Internet and Biometric Web Based Business Management Decision Support

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CONTENT

1. Emotions analysis in public spaces for urban planning

1.1. Introduction

Academics have been expounding on the demand for knowledge regarding how the perception of urban areas by inhabitants could be applied in the urban planning process ever since the 1960s (Zeile et al., 2015). However, during the course of the Fourth and Fifth Industrial Revolution, technical and technological opportunities appeared for implementing contact and remote analyses of emotions in urban areas in actual time along with the use of the latest technologies for smart urban planning. Nonetheless, remote technologies are rarely used to date. These can assist in analyzing the emotions of people and their physiological states along with weather conditions and pollution in an integrated fashion. Such results can be used as supplemental information for city planning purposes. The Affective System for Researching Emotions in Public Spaces for Urban Planning (ASP System) was developed for this purpose.

Urban planning encompasses a technical and political process aiming to improve the welfare of inhabitants, control of the use of land, design of the city environment as well as of the communication and transportation networks, protection and improvement of the natural environment (McGill, 2015), also impacts on economic and social practices (Liang et al., 2020). According to Van Assche et al. (2013), several urban planners deliver designs for parks, streets, buildings and other urban areas. Scholarly research studies (Gibbs, 2012, Rose, 2017, Levy,, 2016, Berke and Godschalk, 2006) present the following typical responsibilities of urban planners: master planning (land, roads, parks, schools, public transport and such), land use planning, city design of urban areas, city regeneration, acquiring funds from governmental foundations, environmental planning (flora and fauna, land, water), conservation and restoration, collaboration and discussions with different stakeholders (specialists, community members, landowners, governmental agencies). Also, city planners analyze sustainability (Abubakar and Dano, 2020), land values (Aziz et al., 2020), pollution (Xing and Brimblecombe, 2020), safety and crime (Yang, 2019), social equity (Meerow et al., 2019), urban governance and planning trends and future trajectories (Das and Dahiya, 2020), optimizing various planning alternatives (Natanian et al., 2019, Shu and Xiong, 2019, Yoon et al., 2019), etc.

The analysis conducted by the USA Healthy People 2020 initiative includes the following determinants:

- physical aspects like the natural environment including pollution, esthetics and green spaces;
- housing and community design with its worksites, schools and recreational settings;
- built environments;
- social aspects like access to educational, economic and job opportunities;
- availability of resources to meet daily needs;
- quality of education and job training;
- access to health care services and cultural, recreational, sports and leisure-time activities;
- available transportation means;
- socioeconomic conditions, public safety and social support, social norms and attitudes.

All of the previously named determinants could relate in one form or another with residential and urban segregation. A description of the level of residential segregation with its various hues can include the emotions felt by residents and experts. A brief analysis of segregation in European cities follows.

European cities are a widening gap between rich and poor, which leads to greater segregation. This means that both groups wind up living in homogenous, separate and impermeable areas. To go beyond the boundaries of a segregated area, the causes and solutions to segregation must be reviewed to come up with place-based policies that are inclusive, equitable and effective. Berlin with its implementation of the Future Initiative City District Program can serve as one example. The focus of this program consists of deprived neighborhoods and the means to regenerate their physical and socio-economic conditions, which would improve the environment. Disadvantaged residents must be provided with educational opportunities, both higher and lower levels of education, and actions must be taken to accomplish this. Further, these people need improved urban areas in their local area. The local people themselves must participate in renewing and vitalizing their neighborhoods. Social cohesiveness must gain strength. Additionally social and ethnic integration needs to be promoted (European Commission).

Lane (2005) deliberated several planning models (communicative, bargaining, advocacy, transactive) according to the level of public participation (citizen control, delegated power and partnership), the tradition of Societal transformation planning and the Pluralism planning school. Lane (2005) holds the opinion that advocacy, transactive, bargaining and communicative planning approaches characterize the contemporary era. Several procedural theories of planning (participatory, transactive, advocacy, bargaining and communicative) are further analyzed in brief. These theories differ among one another by their level of public participation.

According to Hacking and Flynn (2017), advocacy planning, transactive planning, collaborative planning and Deleuzian planning likewise declare uneven power relations among diverse individuals. In the opinion of Bojesen et al. (2015), the state of present planning requests a planning process (transactive planning and such), which can accommodate transparency and the expert viewpoints of numerous interested groups present.

Different researchers perform studies on urban planning in the area of participatory planning (Boukherroub et al., 2018, Hornsby et al., 2017, European Commission, 2014). These highlight interconnecting an entire community in strategic and management processes of urban planning in order to match opinions between all of its partakers and members of community development (European Commission, 2014).

According to (Lane, 2005), in advocacy planning, the function of a planner is basically that of a facilitator who either supports underrepresented groups directly or inspires them to become part of the process. Participatory mapping methods became more predominant in design and planning occupations with the rise of advocacy planning (Boone, 2015).

Various researchers have analyzed the bargaining model, where the community contributes to the decision-making process (Gao et al., 2018, Ghodsi et al., 2016a, Ghodsi et al., 2016b). Ghodsi et al. (2016a) deliberated the stochastic conflict resolution model for quality management of city runoff. Gao et al. (2018) analyzed spatial restructuring and the logic of industrial land redevelopment in urban China. Ghodsi et al. (2016b) suggested a multi-stakeholder framework for quality management of city runoff, paying special attention on the application of social choice and bargaining methods.

It is apparent that the responsibilities of typical urban planners encompass alliances and discussions with different stakeholders (specialists, community members, landowners, governmental agencies). Furthermore there are different levels of public participation in the mentioned planning models (inhabitant control, partnership and others). Recently it has become possible to learn the views and emotions of a community on city planning by applying the latest technologies, which are briefly described next.

Now advanced technologies and tools are applied in a more effective and inhabitant-centered way (Zeile et al., 2015). Related emotion data can be a novel kind of validation on the monitoring processes of urban areas (Resch et al., 2015). Li et al. (2016) assess the degree to which the emotional reactions of inhabitants are influenced by the city context (building shapes and textures, isovist parameters, visual entropy, visual fractals and such). Traditional, deductive planning methods can be supplemented with inductive and bottom techniques and strengthened with sensor technology (Streich, 2012). By applying sensor technology, it is possible to get straight feedback on urban planning from inhabitants and additional data for official planning processes using related emotion data (Zeile et al., 2015). According to Zeile et al. (2015), a rational planning process weighs all public and private issues to diminish conflicts and to get a worthy planning outcome.

1.2. Planning practice by integrating an involved public

Planners often have to deal with unprofessional behavior, mixed loyalties, moral dilemmas, public frustration and other emotionally challenging situations. As they handle planning conflicts, planners can start questioning planning theory and be exposed to situations ripe with planning dilemmas, uncertainties, interpersonal difficulties and job-threatening conflicts; they might benefit from being mindful in such situations. Emotions are also important in organizational hierarchies. As a team of planners start a new project they might initially feel satisfaction and view the project as an endeavor close to their values and interests. They, then, feel the urge to be effective contributors to the project and master the necessary skills. Later, however, disappointment might set in when they see their managers handling the process in a way contrary to what they believe should be done, or they might feel wronged because of insufficient intellectual feedback and professional recognition from the decision-makers. Each person judges differently whether an action is acceptable or not: what one planner deems good, another one might think is unacceptable. Because of such uncertainties planners are likely to be exposed to stressful situations (Ferreira, 2013).

Inch et al. (2017) discuss the value of conflict and opposition in planning and how these concepts should be understood highlighting the fact that for anyone directly involved opposition may be helpful, valuable, heroic, harmful or disruptive and plays a role in determining the shape of urban change with important wider consequences for other stakeholder who may never be given a chance to voice their opinions.

Sweet (2018) looks at the philosophical origins of Western colonial thinking and its impact on planning. A transformation of planning practice may be possible by supplementing cultural competency with cultural humility in planning theory and education. Such a change could prevent a repetition of certain planning practices, often destructive, in communities of color (Sweet, 2018). Trained and armed with cultural competency, professionals might be more likely to identify cultural, gender, social, and racial differences and take them into account. By learning about other, different cultures, practitioners will then be better prepared to understand the difference and be better at communicating with communities or providing them services in a respectful manner. More effective interactions will then be possible (Betancourt et al., 2016).

Wahlström et al. (2018) claim that multiple social, personal, and contextual factors determine city love. The elements that shape this multidimensional appreciation residents or visitors feel for the 'soul' and 'body' of a city may be very different among different cities, as well as within a single city. Loving attachment, according to Umemoto, is a combination of the emotional connection to a place (either symbolic or real), to close and dear people, and to past times (Porter et al., 2012). In the conceptual model proposed and empirically tested by Wahlström et al. (2020), the same kind of love, or the urban appreciation for a neighborhood, as they also call it, is linked to the neighborhood's material and immaterial amenities, or its 'body' and 'soul'. Residents 'love' their neighborhood for its built and natural environment, public and commercial services (material amenities) and its cultural, lifestyle, emotional and rational elements (immaterial amenities) (Wahlström et al., 2020).

Lyles et al. (2018) examine the prospect of transforming our communities by applying compassion as an emotional state in planning. Compassion complements and extends prominent organizing concepts such as seeking equity and social justice, and can offer benefits in many areas of planning, including in advancing integrative conceptual frameworks such as sustainability and promoting the public interest, as well as in serving as facilitators, negotiators, mediators, and advocates (Lyles et al., 2018). Compassion and care complement and extend planners' efforts to seek social justice and offer a highly emotional, personal, relational and individually actionable orientation. Individual awareness, emphatic motivation and outlooks are in such case emphasized to achieve transformation. Our soul-searching often reveals undesirable patterns of bias, anger, ignorance, and other aspects that obstruct empathy, compassion, and, what concerns planners, service of the public interest. In public engagement, planners act as mediators, facilitators, conveners, conflict resolvers, and managers and, therefore, have many opportunities to create situations where participants will naturally come to feel compassion; it then can become an organizational culture. More focus on compassion for others, thus, can be beneficial to the core organizing concepts in planning such as sustainability, social justice, and serving the public interest (Lyles et al., 2018). There are many ways to cultivate compassion even in planning organizations that are practice oriented, such as private consultant firms, government agencies or non-profit entities. Elected officials, commissioners, staff, and stakeholders in some communities, for instance, may use compassion as a core framework (social justice or sustainability) and then organize goals, objectives, and policies around the framework. Compassion could also serve as a trust-building medium to shed light on different perspectives and interests, understanding of which may help solve unpleasant problems that may seem unyielding (Lyles et al., 2018).

A determination was made while conducting an analysis of pertinent literature that more attention is needed on emotional, social and cultural intelligence during the course of the city planning process.

A point of awareness that planners require is how to put emotions to work in their projects. Next, they need to be aware of how their approach inhibits or enables the effectiveness of those emotions. More compassionate and inclusive communities constitute an aspirational goal of the real estate and construction field. There is considerable potential for fostering this goal requiring a more in-depth, emotional, social and cultural intelligence (Lyles and Swearingen White, 2019). At times planners might consider emotions as flaws, interferences or annoyances in the course of work. This gives rise to an emotional paradox as planners employ emotions for motivation in their public commitments and public engagements. The history of planning contains deep intellectual roots in just such a paradox. This applies to planners in different areas, such as engineering, architecture, public administration and other related fields. There are certain individuals and organizations that are now generating effective and authentic dialogs and community cooperation by engaging their emotional, social and cultural intelligence. Their stories along with their respective emotional dimensions deserve a front row seat in educational instructions, practical training and ongoing evolution as a unique field (Lyles and Swearingen White, 2019).

In their interactions with colleagues and other stakeholders, planners need emotional intelligence to be able to read people's emotions from their body language, verbal cues, and other signals (Goleman, 2007). The concept of "constructed view" proposed by Feldman Barrett (2017) incorporates other insights and sees emotions as a fluid outcome of things happening in human brains and bodies, also influenced by social and cultural contexts.

1.3. Affective method for analyzing emotions in public spaces for urban planning

Global research indicates that a rationally performed, quantitative and qualitative, integrated data analysis and interpretation is more reliable, when a huge volume of data is under analysis. The Affective Method for Analyzing Emotions in Public Spaces for Urban Planning (ASP Method) was developed during the course of this research (see Fig. 1.1). Section 1.3 contains a detailed description of the entire research Method. Meanwhile Fig. 1.1 presents the overall diagram of the study. This Method is further described in brief.

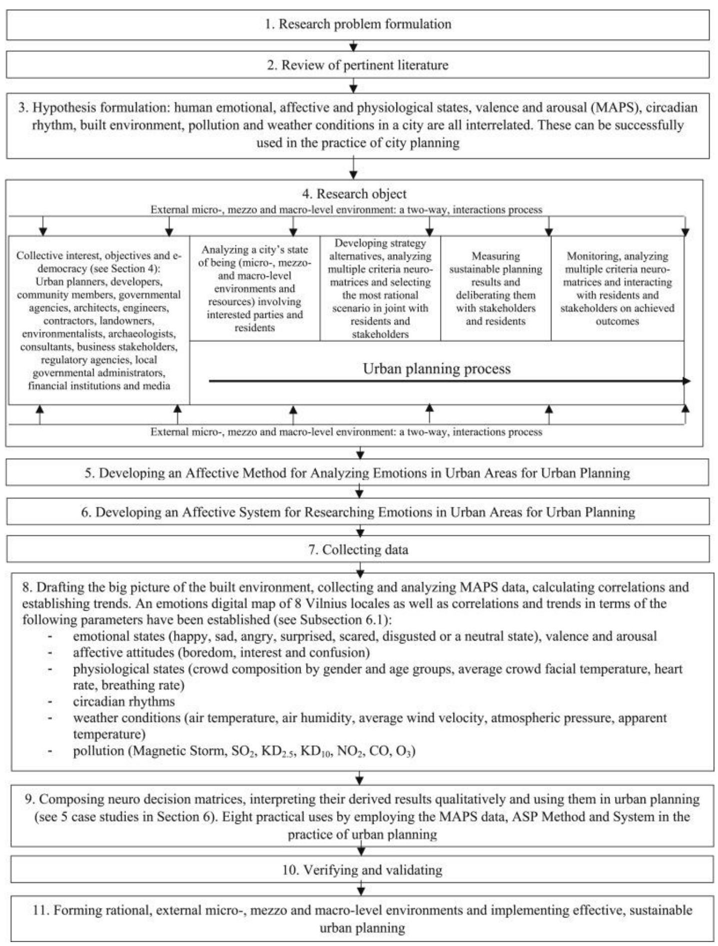


Fig. 1.1. Affective method for analyzing emotions in public spaces for urban planning.

