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Diurnal emotions, valence and the coronavirus lockdown analysis in public spaces

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ABSTRACT

A large-scale analysis of diurnal and seasonal mood cycles in global social networks has been performed successfully over the past ten years using Twitter, Facebook and blogs. This study describes the application of remote biometric technologies to such investigations on a large scale for the first time. The performance of this research was under real conditions producing results that conform to natural human diurnal and seasonal rhythm patterns. The derived results of this, 208 million data research on diurnal emotions, valence and facial temperature correlate with the results of an analogical Twitter research performed worldwide (UK, Australia, US, Canada, Latin America, North America, Europe, Oceania, and Asia). It is established that diurnal valence and sadness were correlated with one another both prior to and during the period of the coronavirus crisis, and that there are statistically significant relationships between the values of diurnal happiness, sadness, valence and facial temperature and the numbers of their data. Results from the simulation and formal comparisons appear in this article. Additionally the analyses on the COVID-19 screening, diagnosing, monitoring and analyzing by applying biometric and AI technologies are described in Housing COVID-19 Video Neuroanalytics.

1. Introduction

Daily fluctuations in the rhythms of human behavior and physiology, which occur due to light and social cues, show remarkable differences due to their individuality (Leone et al., 2017). Diurnal rhythms, either under constant conditions or in idealized light-dark surroundings, have been the focus of many research studies, although the effects of social pressures such as timetables for employment and education on the daily and seasonal activity rhythms of individuals have attracted relatively little attention, and few studies have been carried out in this area.

Physiology organization on a timely basis is critical for human health. Sleep–wake behavior, hormone secretion, cellular function and gene expression are systems that recur in strict rhythms on a twenty-four-hour basis (Bedrosian and Nelson, 2017). A biological network of fundamental value for harmonizing human biology with its surroundings, in the opinion of Yang et al. (2013), is the molecular clock. This clock affects the daily fluctuations in human activities, body temperature, mood, blood pressure and hormonal secretion patterns.

Surveys assessing diurnal collective emotions have typically been carried out by administering questionnaires to several dozens or hundreds of people. Very large scales have been available currently due to big data of written texts on the Internet relevant to collective emotion analyses (Sano et al., 2019). An analysis of affective cycles in global social networks has been successfully conducted over the past 10 years using Twitter (Dodds et al., 2011; Lampos et al., 2013; Roenneberg, 2017; Dzogang et al., 2018), Facebook (Pellert et al., 2020) and blogs (Sano et al., 2019). As reported by Liang and Shen (2018), social media platforms have shown regular daily patterns of user activities in prior studies. Clear cycles based on weekly and seasonal behaviors appear as collective emotions. Sano et al. (2019), who spent 10 years examining collective emotions based on 3.6 billion blog articles originating in Japan, have identified such periodic behavior using a dictionary-based method. Dzogang et al. (2018) conducted another study that involved taking samples of Twitter contents in the United Kingdom at hourly intervals over four years. Their work revealed a strong, diurnal rhythm in most psychometric variables, and showed that 85% of the variance across 24-hour profiles could be explained by only two independent factors. Dodds et al. (Golder and Macy, 2011) also examined expressions made on Twitter, finding temporal variations in happiness and information levels when viewed on hourly and annual scales. Their dataset consisted of over 46 billion words making up nearly 4.6 billion expressions, which were posted by over 63 million individual users over 33 months. Pellert et al. (2020) empirically tested a computational model of affective dynamics, studying a large-scale dataset of updates on Facebook statuses by employing text analysis techniques. After stimulation was applied, affective states returned

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exponentially to an individual-specific baseline. The quantification of these states is as valence and arousal. A somewhat positive valence value and a moderate arousal point below the midpoint are, on average, at this baseline (Pellert et al., 2020). The two fundamental dimensions of mood, i.e. positive affect (PA) and negative affect (NA), and their diurnal rhythms were studied by Clark et al. (1989), who found that there was significant diurnal variation in PA but none in NA.

Updated outlooks on collective human behaviors are now part of the data available to people involved with the Internet, and more and more people are partaking of such innovations in current times. The identification and analysis of collective diurnal and seasonal emotions were a previously non-existent area of research, as social media have taken off in popularity and become widespread only over the last 10 years or so (Sano et al., 2019). Policies regarding actions and decision making and their diurnal rhythms require not only the application of extracted and traced collective emotions (Leone et al., 2017) but also analyses of language changes (Dzogang et al., 2018), hedonic behavior, music (Park et al., 2019), natural disasters (Sano et al., 2019), reproductive cycles (Wood et al., 2017), and so on. Constant diurnal rhythms in policies regarding actions and decision-making have also been discovered by Leone et al. (2017), who report that in the morning, actors are likely to follow policies focused on prevention and involving slower, more accurate decisions. Later in the day, actions tend to focus more on promotion, involving faster but less accurate decisions. Language undergoes dramatic changes between day and night, as conclusively shown by Dzogang et al. (2018). These changes reflect the differences in the concerns of individuals and their fundamental cognitive and emotional processes. Major changes in neural activity and hormonal levels give rise to these shifts (Dzogang et al., 2018). A pattern of monotonically improving, weekly returns characterizes the day-of-the-week effect, as revealed by the enormous amount of evidence found by Zilca (2017). There is a day-of-the-week effect, which can be explained by behavior. A monotonic improvement in mood is seen over the course of a week (Zilca, 2017). One hypothesis for this is based on biology, and claims that human reproductive cycles adapt to seasonal cycles that are hemisphere-dependent. Another hypothesis is cultural, and claims that cultural factors such as holidays primarily cause this variance in conception dates (Wood et al., 2017). There is a strong relevance of a weekday to long-short anomaly returns. An analysis by Sano et al. (2019) examines collective emotion caused by natural disasters. One example is in Japan, showing much tension in April when school starts, which is likely to be the reason. Again, in Japan, whenever there are consecutive holidays, the incidence of suicide increases (Sano et al., 2019). Park et al. (2019) studied the diurnal and seasonal patterns in affective preference by analyzing global music streaming data.

Global research (Zillmann, 1988; Damasio, 1994; Simon, 1997; Kahneman, 2011) indicate that emotions play an exceptional role in decision-making (see Method). The studies conducted as part of this research are innovative, since this is the first time biometric data have been gathered remotely on a large scale for the testing of collective emotions. The purpose of this research is to establish human affective rhythms (diurnal rhythms and seasonal patterns).

Until now biometric research has been executed on a large scale, not remotely. Various vendors, including Fitbit, Microsoft, Google, Android, Apple and Samsung, adopt particular approaches to the way continuous data, such as skin temperature, heart rate and others, can be collected from wearables, including from sensors, into third-party systems (Arriba-Pérez et al., 2016). Fitbit (an activity tracker) followed with analogous research. This was the biggest ever collection of heart-rate data with more than 150 billion hours of data taken from users of the widespread fitness tracker (Sherman et al., 2019). Various Emotion APIs including Microsoft Azure, Affectiva, Face Reader by Noldus and the Kairos API execute emotion recognition and analysis from the facial expressions in any image or video. For example, Affectiva has examined 3,289,274 faces worldwide, both online and offline (Magdin et al., 2019). AffectNet, a large-scale facial expression image database, includes one million facial images along with the labeling of expressions, valence and arousal (Ueda and Okajima, 2019).

There have previously been no tools for analyzing biometric data remotely on a large scale (Kaklauskas et al., 2019, 2020), and studies of diurnal and seasonal mood techniques, technologies and systems have therefore been primarily limited to Twitter, Facebook and blogs for large-scale research. Nonetheless, technical and technological opportunities have been developed over the course of the Fourth Industrial Revolution for implementing remote biometric analyses on emotions in public spaces in real time. The biometric data that have been gathered in this way have permitted researchers to analyze the behaviors of large, diverse groups of people in real time. The use of remote biometric technologies has hitherto been rare (Kaklauskas et al., 2019, 2020), although such studies could prove helpful in analyzing human diurnal rhythms and seasonal patterns when integrated with data on the environment, levels of pollution, weather cycles and social activities.

The contents of this manuscript are as follows. Section 2 describes the screening, diagnosing, monitoring and analyzing of COVID-19 by applying biometric and AI technologies. Subsequently Section 3 presents the Diurnal, Seasonal and COVID-19 Analysis, Multimodal, Biometric (CABER) Method. Section 4 explains the ROCK and Housing COVID-19 Video Neuroanalytics. Lastly, the results, a discussion, conclusions and potential future work are described in Sections 5 and 6.

2. Screening, diagnosing, monitoring and analyzing COVID-19 by applying biometric and AI technologies

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 (SpO_2) 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, SpO_2, 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).

3. Diurnal, seasonal and COVID-19 analysis multimodal biometric (CABER) method

Lately, one of the main worldwide topics of the motivation of COVID-19 research constitutes large-scale screening, diagnosis, monitoring, and categorization of people based on the presence of COVID-19 symptoms. The motivation and goals for having the willingness to conduct all such studies is to minimize or entirely eliminate the ongoing coronavirus pandemic. Motivation and objective have been upgraded for the present research under performance here by employing the Diurnal, Seasonal and COVID-19 Analysis Multimodal Biometric (CABER) Method. Its use is meant to establish people's emotions as well as their affective and physiological states with an objective to minimize bad moods during the COVID-19 period. This is accomplished in conjunction with analyzing public spaces for improving urban activities during coronavirus lockdown in six ways (see Section 4 "Discussion and conclusions").

Theories, data, location and time

The Diurnal, Seasonal and COVID-19 Analysis Multimodal Biometric Method was developed during this research. This method measures and analyzes the human diurnal and seasonal rhythm correlations and patterns by biometrical techniques.

