise level	–	Points	0.04	7 0.0175	9 0.0225	7 0.0175	9 0.0225
Soft landscaping	+	Points	0.01	8 0.0053	7 0.0047	8 0.0053	7 0.0047
Magnetic storms	–	Kp	0.03	3 0.015	3 0.015	3 0.015	3 0.015
Atmospheric pressure at the station level	–	hPa	0.03	993.98 0.015	993.97826 0.015	993.98 0.015	993.97826 0.015
Emotional and biometrical criteria						–	–
Happiness	+	Points	0.1	0.158225 0.0551	**0.129154** 0.0449	–	–
Sadness	–	Points	0.1	0.200443 0.0558	0.158545 0.0442	–	–
Anger	–	Points	0.1	0.108799 0.0502	0.108075 0.0498	–	–
Surprise	+	Points	0.1	0.051358 0.0356	0.092899 0.0644	–	–
Fear	–	Points	0.1	0.042741 0.0618	0.026442 0.0382	–	–
Disgust	–	Points	0.1	0.036638 0.0487	0.038552 0.0513	–	–
Valence	+	Points	0.1	0.905851 0.0502	**0.897404** 0.0498	–	–
Arousal	+	Points	0.1	0.36 0.0537	**0.31** 0.0463	–	–
Respiratory rate	+	Respiration per minute (RPM)	0.1	14.506207 0.0485	15.3982 0.0515	–	–
Heart rate	+	Beats per minute (BPM)	0.1	76.00119 0.0505	74.61746 0.0495	–	–
Normalized weighted maximizing alternative indices, totals				0.6885	0.6215	0.3949	0.3151
Normalized weighted minimizing alternative indices, totals				0.8607	0.8293	0.6442	0.6458
Significance of the alternative				1.5178	1.4822	1.0407	0.9593
Priority of the alternative				1	2	1	2
Utility degree of the alternative (%)				100%	97.65%	100%	92.18%

Pilies St. (a_1) data for a multiple-criteria analysis of IEMR and MR alternatives (see Table 1) appear in graphic form in Fig. 3. This illustration also provides an emotional, biometrical and the surrounding environment map relevant to the same area under study.

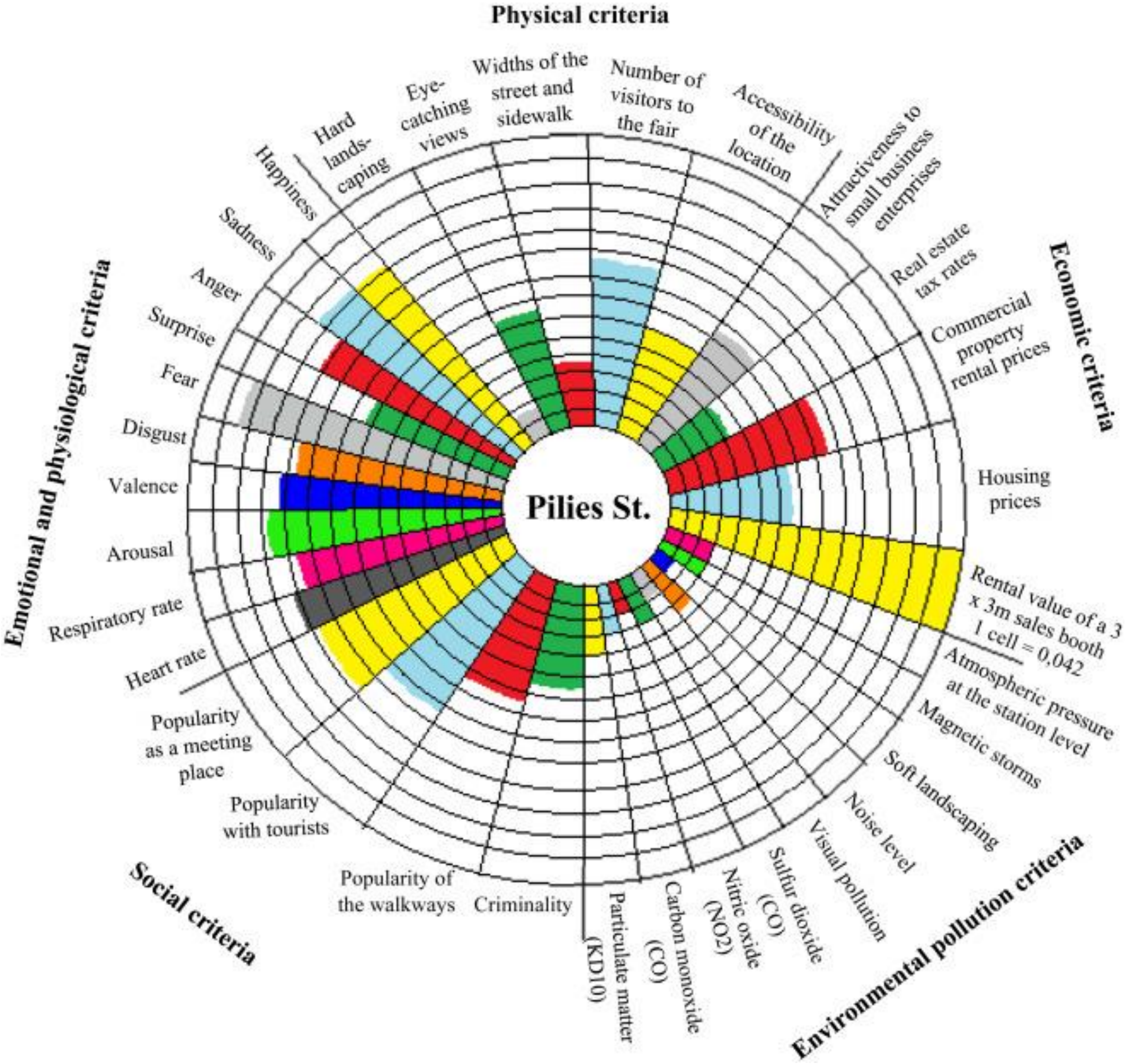


Fig. 3. Pilies St. (a_1) map of emotions, biometrics and the surrounding environment

Table 1 (see left side) shows the results of the criteria assessment of the IEMR values of the sales sites under analysis. That the utility degree U_1 = 100% for the Pilies St. Site a_1 is greater than the utility degree U_2 = 97.65% for the Lukiskiu Square Site a_2 is obvious. The difference is equal to 2.35%.

The compilation of an analogical matrix (see right side of Table 1) was an endeavor to calculate the MR value and to prove the influence of emotions on the results. Therefore, the criteria groups of emotions were not included herein (http://iti3.vgtu.lt/vgtu_lomonosov/simpletable.aspx?sistemid=6852).

The results also indicate that the priority alternative among the alternatives under deliberation had not changed. However, a difference began to appear between it and the "Utility degree of the alternative (%)" indicator. The derived result of the difference between the sites at Pilies St. a_1 U_1 = 100% and Lukiskiu Square a_2 U_2 = 92.18% is equal to 7.82%. A comparison of the difference between the results of IEMR and MR alternatives showed that the difference between the utility degrees of the IEMR alternatives was three times lower. An explanation for the difference between the IEMR and MR alternatives results could be that the assessments by experts and the existing data are more likely to favor the first alternative, whereas the emotional and biometrical states of the passersby indirectly voted for the second alternative.

8. O3/A8: MICROBE Correlation Subsystem (Correlation Metrics Subsystem)

The MICROBE Correlation Subsystem is a suitable tool for assessing a human-centered built environment. Analyses presented here are on various metrics correlations of a human-centered built environment according to the values of correlation coefficients (average, strong, very strong) and their influence on inhabitants.

The MICROBE Correlation Subsystem is a non-experimental research design technique, which discovered a connection among related variables. Two different groups are required to conduct this research design method. Statistical analysis is applied to compute the correlation between two variables by employing a correlation coefficient. The value of the correlation coefficient can be equal to 0 (no link), positive amounts fluctuating between 0 and 0.2 (very weak), from 0.2 to 0.5 (weak), from 0.5 to 0.7 (average), from 0.7 to 1 (strong) and +1 (very strong). Negative correlation coefficient values can be equal to -1 (very strong), fluctuating from -1 to -0.7 (strong), from -0.7 to -0.5 (average), from -0.5 to -0.2 (weak) and from -0.2 to 0 (very weak). The closer the value of the correlation coefficient approaches +1, the more it shows a positive relationship between two variables; whereas, -1 specifies a negative relationship between two variables.