Stage 1 of the research involved formulating the problem under study. Remote means have not been applied to date for performing urban planning research that uses big data. In other words, multiple, non-contact biometrics have not been employed. The key to compiling over 80,000 average and strong correlations involves gathering data in an integrated manner. Here, the discussion involves MAPS data, circadian rhythm, pollution and weather conditions. A realistic picture of a situation in a city requires definition by the bigger picture. The requirements for a evaluation of urban planning involve use of multiple criteria neuro decision tables along with the establishment of several values – market, investment, customer-perceived, hedonic, emotional, synergistic and fair values. Additionally stakeholders require different recommendations devised especially for them. Thereby there has been a broadening and deepening of the scientific problem, when considering earlier researches conducted by other scientists. The analysis presented herein includes the application of the integrated ASP Method. Included in this Method are multimodal, non-contact biometrics; recommenders; statistics like Logit, KNN and MBP and four multiple-criteria, decision analysis methods. The development of the ASP Method also involved use of the research by Kahneman pertinent to the results found in behavioral economics (Kahneman, 2003) and in the areas of psychology of judgment and decision-making (Kahneman, 2011) as well as the research results found by Simon (1997) in the areas of integration of emotions in decision-making and artificial intelligence. The key idea stated by Kahneman (2011) is noteworthy regarding the integration of two modes of thought ─ System 1 (emotional) and System 2 (more logical).

A review of scholarly literature constituted Stage 2. The objective of the literary review was to disclose the state of art in this field (see 1 Introduction, 2 Planning practice by integrating an involved public, 4 Collective interest, objectives and e-democracy).

The review conducted of literature pertinent to the field shows that the existing practice of city planning does not encourage considering analyses of the emotions and affective attitudes of its residents. Planning Advisory Service (PAS) reports include descriptions of current planning research and best practices. The American Planning Association website is presenting these reports. Although information, advice, and tools for advancing legal, policy, and technical dimensions in planning practices abound within PAS resources, unfortunately, these resources contain little or no information on emotional aspects (Lyles and Swearingen White, 2019). Planning departments are usually subdivisions that belong to faculties of architecture, design and engineering. This fact may explain the lack of people trained in psychology among planning teachers and students (Aftab Erfan, 2017). Planning researchers often treat emotions as a problem planners face, an approach that might be explained by the fact that this discipline has a strong technical–rational tradition (Ferreira, 2013).

This literature review also revealed that planning needs to pay greater attention to emotional dimension. Emotional expression happens to be basic when endeavoring to bring about progressive change, as the discipline of urban planning purports (Fischer, 2010). Therefore Sandercock (2003) and Hoch (2006) have been urging planners to begin recognizing this perspective in their work. Especially for the larger projects, like parks or housing projects, emotional and symbolic issues generally remain more hidden although, all the while, they tend to be far more important than the physical structures actually defining them (Fischer, 2010). Fischer (2010) holds the opinion that, although there has typically been an overemphasis on the physical dimensions of planning, planners truly need to reflect on the more emotional side of the planning process in their practice, even when handling buildings, property protection, safe parks and other major projects. A Ladder of Citizen Participation by Arnstein (1969) work reveals that planners might enter into public engagements feeling eagerness or, possibly, fear or even contempt, and how this happens. Barrett (2017) presents a "constructed view" containing more insights. A worldview recognizing the inherent worth of all beings is fundamental to planning with compassion. This calls for a mature awareness of thoughts and emotions along with their interplay in the self and in others. Awareness can thus extend into an empathy for all people. This is what nurtures motivation to lessen suffering, both for oneself and for others (Lyles and Swearingen White, 2019). Emotions generate wisdom, which planners can embrace, comprehend and employ. Relationships are inherently emotional, and, once planners are able to grasp this, they can become more intelligent and effective in their work. There are very difficult emotions involved in planning due to social interactions in planning. Deeply entrenched suffering exists caused by inequality, racism, sexism and other systematic failures, and there does not appear to be any cessation of such in society. Effective engagement with the full spectrum of diversity and difference in society provides the means for planners to work with emotions with greater skill. This is especially true for planners who endeavor for social advancements in equity and justice (Lyles and Swearingen White, 2019).

Worldwide research is also recommending the performance of text and perceptions analyzes on the emotional, affective and physiological conditions of residents by employing biometric and social network technologies. Spatial planning, geoinformatics and all the way to computer linguistics provide combinations of methods for detecting emotions/perceptions. These lead to a firmer grasp of people's perceptions and responses to static and dynamic urban contexts, in time and in geographical space (Zeile et al., 2015). Zeile et al. (2015) extract contextual emotion information by employing technical and human sensors along with georeferenced social media posts to collect and analyze data on emotional perceptions to urban space. Thereby urban planners gain a different, citizen-centric perspective, which has resulted from this unique, information layer.

Stage 3 raises the Hypothesis. In brief, a description of this hypothesis is that there is an interrelationship between human emotional, affective and physiological states, arousal and valence (MAPS), circadian rhythm, built environment, pollution and a city's weather conditions; furthermore these interrelationships are applicable in city planning. Additionally a multiple-criteria analysis pertinent to some city can incorporate these and other data, which are also useful for issuing recommendations for city stakeholders by utilizing neuro decision tables as aides.

City spaces become very attractive to all stakeholders and residents when they contain a positive emotional charge. Such affected stakeholders include developers, community leaders, architects, businesspeople, contractors, environmentalists, consultants and landowners. Meanwhile positively charged locations are especially popular among residents, because such locales develop into well-visited recreational sites. Businesses are attracted to areas that attract visitors with high valence levels, causing them to compete in opening retail outlets, which offer an entire array of products and services.

Stage 4 describes the object of the research. An effective city planning process must be implemented with the participation of the entire community. The purposes and capabilities of the interest groups participating in this process must be considered. Furthermore attention must be paid to the micro-, mezzo- and macro-level environments. This two-way process of interactions between the environment of the city under planning and city's stakeholders are highly related. Special focus turns on how the planned city's environment will affect the wellbeing of its residents, and how the residents will affect the city's environment.

Successful planning processes require healthy foundations, such as those offered by public engagements. The benefits of such should be understood by all planners. Naturally some of the most meaningful works of planners, their favourites, which fill them with hope and inspiration, come about by their public involvements. The planners who foster strong desires to have everyone in a community flourishing rather than suffering are often driven by their emotions, which motivate their endeavors (Lyles and Swearingen White, 2019). An intentional reinforcement of experiences tends to support the capabilities of planners in working with other people who are also in a continual state of change. Conversely, there might be an inadvertent reinforcement of patterns involving thoughts and feelings, which act to inhibit the capabilities of planners (Lyles and Swearingen White, 2019). An element critical to skillful planning involves grasping how the inner and outer lives of people take shape; how it requires an interplay of thoughts and emotions. Arnstein's writing carries a sense of pervading threat. Once planners experience this pervasive feeling, they frequently and naturally respond with a sense of flight, fight or freeze. Yet, this greatly reduces any further opportunity for engaging in productive discussions and ultimate collaboration. Emotions relate to what is named the mammalian brain, or the human limbic system. Affection, anger, sadness and other feelings operate in people's efforts to bring up their offspring and to enable basic cooperation (Lyles and Swearingen White, 2019). One of the research object's components is collective interest, objectives, and e-democracy, which we analyze in Chapter 4.

The external, micro-, mezzo- and macro-level environments affect its residents, whereas the residents affect these same environments. Urban stress is a condition either of bodily or of mental tension arising from city life, as per the General Multilingual Environmental Thesaurus. Such tension grows due to physical, chemical or emotional factors. The physical and social environment of a city usually identify the "urban stress" idea. This is often the major channel between an emotional or mental experience (Pykett et al., 2020). Neuroscientists have employed laboratory research to derive their findings. Their discoveries show interconnections between upbringing endemic to city life, urban life itself and personal mechanisms for responding to stress among people (Lederbogen et al., 2011). Europe has experienced fluctuations in the quality of its city environments over the past several decades, which have proven important. The worrisome aspects that the urban areas in Europe face include air and acoustic quality along with traffic congestion. Land resources have become limited causing tremendous competition for its use, which generally threatens expansions of open and green spaces. Meanwhile deteriorating buildings and infrastructures negatively affect the quality of life in cities while, at the same time, degrading the urban landscape. An investigation into the effects of different environmental components and the levels of their quality on the health conditions of the people living in a city and their quality of life is bound to unearth symptoms of environmental stress. Numerous interdependent variables interact along with the manner in which different urban activities interact with a city's structure determine the quality of an urban environment. A local environment must withstand the tremendous pressures caused by a high concentration of people and their ongoing activities within cities. One way or another, there is an effect on the health of an exposed population by local environmental conditions. Nevertheless, regional and global problems have causes in common resulting in interdependent effects, which, in turn, closely relate to environmental problems that affect urban areas (European Environment Agency, 2016). Also laboratory-based mental stress tasks have been used to ascertain the mediating effects of city environments on stress (Steinheuser et al., 2014, Olafsdottir et al., 2017).

Meanwhile emotional expressions vary considerably among people. Thus planners can never assume anyone, much less themselves personally, are capable of consistent and accurate interpretations of emotions expressed by others. There are inherent limitations to personal perceptions including cognitive biases that are further colored by innumerable emotions. Here the conception of emotion shows it to be an endlessly evolving manifestation originating in people's brains and bodies as well as in social and cultural contexts (Lyles and Swearingen White, 2019). Then there is “moral environmentalism”, as named by Corburn, which is the conviction that some types of built environments can generate behaviors that have greater wholesomeness and productivity along with other behaviors deemed as positive. Such a concept punctuates the histories of city planning and urbanism, both the practical and the theoretical (Corburn, 2004). Thus far, high crime rates along with noise and air pollution in environments containing inferior and unstable housing conditions continue to plague neighborhoods and cause chronic stress. Such areas extend far and wide, well beyond communities planned along strict, moral environmentalist paradigms (Śliwińska-Kowalska and Zaborowski, 2017, Pykett et al., 2021, Gong et al., 2016).

Writing about the planning of multicultural cities with diverse populations, Sandercock (1998) states that desire, loathing, fear, and hope are constant companions of interactions in such cities. She believes that only when the traumas and conflicts of such populations are taken into account a humanistic approach to planning is possible. Therapeutic approaches are discussed in psychology literature including minimally assisted or self-initiated processes based on semi-structured activities such as therapeutic community-based music, therapeutic photography, and therapeutic play. An emerging orientation, therapeutic planning is a natural result of the need to handle the range of emotions that play out in modern life (Aftab Erfan, 2017). Offering an expanded definition of therapeutic planning, Aftab Erfan (2017) argues that the challenges facing today’s communities demand an emotionally engaged planning approach with therapeutic orientation. In a different research project related to therapeutic landscape design, Schulte (2019) city sustainability literature on existing therapeutic outdoor spaces and on the way nature affects minds and emotions, and works with input from experts in trauma therapy and treatment, political conflict, and therapeutic landscape design to propose design strategies with a therapeutic effect for a busy urban area in urban Cairo, Egypt, as a form of relief for victims of trauma and traumatic stress. As more and more people around the world move to cities, one way to improve the health of populations is by making the cities healthy and vibrant. Urban green spaces and parks offer many health benefits, with the wild aspects of parks reported as a highly significant factor. But the therapeutic value of the park as a green space stems from a combination of all its features rather than from any single component. People with access to wilderness have more chances to relax, feel deep connection, and reflect (Cheesbrough et al., 2019).

Rupprecht (2019) believes that the planning stage should not be the point where any engagement and communication with local people ends. In a sustainable urban planning process, local people need to be involved at all of its stages with the public informed about the progress at each step of the implementation. Citizens need to hear which points of the agreed vision and objectives have been achieved. They should be encouraged to give feedback on ways to make measures better, as well as provided with opportunities to share their views, because they are the people with the immediate experience of how the measures actually perform in real life. To achieve the best results possible and use resources effectively, urban planners should seek as much contribution from citizens to the monitoring and implementation process as possible. This way they can make use of both the first-hand knowledge of citizens and the expertize of professionals (Rupprecht, 2019).

Use was made of the Affective Method for Analyzing Emotions in Public Spaces for Urban Planning (ASP Method) (see Stage 5). This Method involves different MAPS data gathering and analyses methods including non-contact biometrics, statistical and recommenders techniques and data mining. There is the additional inclusion of four multiple-criteria, decision analysis methods (INVAR, etc.) that the researchers of this study developed as well as the biometric methods and research results found by Kahneman (2011) and Simon (1997). The research results of Nobel Prize winners Kahneman (2011) and Simon (1997), who integrated the rational thought processes and emotions of interest groups, can be put to practical use for planning cities and their surrounding regions. Two categories (or systems) of thought processes are defined by Kahneman (2011), a founder of behavioral economics. Fast thinking constitutes the first system, whereas slow thinking constitutes the second system. The first system includes impulses, emotions and exaggerated optimism. Since everything occurs nearly involuntarily, the first system requires little effort. However, the second system of slow thinking involves analytical skills, which generate control over behavior and thoughts. Clearly the first system of slow thinking pertains to advertising promoting rational concepts. Meanwhile the second system of fast thinking pertains to emotional advertising. There is no intrinsic conflict between rationality and emotions, as purported by Simon (1997), an analyst of factors in decision-making of which emotions constitute one factor. This researcher concludes that emotions can and do foster appropriate decision-making.

A popularly accepted fact involves purchasing decisions known as the 80%/20% rule. Simply put, the basis for making a decision to buy something is 80% emotions and only 20% logical analysis or facts.

The use for a multiple criteria assessment of sustainable alternatives involves the INVAR (Kaklauskas, 2016) Method for a multiple criteria analysis (Degree of Project Utility and Investment Value Assessments along with Recommendation Provisions). The hedonic, customer-perceived, integrated, hedonic-market and hedonic-investment values of a project under deliberation can also be determined with the assistance of the INVAR Method. Furthermore it can submit digital recommendations for improving projects. Another use of the INVAR Method involves optimizing select criteria that would lead to making the project under deliberation equally competitive on the market as other projects under comparison. The INVAR Method is capable of additionally calculating a projected value for the project under deliberation for making it the leader among other projects under deliberation.

The development of Affective System for Researching Emotions in Public Spaces for Urban Planning (ASP System) occurred during the implementation of Stage 6. The basis for this development consisted of the results from Stages 1 through 5. Section 5 presents these results in greater detail.