Mood stimulates the choices of activities (e.g. entertainment) to pursue, thereby providing quite a thorough explanation known as the Mood Management Theory (Zillmann et al., 1980). An inherent assumption of this theory is that people are generally motivated towards pleasure, a state of a positive mood as well as an opposition towards negative states. The premise that is fundamental to mood management is that the motivations of people are to increase or retain pleasurable states and to reduce or eliminate painful states; therefore people will arrange their surroundings to accommodate such states[S1]. For example, media selection seem to contain two primary factors that associate with mood management. For one, consumers generate surroundings that will foster desirable levels of arousal, or a good mood, also associated with pleasure. The other is generating surroundings that will reduce or eliminate a painful, or bad mood (Strizhakova and Krcmar, 2007).

Behavior and decision-making choices develop as a result of how emotions arise, which constitutes the essence of the Somatic marker hypothesis expounded by Damasio (1994). A brief explanation is that somatic markers denote the sorts of feelings, which emotions stimulate. Learning entails a connection of certain emotions and feelings, which can forecast the results of certain kinds of scenarios. An alarm sounds whenever a negative somatic marker associates with some specific future result. Meanwhile, incentive becomes aroused whenever the association involves a positive somatic marker (Damasio, 1994).

Various diurnal and seasonal cultural activities influence happiness, valence and face temperature values. Additionally weather and climate affect human behavior to an important degree. Nevertheless, people always have an entire array of similar alternative choices, which they can select depending on their internal state of mind, needs, temperament, personality, surrounding environment, time of the year, weather (temperature, rain, humidity) and climatic conditions. For example, the length of the day and happiness correlate with the overall level of sunshine, its duration and air temperature, which, on their own accord, influence the priorities people set for themselves and the activities they choose.

An investigation was performed in Vilnius from the end of 2017 and during 2018. The study was on the influence of the holidays and events on the happiness (H) and valence (V) of people by employing remote biometrics. The studies indicated that people are happier during the holidays and various events. They are the happiest during Christmas ($H_{Chr} = 0.136$, $V_{Chr} = -0.078$), the New Year ($H_{NewYear} = 0.128$, $V_{NewYear} = -0.096$), the March 2–4, 2018 Kaziukas Fair ($H_{KF} = 0.193$, $V_{KF} = -0.09709$), February 16 Restoration of Lithuania's independence ($H_{Feb16} = 0.140176$, $V_{Feb16} = -0.046$), when the average monthly levels of happiness and valence were generally lower at the time ($H_{Dec} = 0.121$, $V_{Dec} = -0.10727$, $H_{Jan} = 0.115$, $V_{Jan} = - = -0.1047$, $H_{Feb} = 0.135$, $V_{Feb} = -0.136$, $H_{March} = 0.140$ and $V_{March} = -0.13433$). For example, celebrating the beginning of the New School Year on 2018 September 3 (H = 0.2527, V = −0.0339) shows an increase in the average level of happiness by 27.11% and in valence by 55.91%, compared to the average during the rest of September (H = 0.1988, V = −0.0762).

Positive thoughts assist an organism to release chemical materials for aiding the production of happiness hormones. An elevated mood forms conditions for more effective brain activity, greater creativity, stronger immunity and, therefore, greater success at life itself. The brain is hardwired by nature to scan for the negative (Ho et al., 2015). Thus, it is advisable to analyze emotional issues in the morning and at night, when the mood is at its best.

This research investigates changes in levels of happiness, sadness and valence among depersonalized individuals on hourly, daily and seasonal bases, and measurements and recordings were taken in Vilnius in real time, between November 22, 2017 and May 20, 2020. An impact assessment regarding data protection for the Sensor Network was completed prior to beginning data gathering, as required by GDPR requirements and the applicable laws of the Republic of Lithuania. IP cameras and FaceReader 8 devices were set up to record data from anonymous passersby at seven corners of Vilnius city streets: Kareiviu St., Kalvariju St. and Ozo St.; Zygimantu St. and T. Vrublevskio St.; Santariskiu St. and Baublio St.; Sventaragio St. and Pilies St.; Sventaragio St. and Gedimino Pr.; Pamenkalnio St., Jogailos St., Islandijos St. and Pylimo St.; and Sventaragio St., T. Vrublevskio St. and Gedimino Pr. A total of 180 million data items relating to emotions and valence were gathered from these seven sites. The values assigned to the emotional states (happy, sad, angry, scared and disgusted) ranged between zero and one, whereas the values of valence ranged between −1 and one.

The results of worldwide research (Bryant and Zillmann, 1984; Kosonogov et al., 2017; Cruz-Albarran et al., 2017) indicate that human skin temperature rises as positive or negative emotions rise. Homeostasis is a manifestation when the system retains a stable condition for itself. Even though hormones partly regulate homeostasis, it is the nervous system that ultimately regulates it. The nervous system returns some standard parameter such as temperature, which has deviated from its normal level. An argument promoted by Zillmann et al. (1980) regarding mood involves the subconscious of people when they selects certain activities like media choices. The subconscious directs the retention of homeostasis (beings required to regulate body temperature, etc.) by normalizing arousal, which has been at an overly high state (Bryant and Zillmann, 1984). It acts to better states of negative moods (Zillmann et al., 1980; Strizhakova and Krcmar, 2007).

The FLIR A35SC infrared camera took 27,948,477 temperature measurements from depersonalized passersby between September 19, 2020 and November 2, 2020, in Vilnius, at the corner between Šventaragio St. and Pilies St.

A value, the date and time of collection and the location of the collected measurement identified every single item of collected data on happiness, sadness, valence and temperature. Local times were used in this study. FaceReader 8 was used to analyze the incidence of positive or negative valence for the emotions experienced by the passersby. There was one positive emotion (happy), and the remainder were negative (sad, angry, scared and disgusted). Valence was calculated by taking the intensity of "happiness" and subtracting the intensity of the strongest negative emotion (FaceReader, 2016). In this way, we merged positive and negative emotions into a single value, known as valence.

No demographic data (such as gender, nationality, ethnicity, education, age, religion and socioeconomic status e.g. income, education and occupation) were gathered on the passersby in this study. This research involved innovative experiments with primary, remotely accumulated, biometric data, and testing was conducted on a large scale in order to examine collective emotions. This study therefore extends existing research involving daily and seasonal biometric studies of collective emotions, to the best of our knowledge, since it covers a much more varied range of socioeconomic and demographic groupings.

Assessing the accuracy of data and results through verification and validation

All the accumulated data were validated and verified in a double-checking process.

Two objective datasets of basic human emotions, both of which are available to the public, served as the basis for validation of FaceReader, performed by Lewinski et al. (2014). These authors also assessed the accuracy of facial expression recognition. There were scores reported to FaceReader of which 89% were matching in 2005. FaceReader 6.0 was shown to be capable of distinguishing 88% of the target emotional labels from the Warsaw Set of Emotional Facial Expression Pictures (WSEFEP) and the Amsterdam Dynamic Facial Expression Set (ADFES). Then, there is the agreement index pertinent to the Facial Action Coding System (FACS). It achieved an average score of 0.69 for both datasets, which indicates an 85% rate for the recognition of human emotions. The first two datasets were also examined by Lewinski et al. (2014), who calculated an 87% accuracy of recognition of human emotions for ADFES and an 82% rate for WSEFEP. The authors of these studies claim that over the past decade, FaceReader has been proven to be a reliable indicator of basic human emotions based on facial expressions. They also assert that it can be similarly reliable when used with FACS coding. Researchers report an 88% accuracy for the recognition of basic emotions by FaceReader 6.0. The FaceReader agreement index accuracy for FACS is 0.69 (Lewinski et al., 2014). Other scholars have obtained similar results in tests of the validity of FaceReader and its accuracy, and their outlooks on Noldus Information Technology, the producer of this equipment, tend to be similar.

FaceReader 8.0 software has been applied for writing this article on an artificial intelligence technique regarding machine learning. This FaceReader 8.0 software for an artificial intelligence technique in machine learning has also been applied in other studies, which are further briefly presented. The validation of automated facial coding (AFC) by FaceReader artificial intelligence software was presented by Lewinski et al. (2014). Another study relevant to consumer preferences of beverages, which was conducted by Gonzalez Viejo et al. (2019), applied artificial intelligence as the basis for analyzing emerging technologies for the purpose of quality assessments. This same FaceReader software had been used by Viejo et al. (2019) for assessing food and beverages. It involved recognizing facial expressions to study their relationships to emotions. An interesting combination of robotics and computer vision techniques with non-invasive consumer biometrics appears in the study by Viejo et al. (2018). These biometrics consist of FaceReader™ 7.0 software, an infrared thermal camera and an eye tracking device. This study also involves a sensory questionnaire, which used machine learning for evaluating different features of beer foamability. Viejo et al. (2018) hold the view that their study shows potential opportunities for applying artificial intelligence (AI) by using robotics, computer vision and machine learning algorithms. These then perform quick screenings of carbonated brewages.

The accuracy of the infrared camera FLIR A35SC was ±2% (FLIR), while its thermal sensitivity was < 0.05 °C. A calibration certificate issued by the manufacturer of this camera confirms all pertinent calculations and measurements. Annual metrological verifications are also issued for thermographic cameras to ensure that the error rate pertinent to the manufacturer-set measurements does not deviate. The thermal data transferred are processed as part of the data validation, thus ensuring high quality in terms of accuracy, update status, completeness, consistency across data sources, relevance, reliability, appropriate presentation, meaningfulness and accessibility. The processing also double-checks the accuracy and suitability of the data. Such a step in data processing has uncovered inaccuracies in some of the data, thereby assuring immediate next steps to resolve the problems. Data can also be deleted whenever problems prove insurmountable, and, thereby, inaccurate, incomplete, rounded off, heaped, censored and/or missing data then cease to be problematic. An analysis of average facial temperature involved a selected range that was segmented using thermal imaging. However, this sort of measurement is only applicable to the average facial temperature of a crowd, and temperature values that could distort the results of the study were deemed unnecessary and eliminated. At the data processing stage, we also eliminated the average temperatures of people in the background, that is, outside the observation zone (Kaklauskas et al., 2019).