The expectation for future research is to establish, which of these metrics and correlations indicate a high, medium or low importance for inhabitants. The parameters measured in the built environment with strong correlations and substantial influence on the inhabitants should be analyzed in detail. Then specific decisions need to be made rapidly to avoid problems and to gain advantage from the existing situation.

As an example of the Correlation Subsystem, we will briefly analyze the research results obtained with it in Vilnius.

Urban areas should, according to sustainable cultural heritage principles (ECOCITY World Summit, 2017), remain active in formulating ongoing processes that would be able to handle the frequently unpleasant crossovers of identity and differences, which would encompass the current tensions between culture and nature. The position stated by the United Nations, Unesco, Agenda 21 for culture, United Cities and Local Governments (United Cites and Local Governments, 2010, Magee et al., 2012, Öberg et al., 2017), regards the Circles of Sustainability approach, proposes that people direct their efforts to realize all their desires and goals via four modalities (economic, ecological, political and cultural), which can be analyzed across four hierarchical scales. This research endeavors to assess urban cultural heritage sustainability by virtue of human MAPS states.

Improved living conditions for the residents of a city are drafted in detail when planning the designations of that city's territory. Engaging local communities in discussions is the effort made in Lithuania, where requirements for public discussions have been established, whenever an object is meant for construction. The key points in Lithuania regarding community, i.e., public, interests regarding urban planning are as follows: the objective needs of a community relative to its quality of life, public information, decision-making involving public participation and the like. A community must be familiarized with territorial planning documents at the State level by no less than 2 months prior to implementation. The plans must be on public display for no less than one month of this time (Law on Territorial Planning of the Republic of Lithuania).

The research object that Vilnius Gediminas Technical University and Vilnius Municipality City chose relevant to their ROCK and VINERS projects implementation was Vilnius Old Town, which has been named a cultural heritage object by UNESCO. The Old Town object included the key urban areas within its security zone. The urban areas considered key include Gedimino Prospect, Pilies and Švitrigailos Streets and Lukiškių Square. These sites have their differences. For example, (1) Pilies St. is historical as part of the Old Town's 16th century urban structure, and large numbers of both city residents and touring visitors visit this area. In contrast, (2) Gedimino Prospect was built as a main avenue of the city during the 19th century modernization of Vilnius. Its renovation came early in the 21st century to include use during holiday events and fairs as well as its functioning as a pedestrian walkway and bicycle path (see attached maps). Finally, there is the 8 ha (3) Lukiškių Square, formerly Lenin Square during Lithuania's soviet period, which is currently under maintenance. This site was the object of lengthy, harsh debates regarding reconstruction into a site earmarked for recreational use. The general plan for this square only called for the start of maintenance work in 2016, which is still ongoing but with functioning pathways. What were the desires of the urban planners themselves? City planners undertook studies of human emotions; thus they selected different objects for review. Their studies were meant to review the following:

- Evaluations of diverse urban areas relevant to their quality by attendance rates with relevant visitor emotions, age group(s) of visitors and the average length of their stays.
- Factors of importance established for urban area developments along with recommendations to include planning for fostering positive emotions thereby guaranteeing good health and for stimulating attendance.
- Investigations of urban areas regarding their contributions to the satisfaction of city residents.

Table 2 introduces the correlations of happiness values by weekday. The values of all the happiness indices during every weekday correlate with each other. The strongest correlation falls between the values on Wednesday and Thursday (r = 0.987, p < 0.01), whereas the weakest correlation falls between the values on Monday and Tuesday (r = 0.553, p < 0.01).

Table 2. Happiness values correlated by weekdays.

	MON	TUE	WED	THU	FRI	SAT	SUN
MON	1						
TUE	,573[a]	1					
WED	,553[a]	,973[a]	1				
THU	,592[a]	,980[a]	,987[a]	1			
FRI	,647[a]	,930[a]	,947[a]	,926[a]	1		
SAT	,739[a]	,772[a]	,766[a]	,786[a]	,843[a]	1	
SUN	,754[a]	,861[a]	,866[a]	,894[a]	,879[a]	,852[a]	1

[a]Correlation is significant at the 0.01 level (2-tailed).

Average happiness values by weekdays appear in Fig. 4a. The graphs of happiness per hour for each weekday appear in Fig. 4b. It can be seen that the happiest day of the week is Saturday, and the least happy – Monday. This is in line with global practices. More than 29 million items of data on happiness were measured. The values of average happiness and their changes among passersby in Vilnius are taken and recorded every hour. Meanwhile happiness measurements are recorded every second. The accumulated values by weekdays are at a 95% confidence interval. The x axis shows each hour starting at 12:00 midnight, while the y axis shows 7 days of the averages of happiness values. The fluctuations of happiness measurements are between 0 and 1.

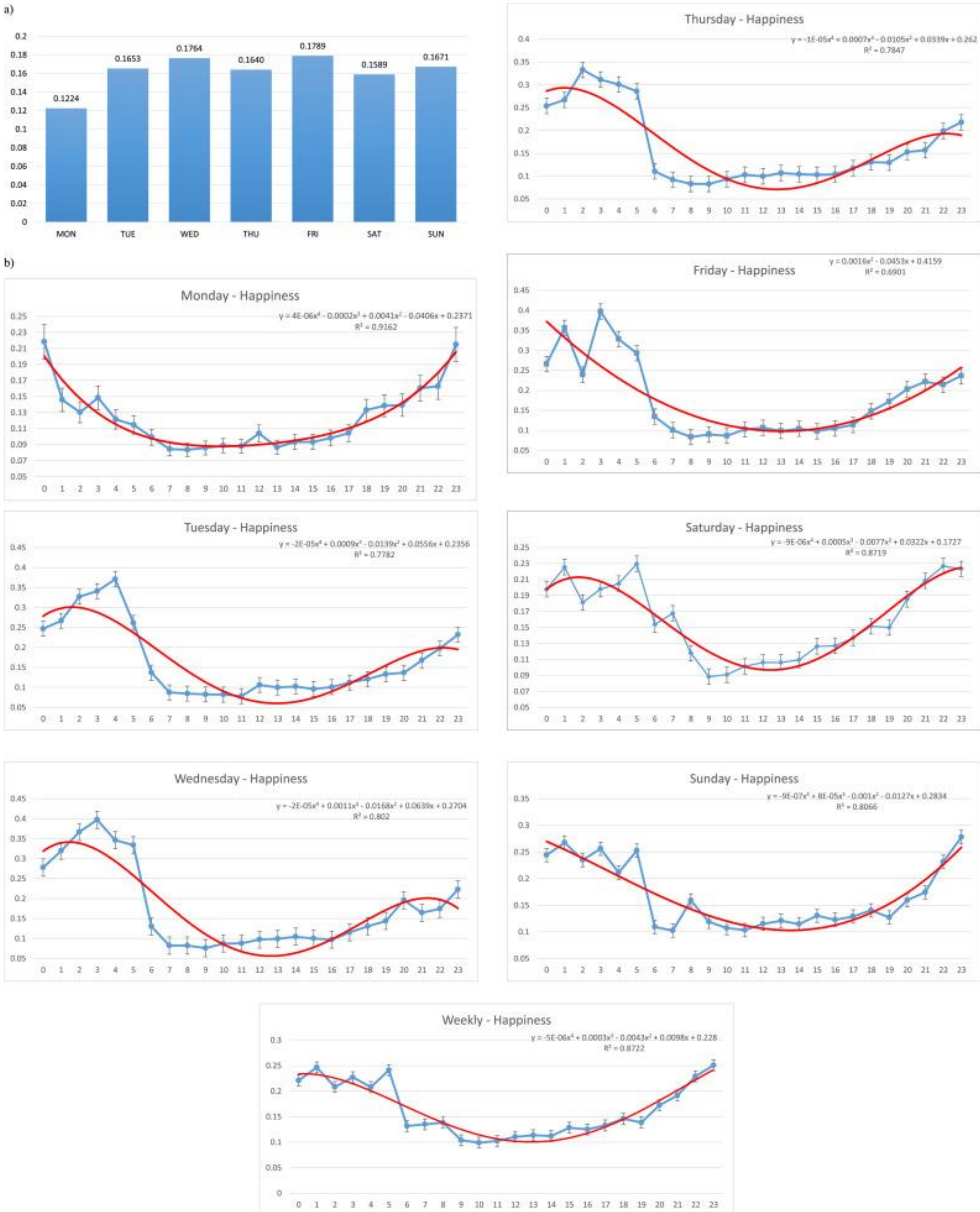


Fig. 4. Diagrams of (a) average happiness values by weekdays and (b) happiness per hour for each weekday.