Stage 7 involves collecting MAPS data upon conducting the scanning of human-centered urban areas. Anonymous passersby were administered biometric/emotional tests between 2017 November 6 and 2020 September 8 at ten defined sites in Vilnius city. By applying ASP, six layers of data were gathered in different formats requiring processing, integration and analysis. All measurements are performed under real time conditions. The ASP is usable in the evaluation of "in situ" urban planning. Over 0.5 billion items of data have been accumulated at this time. This number continues to increase.

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

Fresh layers of information about urban processes are needed for greater insight into the “city as an organism”. An entire array of researchers, including Chaudhuri (2002), Osborne and Grant-Smith (2015), Hedström (2019) and Trejo (2019), assert that, since emotions comprise knowledge, then emotions are knowledge. That emotions are knowledge-making was an assertion made by Aristotle back in the Classical era (Nussbaum, 2001). That emotions are data is the opinion held by many scholars, such as Svalgaard (2016), Goya-Martinez (2016), Hansen and Trank (2016), and Fritz and Vandermause (2018). That emotions are information constitutes the opinion of other scholars, such as Goya-Martinez (2016), Brackett (2019), Copenhaver and Odenbaugh (2020) and Ching and Chan (2020). As one person emotes, another person receives information by the expression of those emotions. Actually, the intentions of some transfer to others via emotions. The information that someone does not want to do something can be expressed as fear. When a person experiences anger, the information conveyed is that the person does not want to be treated in the way he/she had been treated. In brief, persons in the immediate surroundings have learned what has happened by the emotions expressed (Ching and Chan, 2020). Then, there is an appraisal process stemming from another person’s reaction, which becomes information taken into account (Butler, 2015). What is happening in a group, according to the opinion of Svalgaard (2016), can be surmised by thoughts and emotions, which become the data regarding the situation. An explanation of why positive emotions are not easily separable from cognition is offered by Kiken and Fredrickson (2017).

Every particular emotion has its physiological, psychological and behavioral characteristics. Their analyses can relate them to becoming design features, necessary for dealing with the threats and opportunities appearing in the current situation. Emotions consist of evolutionary functions that can be understood by the relationship between three factors: (1) fear with its subtypes pertinent to varying levels of threat; (2) happiness and sadness traits and their possible variances that could prove advantageous under encouraging and under discouraging conditions; (3) emotions under social situations along with needed adaptations for mutual interrelationships. Every distinct emotion has an adaptive meaning to the sort of situation that gives rise to it. Thus an understanding of such a situation is needed to define any specific emotion. There is a complicated relationship between the elements making up an emotion and the condition that forms it (Nesse, 1990, Nesse, 2019).

External demonstrations of feelings in an environment of war exhibit the emotions of soldiers in battle. An evaluation of a battle and even a forecast of the tendency inherent to the war itself requires an accumulation of the emotions soldiers are feeling for a greater understanding of the situation (Lin et al., 2019). For example, visual, emotional evidence exhibiting a high positive valence and low arousal, as Surakka et al. (1998) propose, signals a nonthreatening and nonappetitive environment. A good source of information consists of the emotions people are feeling. Tiredness, e.g., indicates information about a person’s energy level or sense of fatigue, coldness ─ the temperature of the surroundings and feelings of warmth and trust between more than one person ─ their friendship or their attraction to one another (Frijda, 1988). There are consequential emotions relevant to actions such as, e.g., selecting words carefully to avoid hurting the feelings of another or when emoting personal feelings in instances of frustration involved with a difficult task. Emotions become a form of reasoning, assisting people in understanding their own positions and interactions with others, and providing means to respond in an adaptive manner (Mayer et al., 1999).

Emotions can represent desirable goals in addition to being a means for encouraging appropriate activities. Nearly everything humans endeavor to think or do intend to prompt positive emotions and evade negative ones. Thereby there is an inducement of Darwinian fitness, which is a result of factors that are vague in the awareness of most people. Synergistic efforts by cognitive and evolutionary psychology constitute people's attempts to improve their grasp of the link between emotions and adaptive behavior (Cosmides and Tooby, 1989). The engineering perspective regarding emotions is an adaptationist approach. This perspective sees every emotion as designed by selection to resolve certain problems coming up in some certain realm. Emotions can be seen as goal-directed by a certain level of abstraction, meaning their evolution ad been in response to resolving certain adaptive problems (Sznycer et al., 2017).

Since information that is more emotional is likely to affect attitudes more strongly than neutral information does, information that is highly positive or highly negative could prompt citizens to rely more on EU media evaluations (Soroka and McAdams, 2015). There is a greater frequency of negative news. The guess regarding this situation is that people tend to have a stronger reaction to negative information. The clear pervasiveness of negativity biases on average seemingly account for the tendency of news anywhere around the world to be primarily negative, since all media are seeking to expand their audiences (Soroka et al., 2019).

Additional insights into the complex human-city relationship can be provided for urban planners by correlating extracted and measured human emotions (Zeile et al., 2015). An understanding regarding the perceptions and judgments people make regarding some large-scale urban regions at a high resolution proves to have great significance for researchers, urban planners and decision makers (Zhang et al., 2018). Zhang et al. (2018) present a method for identifying the visual elements of a site. This method identifies the visual elements possibly causing a safe, lively, depressing or some other description of a locale. This perception has a strong correlation with human perceptions. A variety of objects were first identified as having a positive or negative correlation with every one of six perceptual indicators out of 150 object categories that had been segmented from street view images. These results increase the understanding researchers and urban planners may have regarding the interactions of place sentiments and semantics. Dependence between multiple variables can be established by using multivariate regression analyses for an investigation (Zhang et al., 2018). Some pairs of indicators correlated strongly, as Zhang et al. (2018) discovered. Concepts like "beautiful – wealthy" and "depressing – safe" correlated with one another; however, some pairs like "beautiful – boring" were really quite independent. Nonetheless, the specific connections between these indicators would differ between Beijing and Shanghai. The correlation of "wealth – depressing" was found to be strong in Beijing, for one example; however, it proved quite low in comparison with results found in Shanghai (Zhang et al., 2018). The remote, biometric tests conducted for this research derived quite many dependencies and trends (see Fig. 1.6, Fig. 1.7, Fig. 1.8, Fig. 1.9, Fig. 1.10, Fig. 1.11, Fig. 1.12, Fig. 1.13, Fig. 1.14). These are next described in brief.

Correlations and trends were established for ten locales in Vilnius as well as for the entire city with assistance from the ASP Subsystem of correlations. The calculations of these correlations were according to the emotional, affective and physiological states of passersby along with their valence and arousal levels while including, as well, weather conditions, pollution and circadian rhythm (see Fig. 1.9, Fig. 1.10, Fig. 1.11, Fig. 1.12, Fig. 1.13, Fig. 1.14). This Correlations Subsystem helped in calculating more than 80,000 average and strong correlations. The metrics and correlations indicating high, medium or low importance for residents constitute a field to be defined by future research. The measurements taken in Vilnius require a more detailed analysis relevant to parameters with strong correlations and substantial impact on residents. Upon successful accomplishment of this, concrete decisions can be made quickly. This is needed to avoid further problems as well as to gain a level of benefit from the matters, as they currently exist.

Stage 9 involves application of the multiple criteria decision analysis (MCDA) to study the effectiveness levels of urban areas and buildings.

An involvement of people from some specific area into various planning processes constitutes the main idea presented here. People have different expectations about specific areas, and these are urban emotions. This reveals what additional features can be added to an area for greater desirability. Linked to one another, a resident's perception and urban space spark emotional reactions, thereby generating a unique atmosphere for the resident viewing it. Green places, rivers, lakes, pollutions, industry areas, street conditions and further geographical aspects affect the feeling of residents within their current environment. How this happens is what urban emotion endeavors to understand. The accessibility of infrastructures can be rated by methods such as barrier free planning. The identification of a planning deficiency can be eased either by a temporal barrier or by merely a negative impression of some residents. The conceptualization of city feelings was not as simply some comprehensive instrument of explaining various sorts of planning responsibilities. Instead, this concept can generate a different view for a better understanding of a city's formation. Extracted contextual emotion information can constitute the direct feedback needed for urban planning, decision support and evaluating ongoing processes involved in planning and designing (Choudhury et al., 2016).

The comprehensive study of analyze specific tasks employed five case studies, presented in Stage 9. The evaluation of certain parts of the integrated ASP Method required such a study. The proposed, integrated ASP Method was substantiated by these five case studies.

A qualitatively interpretation of the results from the study presented here can be used in urban planning. The objective of urban emotion is to grasp the effect on people's feelings caused by the surrounding environment. Informed decisions in city planning are made by specified target-groups. A better understanding can be achieved among different stakeholders concerning how individuals react to dynamic and static city environments. A unique layer of information results, which offers urban planners an additional, citizen-centric perspective.

Users can compile neuro decision matrices based on the derived MAPS data. Thereby, planners applying the INVAR Method and neuro decision matrices can establish the most effective alternatives for urban planning and calculate the hedonic, customer-perceived, integrated, hedonic-market, and hedonic-investment values. This is the reason that a multicriteria analysis truly corresponds with urban planning issues concerning the analysis of emotions. Urban planners are able to employ the ASP Method and System according to eight different directions (see Section 1.7). The endeavor of this study was to demonstrate the innovativeness and practical usefulness of the ASP System on a global level.

Stage 9 involves a quantitative interpretation of the derived results for their further use in urban planning. A provision of automated recommendations appears in this case (see Section 1.6.2.2). These are pertinent to market, investment, customer-perceived, hedonic, emotional, synergistic and fair value calculations (see Section 1.6.2.4) for urban planners. Those who formulate city planning policies also need to focus attention on the micro-, meso- and macro-factors that have the least significance for improving their city or its regions. The reason for this is because, in the opinion of Tofallis (2020), these will provide a greater conditional benefit for subjective well-being. Tofallis (2020) believes it is important to improve conditions at an individual level for those who feel the lowest level of wellbeing.

Stage 10 regards the verification and validation processes necessary to assess ASP Method and System precision. The accuracy of the ASP was assessed by the verification process, assuring that the results from the system reflected the actual situation. The ASP Method was first confirmed to measure its accuracy and verify that the ASP Method's outcomes showed the real condition by adapting correlations (see Section 1.6.1). The steps relevant to the proposed ASP Method are accurate, as shown by the calculated correlations. The validation and verification of the ASP Method, which appears in the next step, was expert-assisted. This assessment was conducted by twelve urban planning and real estate development experts. Opinions were submitted by those experts who validated the analysis of the urban areas. The validation provided was in terms of the affective, emotional and biometrical conditions of passersby, their valence and arousal levels and by cultural heritage objects. Furthermore experts have tested all the possible states of the ASP Method to double check the results to see if the desired features of the method had made them satisfactorily. The hypothesis must coincide with the ASP Method, which the verification identifies. Four cases of cultural heritage sustainability (see Section 1.6.2) were verified and validated by the proposed hypothesis, which also validated the accuracy of the ASP Method and System.

Stage 11 involves performance of the rational formation of the external, micro-, mezzo- and macro-levels of a city environment as well as of the implementation of effective, sustainable urban planning. A graphic illustration of the interactions among optimal, rational and negative urban environments appears in Fig. 1.2. The constructive influence of specific urban environmental dimensions on the efficiency of city sustainability is featured by the zone within the ellipse. Meanwhile the adverse effect that urban environmental dimensions have on the sustainability of the city appears in the zone outside the ellipse. Wherever the urban environmental dimensions overlap, the result is a better sustainable city. When all three ellipse areas cross over one another, such as, in this case, the social, environmental and economic areas, the sustainable city has reached an optimal state. The larger the crossover area is, in consideration of the weight of the dimensions, the more sustainable the city is. There are urban environmental variables that affect city sustainability. Such variables have been investigated to identify them and to establish the differences between the most sustainable cities in the world and in Vilnius City. Once such differences were determined, key proposals for Vilnius were established. Boundaries on the city sustainability are forced directly by the presence of variable dimensions of some specific urban environment. Thus the efforts to implement urban planning by appropriate stakeholders are more rational once such objective boundaries are known.

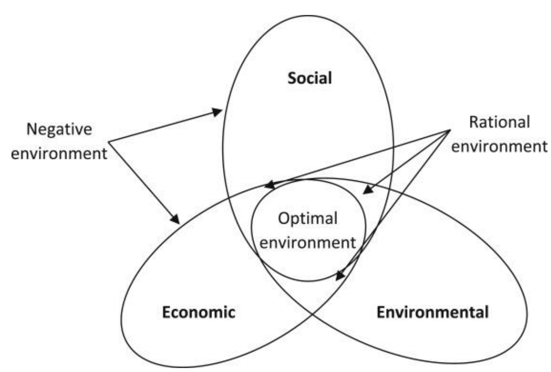


Fig. 1.2. Fluctuation of efficient boundaries of social, economic and environmental dimensions influencing sustainable city efficiency and determination of optimal, rational and negative urban environments.

1.4. Collective interest, objectives and e-democracy

One of the research object's components is collective interest, objectives, and e-democracy, which we further analyze. The analysis in this section includes collective interest, objectives and e-democracy (see Fig. 1.3). One of the more popular areas of study regards the effect of the surrounding environment on people's emotional, affective and physiological states. The topics of study by Van Kleef and Fischer (2016) include their analyses on collectives forming emotions and emotions forming collectives, on expressions of emotions that form group processes and outcomes and the manners in which these occur. As one example, one's own emotional experience may have been formed by emotional and behavioral reactions to events of other people, which affect the personal evaluation of an event that, in turn, forms a personal emotional experience. Reactions to emotional expressions and/or these might impact accomplishing personal goals are matters anticipated by individuals when viewing their surroundings (Bruder et al., 2014). Group-based anger, which disadvantaged groups suffer, can prompt their members, under special circumstances, to erupt in collective actions, as Van Zomeren et al. (2004) have shown in their research. Another study by Tausch et al. (2011) indicate that group-level anger prompts protests in relatively normative forms. Adjusting to changing environmental demands are matters of efficient modes of emotions, which are brief, psychological-physiological phenomena (Levenson, 1994). A present-day environment presents numerous problems to which humans adapt by means of emotions (Keltner and Gross, 1999). Emotional response systems and changes in the physical and social environment prompt interactions from which emotions emerge as dynamic processes, according to the systems approach (Fogel et al., 1992, Lazarus, 1991). Feedback processes regarding changes in the environment are most likely involved in emotions by generating information that brings about modified and varied, emotional response systems, as discovered, for one, by Lazarus (1991). Furthermore control processes co-ordinating different subsystems of emotion also involve emotions as means for reacting to a changing environment (Johnson-Laird and Oatley, 1992). One example of a common attentional control behavior involves visual avoidance of unpleasant stimuli by, e.g., strategically positioning eyes, head and body away from an environmental stimulus. Such a move is meant to down-regulate an emotion by reducing or eliminating visual input (Otero and Levenson, 2019). Nature may well impact the well-being of people. Anderson et al. (2018) propose accounting for emotional experiences while engaging in activities outdoors as a means to understanding nature's effect on emotions.