Non-normal distributions prior to and during the quarantine period

In this subsection, we give a brief discussion of non-normal distributions of happiness, valence, sadness and temperature.

Figure S1 displays the non-normal distributions of the average values of (a) happiness, (b) valence, (c) sadness and (d) temperature among all passersby in Vilnius City, prior to and during the coronavirus quarantine period.

A total of 29,129,036 (657,574) data items were collected on diurnal happiness in Vilnius before (during) the coronavirus crisis, and a non-normal distribution histogram was generated (see Fig. S1a). The average value of happiness prior to the quarantine period was $\mu = 0.1168$, with standard deviation $\sigma2 = 0.1758$. However, the average happiness value during the quarantine period was $\mu = 0.1022$, with standard deviation $\sigma2 = 0.1447$. As we can see, the average value of happiness decreased by 12.5% during the quarantine period. In both instances, a Kolmogorov–Smirnov test for normality indicates that the values of this variable both prior to and during the quarantine period do not show a normal distribution ($p < 0.05$). The non-normal distributions prior to and during the coronavirus quarantine period are similar since, in both instances, their skewness is positive and the kurtosis is greater than three. The extra value noted at the left of the distribution is due to more happiness scores taken from passersby equaling less than 0.1 (see Fig. S1a and Table S1a).

The stimulus associated with a valence value can be represented as a continuum, from pleasant to unpleasant or from attractive to aversive. Emotional valence forms one of the two axes (or dimensions) on which an emotion can be located in factor analysis and multidimensional scaling studies; the other is arousal (APA Dictionary of Psychology). A total of 29,169,150 data items on valence were gathered in Vilnius before the coronavirus crisis, and 675,294 during the quarantine period. The mean of the valence prior to the quarantine period was $\mu = -0.1280$, while the standard deviation was $\sigma2 = 0.2897$. However, the average valence during the quarantine period was $\mu = -0.2138$, while the standard deviation was $\sigma2 = 0.3257$. A possible conclusion is that before the quarantine period, the values of valence were more concentrated near the average, whereas during quarantine, the values were more scattered around the average. The mean value of valence decreased by 67.03% during the quarantine period. In both instances, a Kolmogorov–Smirnov Test indicates that these values are not normally distributed ($p < 0.05$). Prior to quarantine, the asymmetry and excess coefficients of the valence variable were 0.312 and 1.335, respectively. The Kolmogorov–Smirnov test criterion of $p < 0.001$ for valence indicates that the skew was statistically significantly different from normal during the quarantine period. During quarantine, the asymmetry and excess coefficients of the valence variable were −0.029 and 0.124, respectively. The distribution of the variable therefore has a noticeably negative asymmetry (although this is not especially large, as defined by a value of ±2 or more). The distribution curve differs only in the sense that during quarantine, the distribution curve of the values has a longer left slope. Nevertheless, in both cases, parametric tests are applicable in the analysis (see Fig. S1b and Table S1b).

We collected 30,538,597 (878,167) items of data on sadness before (during) the coronavirus crisis. The average value of sadness prior to the quarantine period was $\mu = 0.1338$ and the standard deviation was $\sigma2 = 0.1603$. During quarantine, the mean sadness was $\mu = 0.1540$ and the standard deviation was $\sigma2 = 0.2038$. The mean value of sadness increased by 15.1% during the quarantine period. A Kolmogorov–Smirnov test of normality indicates that the values of this variable were not normally distributed ($p < 0.05$) in both cases, i.e. prior to and during quarantine. The skewness of the sadness variable and the parameters of kurtosis serve as the basis for concluding that the sadness values were concentrated closer to the average before the quarantine period, whereas the values during quarantine were distributed more to the right of the average. The scores for the sadness variable were not normally distributed during the quarantine period, and had a positive skew (skewness = 1.667) and a platykurtic distribution (kurtosis = 1.989) (see Fig. S1c and Table S1c).

A total of 27,948,477 items of data were gathered in Vilnius to establish circadian temperature, between September 19, 2020 and November 2, 2019. The 95% mid-range value of the facial temperatures of passersby (between the 2.5th and 97.5th percentiles) was between 22.4861 °C (72.47498°F) and 22.4870 °C (72.47660°F). Facial temperatures had a standard deviation of 0.0002416 °C (32.00043°F) (see Fig. S1d and Table S1d). The cycle of mean body temperature varied during the day, with lower temperatures in the morning and higher ones in the afternoon and evening.

4. ROCK and housing COVID-19 video neuroanalytics

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).

The Housing COVID-19 Video Neuroanalytics will be developed over the course of implementing the MICROBE Project by adapting the ROCK Video Neuroanalytics for a potential analysis of negative emotions and the coronavirus. The Housing COVID-19 Video Neuroanalytics framework consists of the ROCK Video Neuroanalytics and e-Questionnaire COVID-19 Symptom Surveys, e.g., see https://covid-19.ontario.ca/self-assessment/ and https://www.mayoclinic.org/covid-19-self-assessment-tool. It additionally contains a Correlation Subsystem and a COVID-19 Subsystem and User Interface. The Correlation Subsystem (see Section 5 "Results") is capable of analyzing different correlations relevant to the MAPS metrics on the diurnal, seasonal and coronavirus lockdown along with their impact on people. Meanwhile users can manage the Housing COVID-19 Video Neuroanalytics by the convenience of the provisions from the User Interface.

Also, the developed Housing COVID-19 Video Neuroanalytics will include specific measurements from wearable devices and the COVID-19 Subsystem. Further, there is brief mention of some wearable measurement devices, which collect different physiological data like heart rhythm in a peaceful state and its variability, fatigue, bodily pain, taste and smell, cough, fever and pf activity rate. The expectation is to integrate all of these into the Housing COVID-19 Video Neuroanalytics. Currently wrist monitors predominate in the market. Such monitors include WHOOP, Apple Watch Series 4/5, Chest Patch sensor, Garmin Vivoactive 4, Garmin Forerunner 945, Garmin Fenix 5, Garmin Venu, Biostrap, Empatica Embrace, Fitbit Ionic, Fitbit Charge 4, Fitbit Versa 2 and Biobeat devices. The other monitoring devices under analysis at this time include those made by the following companies: the Oura ring, VivaLNK Vital Scout and VivaLNK Fever Scout epidermal patches, BioIntellisense epidermal patch, Spire health tag that attaches to clothing, Hexoskin compression shirt, Biovotion Everion armband, Equivital LifeMonitor chest strap, Cosinuss Two in-ear device, AIO Sleeve 2.0 arm. The prices for such monitoring devices range from $30 to $500 USD. Global practice indicates that the integration of multidimensional biometrics and measurements show greater value for their predictive abilities.

The Housing COVID-19 Video Neuroanalytics will include possible monitoring COVID-19 infected by analyzing them in practical scenarios such as universities, housing, and a neighborhood under the threat of an oncoming outbreak of illness that vitally needs immediate intervention.

The COVID-19 Subsystem can trace symptoms relevant to a COVID-19 infection in the future, which collects a human body's heart and breathing rates, temperature and other physiological (heart rhythm in a peaceful state and the variability of heart rhythm, fatigue, bodily pain, taste and smell, cough, fever, rate pf activity) data. This data is then joined with the responses gathered from the surveys of daily symptoms, thus predicting the possible onset of the illness. An upsurge in temperature and other physiological data can denote a potential COVID-19 infection in a person, whenever data from the e-Questionnaire COVID-19 Symptom Surveys combined with data from the Sensor Network so indicate.

5. Results

Diurnal happiness, valence and temperature

The development of the Diurnal, Seasonal and COVID-19 Analysis Multimodal Biometric Method took place while conducting the research described herein. Biometrical techniques employed for this method measure and analyze correlations and patterns relevant to human diurnal and seasonal rhythms.

The research presented here involves an analysis of hourly, daily and seasonal changes in affect at the individual level between November 22, 2017 and May 20, 2020, in real time, in the city of Vilnius. 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) (FaceReader, 2016); 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. Fig. 1 presents the average values of (a) happiness, (b) valence and (c) temperature per weekday hour.

This research along with studies conducted worldwide (Kaklauskas et al., 2019, 2020) indicate a dependent interrelationship between happiness, sadness, valence and temperature. Other studies (McIntosh et al., 1997; Robinson et al., 2012; Hahn et al., 2012) 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.

In this research, a comparison was drawn between happiness (29,129,036) and valence (29,169,150) biometric data gathered in Vilnius and Golder and Macy (2011) positive affect data. Golder and Macy (2011) 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 (2011) and Vilnius biometric data.

The correlation between hourly changes in positive affect in UK/Australia (US/Canada) as obtained by Golder and Macy (2011) 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 2). The patterns of happiness and valence diurnal rhythms (based on local time) found in our research (Fig. 1) 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 (2011) and diurnal happiness in Vilnius was $r = 0.533$, $p < 0.001$, and for valence, $r = 0.585$, $p < 0.001$ (Table 2). 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. 1).

Results of the correlation analysis appear in Table 2. 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.