An analysis of happiness and arousal (see Fig. 5) shows that the two parameters are linked by an average relationship. The values measured in Gedimino Avenue indicate an average dependency of 0.5282. In Fig. 5, the left y-axis shows the aggregate daily happiness values (recorded between 23/01/2018 and 04/03/2018) and the right y-axis shows the aggregate daily arousal values; a total of 170,223 records were considered. It was established that growing happiness of a passer-by is accompanied by an increase in the passer-by's arousal. The same relationship was noted by foreign scientists (Minhad et al., 2017, Zimasa et al., 2017, Gilet and Jallais, 2011, Jefferies et al., 2008, Masmoudi et al., 2012). High intensity emotions are expressed by happiness or anger, as Minhad et al. (2017) explain. However, classification of these emotions is extremely difficult due to a high level in the arousal (activation) dimension. Zimasa et al. (2017) claim that "happy mood is considered to be a high-arousal physiological state".

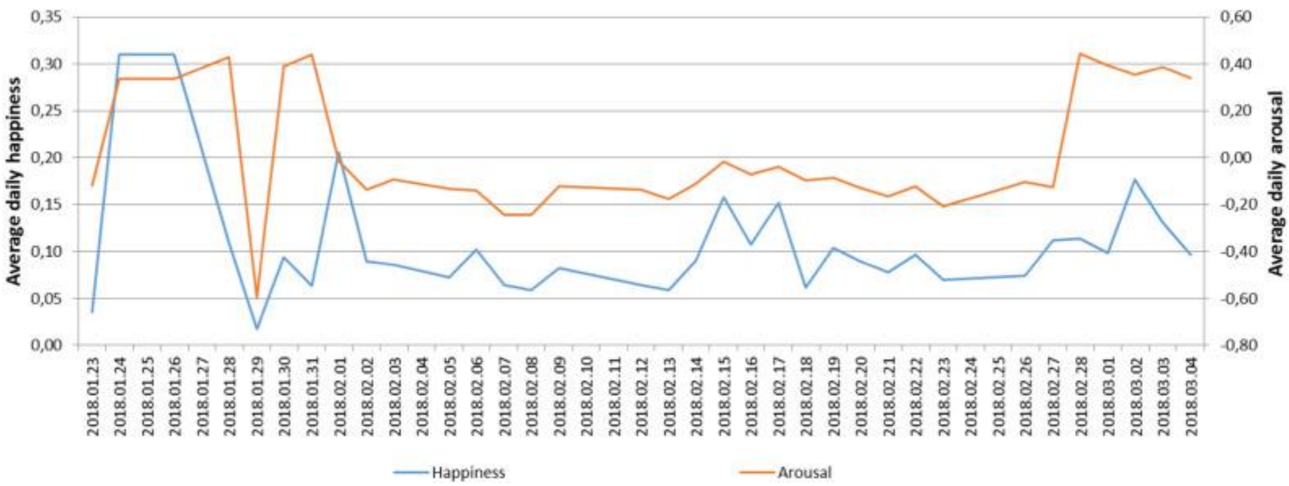


Fig. 5. The dependency between average daily happiness and arousal (r = 0.5282) based on the values measured in Gedimino Avenue.

Scientists argue that happiness and valence are also linked (Ma et al., 2016, Calvo and Beltrán, 2013, Stavrova and Luhmann, 2016, Wojcik et al., 2015). Upon seeing a happy virtual face, research participants in a study by Ma et al. (2016) would mimic the expressed emotion. The verification of this included their higher valence scores as well as their improved mood-sensitive, divergent-thinking, task performances. Calvo and Beltrán (2013) claim that happy expressions cause positive valence. The measurements in Pilies Street indicate the same trend. Our analysis of the aggregate data for the period between November and February (Fig. 6; a total of 395,157 records were considered) shows an average relationship between happiness and valence (r = 0.62). It can be argued that as the sense of happiness is growing or diminishing, so is the valence.

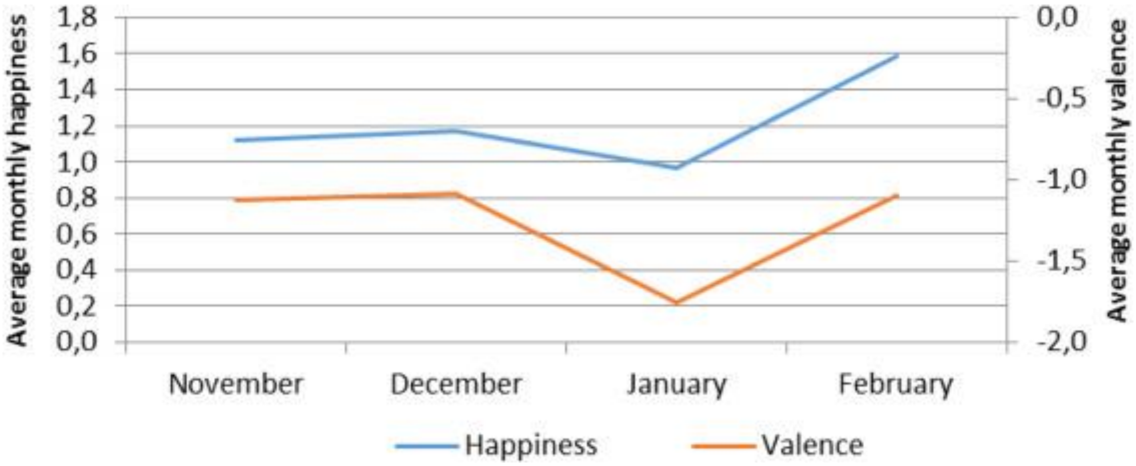


Fig. 6. A comparison of average monthly happiness and valence values measured between November and February in Pilies Street (r = 0.62).

Weather is another important aspect that contributes to variations in human physiological and biometric parameters. This dependence was examined by many foreign scientists (Sharp, 2011, Spasova, 2011, Tsutsui, 2013). Differing weather conditions prompted emotional state changes, which also resulted in positive or negative characteristics for the human organism, as Spasova (2011) proclaimed. Pertinent to this, Klimstra et al. (2011) studied correlations between happiness, anxiety, and anger, the three indicators of mood, and temperature, sunshine and precipitation, the three weather possibilities. These scholars established significant correlations between these variables, in most cases. Sharp (2011) argues that wind is also a factor contributing to changes in human emotions. A wind speed increase of over 12 miles/hour makes the person feel physical discomfort. Our physiological and biometric measurements in Gedimino Avenue and Pilies Street also show a dependency between emotions and weather. Fig. 7 presents the aggregate arousal and outdoor temperature values measured in Pilies Street between 21/12/2017 and 20/02/2018. An average correlation was determined between arousal and outdoor temperatures (0.4831). The results suggest that outdoor temperature is one of the factors contributing to changes in arousal. The same trend is noticeable when we look at the effect of the wind on human emotions and moods. Fig. 8 shows that the stronger the wind, the higher the arousal, with a correlation of 0.5035.