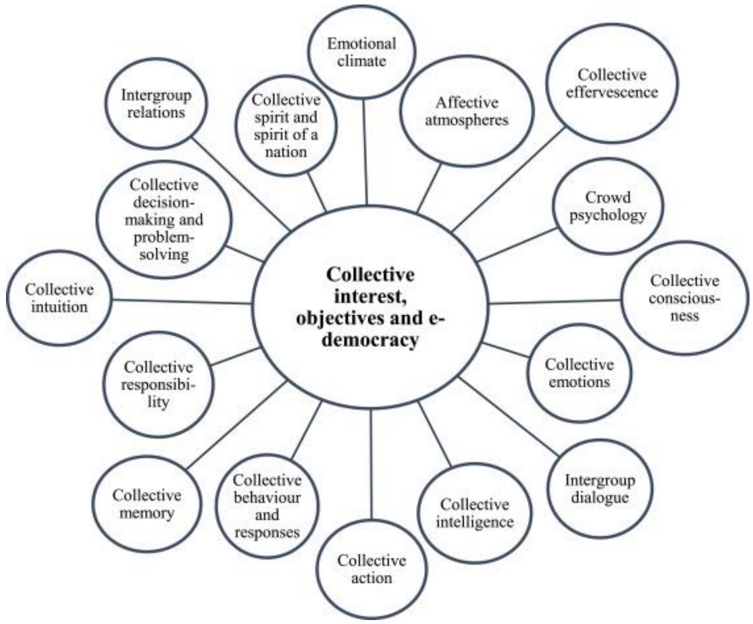


Fig. 1.3. Collective interest, objectives and e-democracy.

It is a mistake, according to Gabriel et al. (2020), to view collective effervescence merely as a useful means for understanding rare, unusual and intense collective events. These scholars hypothesize that this particular sort of sense of connection and meaning coming from collective events can also serve as a framework for greater understanding of "everyday events". No matter how seemingly insignificant a collective gathering might be, how presumably meaningless, it actually can provide a sense of connection among people, thereby adding to the joy in life. The argument developed by Gabriel et al. (2020) lays out that, even though collective effervescence is most commonplace and seems virtually banal, it carries extremely important psychological meaningfulness. The reason interacting people affect and intensify one another's emotional state is due to collective effervescence. Its interactional effect contains an underpinning mechanism causing "emotional contagion" (Heinskou and Liebst, 2016).

Organizations, groups and societies carry responsibilities, which are termed "collective responsibility". Some defined group of people is generally said to be collectively responsible for what has happened, whether good or bad (Durkheim, 1960). Nevertheless, Durkheim (1960) asserts that even a genuine example of collective responsibility will still retain the core intuitions of individualism. This relates to the argument posed by Giubilini and Levy (2018). They note that use of the term in most debates actually references a means of responsibility, which is not genuinely collective. Rather, it arises due to some sort of individual responsibility; however, it becomes attributed to one form or another of collective responsibility.

An academic field that encompasses the behaviors and thought patterns of individuals forming a crowd as well as of the crowd itself as an entity is crowd psychology (Manstead and Hewstone, 1996). An individual seemingly has little responsibility when part of a crowd, which now displays a sort of universal behavior. The greater the size of the crowd, the more universal the behavior seems to be (Greenberg, 2010). A fear of a "mass society" arose during the nineteenth century, which a crowd seemed to symbolize, according to Stott and Drury (2017). They argue that such fears resulted in "classical" crowd psychology. The current ruling elites needed a means to control crowds, and classical crowd psychology seemed to offer such an opportunity. Therefore the study in the field related to making a pathology of crowd behavior, specifying its characteristics and decontextualizing it (Stott and Drury, 2017). Meanwhile the social identity project has now rejected the classic model of a crowd and began, in its stead, transforming the comprehension of the social psychology of the self. It evolved into a recognition of social action as something crowd psychology creates meaningfully, not merely reflects it (Stott and Drury, 2017). Crowd movement behavior is being monitored and predicted more and more often with the aid of computer simulations. The benefits include increased efficiencies due to improved crowd safety at large events and transport hubs and maximized capacity utilization of public transport systems (Seitz et al., 2017).

A community or society shares fundamental beliefs, customs, norms and values in common, which is referenced as a collective consciousness. This encompasses numerous matters such as how men and women are supposed to dress and act accordingly, for one example. Concepts of "right" and "wrong" socialize all societies by means of laws aimed at their own defined communities. Furthermore there are all the rituals involved among people, such as parades, holidays and weddings. Presently the research focuses on the macro-level of society. The field promises capabilities of predicting and generating positive impacts on a society's collective consciousness as well as measuring the consequent influence of such (Dillbeck and Cavanaugh, 2016).

The furtherance of diversity involves work requiring an ability to grasp the meanings and consequences of group differences at a very deep level (Zúñiga, 2003). Another field for assisting people in understanding one another, in the opinion of Zúñiga (2003), is intergroup dialog. This is also a promising study for investigating social and cultural differences, identifying common grounds and increasing honest communicates. This intergroup dialog model incorporates knowledge, awareness and skills into group work, when it comes to areas such as social justice education and psychodynamic practice (Varghese, 2020).

A blunted cortisol, according to Kliewer et al. (2016), relates to environmental risk factors like parental substance use, childhood physical abuse and repetitions of violent experiences. These are examples of environmental stressors, which, when young people habitually experience them, develop into a negative emotional climate. A negative home climate affects the interactions of family members, causing them to be irritable, angry, disagreeable, critical, disrespectful, blaming or, even possibly, threatening (Kliewer et al., 2016). A main component to responsive teaching is a positive emotional climate, which denotes a high-quality program. One of the main contributors to developmental successes in children has to be high quality (Iruka and Morgan, 2014). Children are able to interact at productive and high-quality levels in a positive emotional climate (Howes, 2011). The research literature on classroom quality in preschools has strongly established a positive emotional climate as essential (Pianta et al., 2016, Sanders et al., 2019). Hong et al. (2020) pursued a study of correlations between the emotional climate of a classroom, a student's social self-efficacy and a student's psychological health. The importance of classroom emotional climate is stressed by this study for its significant effect on social self-efficacy. Meanwhile social self-efficacy can predict self-esteem and depression at a significant level, whereas self-esteem, in turn, can significantly predict depression as well (Hong et al., 2020).

Interactions among individuals, as per organizational theory, constitute intergroup relations. This term envelopes behaviors of members from different groups along with the collective behaviors of groups as well as their interactions with other groups, both at the intra- or inter-organizational levels (Kramer and Schaffer, 2015). Literature on psychology reports some new developments in the field. New considerations in the study of diversity and multiculturalism appear in, e.g., the discussion by Verkuyten and Yogeeswaran (2020). The work includes the implications of intergroup relations categorized under: (a) demographic diversity, (b) national policies on diversity and multiculturalism and (c) ideological beliefs and discourse about diversity and multiculturalism.

When a group undertakes an action together for the purpose of upgrading the positions of every member and accomplishing a common goal, it references collective action (Encyclopedia Britannica). Joint work by diverse parties is a natural requirement for environmental governance. Despite this, there are a number of different types of stakeholders, studies show, who will pull back from contributing to joint negotiations or even deliberating them to uncover solutions for commonly occurring environmental problems. One factor for consideration consists of all the features describing an underlying collective action issue. Another factor consists of the features describing the underlying biophysical system, which align with collaborative governance manners regarding the construction of arrangements and institutional entrenchments. Nonetheless, the factor that actually establishes effects from other factors on the ability of a collaborative arrangement to solve environmental problems relates to the patterns by which joint actions take place, or do not take place, between involved persons (Bodin, 2017).

Synergies occur among data-information-knowledge, software-hardware and experts or members of the public who continually learn from feedback and produce knowledge in the nick of time for better decisions than when the aforementioned three elements act alone. The property that emerges from such synergies are known as collective intelligence. A narrower view of the same concept would be an emergent property between people and different ways of processing information (Glenn, 2009, Glenn et al., 2014). An opposite view appears in the work by Lollini et al. (2019). Their idea of collective intelligence involves human beings contributing to the construction of a common intellect, naturally for personal benefit, not as some universal intelligence emanating toward humans. Here, the idea of collective intelligence presented by Lollini et al. (2019) does not involve the concept of a hierarchy; in other words, the impulse moves from bottom up, not from the top down. Human development associates closely to the degree of collective intelligence achieved. The reason reverts to the symbiosis of collective intelligence, or its circular causality between human collective intelligence and human development. Collective intelligence can be viewed like the engine of human development, because collective intelligence combined with human development is the basis of collective intelligence. Driverless cars can serve as one example. By means of their connection to collective intelligence, such as to Google maps, these cars can see where traffic is heavy and they maneuver to the best and fastest route. A person is not likely to make such an optimal selection with the use of merely two eyes and two ears. Therefore driverless cars seem destined to become safer than those driven by a human driver by operating as a smart city segment (Lollini et al., 2019).

There are instances when arrangements made in joint between people can potentially result in better net performance outcomes than singular people acting on their own accord. Such instances can be said to involve collective decision-making (Larson, 2010). Assuming there is sufficient time for appropriate considerations, discussions and/or dialogs, collaborative or group decision-making would often be preferential for resolving normal, everyday events and issues and result in greater all-around benefits than individual decision-making would prompt (FEMA, 2010). The cognitive capacity of any individual is taxed beyond capacity due to the intensity of contemporary problems, as has been noted by numerous scholars. One answer seems to be the application of collective problem-solving, which offers different albeit complementary expertize and collective problem-solving abilities (Hung, 2013).

Remembering the past in terms of one's group membership falls under an umbrella term ─ collective memory. This field can be viewed as a body of knowledge. It offers a diagram of people's attributes as group members as well as of a contestation and change process. Group identity and the sort of social and political discourse that a group shares have to do with such collective memories (Roediger and Abel, 2015). Historical imagery and architectural accomplishments are aspects for studying the collective memory of a city (Boyer, 1996). Alternatively, disputes spark dynamic and continuous processes regarding the shape and form of historical remembrances and representations, which constitutes collective remembering (Roediger and Abel, 2015).

Riots or mob violence are examples of highly destructive collective behavior. Nonetheless collective behaviors can also be something light and silly like fads and current trends. Meanwhile collective behavior can also fall anywhere in between such extremes. Group dynamics is the driving force for collective behavior. Thus people may act in ways they might consider unthinkable in the course of their accustomed lives (Locher, 2002). People mass together in their social lives, both in time and in space, whether they are engaging in religious activities, recreational pursuits or community functions in cities. Such behaviors include those needed for emergency responses as well as for social movements and upheavals. The need to define situations causes people to seek out one another. It takes a group to bring order in times of crisis as well as to generate social change involving social, cultural and political movements. All forms of collective behavior are thriving (Van Ness and Summers-Effler, 2016). Complex dynamics stem from the social nature of humans. Individuals engage in activities, which can contain the possibility of triggering unexpected collective reactions. Therefore laws relevant to how individual actions associate with collective responses of social systems must be unearthed to arrive at an understanding of human collective behavior.

Collective intuition is a concept defined by Akinci and Sadler-Smith (2019). These scholars regard collective intuition as domain-specific knowledge, experience and cognitive ability that shapes independent judgment, which is then collectively shared and interpreted. An intuition becomes stronger when a number of people think about it in a similar way. This then becomes a synthesis-forming, collective intuition (Kuusela et al., 2019).

Listening with zest by a group of people to something becomes the central core of team dialog. In other words, a group hears something individually but with a selfless receptivity to the ideas of others. A collective spirit arises as each individual empties him/herself and transfers what is within into a power of collective listening, now a sort of common vessel for the matters being heard, which become something the entire group receives and contains (Levine, 1994). Hegel was one of the first in the world to deliberate the notion of collective emotions as long ago as in 1793. National attributes such as history, religion and degree of political freedom reflect the spirit of a nation. One attribute, low mortality rate, is an outcome involving self-proclaimed religious faith, the parental line, a person's individual endeavors and a specific, personal situation. Other attributes attributed to folk religious beliefs and specific political branches nurture the spirit of the people, which augments the contributions of a whole entity (Hegel, 1793). Sometimes many people experience emotions together, including those that are positive and negative in situations that may be online or offline. An analysis of such situations intuitively draws a researcher to experience the emotions of each involved individual. Yet, this sort of study does not seem to be complete in one way or another. Actually, macrolevel affective processes emerge in numerous cases of people jointly experiencing emotions. Thus such processes cannot be easily revealed at individual levels (Goldenberg et al., 2020). Mass gatherings, crowds or actions responding to widely prominent events generally reveal collective emotions, which are at the heart and soul of every community (Von Scheve and Ismer, 2013). Many bottom–up mechanisms, which Von Scheve and Ismer (2013) have analysed, offer a look at levels of social cognition, expressive behavior and social practices, where collective emotions are expressed. Other scholars, such as Goldenberg et al. (2020), have investigated such macrolevel affective phenomena, which are also known as collective emotions. Emotional dynamics among individuals who are responding to the same situation prompt the emergence of macrolevel phenomena ─ such is the definition of collective emotions (Goldenberg et al., 2020). Emotions experienced at a collective level will frequently generate different collective behaviors, such as a movement for a social cause (Van der Linden, 2017) or even violent actions by an interest group (Van Zomeren et al., 2012). Altruistic and productive movements generally consist of actions prompted by collective emotions (Baumeister et al., 2015). Yet, in different situations, collective emotions can just as well prompt collective groups to engage in violence and destruction (Goldenberg et al., 2016). Collective emotions can potentially generate true contributions to communities, helping them to flourish. Researchers like Goldenberg et al. (2020) have the opinion that research is needed to uncover ways to reduce destructive collective emotions and foster more beneficial collective emotions aiding the unification of communities.

Cultural geography has contributed the concept of affective atmospheres. These involve specific spheres and locales where emotions and feelings arise due to humans and non-human beings interacting and their movements therein. The effect of affective atmospheres can be intense in regard to how people conceptualize and emote when it comes to locales they inhabit, the areas they move around in, and the other beings moving about within those same areas (Lupton, 2017). The constitution of affective atmospheres is an area of research by Yu (2019), who has studied how these nourish regeneration megaprojects. Specific affective atmospheres produced within particular urban contexts, as Yu (2019) argues, are central to fostering change and transformation in present day cities. Forging and circulating affective atmospheres are necessary for legitimate political decisions and urban policies, which occur by a process of converging affective encounters, spatial imaginations and community-wide goals in performative manners (Yu, 2019).