An effort was undertaken to verify the possible forecasting capabilities of Vilnius city happiness and valence of the positive emotion variables pertinent to the UK/Australia, USA/Canada and all the other English-speaking countries. Then the significance of each positive emotion variable pertinent to the forecast was established by employing a simple neural network with one input neuron, one hidden layer and one output neuron. Upon performance of the analysis regarding the forecasting abilities of Vilnius city happiness, it was established during the testing process that 4.8 percent of the predictions were inaccurate. Such a result is a sufficiently reasonable. We also found that the most critical variable in predicting Vilnius city happiness is the positive emotion variables in the UK/Australia. In the meantime, upon performance of the analysis pertinent to the ability of Vilnius city valence, as one of the variables, in forecasting, 9.1 percent of the predictions proved to be inaccurate. The most significant variable in predicting Vilnius city valence is the positive emotions UK/Australia variable. We noticed that the analyzed positive emotion variables are better suited to predict Vilnius city happiness. Meanwhile, the UK/Australia positive emotions variable is the most significant for forecasting both Vilnius city valence and happiness.

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. 2).

A total of 30,538,597 data entries on average diurnal sadness were made before the coronavirus crisis and 878,167 during the quarantine

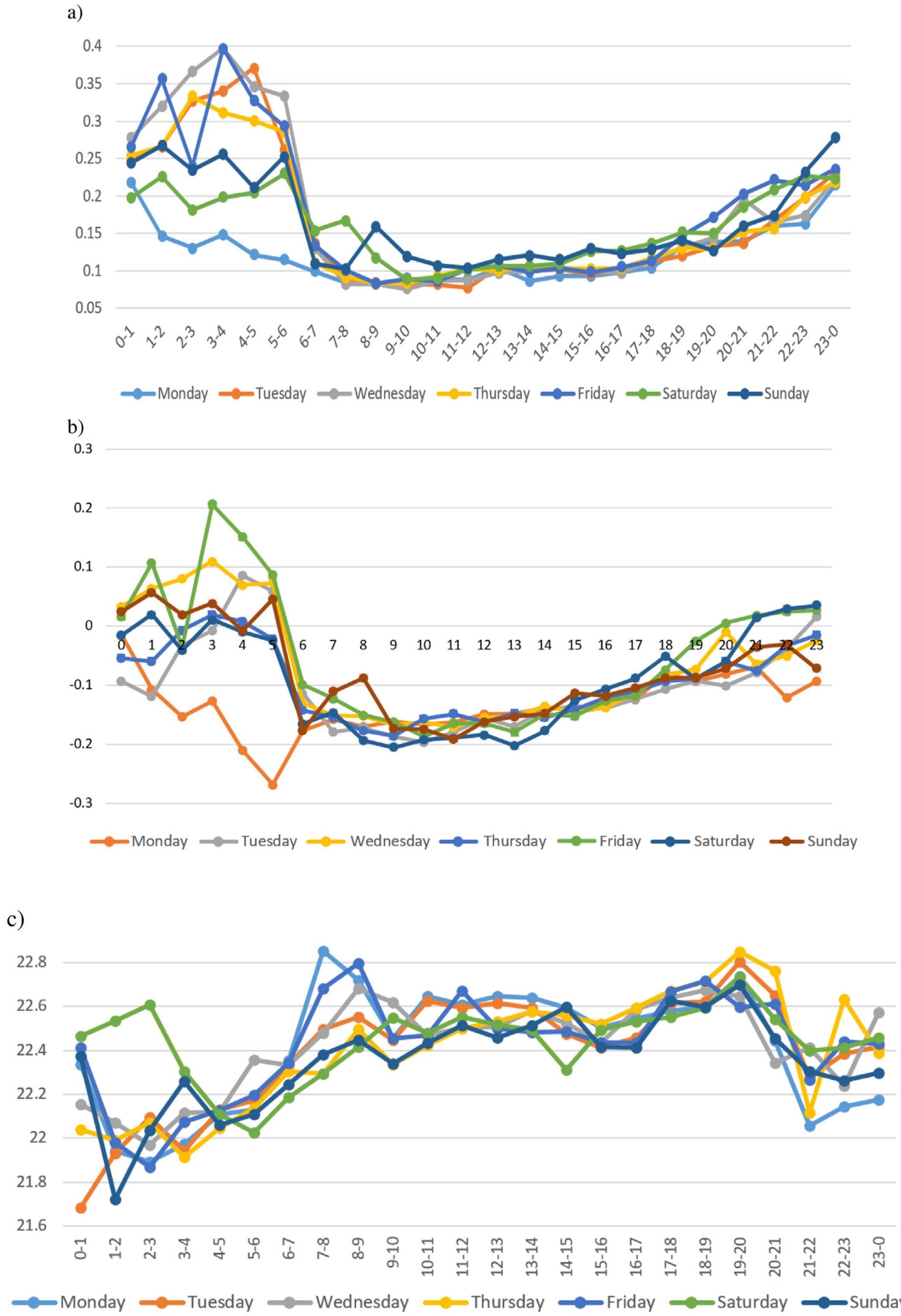

Fig. 1. Average happiness (a), valence (b) and temperature (c) values on weekdays, by hour. Recordings are gathered every hour about changes among Vilnius passers-by on the values of average (a) happiness, (b) valence and (c) temperature by Celsius degrees. Measurements of emotional (happiness, sadness, etc.) states and valence were recorded every second. There were 22 temperature measurements taken per second and recorded. These values accumulate by weekdays at 95% confidence intervals. Colors clarify the pertinent weekday. The hour beginning at midnight appears on the x axis. Meanwhile the y axis shows the average values of (a) happiness, (b) valence and (c) temperature by Celsius degrees for each 24-hr. day, for 7 days. The measure of happiness can fluctuate between 0 and 1, while valence fluctuates between −1 to 1. The manuscript presents a detailed description of Fig. 1 along with the derived results in comparison to studies from other parts of the world.

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. 2b shows the average diurnal pattern of sadness in Vilnius before and during the quarantine period on a weekly basis, as per each 24 h. 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, 2018). 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 (Garbazza and Benedetti, 2018). 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 (Lambert et al., 2002) 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

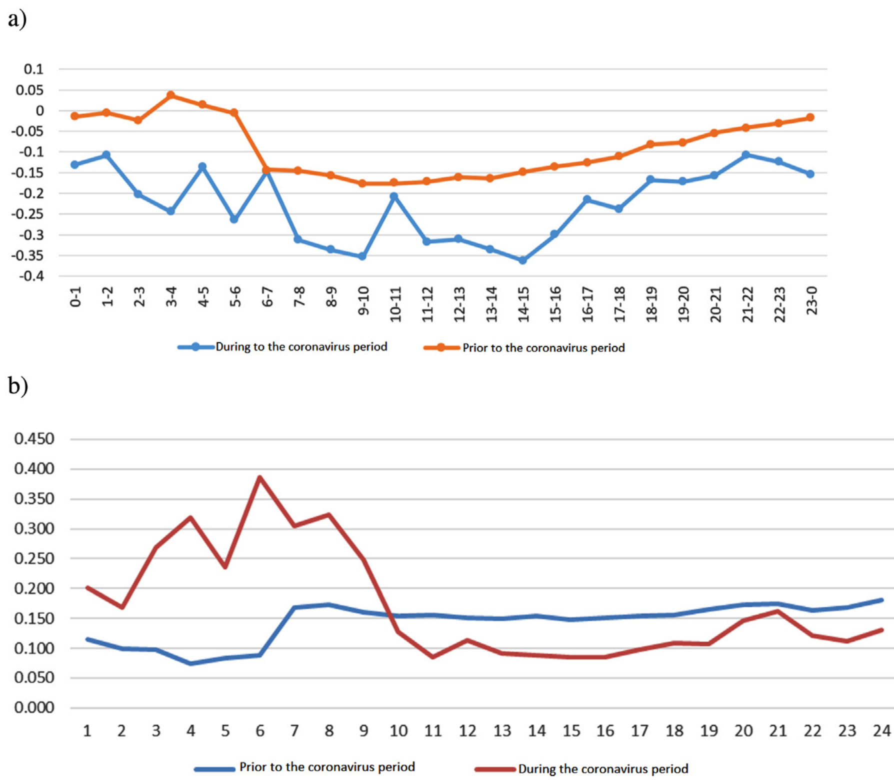

Fig. 2. Average diurnal patterns of valence (a) and sadness (b) over 24 h, before and during coronavirus quarantine. The average pattern of hourly changes in (a) valence and (b) sadness before and during the coronavirus period among passers-by in Vilnius as it appears when broken down by weekday at 95% confidence intervals. Colors indicate the average, diurnal pattern before and during the coronavirus period. The x axis shows the hour, beginning at midnight, and the y axis, the average values of (a) valence and (b) sadness each 24-hr. period, before and during the coronavirus period. The value of sadness fluctuates between 0 and 1. There is a positive relationship between the valence values before the quarantine and during the quarantine. This relationship has an average strength ($r = 0.664$) and it is statistically significant ($p < 0.001$). Valence decreased in Vilnius during the time of the coronavirus epidemic by 67.03 percent, falling from −0.1280 to −0.2138. The derived sadness relationship proved to be negative with an average strength at $r = -0{,}508$ and with statistical significance at $p < 0.05$. The mean value of sadness increased by 15.1% during the quarantine period.

therefore focused on variances in happiness and valence among individuals as the days changed in length due to the season. Variations of happiness (Fig. 3a) and valence (Fig. 3a) 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.

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. 4) 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 ($p < 0.001$).

Happiness, sadness and valence correlations

Weekly correlations of happiness, sadness and valence, obtained between November 22, 2017, and March 16, 2020, are discussed in this addendum.

Table S2 presents the correlation of happiness, sadness and valence values by weekday.

The values of the diurnal happiness indices for all weekdays are correlated with each other. The strongest correlation is between the values for Wednesday and Thursday ($r = 0.987$, $p < 0.001$), and the weakest is seen for Monday and Tuesday ($r = 0.553$, $p < 0.001$) (see Table S2a).