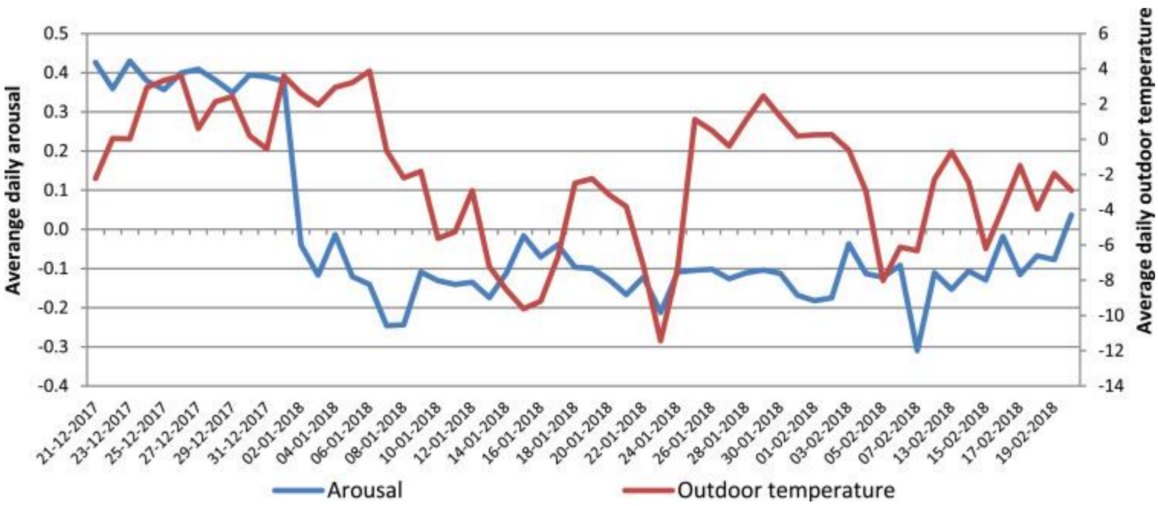


Fig. 7. The dependency between average daily arousal and outdoor temperatures (r = 0.4831) based on the values measured in Pilies Street.

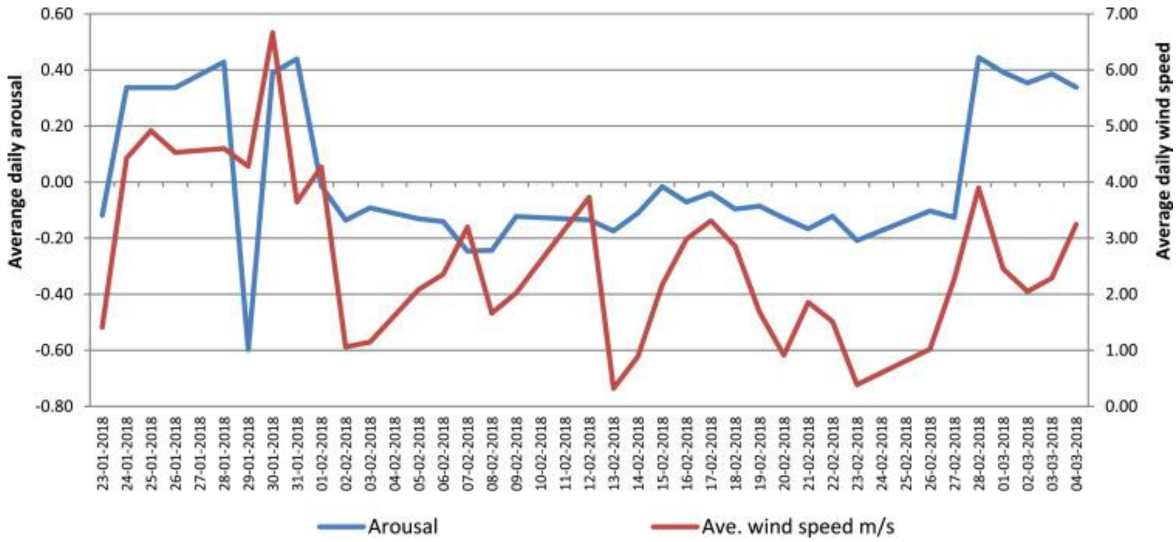


Fig. 8. The dependency between average daily arousal and wind speeds (r = 0.5035) based on the values measured in Gedimino Avenue.

Fig. 9 shows the happiness values per day recorded between 15/12/2017 and 01/01/2018 with happiness peaking on 24 December 2017 (Christmas Eve) and on 31 December 2017 (New Year's Eve). The holiday season also produced higher respiratory rates (see Fig. 10). The values measured in Pilies Street between November and February presented in 10 show higher respiratory rates on December 24–26 and December 31 and throughout the month of December.

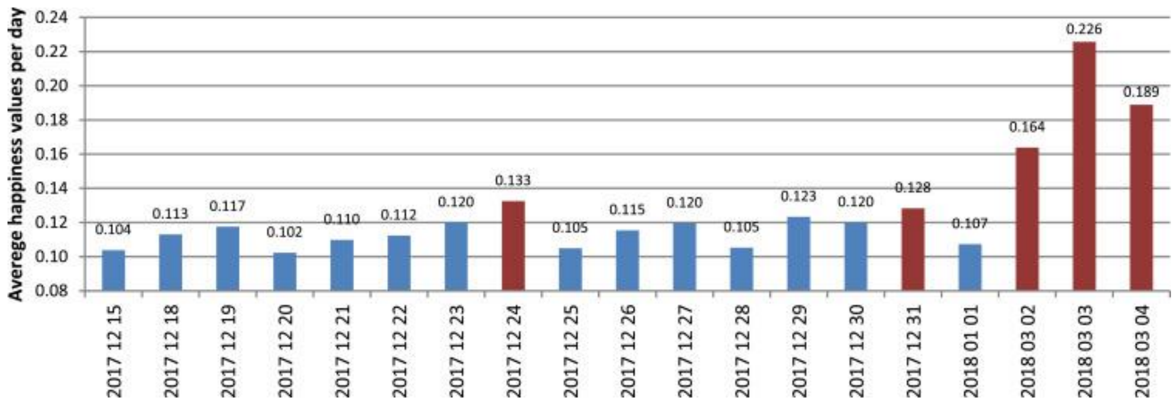


Fig. 9. The changes in happiness per day between 15/12/2017 and 01/01/2018. Compared to the months analysed, residents were happier during the St. Casimir's Fair.

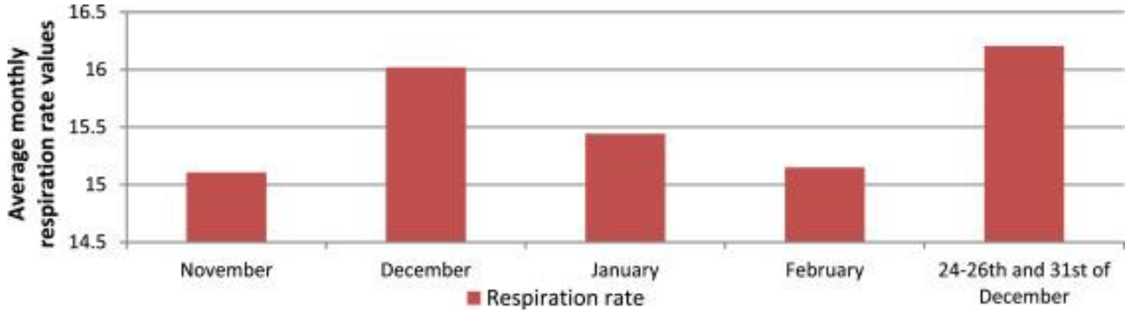


Fig. 10. The average monthly values measured in Pilies Street between November 2017 and February 2018 show higher respiratory rates on December 24–26 and December 31 and throughout the month of December.

Gomez and Danuser (2007) have stated that the heart rate (HR) and the respiratory rate increased, as did the subjective arousal. Other scientists examined this relationship as well (Briefer et al., 2015, Gomez et al., 2016, Vlemincx et al., 2013). The same trend has been determined after comparing the aggregate values measured in Vilnius among 2017.12 and 2018.02. Fig. 11 compares the results for the arousal (a), heart rate (b) and respiratory rate (c). It has been determined that the average arousal, heart rate and respiratory rate between December and February were higher in Gedimino Avenue than in Pilies Street. A comparison of the January data, for instance, shows the arousal higher by 11.9%, the heart rate higher by 1.2% and the respiratory rate higher by 7.31%. It can be argued then that Gedimino Avenue triggers stronger emotions in passers-by than Pilies Street and therefore their arousal (a), heart rate (b) and respiratory rate (c) are higher (see Fig. 11).