Change is constant in all things and matters. Actions naturally respond to such changes in reaction to emotions that are responsible for people’s primary means of tracking, evaluating, organizing and motivating such responsive actions (Butler, 2015). The cognitive-motivational-relational theory of emotion presented by Lazarus (2000) provides a certain concept of emotion. Emotions, according to this researcher, reflects person-environment relationships by an organized psychophysiological reaction. Goal relevance and congruence are the matters a person appraises in some certain situation that then results in emotions. Lazarus (2000) considers facilitation of adaptation as a function of emotions. The state of feeling to the level of goodness, joyfulness and happiness or satisfaction experienced by a person in some specific occurrence, as Adelaar et al. (2003) relate, defines an emotional response. The coherence of an emotional response system has been analysed by Matsumoto et al. (2007). For an organism to respond efficiently to the environment, there must exist coherent responses to prepare and enhance the reliability of emotional signals. There must be a quick coordination of social actions between parents and children, romantic partners, bosses and subordinates and other individuals involved in joint endeavors (Matsumoto et al., 2007). Emotional reactions are routine among people assuming their behaviors relate in some way to their objectives and sense of common well-being (Semin and Cacioppo, 2008). Higher levels of emotional synchrony relate both to negative influences and to mutual cooperation was a finding of research by Butler (2015). Such a result suggests that, on its own, synchrony, or simultaneous action, is a weak indicator of the quality of some relationship. Rather, the overall relational context must be first understood.

Davidson and Milligan incorporated consideration of emotions in a review of geographic research. They demonstrated that emotions often serve as “a form of connective tissue that links experiential geographies of the human psyche and physique with (in) broader social geographies of place” (2004). A conceptual map drawn by Woods et al. (2012) indicates the process of transforming emotions into collective action by developing group identity, solidarity and mobilization. They visualize a model showing a ladder of emotions covering six major stages to the process of transformation before it mobilizes into a protest (Woods et al., 2012).

Numerous researchers have substantiated that behavior form human emotions, which have been formed by an environment, something that is not a new notion. Depression, for one example, is expected to be a major health dysfunction by 2030 due to people spending most of their time within buildings. Therefore, it has been suggested, that a major solution for improving the quality of life requires "re-connecting architecture with emotions" (Zaino and Abbas, 2020).

Today the widely used term – e-democracy – describes the political decision-making and opinion-forming by the public as it engages in very many different practices online. There have been two decades of e-democracy in the European Union, which did not live up to the far-reaching expectations of fundamental reforms to modern democracy by the use of online tools to participate politically and to engage in public discourse. Nonetheless, e-democracy has undoubtedly brought in unique modes of communication among its participants, especially between the participants of representative democracy and its constituencies (Korthagen et al., 2018a). Various policy options have been proposed by Korthagen et al. (2018a) aiming to discover more successful tools for e-participation at the EU level.

Public and scholarly debates, which have been long-standing and continuing, indicate some deficit of democracy in the European Union. However, unique modes of political communication and participation offered by Internet might play a role in reducing such a deficit, and there seems to be a consensus regarding this. The EU is often criticized that its e-participation practices prove to be successful civic instruments but not convincing policy instruments. Numerous e-participative projects apparently offer personal added value for its participants; however, such projects suffer from a lack of direct and indirect political impact for policies regarding community building (Aichholzer et al., 2018).

Citizens are able to get involved in policy- and decision-making processes by employing ICT tools and social media in greater and greater numbers. The EU democratic deficit might potentially be reduced by a contribution of the stronger connections offered by digital tools between European citizens and EU decision-making processes (Korthagen et al., 2018b). Korthagen et al. (2018b) identifies the most important factors for successful e-participation. These factors consist of the following (Korthagen et al., 2018b):

- close and clear e-participation process links to a concrete, formal decision-making process
- the contribution of the participatory process and its outputs to a clear-cut, overall decision-making process that participants understand from beginning to end
- indispensable feedback to participants regarding their contributions
- an unlimited participative process, rather than relevancy to one event alone, imbedded in an institutional “culture of participation”
- an effective mobilization and engagement strategy accompanying e-participation that involves distinct target groups by devising three distinct communication instruments.

1.5. Affective system for researching emotions in public spaces for urban planning

A Smart Database Management System, a Smart Database, an Equipment Subsystem, A Model Database Management System and an Intelligent Model Database and User Interface constitute the framework of the Affective System for Researching Emotions in Public Spaces for Urban Planning (ASP System). We developed the ASP System based on the ASP Method.

Developed emotional, affective and physiological states, arousal and valence (MAPS) along with the Historical, Recommendations and Simulators Databases and a Smart Database engine constitute the framework of the Smart Database. Collections of MAPS data are accomplished by the Video Neuroanalytics Database. Historical data accumulates in the Historical Database after being collected by the video neuroanalytics, recommendations. Experts in the field assist with the compilations for the Simulators Database. These named subsystems store data for urban planners on sustainability and quality.

The subsystems that constitute the Intelligent Model Database are the Text Mining Subsystem (see Section 1.5), Recommendations Subsystem, Simulators Database (see Section 1.6.2) and Correlation Subsystem. Different stakeholders are able to receive recommendations from the Recommendations Subsystem on air and noise pollution and other issues regarding ways to improve sustainability. Urban planning alternatives can be modeled by the Simulators Database, which offers a System for such modeling. The Simulators Database, which the authors of this article developed, are presented in Section 1.6.2. An analysis of different correlations pertinent to human-centered, urban planning metrics and their influence on people can be performed by the Correlation Subsystem. Applications of the integrated ASP Method for revealing information and patterns in MAPS data layers are assisted by the data Correlation Subsystem (see Section 1.6.1).

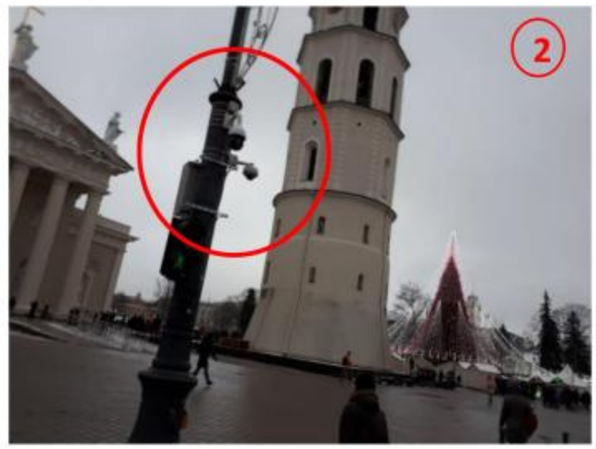
As an example of ASP, we will briefly analyze the Equipment Subsystem and Text Mining Subsystem below.

Section 2.5 presents the description of the Equipment Subsystem regarding data measurements of human emotional, affective and physiological states, arousal and valence (MAPS). Currently the measurements of MAPS data take place in the Vilnius Municipality building, the Business Center on Narbuto Street 5 and at six Vilnius City intersections: 1) Kareivių, Kalvarijų and Ozo Sts. intersection; 2) Žygimantu and T. Vrublevskio Sts. intersection; 3) Santariškių and Baublio Sts. intersection; 4) Šventaragio and Pilies Sts. intersection; 5) Šventaragio St. and Gedimino Pr. intersection and 6) Pamenkalnio, Jogailos, Islandijos and Pylimo Sts. intersection. Furthermore MAPS data was also being gathered at three Vilnius beaches during the summer. The sensors of the Equipment Subsystem are also intended to be attached to four inner-city buses with ever-changing routes. There is an expectation, in this case, to additionally gather data at 400–500 bus stops. Currently there are over 0.5 billion pieces of MAPS data accumulated.

The Equipment Subsystem comprises face emotions (FaceReader 8), temperature (infrared camera FLIR A35SC), Respiration sensor X4M200, people flow counter (H.264 Indoor Mini Dome IP Camera), voice emotions analysis (QA5 SDK), eye pupil (Mirametrix S2 Eye-Tracker), brain signals (Enobio Helmet), heart rate (iHealth Wireless Blood Pressure Monitor) biometric analysis devices. The Equipment Subsystem was used to collect biometrical and physiological data. The User Interface provides convenient conditions for a user to manage the ASP. Anonymous passersby had emotional, affective and physiological states, arousal and valence (MAPS) tests conducted on them between 2017 November 6 and 2020 September 8 at eight distinct locales in Vilnius City (see Fig. 1.4). Different formats of remote data were gathered in three layers, in real-time, with the aid of the Affective System for Researching Emotions in Public Spaces for Urban Planning (ASP System). This MAPS data required processing, integration and analysis.

a)

b)



c)

d)

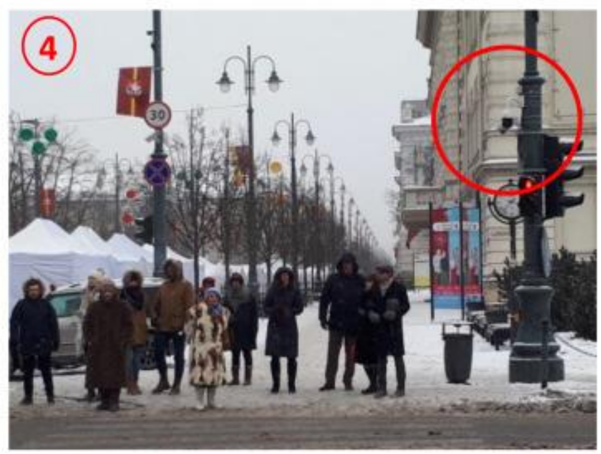


Fig. 1.4. Examples of equipment subsystem hardware at the beginning of Pilies Street (a, c) and at Gediminas Prospect (b, d).

Over 490 million of such MAPS data have been accumulated at this time. These provide a rather accurate definition of "how people feel in a city". The only data established without the use of video streams are the breathing rates of passersby, which are taken with the Respiration sensor X4M200. Instead, a radio-frequency electromagnetic signal is applied to reflect information about a target.

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

The FLIR A35SC infrared camera (FLIR) is $\pm 2\%$ accurate. It has a $< 0.05\ °C$ thermal sensitivity. FLIR has been calibrated and verified by its manufacturer. Next the measurement results were documented by virtue of a calibration certificate. The assurance that the error rate does not deviate from the parameters, which the manufacturer sets, is the metrological verification conducted every 12 months on the thermographic cameras.

Text Mining Subsystem permits selecting the maximally rational information in the coverage that the user urban planning requirements. The Text Mining Subsystem assists an urban planning user for the selection of maximally rational information in the desired area of interest. Planners are able to find information they need by employing the Text Mining Subsystem. Text Mining Subsystem currently available in English. The Text Mining Subsystem was developed according to the methods described in "Electronic information retrieval method and system" in Patent EP 2187319 A1 (see https://patents.google.com/patent/EP2187319A1/en). The Text Mining Subsystem develops many alternatives and chooses the most effective personalized educational texts for every mentee by applying a system of search keywords and weights. The system of keywords and their weights cover:

- Keywords describing learning style,
- Keywords describing the most interesting previous modules,
- Current search keywords.

A description about the search for such keywords follows.
In our case, the learner responds to the Multiple Intelligences Self-Assessment Scales, which then control the education style that is the most suitable for that learner from the available styles:

- verbal-linguistic (frequently related with learning well in a university, speaking and writing by techniques),
- logical/mathematical,
- visual-spatial,
- intrapersonal,
- interpersonal (learning in a group, appropriate in broker and mentor professions),
- musical (sympathy for sounds, videos and audiovisuals),
- bodily-kinesthetic (writing and drawing diagram techniques),
- naturalistic (broad systematic reasoning in the urban planning, appropriate in researcher professions).

Once ASP establishes the learning style of a specific learner, it proceeds to implement the studies process adapted to the learning style for this particular mentee. For example, assuming the

Multiple Intelligences Self-Assessment Scales indicate that the interpersonal learning style is more suitable for some specific mentee and that mentee expects to work as a tangible heritage broker in the future, the System will select learning materials that are most suitable to the interpersonal education style. While this same mentee is learning from the “Tangible heritage development” module, the Text Mining Subsystem searches for a text according to the keywords describing such a learning style: agent, broker, services, sales, tangible heritage, transactions, mentee, seller, commission and deal.

Keywords describing the most interesting previous modules contain course keywords from tests and course projects that a mentee had passed with an excellent or good mark and had a positive evaluation based on the interestedness of the course for that learner. The applicable Module card contains these keywords. The weights of these keywords depend on the grades assigned to exams and course projects and the course interestedness as rated by that mentee for him/herself.

A mentee compiles the current search keywords and their weights with respect to current requirements in real time. It is possible to select such keywords from the Keywords Database, containing the most frequently used keywords and their significances.

A user also can indicate the level of complexity and significance of the material being searched by the interface to include limitations. The evaluation of the complexity level of material being search is on a ten-point scale. Establishing the most rational material to search, the evaluation of its level of complexity and its significance takes place comprehensively, along with other criteria. The most rational information is established by indexing the text in the module, i.e., finding the number of times the words (their synonyms) being searched or their combinations are repeated in a text.

The developed System described above regarding search keywords is applied for the development of "personalized curricula" for a specific mentee. Ample data and text should be processed and assessed for performing the multivariate development and multiple criteria analysis of a course.

The Text Mining Subsystem executes a multivariate development and a multi-criteria examination of text alternatives. Additionally, it routinely chooses the most rational option according to the above-described system of search keywords, the citation of manuscripts (ScienceDirect, Scopus, Google Scholar), the h_{index} of authors of publications under deliberation (Web of Science, Google Scholar), top 25 papers, impact factor of journals and density of keywords. Furthermore, this Subsystem computes the utility degree and priority for each alternative of a text under deliberation (see Table 1.1).

Table 1.1. Selection of a rational, personalized text variant – a fragment.