The diurnal valence values for Monday are not correlated with the valence values for any other weekday, although the valence values for the other weekdays are correlated with each other. The strongest correlation is between the values for Wednesday and Sunday ($r = 0.929$, $p < 0.001$), and the weakest correlation is observed for Sunday and Tuesday ($r = 0.719$, $p < 0.001$) (see Table S2b). Two daily peaks in valence can be seen, one at 4 a.m. and the other close to midnight (see Fig. S2a).

The values of diurnal sadness were correlated with each other over each entire day, excluding Saturday and Sunday; a correlation between these two days was not established. The strongest correlation appears between Tuesday and Wednesday, with $r = 0.949$, $p < 0.001$, whereas the weakest correlation is seen for Tuesday and Saturday with $r = 0.424$, $p < 0.05$. All correlations (except those for Saturday and Sunday) are statistically significant (see Table S2c).

There are strong and average statistically significant relationships between the values of diurnal happiness ($r = -0.834$, $p < 0.001$), valence ($r = -0.772$, $p < 0.001$), sadness ($r = -0.676$, $p < 0.001$), face temperature ($r = 0.588$, $p < 0.001$), and their numbers of measurements.

In the literature on psychology, there is an abundance of evidence that mood increases on Fridays and decreases on Mondays (Birru, 2018). A sample of 74 men and women who were employed in varied occupations formed the object of a study by Ryan et al. (2010), who investigated experiences on weekends and weekdays and their effects on mood and wellbeing indicators, in conjunction with the effects of work and leisure time activities. Both weekends and non-working

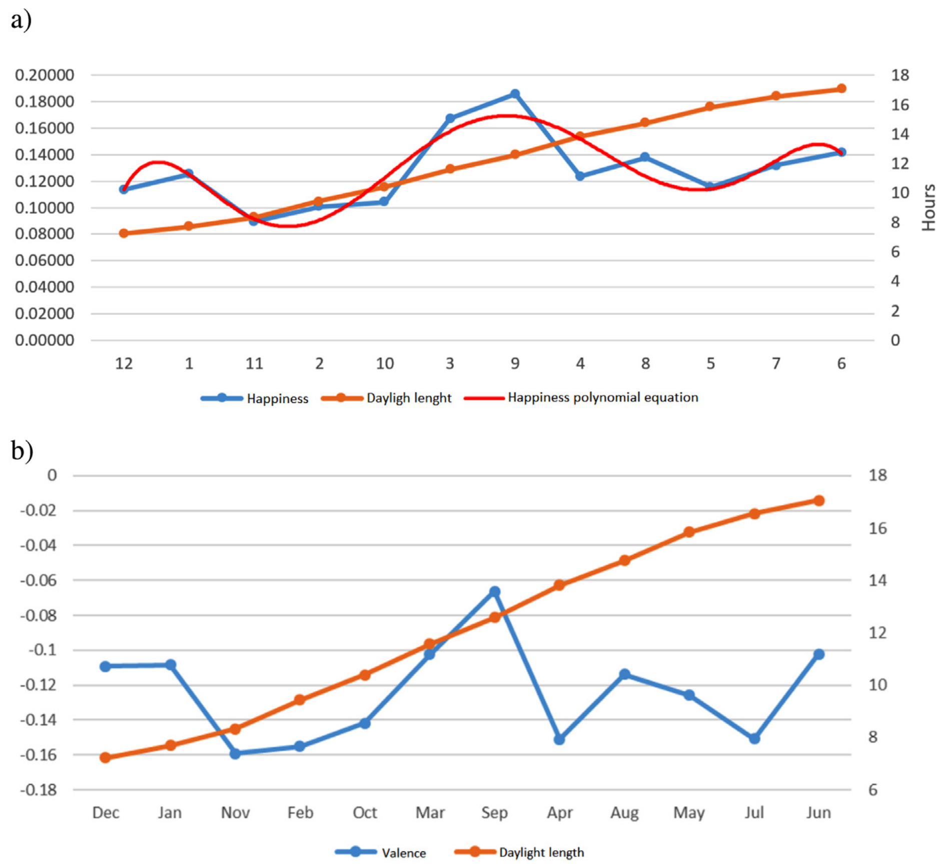

Fig. 3. Variations of (a) happiness and (b) valence relative to duration of daylight per month. Average values of (a) happiness and (b) valence among passers-by in Vilnius are examined by changes per monthly duration of daylight at 95% confidence intervals. The colors represent happiness (valence) and daylight hours. The x axis indicates the month, beginning with the least number of daylight hours and ending with the greatest number of daylight hours. Two y axes show the average values of (a) happiness, (b) valence (left axis) and duration of daylight (right axis) per month, over one year. This research containing 29,129,036 data items indicates a correlation between happiness and the length of daytime of average strength at a 95% confidence level. However, this is statistically insignificant ($r = 0.381$; $p > 0.05$). The relationship between valence and the length of a day is positive, albeit very weak ($r = 0.076$). However, it is statistically insignificant at $p > 0.05$ (Fig. 3b).

times were associated with greater wellbeing. Ryan et al. (2010) also found mediation of greater satisfaction via autonomy and relatedness needs, and our research revealed similar results (Fig. S2b). The greatest average values of valence in Vilnius were seen for Friday ($M = -0.1191$, $p < 0.001$), Saturday ($M = -0.1143$, $p < 0.001$) and Sunday ($M = -0.1060 \pm 0.3028$, $p < 0.001$).

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. 2).

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 (Mucci et al., 2020). 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 (Röhr et al., 2020). 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 (Sawhney et al., 2020). 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 (Willroth et al., 2020).

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 (Boyraz and Legros, 2020). This includes a study by Borgmann et al. (2014), 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. (2014) 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. 2).

The Artificial Intelligence Cluster Analysis

The Artificial Intelligence Cluster Analysis Method using k-means clustering is meant for determining if the primary data of happiness, valence and sadness can be divided into two clusters (see Fig. 6).

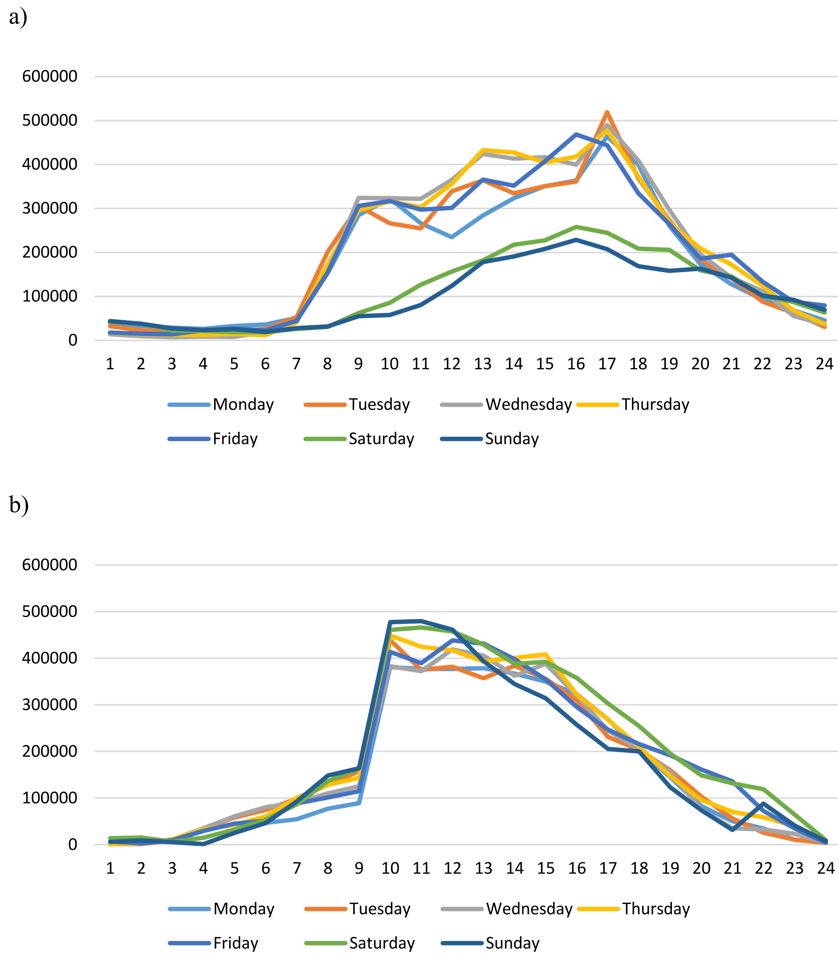

Fig. 4. Diurnal number of data on (a) happiness and (b) facial temperature. Changes in the diurnal number of data on (a) happiness and (b) facial temperature levels among Vilnius passersby appear on a per weekday basis, at 95% confidence intervals. The colors denote the weekdays. The hour of the measurement appears on the x axis, beginning at midnight. The diurnal number of data levels on (a) happiness and (b) facial temperature per 24-hr. day, over a 7-day week appear on the y axis.

Table 1
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	
Temperature	−0.756**	−0.628**	0.862**	1

**Correlation is significant at the 0.001 level (2-tailed).

The performed cluster analysis permitted arriving at the conclusion that the happiness, valence and sadness variables have a significant influence at $p < 0.05$. The values of the variables are assigned to the clusters before and after a quarantine. Upon performing the analysis pertinent to the dates of the variable weights designated by the cluster, a conclusion can be reached. That is that the data falling into Cluster 1 pertain to those prior to the quarantine. Meanwhile Cluster 2 includes the data during the quarantine. Therefore a conclusion can be drawn that a quarantine significantly affects the values of the happiness, valence and sadness variables.