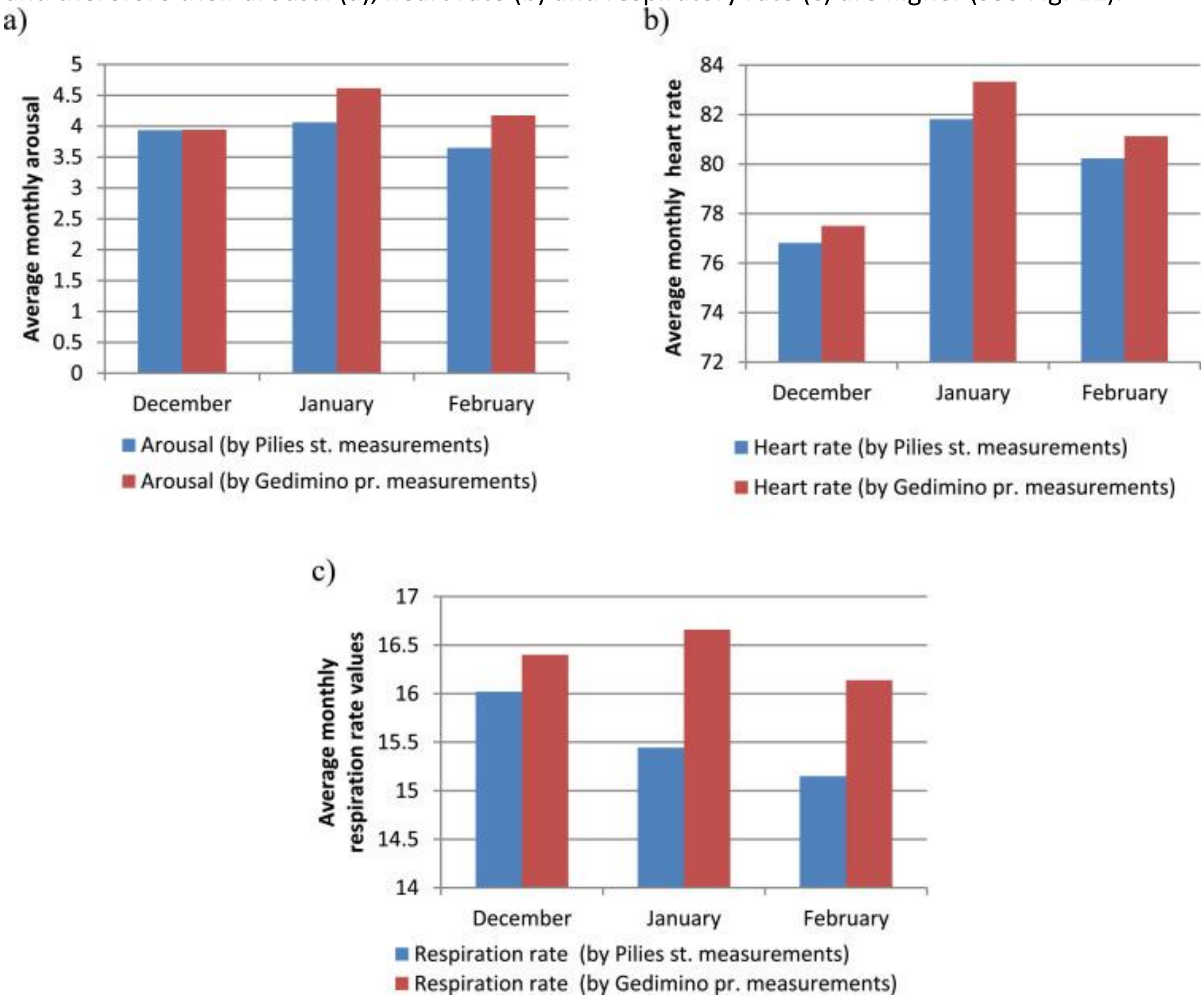


Fig. 11. A comparison of the average monthly arousal (a), heart (b) and breathing rates (c).

Azarbarzin et al. (2014) argue that there is a strong correlation between arousal scale and heart rate within inhabitants. Other scientists have also determined a relationship between the parameters (Pfaff, 2005, Schmidt, 1984, Gomez and Danuser, 2007, Kuo et al., 2015). If we compare the heart rate and arousal looking at the days of the week (Fig. 14), at the beginning of the week (Monday and Tuesday) the heart rate and arousal are the lowest, but by Tuesday the parameters start increasing. Rossi and Rossi (1977) established that positive moods were higher on Friday through Sunday and that negative moods lesser on Saturday and Sunday. This research gives encourage for a weekend effect. Also, McFarlane et al. (1988) detected support for a weekend effect in mood, measured in terms of both valence and arousal among college students. Both mood valence and arousal were highest on Fridays and Saturdays, followed closely by Sundays (McFarlane et al., 1988). We need further studies of the heart rate and arousal, however, to determine how average heart rates and arousal change depending on the day of the week.

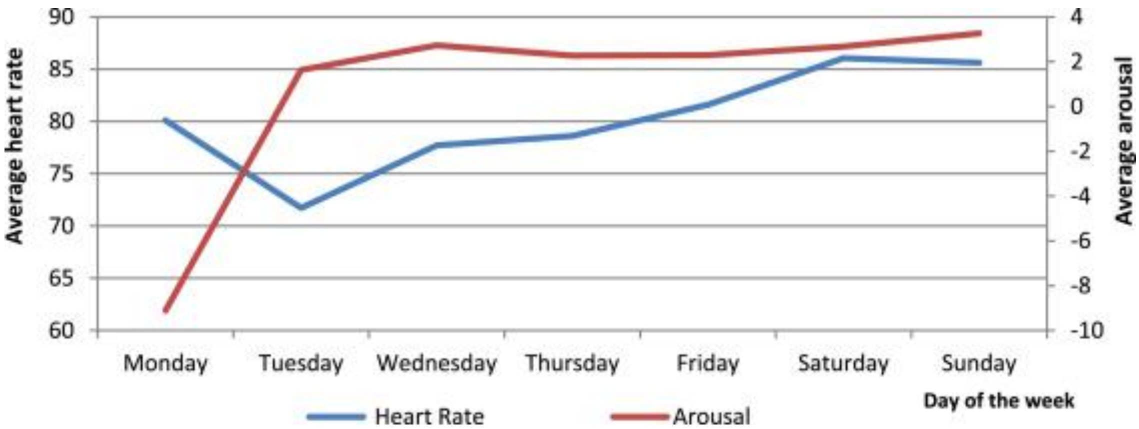


Fig. 12. The average weekly heart rate and arousal compared looking at the days of the week (as measured in Gedimino Avenue).

9. O3/A9: Real-time negative emotions and possible COVID-19 indices in Vilnius

In the opinion of Bell (1999), the case study method is principally suitable for individual academics since it gives a chance for one feature of a problem to be considered in some complexity within a limited time. Case studies thoroughly analyzes specific tasks in order to evaluate certain parts of the Integrated MICROBE method.

Diurnal happiness, valence and temperature

The data were gathered from depersonalized passersby at seven specific sites with minimal intrusion, using IP cameras, FaceReader 8 and FLIR A35SC infrared cameras, and three layers of biometric-emotional data were collected. There was a recording of one happiness, sadness and valence, and 22 temperature measurements were taken per second. These data were collected and analyzed as follows:

- 1st layer: emotional states (happy, sad, disgusted, angry, scared; values ranging from 0 to 1);
- 2nd layer: valence (values of valence ranging from −1 to 1);
- 3rd layer: average facial temperatures of the crowd.

The calculation of valence involved the intensity of "happiness" minus the intensity of the highest-intensity negative emotion (sad, disgusted, angry, scared) *(25)*; in this way, positive and negative emotions were combined into the single score of valence. A total of 208 million above data points were analyzed using the SPSS Statistics software package. Figure 13 presents the average values of (a) happiness, (b) valence and (c) temperature per weekday hour.