The following determine a rational text:	Paragraph 1	Paragraph 2	Paragraph 3	Paragraph 4	Paragraph 5	Paragraph 6	Paragraph 7	Paragraph 8	Paragraph 9
Citation of papers:									
Citation of papers (Web of Science)	3	79	44	81	–	179	155	135	202
Top 25 papers	–	**24**	–	**2**	–	**15**	–	**20**	**18**
Impact factor of journals	0.983	1.59	1.59	1.59	2.046	1.59	1.192	1.59	1.59
Density of keywords (% of a text):									
energy	7.547	9.677	7.895	14.724	16.216	13.102	14.118	11.321	11.321
building	15.094	25.806	21.053	14.724	–	15.287	9.412	15.094	15.094
Citation of authors:									
Author 1									
Web of Science									
Sum of the Time Cited	3	18	715	82	–	69	179	140	104
Sum of Times Cited without self-citations	3	18	582	82	–	67	179	140	99
Citing Articles	3	15	499	82	–	66	177	140	88
Citing Articles without self-citations	3	15	458	82	–	64	177	140	84

1.6. Case studies

1.6.1. Practical application of the correlation subsystem

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

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

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

The research object that Vilnius Gediminas Technical University and Vilnius Municipality City chose relevant to their ROCK and VINERS projects implementation was Vilnius Old Town, which has been named a cultural heritage object by UNESCO. The Old Town object included the key urban areas within its security zone. The urban areas considered key include Gedimino Prospect, Pilies and Švitrigailos Streets and Lukiškių Square (see Fig. 1. 4d for the locations of these sites on a city map). These sites have their differences. For example, (1) Pilies St. is historical as part of the Old Town's 16th century urban structure, and large numbers of both city residents and touring visitors visit this area. In contrast, (2) Gedimino Prospect was built as a main avenue of the city during the 19th century modernization of Vilnius. Its renovation came early in the 21st century to include use during holiday events and fairs as well as its functioning as a pedestrian walkway and bicycle path (see attached maps). Finally, there is the 8 ha (3) Lukiškių Square, formerly Lenin Square during Lithuania's soviet period, which is currently under maintenance. This site was the object of lengthy, harsh debates regarding reconstruction into a site earmarked for recreational use. The general plan for this square only called for the start of maintenance work in 2016, which is still ongoing but with functioning pathways. What were the desires of the urban planners themselves? City planners undertook studies of human emotions; thus they selected different objects for review. Their studies were meant to review the following:

- Evaluations of diverse urban areas relevant to their quality by attendance rates with relevant visitor emotions, age group(s) of visitors and the average length of their stays.

- Factors of importance established for urban area developments along with recommendations to include planning for fostering positive emotions thereby guaranteeing good health and for stimulating attendance.
- Investigations of urban areas regarding their contributions to the satisfaction of city residents.

The objective of the H2020 ROCK (Regeneration and Optimization of Cultural Heritage in Creative and Knowledge Cities) Project is to regenerate and adapt the reclamation of historic city centers by developing an innovative, collaborative and circular systemic approach. An aim of the ROCK Project involves promoting synergies, popularizing places of interest and transforming historic areas into technology-driven hubs of knowledge and culture for contributions to creative and innovative historic building and cultural equipment reclamations. This aim also encompasses the discovery of areas with high cultural potential that are currently barren. The development of an ICT infrastructure is for improving knowledge sharing and discovering new and innovative ways to employ cultural heritage objects. This is being accomplished within the framework of the ROCK and VINERS Projects and the Affective System for Researching Emotions in Public Spaces for Urban Planning (ASP System).

Development of the Video Neuro-advertising Method and Recommender System (VINERS) Project involved two Subsystems, VINERS1 and VINERS2. An analysis and evaluation of the impact made by the content of electronic advertising by the VINERS1 Subsystem permits learning more about the effectiveness of an advertisement at each state of its creation. It helps to establish the strengths and weaknesses of an advertisement as well as to improve it until it reaches a point of being most attractive to a viewer. The VINERS2 Subsystem permits performing an integrated evaluation of viewer neurobiological feedback during intuitive broadcasts of an electronic advertisement with already composed contents. Furthermore it allows selecting the most effective advertising variant in real time.

The ROCK project implementation, conducted by Vilnius Gediminas Technical University (VGTU) and the Vilnius Municipality, involved mounting Equipment Subsystem hardware at six, different, Vilnius Old Town intersections (see Fig. 1.4) and two buildings. Examples of such mountings from the Equipment Subsystem have been photographed at the head of Pilies St. (see Fig. 1.4a, c) and at Gediminas Prospect (see Fig. 1.4b, d). The MAPS states of viewers are under analysis by ASP, which then rates cultural heritage sites accordingly.

The happiness indexes of Vilnius City and the municipal building are currently presented in the official website of Vilnius City (see Fig. 1.5; https://api.vilnius.lt/happiness-index). A map of the happiness indexes at eight Vilnius sites is also presented in real time (see https://experience.arcgis.com/experience/8c1856f8ca924ab89052e19650d80746/).

Fig. 1.5. Happiness indexes, in real time, at Vilnius City (on the left side) and the municipal building (on the right side).

Table 1.2 introduces the correlations of happiness values by weekday. The values of all the happiness indices during every weekday correlate with each other. The strongest correlation falls between the values on Wednesday and Thursday ($r = 0.987$, $p < 0.01$), whereas the weakest correlation falls between the values on Monday and Tuesday ($r = 0.553$, $p < 0.01$).

Table 1.2. Happiness values correlated by weekdays.

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

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

Average happiness values by weekdays appear in Fig. 1.6a. The graphs of happiness per hour for each weekday appear in Fig. 1.6b. It can be seen that the happiest day of the week is Saturday, and the least happy – Monday. This is in line with global practices. More than 29 million items of data on happiness were measured. The values of average happiness and their changes among passersby in Vilnius are taken and recorded every hour. Meanwhile happiness measurements are recorded every second. The accumulated values by weekdays are at a 95% confidence interval. The x axis shows each hour starting at 12:00 midnight, while the y axis shows 7 days of the averages of happiness values. The fluctuations of happiness measurements are between 0 and 1.

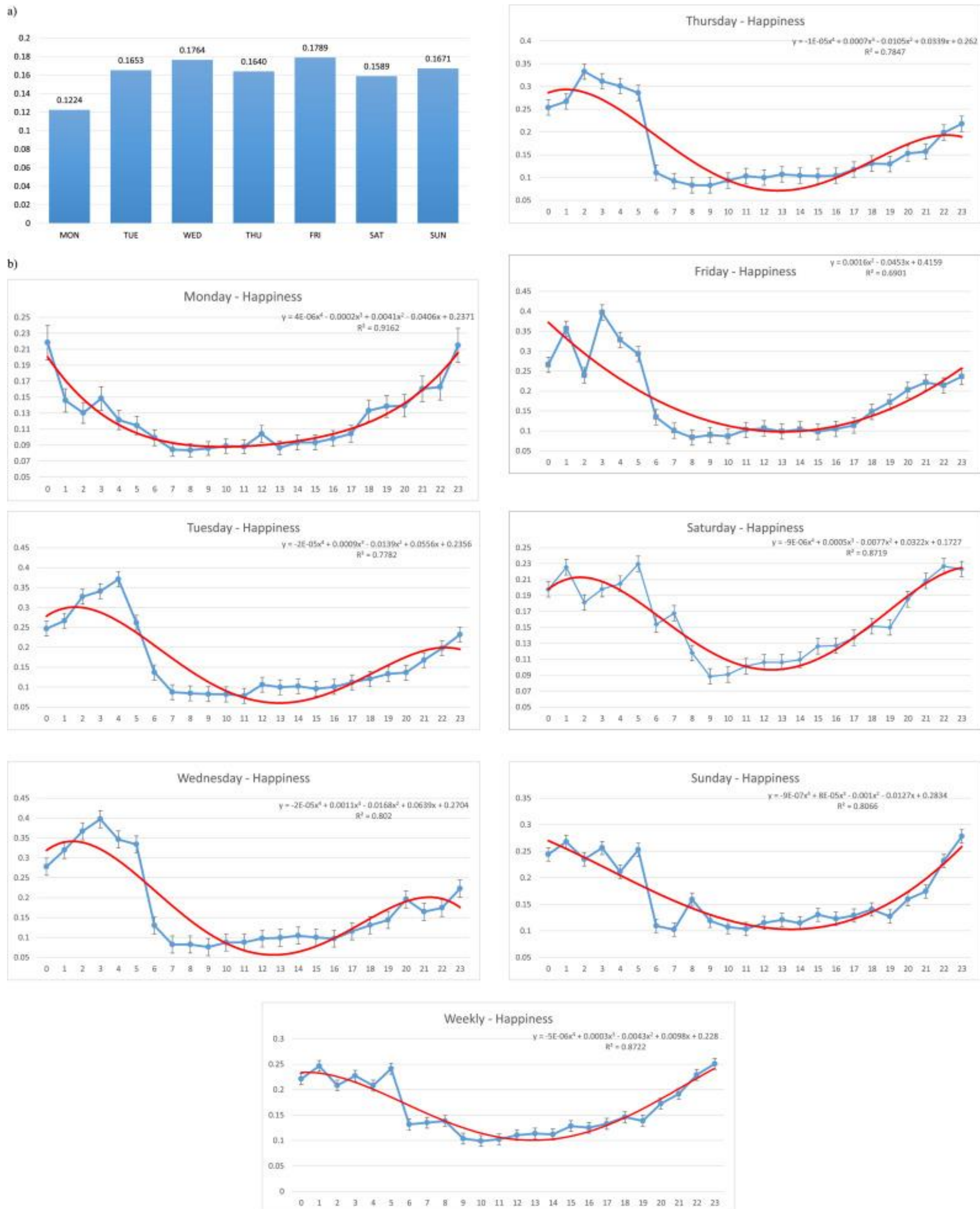


Fig. 1.6. Diagrams of (a) average happiness values by weekdays and (b) happiness per hour for each weekday.

An analysis of happiness and arousal (see Fig. 1.7) shows that the two parameters are linked by an average relationship. The values measured in Gedimino Avenue indicate an average dependency of 0.5282. In Fig. 1.7, the left y-axis shows the aggregate daily happiness values (recorded between 23/01/2018 and 04/03/2018) and the right y-axis shows the aggregate daily arousal values; a total of 170,223 records were considered. It was established that growing happiness of a passer-by is accompanied by an increase in the passer-by's arousal. The same relationship was noted by foreign scientists (Minhad et al., 2017, Zimasa et al., 2017, Gilet and Jallais, 2011, Jefferies et al., 2008, Masmoudi et al., 2012). High intensity emotions are expressed by happiness or anger, as Minhad et al. (2017) explain. However, classification of these emotions is extremely difficult due to a high level in the arousal (activation) dimension. Zimasa et al. (2017) claim that "happy mood is considered to be a high-arousal physiological state".

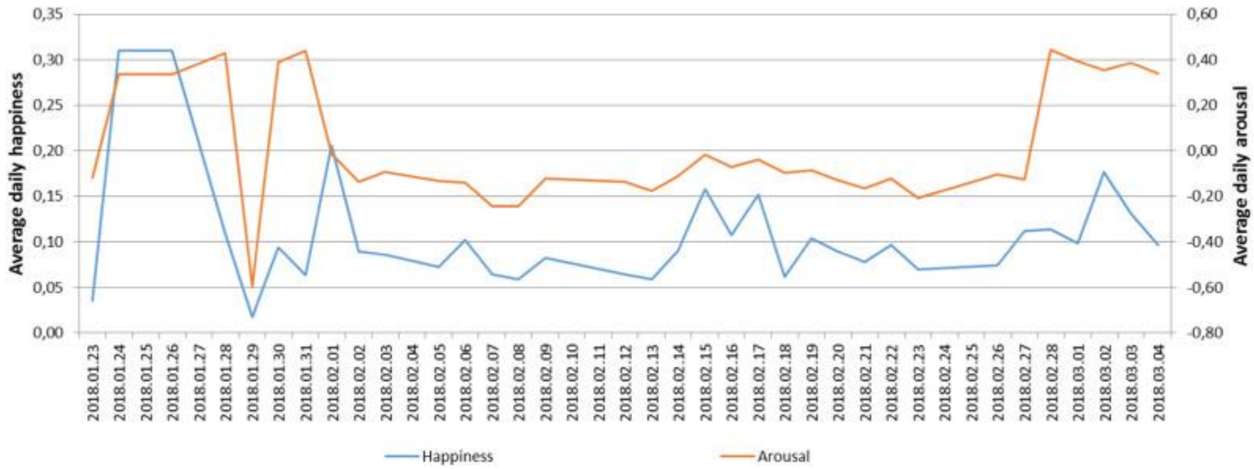


Fig. 1.7. The dependency between average daily happiness and arousal (r = 0.5282) based on the values measured in Gedimino Avenue.

Scientists argue that happiness and valence are also linked (Ma et al., 2016, Calvo and Beltrán, 2013, Stavrova and Luhmann, 2016, Wojcik et al., 2015). Upon seeing a happy virtual face, research participants in a study by Ma et al. (2016) would mimic the expressed emotion. The verification of this included their higher valence scores as well as their improved mood-sensitive, divergent-thinking, task performances. Calvo and Beltrán (2013) claim that happy expressions cause positive valence. The measurements in Pilies Street indicate the same trend. Our analysis of the aggregate data for the period between November and February (Fig. 1.8; a total of 395,157 records were considered) shows an average relationship between happiness and valence (r = 0.62). It can be argued that as the sense of happiness is growing or diminishing, so is the valence.

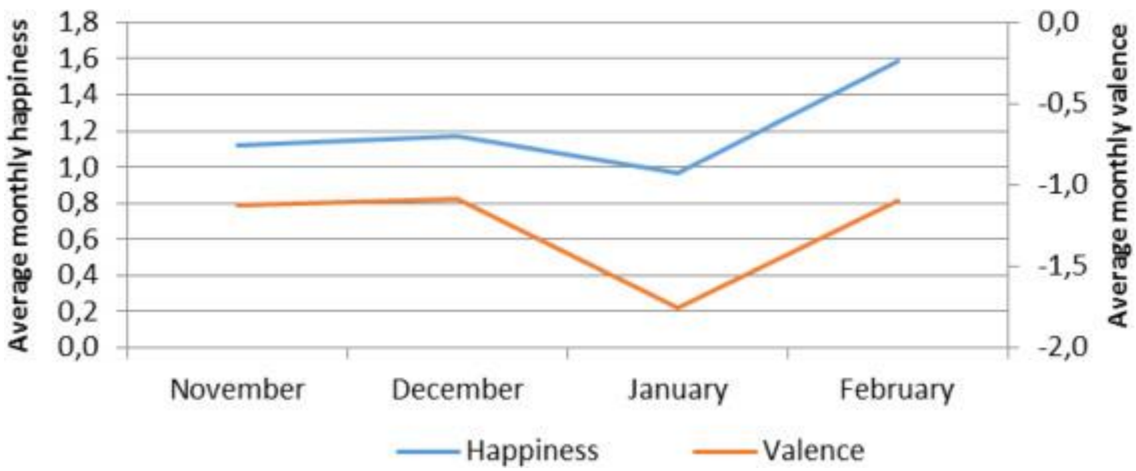


Fig. 1.8. A comparison of average monthly happiness and valence values measured between November and February in Pilies Street (r = 0.62).