Diurnal facial temperatures in Vilnius City: A regression equation

This section submits a diurnal regression equation. Its bases consist of the data derived from the facial temperatures of passersby measured for this research as well as from the mean diurnal musical intensity data studied by Park et al. (2019). The calculation of this equation comes from the regression of facial temperatures taken from passersby in Vilnius City taken on a diurnal basis. Meanwhile the GetData Graph Digitizer digitizing software scanned the mean musical intensity data from the original article by Park et al. (2019).

Measurements of diurnal patterns of affective preferences were taken from 765 million online music plays, which one million individuals had streamed from 51 countries, constituting the dataset that Park et al. (2019) had used for their analysis. Their study regarded the mean measurement of musical intensity that could compare to arousal. These scholars believed that there were highly comparable characteristics between the arousal dimension and a measurement of their intensity.

Yet, different scholars (Dabbs and Moorer, 1975; Zenju et al., 2002, 2004; Salazar-López et al., 2015; Kosonogov et al., 2017) conducting research expressed different opinions regarding how human arousal and temperature correlated. Dabbs and Moorer (1975) found that an index of arousal can be provided by human core temperature. A new marker of emotional arousal is functional infrared thermal imaging, which promises to become a method for measuring autonomic emotional responses via facial, cutaneous, thermal variations (Kosonogov et al., 2017). For example, participants involved in the study conducted by Kosonogov et al. (2017) reacted with thermal responses more than with emotional ones while viewing neutral pictures. These people indicated no difference in responses between pleasant and unpleasant pictures. However, their nose temperatures tended to fall in the presence of negative valence stimuli and rise in the presence of positive emotions and arousal patterns. This was the most important finding resulting from the research. Additionally the changes in temperature were not limited to the nose. Changes also appeared at the forehead, oro-facial

Table 2
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 and Macy (2011).

	Vilnius diurnal data		Golder and Macy (2011) diurnal positive affect data		
			Hourly changes in positive affect in		English-speaking persons worldwide
	Happiness	Valence	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

**Correlation is significant at the 0.01 level (2-tailed).

Table 3
Descriptive statistics.

	N	Minimum	Maximum	Mean	Std. Deviation
Facial temperature for passers-by in Vilnius	24	22.025	22.724	22.403	0.203
The mean diurnal musical intensity data studied by Park et al. (2019)					
Latin America (LA)	24	0.787	1.062	0.982	0.092
North America (NA)	24	0.507	0.809	0.711	0.102
Europe (EU)	24	0.533	0.751	0.688	0.074
Oceania (OC)	24	0.484	0.769	0.680	0.097
Asia (AS)	24	0.284	0.658	0.549	0.133

Table 4
Correlation analysis results.

	Temperature for passers-by in Vilnius	The mean diurnal musical intensity data studied by Park et al. (2019)				
		Latin America	North America	Europe	Oceania	Asia
Temperature	1					
Latin America	0.890**	1				
North America	0.859**	0.930**	1			
Europe	0.950**	0.937**	0.876**	1		
Oceania	0.866**	0.897**	0.983**	0.879**	1	
Asia	0.850**	0.866**	0.923**	0.858**	0.945**	1

**Correlation is significant at the 0.01 level (2-tailed).

area, cheeks and, overall, over the entire facial area. Regardless of this, it was primarily the temperature changes at the nose and, less importantly, over the entire thermic face that indicated positive correlations with how the participants scored on empathy and how they ultimately performed (Salazar-López et al., 2015). Another study, conducted by Zenju et al. (2002, 2004), discovered a rise in nasal skin temperature whenever the mood changed to a pleasant one and a drop whenever the mood became unpleasant.

Meanwhile this research involved a comparison of the diurnal facial temperatures discovered among passersby in Vilnius City with the diurnal musical intensity measure found by Park et al. (2019). The basis for this comparison consisted of the previously mentioned researches. The results of this study appear next. Table 3 presents this study's descriptive statistical indicators relevant to its variable.

Forecasting temperature by AI methods requires employing a simple neural network, containing one input neuron, one hidden layer and one output neuron. Such a neural network is necessary for the establishment of a teaching function. Linear regression establishes this sort of function. Upon performance of the Shapiro–Wilk Test, it was established that the values of all the variables are not distributed according to the Law of Normal Distribution ($p < 0.05$). Then, upon performance of the regression analysis of the variables, the Spearman's correlation coefficient is calculated. The results of the correlation analysis appear in Table 4.

All variable correlate with one another. This means there is a statistically significant relationship between any two variables ($p < 0.01$). The strongest relationship established is between the variables OC and NA (rs = 0.983), while the weakest, between variables AS and EU (rs = 0.858).

Table 5
Regression analysis results.

	B	Std. Error	Beta	t	p
(Constant)	21.002	0.906		23.174	0
Latin America (LA)	−0.622	1.878	−0.282	−0.331	0.744
North America (NA)	−0.165	2.451	−0.083	−0.067	0.947
Europe (EU)	1.646	1.464	0.602	1.124	0.276
Oceania (OC)	1.459	1.54	0.697	0.947	0.356
Asia (AS)	0.008	1.278	0.005	0.006	0.995

In order to establish the influence the independent variables (LA, NA, EU, OC and AS) have on the analytical expression of the dependent variable (Temperature), a regression analysis is performed. Its results appear in Table 5.

It has been established that the linear regression model is suitable for deliberation ($p < 0.01$). Meanwhile the changes in the values of the independent variables (LA, NA, EU, OC and AS) are able to explain 87.2 percent of the dispersion of the dependent variable (Temperature). Then the linear regression model is compiled:

$$\begin{aligned}\text{Temperature} = {} & 21.002 - 0.622 \cdot LA - 0.165 \cdot NA + 1.646 \cdot EU \\ & +1.459 \cdot OC + 0.008 \cdot AS \end{aligned} \tag{3}$$

The Temperature values calculated according to the compiled regression equation and the measured Temperature values appear in Fig. 5.

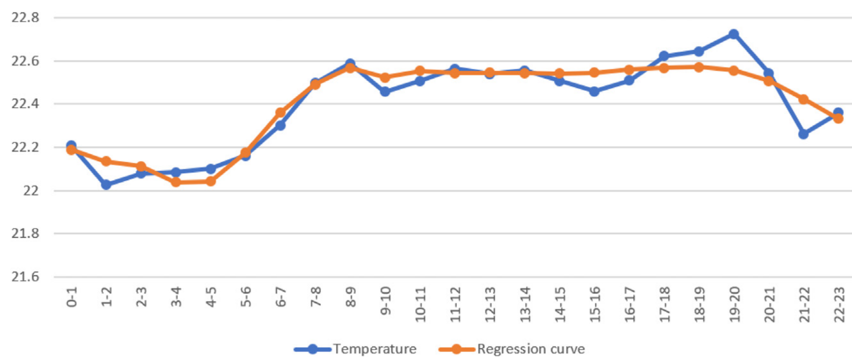

Fig. 5. Measured and calculated temperature for passers-by in Vilnius values.

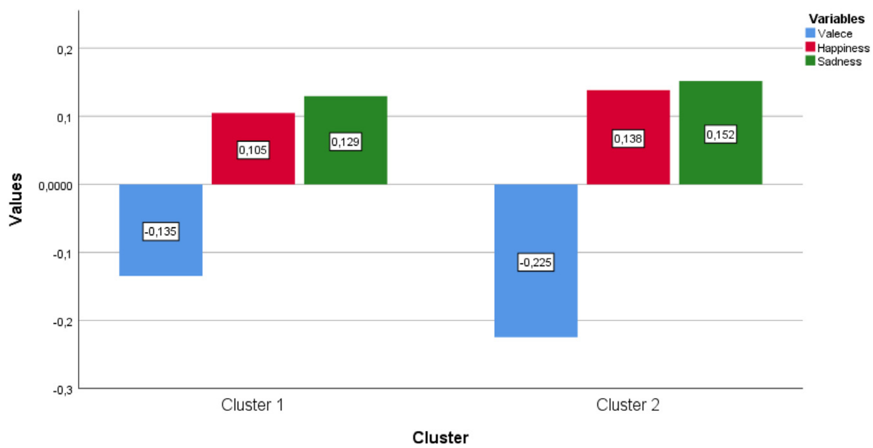

Fig. 6. Clusters analysis results and final cluster centers.

Table 6
Elasticity coefficient calculations results.

	β	$\overline{x}$	$\overline{y}$	E
Latin America (LA)	1.990	0.981	22.403	0.087
North America (NA)	1.835	0.711	22.403	0.058
Europe (EU)	2.500	0.688	22.403	0.077
Oceania (OC)	1.939	0.680	22.403	0.059
Asia (AS)	1.407	0.549	22.403	0.034

In order to establish the influence of different variables on a dependent variable, an elasticity coefficient is calculated for every pair of dependent and independent variables according to the following formula:

$$E = \beta \cdot \frac{\overline{x}}{\overline{y}} \tag{4}$$

here: β – the coefficient of the linear regression equation pertinent to the pair of a dependent and an independent variable, where:
$\overline{x}$ – average independent variable value
$\overline{y}$ – average dependent variable value
E – elasticity coefficient indicating the percentage of change in the independent variable upon a one percent increase in the independent variable.

The results of the elasticity coefficient calculations appear in Table 6.

The performed analysis permits drawing a conclusion that the variable Musical Intensity Europe (EU) has the greatest influence on the variable Temperature. Upon a one percent increase in the value of this variable, the value of the variable Temperature increases by 0.077 percent. This way a conclusion can be drawn that the variable Musical Intensity Europe is the most suitable variable for forecasting the value of the variable Temperature.