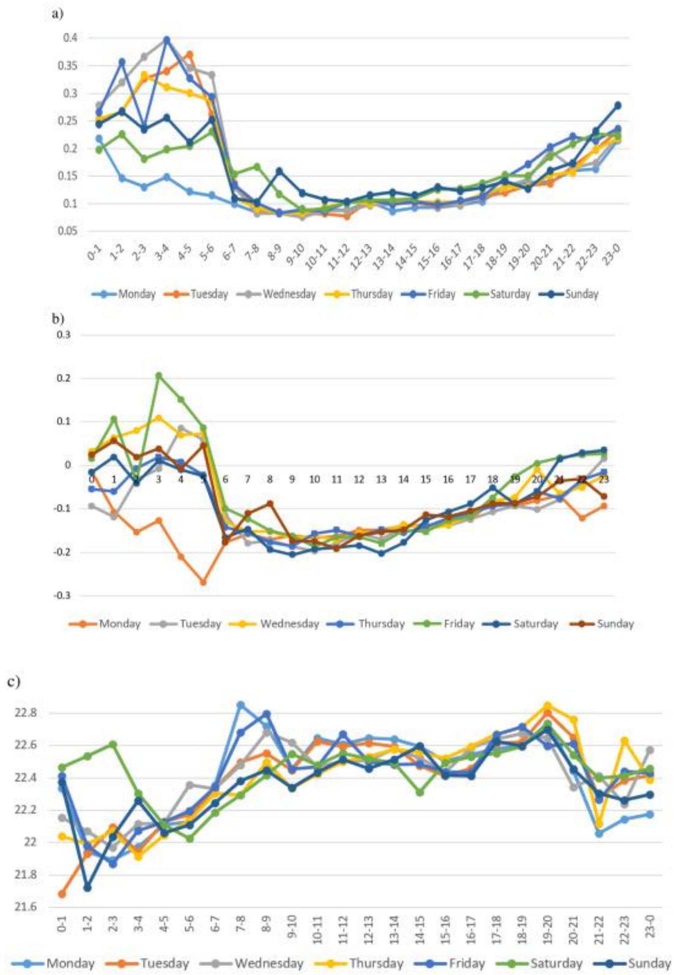


Fig. 13. Average happiness (a), valence (b) and temperature (c) values on weekdays, by hour.

This research along with studies conducted worldwide *(23, 24)* indicate a dependent interrelationship between happiness, sadness, valence and temperature. Other studies (*26-28*) as well as this research indicate a cyclical nature of happiness, sadness, valence and temperature over the course of a day. This became the basis for raising the first hypothesis for this research that diurnal happiness, sadness, valence and temperature have statistical interrelationships among passersby in Vilnius. All of these variables were found to be correlated with one another, with the strongest correlation between happiness and valence ($r = 0.964$). This was a positive, statistically significant relationship with $p < 0.001$. There was a strong, negative relationship between temperature and happiness ($r = -0.756$), which was statistically significant with $p < 0.001$. Meanwhile, the relationship between temperature and valence was negative with an average strength $r = -0.628$, and was statistically significant with $p < 0.001$. This means that as the values of happiness and valence decrease, the values of temperature increase, and vice versa.

Table 3. Statistical interrelationships between diurnal happiness, valence and temperature for passersby in Vilnius.

	Happiness	Valence	Sadness	Temperature
Happiness	1			
Valence	0.964**	1		
Sadness	−0.871**	−0.741**	1	

	Happiness	Valence	Sadness	Temperature
Temperature	−0.756**	−0.628**	0.862**	1

In this research, a comparison was drawn between happiness (29,129,036) and valence (29,169,150) biometric data gathered in Vilnius and Golder, Macy *(29)* positive affect data. Golder and Macy (*29*) employed the Twitter data access protocol to collect data on some 2.4 million English-speaking persons worldwide, gathering 509 million messages written between February 2008 and January 2010. Positive affect data were scanned from the original article using DigitizeIt and GetData Graph Digitizer software. This comparison permitted cross-societal tests of the cultural and geographic influences on positive affect patterns identified by Golder and Macy (*29*) and Vilnius biometric data.

Table 4. Correlations derived from the diurnal happiness and valence data of passersby in Vilnius with diurnal data on positive affect (PA) taken from Twitter by Golder, Macy *(29)*.

	Vilnius diurnal data		**Golder and Macy (2011) diurnal positive affect data**		
	Happiness	**Valence**	**Hourly changes in positive affect in**		**English-speaking persons worldwide**
			UK/Australia	**US/Canada**	
Happiness	1				
Valence	0.964**	1			
UK/Australia	0.540**	0.595**	1		
US/Canada	0.586**	0.614**	0.960**	1	
English-speaking persons worldwide	0.533**	0.585**	0.835**	0.900**	1

The correlation between hourly changes in positive affect in UK/Australia (US/Canada) as obtained by Golder and Macy (*29*) and happiness in Vilnius was $r = 0.540$, $p < 0.001$ ($r = 0.586$, $p < 0.001$), and for valence, $r = 0.595$, $p < 0.001$ ($r = 0.614$, $p < 0.001$). This shows a positive, statistically significant relationship of average strength (Table 4). The patterns of happiness and valence diurnal rhythms (based on local time) found in our research (Fig. 13) have similar shapes for positive affect in UK/Australia and US/Canada.

The correlation between hourly changes in positive affect in English-speaking persons worldwide as obtained by Golder and Macy (*29*) and diurnal happiness in Vilnius was $r = 0.533$, $p < 0.001$, and for valence, $r = 0.585$, $p < 0.001$ (Table 4). The pattern of diurnal rhythms for happiness in Vilnius and valence in this research (based on local time) has a similar shape in comparison with positive affect in English-speaking persons worldwide (Fig. 13).

Results of the correlation analysis appear in Table 4. The results of the correlation analysis serve as the basis for drawing a conclusion that there are statistically significant relationships ($p<0.01$) between all the variables used in this study. The strongest relationship is between happiness and valence ($r=0.964$), whereas the weakest, between happiness and English-speaking persons worldwide ($r=0.533$).

A regression analysis is performed to establish the dependency of the happiness and valence variables (the dependent variables) on positive emotions UK/Australia, US/Canada and English-speaking persons worldwide (ES) (the independent variables). The results of the regression analysis for establishing the dependency of the independent variable happiness and valence on the selected dependent variables appear in regression equations:

$$Happiness = -1.022 - 11.381 \cdot \frac{UK}{\text{Australia}} + 34.324 \cdot \frac{US}{\text{Canada}} - 0.093 \cdot ES \tag{1}$$

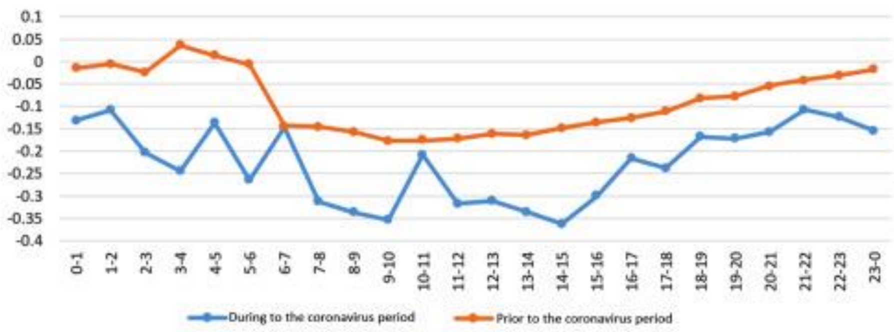
$$Valence = -1.606 + 5.802 \cdot \frac{UK}{\text{Australia}} + 11.804 \cdot \frac{US}{\text{Canada}} + 1.515 \cdot ES \tag{2}$$

The compiled regression models can be considered appropriate upon finding that $p<0.05$. The finding is that 35.0 percent of the changes in the variables relevant to the UK/Australia, US/Canada and other English-speaking persons worldwide (ES) are explainable by fluctuations appearing in the happiness variable. Thus, there is the formulation of a regression equation. 38.4 percent of the variations in variables UK/Australia, US/Canada and English-speaking persons worldwide can be explained by the fluctuations in the valence variable. The compiled regression equations serve as the basis for potentially forecasting the diurnal happiness and valence levels in Vilnius City. Therefore, similar regression equations can be derived and applied anywhere in the world.