Weather is another important aspect that contributes to variations in human physiological and biometric parameters. This dependence was examined by many foreign scientists (Sharp, 2011, Spasova, 2011, Tsutsui, 2013). Differing weather conditions prompted emotional state changes, which also resulted in positive or negative characteristics for the human organism, as Spasova (2011) proclaimed. Pertinent to this, Klimstra et al. (2011) studied correlations between happiness, anxiety, and anger, the three indicators of mood, and temperature, sunshine and precipitation, the three weather possibilities. These scholars established significant correlations between these variables, in most cases. Sharp (2011) argues that wind is also a factor contributing to changes in human emotions. A wind speed increase of over 12 miles/hour makes the person feel physical discomfort. Our physiological and biometric measurements in Gedimino Avenue and Pilies Street also show a dependency between emotions and weather. Fig. 1.9 presents the aggregate arousal and outdoor temperature values measured in Pilies Street between 21/12/2017 and 20/02/2018. An average correlation was determined between arousal and outdoor temperatures (0.4831). The results suggest that outdoor temperature is one of the factors contributing to changes in arousal. The same trend is noticeable when we look at the effect of the wind on human emotions and moods. Fig. 1.10 shows that the stronger the wind, the higher the arousal, with a correlation of 0.5035.

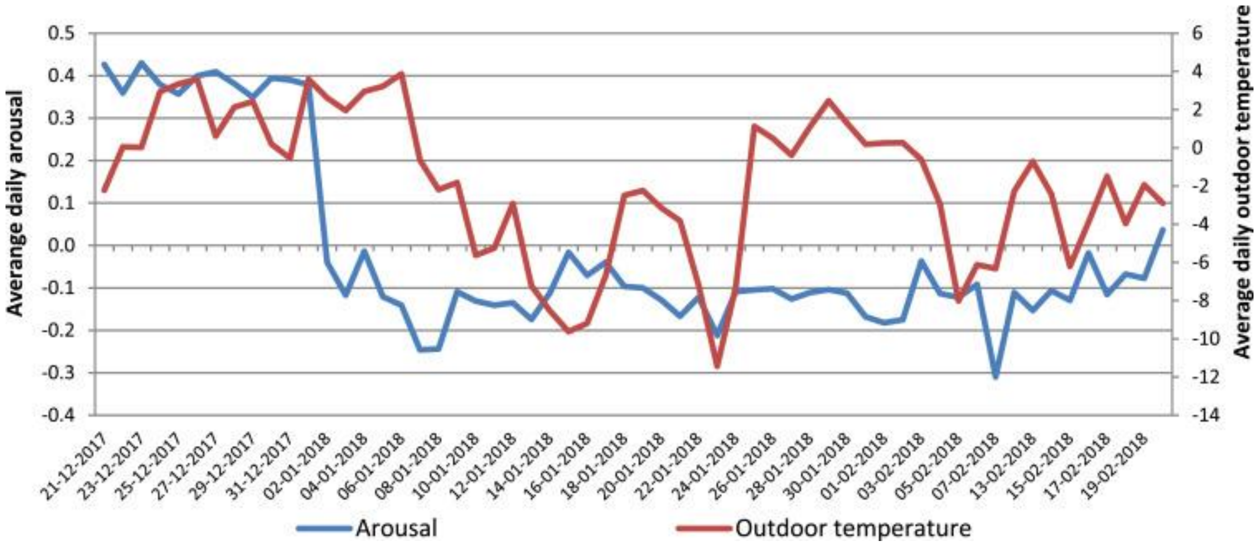


Fig. 1.9. The dependency between average daily arousal and outdoor temperatures (r = 0.4831) based on the values measured in Pilies Street.

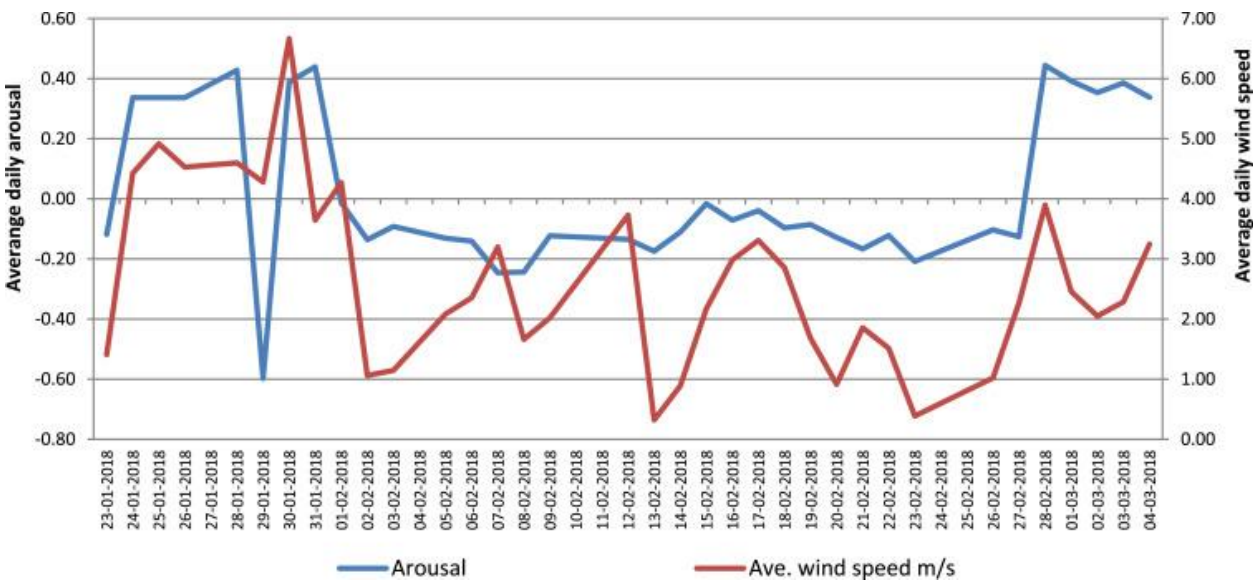


Fig. 1.10. The dependency between average daily arousal and wind speeds (r = 0.5035) based on the values measured in Gedimino Avenue.

Fig. 1.11 shows the happiness values per day recorded between 15/12/2017 and 01/01/2018 with happiness peaking on 24 December 2017 (Christmas Eve) and on 31 December 2017 (New Year's Eve). The holiday season also produced higher respiratory rates (see Fig. 1.12). The values measured in Pilies Street between November and February presented in Fig. 1.12 show higher respiratory rates on December 24–26 and December 31 and throughout the month of December.

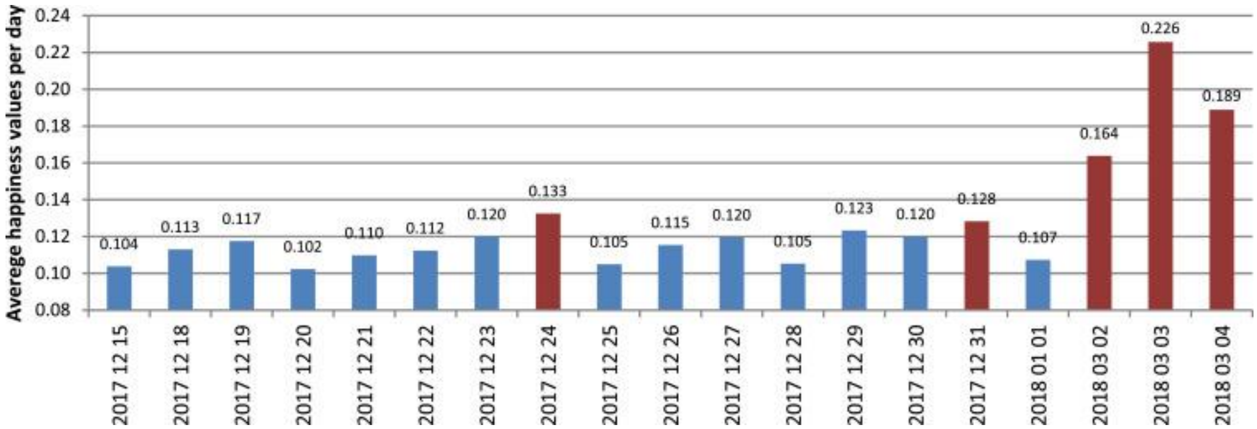


Fig. 1.11. The changes in happiness per day between 15/12/2017 and 01/01/2018. Compared to the months analysed, residents were happier during the St. Casimir's Fair.

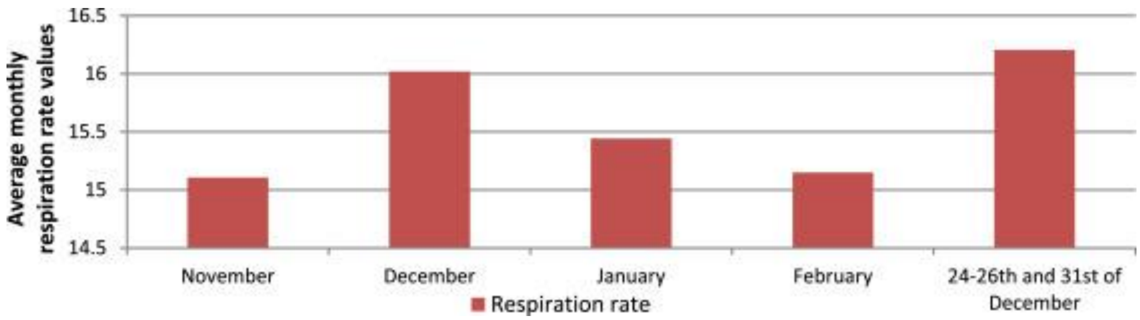


Fig. 1.12. The average monthly values measured in Pilies Street between November 2017 and February 2018 show higher respiratory rates on December 24–26 and December 31 and throughout the month of December.

Gomez and Danuser (2007) have stated that the heart rate (HR) and the respiratory rate increased, as did the subjective arousal. Other scientists examined this relationship as well (Briefer et al., 2015, Gomez et al., 2016, Vlemincx et al., 2013). The same trend has been determined after comparing the aggregate values measured in Vilnius among 2017.12 and 2018.02. Fig. 13 compares the results for the arousal (a), heart rate (b) and respiratory rate (c). It has been determined that the average arousal, heart rate and respiratory rate between December and February were higher in Gedimino Avenue than in Pilies Street. A comparison of the January data, for instance, shows the arousal higher by 11.9%, the heart rate higher by 1.2% and the respiratory rate higher by 7.31%. It can be argued then that Gedimino Avenue triggers stronger emotions in passers-by than Pilies Street and therefore their arousal (a), heart rate (b) and respiratory rate (c) are higher (see Fig. 13).

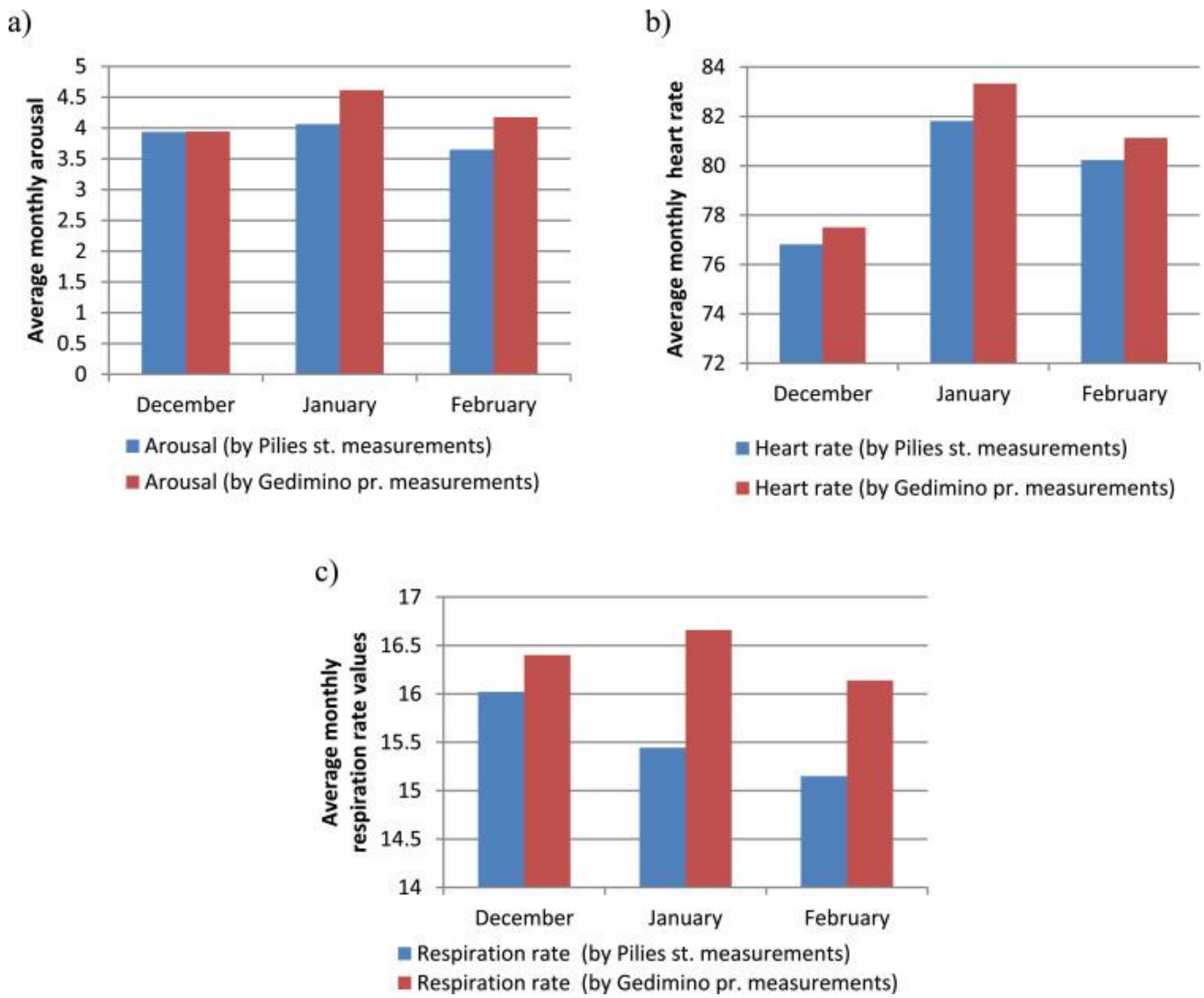


Fig. 1.13. A comparison of the average monthly arousal (a), heart (b) and breathing rates (c).