6. Discussion and conclusions

The purpose of this study is to measure and analyze the human diurnal and seasonal rhythm correlations and patterns by biometrical techniques. The authors of this work made full use of their backgrounds coupled with their intuitive abilities to raise three hypotheses involved in this research. Our three hypotheses also rested on a solid foundation of analyzed worldwide scientific literature pertinent to this field:

- H1: Diurnal happiness, sadness, valence and temperature among passersby in Vilnius show statistical interrelationships.
- H2: Diurnal valence and sadness among passersby in Vilnius, before and during the quarantine period, show statistical dependencies.
- H3: The numbers of data on diurnal happiness, sadness, valence and facial temperature correlate with their values.

The Diurnal and Seasonal Analysis Multimodal Biometric Method, developed by the authors of this research, confirmed the previously described hypotheses.

This research involves comparing 29,129,036 entries of remote biometric data on happiness and 29,169,150 entries of biometric data on valence in Vilnius along with the positive affect data accumulated by Golder and Macy (2011). The Twitter data access protocol was used by Golder and Macy (2011) for gathering data from about 2.4 million English-speaking persons worldwide. These data included 509 million messages sent from February 2008 to January 2010. The changes in positive affect recorded each hour, which Golder and Macy (2011) took from the UK/Australia and US/Canada, were correlated with data on happiness and valence taken in Vilnius. The result indicated a positive relationship of average strength, which is statistically significant. Thus the correlation is a positive, statistically significant relationship of average strength between the hourly, positive affect changes among English-speakers worldwide, which Golder and Macy (2011) gathered, and the diurnal happiness found in Vilnius (see Table 2).

Two peaks appear in the results of the positive affect that Golder and Macy (2011) found among English-speaking persons worldwide and the happiness found in Vilnius and along with the valence that this research indicates. One peak appears relatively early in the morning and the other, at nearly midnight.

The peak positive affect on Saturday and Sunday mornings lagged the peak on weekdays by nearly two hours (Golder and Macy, 2011), reflecting the hours in which people generally enjoy extra sleep, waking as a result of their body clocks rather than an alarm clock. So usually M = 9:48 a.m., although now, M = 7:55 a.m., $P < 0.001$. Our study gave similar results for happiness: the morning peak in happiness at weekends was also postponed by nearly two hours (M = 5–6 a.m. versus M = 3–4 a.m., $p < 0.001$) (Fig. 1a).

The greatest happiness score by hour on weekdays was found to occur at 3:00 a.m., with a value of 0.2927 ± 0.0963, while the lowest occurred at 9:00 a.m., with an average value of 0.0891 ± 0.00140. The largest value of valence was 0.0361 ± 0.1141 at 4:00 a.m. on weekdays, while the lowest was -0.1768 ± 0.00162 at 10:00 a.m.

Both the Twitter and Vilnius data showed a stable repeating shape over all days, with a decrease in positive affect at midmorning on weekdays and an increase in the evening. However, weekends and weekdays showed similar shapes for the affective cycle. Thus, sleep and the biological clock seem to be the key determinants of affect, regardless of differences in environmental stress (Golder and Macy, 2011). The researchers in this study obtained similar results, as the happiness of passersby decreased during weekday mornings, stabilized to approximately the same level during working hours, and increased on weekday evenings. Furthermore, happiness at weekends and on weekdays showed similar shapes for the affective cycle ($r = 0.9057$, $p < 0.001$).

Reports of happiness were more frequent at weekends than on weekdays. Reports of experiences on weekdays tended to include more stress and greater unhappiness, and emotions were less controllable than at weekends (Kunz-Ebrecht et al., 2004). The happiest days of the week, as shown by research conducted worldwide, are Friday to Sunday. Our study employed remote biometric means, and the results were similar to those obtained in other biometric research using contact-based means (Kaklauskas et al., 2019, 2020) performed all over the world. The greatest average value of happiness is found on Friday ($M = 0.1789 \pm 0.0948$, $p < 0.001$), whereas the lowest value is found on Monday ($M = 0.1224 \pm 0.0385$, $p < 0.001$). More than 29 million depersonalized measurements were used as the basis for drafting the valence graph for all weekdays. The greatest average values of valence in Vilnius were found on Friday ($M = -0.1191$, $p < 0.001$), Saturday ($M = -0.1143$, $p < 0.001$) and Sunday ($M = -0.1060 \pm 0.3028$, $p < 0.001$).

According to Kosonogov et al. (2017) and Cruz-Albarran et al. (2017), thermal responses of human skin correlate with subjective ratings. Thus, what is pleasant and what is unpleasant show no differences between them. Just like such responses act on human skin temperature, they also act on social activities (Bryant and Zillmann, 1984).

Research by Smolensky and Lamberg (2001) reported a daily cycle of body temperature that is usually at its lowest at 4:30 a.m., and at its highest at 7:30 p.m.; these results were aligned with those of tests conducted as part of the present research on the facial temperatures of passersby. The testing of passersby in Vilnius shows that a maximal facial temperature is seen in the evenings between 7:00–8:00 p.m., matching the findings of Smolensky and Lamberg (2001) and Harding et al. (2019). In general, body temperatures are lower in the morning and higher in the afternoon and evening. The cycle of mean body temperature displayed the same sort of daytime variance during the day. Research conducted by other scholars (Smolensky and Lamberg, 2001; Harding et al., 2019) and the authors of the current article supports these findings (Fig. 1c).

Other worldwide studies have also reported similar trends regarding statistical interrelationships (McIntosh et al., 1997; Robinson et al., 2012; Hahn et al., 2012) between happiness, valence and temperature. Hence, the first hypothesis that diurnal happiness, sadness, valence and temperature have statistical interrelationships among passersby in Vilnius appears to be valid (Table 1).

Furthermore, the dependency of the happiness and valence dependent variables on the independent variables consisting of UK/Australia, US/Canada and other English-speaking regions in the world (ES), was tested by undertaking a regression analysis. The basis for a possible forecast of diurnal happiness and valence levels in Vilnius City consisted of the amassed regression equations. It is thusly possible to amass like regression equations and to apply them in any country.

Our method was validated using data on sadness in Vilnius city and scores reported in research by Lampos et al. (2013). GetData Graph Digitizer, a digitizing software packaged, was used to scan the data on sadness from the original article by Lampos et al. (2013). Lampos et al. (2013) accumulated around 120 million data points over two 12-week intervals at different times, of which 70 million entries were made during the summer of 2011, and 50 million during the winter of 2011. These data were gathered from 54 of the most populated urban centers in the UK. Hourly changes in sadness in the UK were shown by Lampos et al. (2013) to be correlated with hourly changes in sadness in Vilnius, with $r = 0.705$, $p < 0.001$, a positive, statistically significant result indicating a relationship of average strength.

A second hypothesis was confirmed during this research. This one poses that diurnal valence and sadness are and have been statistically dependent, both before the quarantine period and during it, pertinent to Vilnius passersby. There was a negative relationship discovered, where the average strength was $r = -0.508$ and the statistical significance, $p < 0.05$. This agrees with the results of Borgmann et al. (2014), who reported a negative correlation pertinent to sadness.

The results of the present study support those of other researchers (Bedrosian and Nelson, 2017; Garbazza and Benedetti, 2018), who have reported that changes in day length cause positive mood swings. The length of daylight, including both direct and indirect sunlight, conditionally affects happiness, a dependence shown in Fig. 3a. The findings of this research support the conclusions of the Twitter study of Golder and Macy (2011) regarding characteristic seasonal changes related to happiness, even though valence does not change due to seasonality. Diurnal function and mood have an important dependence on appropriately timed light exposure, due to the known fact that seasonal changes in the length of a day modify moods. As shown by Bedrosian and Nelson (2017), both a lack and an excess of light have significant effects on health and mood. The results of the present research support this, as they clearly show the greatest happiness among Vilnius city residents during March and September, when the day length is neither the longest nor the shortest. Social activities during the Christmas and New Year holidays also increased the sense of happiness (Fig. 3a). It is also notable that these biometric data supplement global studies on seasonality by their great capacity. Analogical studies (Kaklauskas et al., 2019) had previously been conducted with merely several dozen or possibly, several hundred persons.

Global research has shown that human activities such as pedestrian and vehicular traffic flows and the associated pollution are also cyclical over the course of a day. The third hypothesis of this research entailed collecting data that indicated a cyclical nature of number of data of diurnal happiness, sadness, valence and facial temperature (see Fig. 4). Furthermore, these number of data and values correlate, and all their relationships are statistically significant ($p < 0.001$).

Upon analyzing how the temperatures of Vilnius passersby interface with arousal among people residing in different continents (North America, Latin America, Europe, Oceania, and Asia), it became possible to conclude that the strengths of these sorts of interfaces were similar, ranging between 0.850 and 0.890. Europeans alone show exceptional strength in the interface between arousal and the temperatures, relevant to Vilnius passersby, at $rs = 0.950$. It thus may be presumed that Vilnius, as the capital city of Lithuania, determines such an exceptionality by its dependence on the continent of Europe. However, on the other hand, this sort of presumption denies the strength of the arousal interface between Oceania and North America, at rs = 0.983. These two regions are quite culturally apart. Thereby another presumption is possible that the number of economically developed countries in the region or the overall level of economic development determines the strength of the interface. It would be necessary to verify this presumption by analyzing the interactions of arousal interfaces between strongly and weakly developed countries or their groups in future research studies.