Valence and sadness, before and during quarantine period

Research around the world as well as this work described herein indicate the interdependency of valence and sadness as well as their cyclical nature during the daytime. However, it remains unclear whether or not such interdependency and this cyclical nature also prove true during the time of the coronavirus disease pandemic. Therefore, the aim of our research in Vilnius was to substantiate the second hypothesis that diurnal valence and sadness, before and during the quarantine period, have a statistical dependency among passersby in Vilnius. To achieve this goal, data on valence and sadness were compared prior to the period of quarantine imposed due to the coronavirus crisis (November 22, 2017, to March 16, 2020), and during the coronavirus epidemic in Vilnius (March 17, 2020 to May 20, 2020) (Fig. 14).

a)



b)

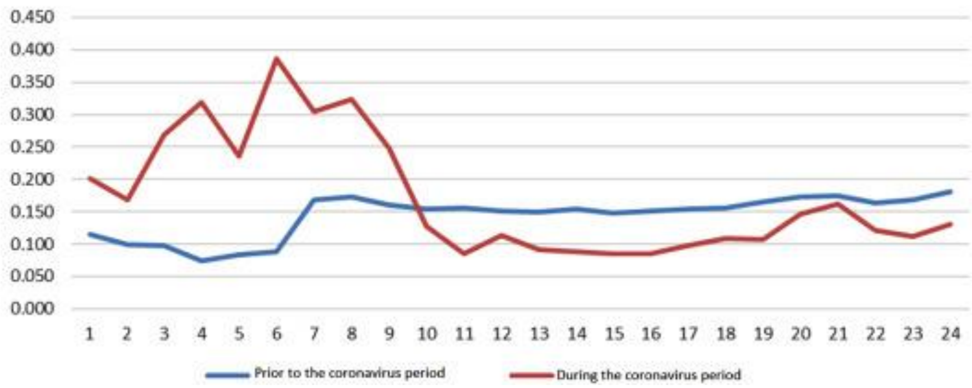


Fig. 14. Average diurnal patterns of valence (a) and sadness (b) over 24 hours, before and during coronavirus quarantine.

A total of 30,538,597 data entries on average diurnal sadness were made before the coronavirus crisis and 878,167 during the quarantine period. The relationship was found to be negative, with an average strength of $r = -0.508$ and with statistical significance of $p < 0.05$. Fig. 14b shows the average diurnal pattern of sadness in Vilnius before and during the quarantine period on a weekly basis, as per each 24 hours. The sadness scores increased by 15.1% during the quarantine period, rising from 0.1338 to 0.1540.

Seasonality

Seasonality has a strong influence on most life on Earth, and is a central aspect of environmental variability, according to Garbazza and Benedetti *(30).* Fluctuations due to the seasons have been widely recognized as affecting moods, and have significant effects on human behavior. Even ancient medical texts mention this effect, and modern fMRI findings have substantiated the same idea *(30)*. Light and sunlight stimulate emissions of serotonin, which contributes to wellbeing and happiness. Serotonin affects mood levels, including anxiety and happiness, and sunshine acts on people by making them happier, both emotionally and physically. Research conducted around the world *(31)* reveals a direct dependency between the duration of sunshine, the conditional length of a day and the rate of serotonin production in the brain. This research therefore focused on variances in happiness and valence among individuals as the days changed in length due to the season. Variations of happiness (Fig. 15a) and valence (Fig. 15a) relative to the duration of monthly daylight were discovered at 95% confidence intervals among Vilnius passersby over the course of this research. These data supplement the global research under investigation, because data under biometric analysis of such a huge capacity had never been employed in the field of seasonality to date.

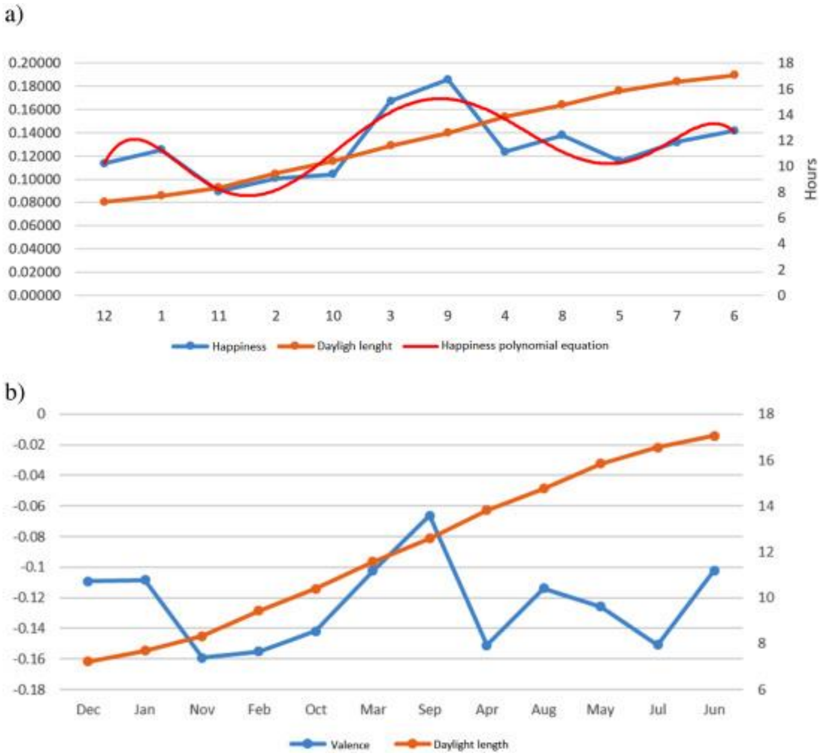
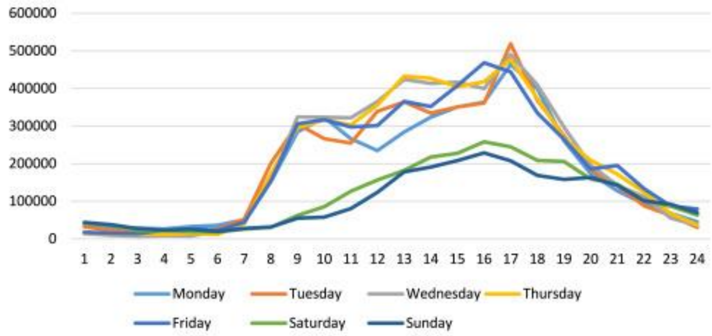


Fig. 15. Variation in happiness (a) and valence (b) with monthly changes in day length.

Diurnal data numbers

Cyclical human activities like the flows by pedestrians and by vehicles traffic flows, which vary over the course of a day, also sometimes have interdependencies, as global research has shown. However, it is still unclear, whether the number of data values of diurnal happiness, valence and facial temperature will correlate upon the performance of biometric studies in real time. The data gathered as part of this third hypothesis indicate that the weekly number of data on diurnal happiness, sadness, valence and facial temperature are cyclical (Fig. 16) and correlate with their values. There is a strong relationship between the average values of diurnal happiness ($r = -0.834$, $p < 0.001$), valence ($r = -0.772$, $p < 0.001$), sadness ($r = -0.676$, $p < 0.001$) and facial temperature ($r = 0.588$, $p < 0.001$), and their numbers of measurements. All relationships are statistically significant ($p < 0.001$).

a)



b)

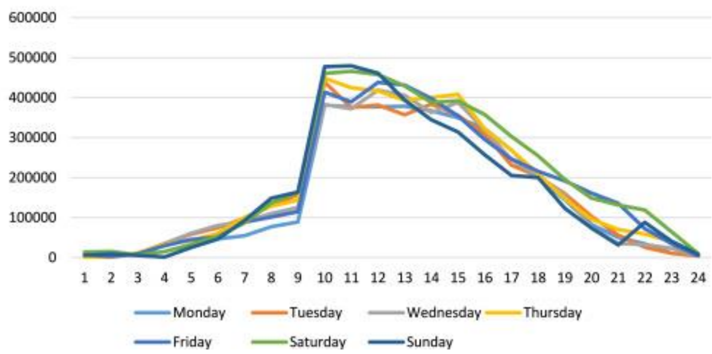


Fig. 16. Diurnal number of data on (a) happiness and (b) facial temperature.