Although remote biometric technologies offer new opportunities for observing changes in emotions, they also have certain significant shortcomings. Tests run in laboratories generally include demographic data such as gender, citizenship, ethnic background, level of education completed, age, religion, income, occupation and possibly some analysis of socioeconomic status. However, the research presented here includes no demographic data regarding the passersby under study, except for data on age, gender, ethnicity and mood, which were gathered remotely for further analysis. Both the present study and prior research indicate that the surrounding environment, cultural norms, traditions, levels of pollution, weather cycles and social activities all influence human diurnal mood rhythms and seasonal patterns. Despite this, the results of the biometric research conducted here confirmed that mood (happiness, sadness and valence) and facial temperature fluctuated cyclically over the course of a day. It was also determined that although valence and sadness worsened during the coronavirus lockdown period, their cyclical nature over the course of a day persisted. The data are also correlated with results from prior to the coronavirus crisis. We have recently carried out calculations based on diurnal (happiness, valence, facial temperature) and other data derived from this research. These calculations are on different values, including hedonic, perceived, integrated hedonic-market, and hedonic-investment values. These calculations are currently being verified and validated.

There are only three, possibly correctable, limitations to the Diurnal, Seasonal and COVID-19 Analysis Multimodal Biometric Method under recommendation. These are:

– One limitation regards ready access to this method, since stakeholders do not always reach reliable, personalized, real-time, biometric data.
– Another limit is the costliness, in terms of time and money, of accumulating data on physiological, affective and emotional states, arousal and valence and other pertinent aspects. This requires utilizing state-of-the-art technology.
– The third limitation is probably the most essential one, which is pertinent to human privacy and data issues. A single set of data protection rules must constitute the guidelines for all to follow equally, since May 2018. These are set forth as the General Data Protection Regulation, and any businesses operating within any part of the EU must adhere to these rules. Data is thus better protected by these added regulations by permitting private individuals greater control over their personal data. Meanwhile businesses thereby also enjoy the benefits of greater equality in their field of operations (GDPR, 2018). What prevents a massive adaptation of wearable sensors and digital health technologies overall in the United States, as Seshadri et al. (2020) presume, are the issues of data privacy, data sharing and underreporting involved in remote patient monitoring. Companies must assure users that their wearable technologies will only share data from those who so desire. This has already been done by WHOOP, which assures the anonymity of the data it gathers along with its use as being aimed for COVID-19 research alone (Seshadri et al., 2020). Population health data is handled with sensitivity regarding privacy in Germany. Germany has become a prime example for its stance on digital data gathering on a highly limited basis (Hodge, 2020).

The human emotional, affective and physiological states, arousal and valence (MAPS) data added to the "big picture" analysis on diurnal emotions and the coronavirus lockdown in public spaces contribute to worldwide research. These added MAPS data are the emotional states of happy, sad, angry, surprised, scared, disgusted and neutral; affective states of boredom, interest and confusion; physiological states measured by average facial temperature in a crowd as well as heart and breathing rates; arousal and valence.

A key contribution constitutes the correlations found by the research presented here. These correlations aided in obtaining appropriate estimates of emotional similarities, biometrical states and diurnal and seasonal mood cycles due to the use of big data for their assessments. The methodology employed by these authors in conducting the study presented herein were taken from computer science and artificial intelligence. These then constitute the means for quantifying and recognizing emotions automatically along with assessing the dependence of these emotions on diurnal and seasonal mood cycles.

This research involves innovative studies employing biometric data for the first time. The biometric data was first accumulated remotely on a large scale to test collective MAPS data.

The potential, practical applications of these findings are the following:

– This Diurnal, Seasonal and COVID-19 Analysis Multimodal Biometric (CABER) method can promise in-depth understanding of realistic affective and emotional preferences held by actual crowd and their prerequisites. The opportunity to analyze and thereby achieve quick and beneficial responses to crowd needs outcrops by the use of this method together with multiple criteria crowd analytics techniques.
– Various business sectors can pinpoint this method with multiple criteria crowd mining methods for their big data analysis and decision-making. The sectors that can beneficially use this method include industry, commerce, trade and services, education, financing, municipal development, media, climate policy, awareness and energy.
– The developed technique could additionally humanize and optimize advertising, mass marketing, and client relationships with momently feedback to a purchaser for a personalized product, multiple criteria analysis of possible purchasers, and a big picture of buyer needs.
– An important, emotional state for various activities during COVID-19, so far as certain stakeholders might consider, happens to be compassion. The MAPS data that are capable of implementing people-centric, urban design processes effectively, e.g., that include therapeutic approaches like therapeutic planning, therapeutic outdoor spaces, therapeutic landscape design and the therapeutic value of green spaces.
– Quantitative and qualitative understandings relevant to feelings are of utmost importance for an analysis of human emotional, affective and physiological states, arousal and valence (MAPS) of passersby before and during COVID-19. These can, therefore, serve as the goal for applying the Diurnal, Seasonal and CABER method. It is possible to measure the feelings of passersby and categorize them by gender, age and the biological circadian clock in static and dynamic surroundings. Static areas include green spaces and cultural markers, whereas dynamic areas involve transportation flows, air and noise pollution and the seasons.
– Applications of neuro decision-making tables and MCDM techniques permit stakeholders to take calculations before and during COVID-19 on hedonic, customer-perceived, integrated, and hedonic-market values along with market and hedonic-investment values in real estate (Kaklauskas, 1999, 2016).

Future research is expected to be performed in two directions.

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 studies presented here, conducted by these same authors, on potential COVID-19 illnesses include supplemental analyses on emotional and affective states.

First, the application of the developed ROCK Video Neuroanalytics and the CABER method are expected in housing, which will involve developing the Housing COVID-19 Video Neuroanalytics throughout implementing the MICROBE Project. The Housing COVID-19 Video Neuroanalytics framework consists of the ROCK Video Neuroanalytics and e-Questionnaire COVID-19 Symptom Surveys, Correlation Subsystem, COVID-19 Subsystem, and User Interface. The CABER method and the Housing COVID-19 Video Neuroanalytics developed by these scientists will additionally analyze in the future the same parameters as the analogues in existence on the market today or their related substitutes are measuring. Such additional parameters include the variability of heart rhythm, fatigue, bodily pain, taste and smell, cough, fever, rate pf activity and the like. However, the following future new features are notable:

1. The Housing COVID-19 Video Neuroanalytics will review the life cycle process of sustainable housing thoroughly regarding the traits involved in the micro-, mezo- and macro-environments relative to COVID-19. Improving housing micro, mezo, and macro environment using the Housing COVID-19 Video Neuroanalytics can play an essential role in diminishing COVID-19 distribution.

2. The current application of the ROCK Video Neuroanalytics is pertinent to a potential analysis of COVID-19 while developing the Housing COVID-19 Video Neuroanalytics. An e-Questionnaire that reports daily symptoms and a COVID-19 Subsystem will be integrated into the developed Housing COVID-19 Video Neuroanalytics along with the measurements taken from certain wearable devices. These will then be entered into the existing ROCK Video Neuroanalytics. The integrated measurements of parameters will be taken both remotely and by the wearable. The existing wearable analogues, such as bracelets and wearable sensors, are available in the market. The potential likelihood of COVID-19 along with its concentration in housing will be established by remote means in real time. This will be performed based on the data on heart and breathing rates, temperature, rate of activity and the like. Maps relevant to potential COVID-19 infection are drafted by physiological (heart and breathing rates, temperature, heart rhythm in a peaceful state and the variability of heart rhythm, fatigue, bodily pain, taste and smell, cough, fever, rate pf activity) and emotional, measurements as well as by pollution levels, which will then be applicable to specific housing units.

3. The use of physiological and emotional maps along with maps on pollution levels as well as maps where potential COVID-19 exists make the system informative. It has applications of big data analytics. Databases capable of storing huge capacities are under development. Furthermore, the system generates a huge amount of multifaceted information along with interdisciplinary recommendations for improving the quality of a housing unit.

4. Compilations of neuro and neuro correlation matrices will allow a thorough analysis of a housing unit viewed with regard to quantitative, qualitative, neuro and COVID-19 perspectives relative to thousands of alternative recommendations. Furthermore, such an analysis allows a user to choose the most rational alternative relative to individual needs. The housing unit can then be priced in terms of its market, investment, hedonic, emotional values. Thereby the quality of a housing unit can be analyzed in its entirety, something that no other neuro or neuro correlation matrix is capable of accomplishing anywhere worldwide. This system even permits submitting appropriate recommendations.

5. Additionally, the analysis conducted by the system is multilayered since it encompasses different aspects relevant to residential housing units. Such aspects include health, emotional and physiological measurements and pertinent economic, social, demographic, legal, technological, technical, environmental, managerial and other data.

6. The Housing COVID-19 Video Neuroanalytics will include possible monitoring COVID-19 infected by analyzing them in practical scenarios such as universities, housing, and a neighborhood under the threat of an oncoming outbreak of illness that vitally needs immediate intervention.

Today's market carries various vaccines, medical preparations and other treatment means, medicaments, necessities for hospitals and medical offices, disinfection means, and safety apparel and means. Some are unreliable or act ineffectively. The proposed CABER method will evaluate their effectiveness by trials and demonstrate their actions in the office building's realistic environment at Narbuto St. 5, Vilnius. The measurements of different parameters for this purpose will include temperature, breathing and heart rates, the variability of heart rhythm, fatigue, bodily pain, taste and smell, cough, fever, rate of activity and the like, as well as emotions. The existing analogues do not measure emotions.

CRediT authorship contribution statement

Arturas Kaklauskas: Conceptualization, Investigation, Formal analysis, Writing - original draft, Methodology, Software, Validation, Supervision. **Ajith Abraham:** Conceptualization, Investigation, Formal analysis, Writing - original draft, Methodology, Software, Validation, Supervision. **Virgis Milevicius:** Software, Data curation, Formal analysis, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data and materials availability

Summary data tables are obtainable in the manuscript and in the Supplementary Materials. The authors can deliver the applied raw data used for obtaining the conclusions in this paper to others upon request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.engappai.2020.104122.

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