Average circadian pattern of sadness during and prior to the coronavirus quarantine period in Vilnius

Data on sadness were also compared during and prior to the coronavirus quarantine period in Vilnius (see Fig. 14).

The WHO declared the respiratory disease caused by the SaRS-CoV-2 coronavirus a pandemic in March of 2020. Governments all over the world instituted measures involving isolation with differing degrees of restriction to curtail the spread of this virus. Physical restraints resulting from instituted lockdowns and social isolation had reasonably good effects in terms of limiting viral contagion, but mental health suffered due to the onset of feelings such as uncertainty, fear and despair. People are likely to suffer a ‘parallel pandemic’ very soon, requiring help from mental health professionals. This ‘pandemic’ is expected to involve acute stress disorders, post-traumatic stress disorders, emotional disturbances, sleep disorders, syndromes of depression and even suicides as a result *(46)*. Thirteen studies have reported results indicating that the imposition of quarantine is related to different negative psychosocial ailments including depression, anxiety, anger, stress, post-traumatic stress, social isolation, loneliness and stigmatization *(47)*. As a disorder, depression can result in major costs to health, but often goes unnoticed when it affects university students. Students’ lifestyles very often cause them to sleep less, which in turn causes low energy, anxiety and sadness. These symptoms are also usually related to depression, and hence this condition does not receive the attention it deserves. It is assumed that students are likely, e.g., to sleep less than needed *(48)*. Sadness-related emotions, which affect people across genders and ages, frequently remain undifferentiated, and are not denoted as better-specified symptoms of depression. Thus, they are simply ascribed to negative emotions without considering their emotional intensity *(49)*.
The first recorded outbreak of coronavirus (COVID-19) was in China in December 2019. The disease has persisted, and has spread across the globe since then. The consequences to both individuals and

entire communities have been devastating in humanitarian and economic terms. Epidemics and pandemics of infectious and contagious diseases can spark experiences of intense trauma for numerous people, which may lead to post-traumatic stress disorder, as discovered in earlier and current research *(50)*. This includes a study by Borgmann et al. *(38)*, who investigated individuals suffering from sadness and consequential post-traumatic stress disorder following sexual abuse in childhood by comparing them with healthy individuals. As in the present research, Borgmann et al. *(38)* found a negative correlation of sadness. Prior to and during the quarantine period of quarantine, sadness among passersby in Vilnius had a derived relationship that was negative. It had an average strength of $r = -0.508$, and was statistically significant with $p < 0.05$ (Fig. 14).

10. O3/A10: Assessing the Accuracy of the MICROBE System by Verification and Validation

There was a verification at first to evaluate MICROBE System for its accuracy. The MICROBE System were practically verified and validated in various public places in Vilnius. The efficiency and usability of the MICROBE System for practical applications were established by a pilot experiment. This way the MICROBE System was evaluated for possibly needed improvements prior to its launch in actual public spaces. The black-box testing method was the means used to test the MICROBE System. Results gained during the verification and validation, along with corresponding data, comprised the information provided to the tester.

According to developed MICROBE Method, Stage 10 regards the verification and validation processes necessary to assess ASP Method and System precision. The accuracy of the ASP was assessed by the verification process, assuring that the results from the system reflected the actual situation. The ASP Method was first confirmed to measure its accuracy and verify that the ASP Method's outcomes showed the real condition by adapting correlations (see Subsection 5.1). The steps relevant to the proposed ASP Method are accurate, as shown by the calculated correlations. The validation and verification of the ASP Method, which appears in the next step, was expert-assisted. This assessment was conducted by twelve urban planning and real estate development experts. Opinions were submitted by those experts who validated the analysis of the urban areas. The validation provided was in terms of the affective, emotional and biometrical conditions of passersby, their valence and arousal levels and by cultural heritage objects. Furthermore experts have tested all the possible states of the ASP Method to double check the results to see if the desired features of the method had made them satisfactorily. The hypothesis must coincide with the ASP Method, which the verification identifies. Four cases of cultural heritage sustainability (see Subsection 5.2) were verified and validated by the proposed hypothesis, which also validated the accuracy of the ASP Method and System.

Two publicly available and objective datasets on basic human emotions were employed by Lewinski et al. (2014) to validate FaceReader and to evaluate the accuracy of recognizing facial expressions. Of the matching scores, 89% were reported to FaceReader in 2005. Tests were run by Lewinski et al. (2014) on version 6.0. These scholars discovered that FaceReader recognizes 88% of the target labels of emotions in the Warsaw Set of Emotional Facial Expression Pictures (WSEFEP) and in the Amsterdam Dynamic Facial Expression Set (ADFES). Meanwhile the average was 0.69 for both datasets when using the Facial Action Coding System (FACS) index of agreement. This means there was an 85% rate of recognition of human emotions when using this index. The accuracy of the recognition of basic human emotions for those same two datasets was also computed at 87% for ADFES and 82% for WSEFEP by Lewinski et al. (2014). FaceReader has been a reliable indicator of facial expressions that divulge basic human emotions over the past decade, as the aforementioned scholars have reported. Furthermore, they report, that there is a potential for similar robustness when used in conjunction with FACS coding. In general, researchers report an 88% accuracy in recognizing basic human emotions by FaceReader 6.0. FACS accuracy pertinent to the FaceReader index of agreement is 0.69 (Lewinski et al. 2014). Numerous other investigators show very similar results regarding the validity and accuracy of FaceReader, thereby also reporting similar opinions regarding the manufacturer of this equipment, Noldus Information Technology.

An assessment of the accuracy of the MICROBE System was performed applying verification. There was assurance during the verification of the MICROBE System that the results from the system reflect the actual situation. The endeavor was to test all possible states of the MICROBE system and, thereby, check the levels of satisfaction of the desired system's features. An assessment of the accuracy of the MICROBE System will be also conducted by applying validation. Furthermore, both the validation and the verification of the MICROBE System was conducted with expert assistance.

The development of added value is foreseen during the course of the proposed project:

- For the first time, adaptive to the market, unique prototype of the MICROBE system wasdeveloped. It will stimulate the development of innovation in digital construction.
- The new research was permit receiving significantly, up to 90% more qualitative and quantitative information, as compared to earlier studies. This was permit more effective assessment and modelling of built environments with consideration of the principles for sustainable development.

There was a consideration regarding a validation of the data on the emotions, physiological and affective (AFFECT) states of passers-by in the urban places. This phase had one principal goal–defining associations between a passers-by's valence and arousal and environmental pollutants, such as SO2. PM2.5. PM10. NO2. CO and O3; magnetic storms; interest and boredom. Verifying the MICROBE System involved data originating from tests taken by 8 Vilnius Gediminas Technical University (Lithuania) employees and passers-by. The data and information were obtained from these passers-by and employees. The questioning of the participants took place at the end of the experiment, when they filled out the questionnaires (Have the air temperature. relative humidity and arousal been correlated appropriately? Do the outdoor environmental qualities of the urban places, such as the levels of pollution, humidity, temperature, light intensity and colors, as well as music affect passer-by arousal by increasing or decreasing it? Does favored levels of passer-by arousal, happiness, and valence can be attained, based on the Yerkes-Dodson Law [48] and the Somatic Marker Hypothesis [51], therefore, guaranteeing the best likely public place wellbeing? Etc.) to evaluate the MICROBE System. For one, this passer-by feedback revealed the added benefits of the MICROBE System providing learning with inspiration and pleasure. This MICROBE System, according to the passers-by and employees participating in the experiment, could be applied in practice to provide conditions for rationalizing the public places, improving the comfort and valence of the leisure, at the same time, increasing happiness. The four scholars who are engaged in this assessment additionally bring with them a deep knowledge from their professional experiences in cognitive public spaces. The reports submitted contain all the assessments pertinent to each review.

11. O3/A11: Education of students

Each university integrated developed MOOC in the study programmes. The gradesheets are attached separately for data protection.