Azarbarzin et al. (2014) argue that there is a strong correlation between arousal scale and heart rate within inhabitants. Other scientists have also determined a relationship between the parameters (Pfaff, 2005, Schmidt, 1984, Gomez and Danuser, 2007, Kuo et al., 2015). If we compare the heart rate and arousal looking at the days of the week (Fig. 1.14), at the beginning of the week (Monday and Tuesday) the heart rate and arousal are the lowest, but by Tuesday the parameters start increasing. Rossi and Rossi (1977) established that positive moods were higher on Friday through Sunday and that negative moods lesser on Saturday and Sunday. This research gives encourage for a weekend effect. Also, McFarlane et al. (1988) detected support for a weekend effect in mood, measured in terms of both valence and arousal among college students. Both mood valence and arousal were highest on Fridays and Saturdays, followed closely by Sundays (McFarlane et al., 1988). We need further studies of the heart rate and arousal, however, to determine how average heart rates and arousal change depending on the day of the week.

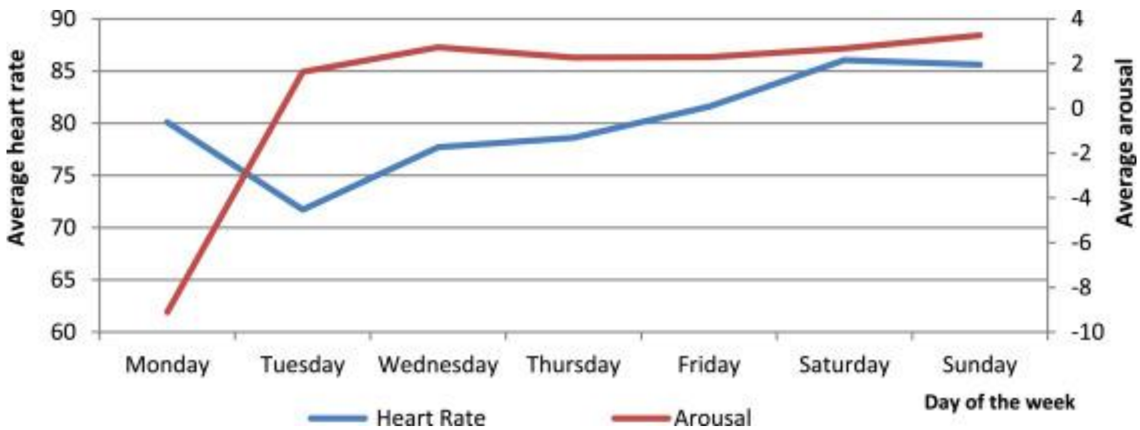


Fig. 1.14. The average weekly heart rate and arousal compared looking at the days of the week (as measured in Gedimino Avenue).

1.6.2. Multiple criteria analysis of heritage buildings by applying the simulators database

1.6.2.1. Applications of the INVAR method for establishing the degrees of priority and utility of cultural heritage buildings

A multiple criteria assessment for sustainable alternatives is enacted by employing the INVAR Method (Degree of Project Utility and Investment Value Assessments along with Recommendation Provisions) for a multiple criteria decision analysis (MCDA) developed by Kaklauskas (2016). Additional features of the INVAR Method include assistance for setting some considered project's investment, hedonic, customer perceived, integrated, hedonic-market, and hedonic-investment values as well as submissions of digital recommendations for improving projects. Another feature of the INVAR Method is the optimization of some criterion selected for the improvement of a considered project, which would make the project equally competitive with other projects on the market. The value of a considered project can be set by the INVAR Method that would make it the best among other considered projects.

Experts in the field performed a multicriteria assessment of the Juozapas Tiškevičius Palace (a_1), Vilnius Basilian Monastery (a_2) and The Abramavičiai Palace (a_3) (see Table 1.3).

Table 1.3. The decision matrix for assessment and the results of multiple criteria evaluation of the cultural heritage objects.

a_1

a_2

a_3

Quantitative and qualitative information pertinent to alternatives

	[a]	Measuring units	Weight	Juozapas Tiškevičius Palace (a_1)	Vilnius Basilian Monastery (a_2)	Abramavičiai Palace (a_3)
Average market value	−	Eur.	0,42	1,343,000	4,581,000	1,644,000
Construction period	+	Century	0,08	16	16	18
Land plot area	+	Ha	0,06	0,69	2,0852	0,19
Total building area	+	m^2	0,11	2,376,92	7,565,81	2,623,1
Number of floors of the building	+	Number	0,03	2	3	3
Value and quality of refurbishment	−	Points	0,04	3,3	8,2	2,8
Value and quality of walls	+	Points	0,05	7,3	8,1	7,7
Value and quality of roof	+	Points	0,03	6,8	7,5	7,1
Quality of engineering communications	+	Points	0,02	8,1	7,8	9,3
Status	+	Points	0,01	8,4	8,7	7,9
Significance level (national/ regional)	+	Points	0,02	6,9	8,5	5,9
Architectural style	+	Points	0,02	9,4	8,9	7,1
Archeological significance	+	Points	0,01	6,3	5,1	6,9
Architectural significance	+	Points	0,01	7,6	9,5	7,8
Historical significance	+	Points	0,01	5,6	8,2	8,6
Art significance	+	Points	0,01	7,7	9,4	4,8
Physical condition of the building	+	Points	0,03	8,4	7,9	5,3
Sums of weighted, normalized, maximizing alternative indices (project "pluses")				0,1411	0,2235	0,1355
Sums of weighted, normalized, maximizing alternative indices (project "minuses")				0,0837	0,2771	0099
Significance of the alternative				0,3552	0,2882	0,3165
Priority of the alternative				1	3	2
Utility degree of the alternative N_j (%)				100%	81,13%	89,11%

[a] The sign +(−) indicates that a greater (lesser) criterion value corresponds to a greater (lesser) significance for stakeholders.

Juozapas Tiškevičius Palace (a_1) is a building located in the Old Town of Vilnius. A masonry structure was already standing on the plot back in the 15th century, and a few of its extant fragments are part of the current building. At the end of the 18th century the site and its buildings were bought by the Tiškevičiai. A mid-19th century addition to the façade was a doorway designed by the architect Nikolay Chagin with a balcony supported by atlantes hinting at the Empire style. The palace was a venue for musical performances and hosted part of Eustachijus Tiškevičius' famous collections of antiquities, including archeological artefacts, artworks and other valuable items. Today Juozapas Tiškevičius Palace hosts the Faculty of Architecture of Vilnius Gediminas Technical University (Kultūros vertybių registras, 2018a).

Vilnius Basilian Monastery (a_2) stands atop the Holy Trinity Hill, known as a place where Lithuania's three first Christian martyrs Jonas, Antonijus and Eustachijus lost their lives. The architecturally unified group of buildings comprising the monastery and the church started taking shape in 1514. Later Vilnius Basilian Monastery became a hub of the Uniate Church and the Basilian Province of the Holy Trinity established in 1617. In 1869 the buildings, then owned by an Orthodox seminary, were reconstructed. Part of the monastery is now occupied by Basilian monks, who established Vilnius Residence of the Holy Trinity, part of the Ukrainian Basilian

Province. Another, larger, part of the monastery hosts the ISM and a hotel (Kultūros vertybių registras, 2018b).

The Abramavičiai Palace (a_3) is a building located in Rotušė Square, the Old Town of Vilnius. The palace comprises wings of various sizes surrounding a rectangular courtyard with two access lanes. The West Wing abutting Didžioji Street shows characteristics of early classicism. Now the building hosts Vilnius Juozas Tallat-Kelpša Conservatoire (Kultūros vertybių registras, 2018c).

The State Enterprise the Centre of Registers has applied mass valuation to establish the average market values of Buildings a_1, a_2 and a_3 categorized as educational (administrative) buildings. At €4,581,000, the average market value of Building a_2 captures its economic value, but not its cultural significance as heritage.

After reconstruction cultural heritage buildings increase in value and last longer. Their adequate maintenance is, therefore, very important, as is important their repurposing, if required, and reconstruction efforts that preserve their high-value characteristics. Buildings a_1 and a_3 were reconstructed several centuries ago, but not in our times. Building a_2, however, was reconstructed ten years ago. Considering this fact the experts assigned 8.2 points for this criterion to the building—the top score.

The centuries-old buildings located in the Old Town of Vilnius were mostly constructed with plastered brick walls that are 70 cm thick or more. Of Old Town's ancient wooden buildings almost none survived. The same building also has the thickest walls, for which the experts assigned 8.1 points to the building, again the top score.

Most cultural heritage buildings have pitched roofs constructed from wooden rafters covered with (red) ceramic tiles. Another important roof element of such buildings is, of course, brick chimneys. The highest-value roof belongs to Building a_2 as well, and the experts have recognized this fact by giving it 7.5 points.

All cultural heritage buildings analysed in this research have modern building services installed such as electricity, water supply, sanitation and heating, and one of them even has gas supply. Building a_3, however, has gas supply installed and thus received the top score.

The criterion "status" means that the building is listed in the Register of Cultural Heritage, is recognized by the Government as a cultural property and is protected by the state. A protected property can be of regional or national significance. Protected buildings a_1 and a_3 are of regional significance; the significance of Building a_2 is national, hence the expert score assigned to it was the highest at 8.5 points.

Vilnius is one of the largest urban complexes in Eastern Europe. The city emerged in the Middle Ages and thus is home to a range of architectural styles—you can come across authentic gothic, renaissance, baroque, classical, modernist buildings and structures (churches, homes, monuments, museums). Because of the fact that in 1600s and 1700s most of its architectural properties assumed some features of the baroque style, Vilnius is sometimes called "a Baroque city". Buildings a_1 and a_2 analysed in this research are considered to represent early and late classicism, and Building a_3 represents only late classicism. At 9.4 points, Building a_1 received the highest score from the experts.

The authors compiled a system of criteria describing the heritage buildings under deliberation (see Table 1.3) based on the authors' and experts in the field experience and on an investigation of related references (The Allen Consulting Group, 2005; etc.).

MCDA of the heritage buildings under analysis was done with the help of the Simulators Database. Table 1.3 presents these results. Upon completing the estimation, a list in order of priorities was set: $Q_2 < Q_3 < Q_1$. The Juozapas Tiškevičius Palace (a_1) achieved an assessment of first position (N_1 – 100%) in comparison with the other two heritage buildings. The Abramavičiai Palace (a_3) took second position (N_3–89,11%), and the Vilnius Basilian Monastery (a_2) took third position (N_2–18,87%), less than that of the Juozapas Tiškevičius Palace.

1.6.2.2. Digital recommendation provision

Digital recommendations were being delivered with the help of the Simulators Database and INVAR techniques (Kaklauskas, 2016) about how to increase the effectiveness of the heritage buildings under analysis. One example could be analyzing the criteria "Physical condition of the building" (see Table 1.4). The Juozapas Tiškevičius Palace (a_1) was assessed as the optimum in terms of the criteria "Physical condition of the building" ($x_{17\ 1} = 8.4$) criteria based on the data from Table 1.3. The physical condition of the Abramavičiai Palace (a_3, $x_{17\ 3} = 5.3$) should be increased by 58,49% by applying various renovation means when endeavoring to have the physical condition of the Juozapas Tiškevičius Palace (a_1, $x_{17\ 1} = 8.4$). In such an instance, the integrated assessment for the Abramavičiai Palace (a_3) would increase by 1,8278% in the overall assessment (see Table 1.4).

Table 1.4. A fragment of digital recommendations matrix.

Quantitative and qualitative information pertinent to alternatives						
Criteria describing the alternatives	*	Measuring units	Weight	Compared alternatives Possible improvement of the analysed criterion by % Possible market value growth of alternatives by % as first impacted by criterion value growth		
				Juozapas Tiškevičius Palace	Vilnius Basilian Monastery	Abramavičiai Palace
…						
Physical condition of the building	+	Points	0.03	8.4 (0%) (0%)	7.9 (6.33%) (0.1978%)	5.3 (58.49%) (1.8278%)

1.6.2.3. Optimization of the value

We also analyzed the Average market value. The aim was to determine, what the value $x_{1\ 3\ cycle\ e}$ of the average market value must be for Abramavičiai Palace (a_3) to be equally competitive on the market, as collated to the other cultural heritage objects under juxtaposition (a_1 and a_2) by a set valuation of all their pluses and minuses. The new INVAR Method gave the possibility to optimize any one of the criteria or their composite parts. The optimization of the score of the average market value, which appears next, will assist as an example (Table 1.5). The setting of the optimized value $x_{1\ 3\ cycle\ e}$ for the average market value under estimation a_3 presented in Table 1.5.

Table 1.5. What score $x_{1\ 3\ cycle\ e}$ should be for Abramavičiai Palace (a_3) to be equally competitive in the market with other heritage buildings under juxtaposition (a_1 and a_2)?

Approximation cycles	Average market value, $x_{1\ 3\ cycle\ e}$	Utility degree N_{3e}	Utility degree N_{1e}	Utility degree N_{2e}	[a]	[b]
0	1,644,000	89,11%	100%	81,13%	90,08%	$\lvert -0{,}97 \rvert > 0{,}01\%$
...	...	...	...	...	...	...
44	1,600,000	90,44%	100%	81,44%	90,63%	$\lvert -0{,}19 \rvert > 0{,}01\%$
...	...	...	...	...	...	...
54	1,590,000	90,72%	100%	81,50%	90,74%	$\lvert -0{,}02 \rvert > 0{,}01\%$
...	...	...	...	...	...	...
56	1,588,000	90,77%	100%	81,52%	90,76%	$0{,}01 = 0{,}01\%$

[a] $(N_{1e} + N_{2e} + N_{3e}) \div 3$.
[b] Inequality to determine, whether the calculation of revised value $x_{1\ 3\ cycle\ e}$ of under valuation a_3 is sufficiently accurate.

Table 1.5 demonstrates that Inequality was insufficient for the first 54 cycles. The value x_{13} was decreased in each cycle (since $x_{13\ cycle\ 0}$ = 1,644,000) by an amount of 1000 till Inequality was sufficient ($x_{1\ 3\ cycle\ 56}$ = 1,588,000). In this case, we optimized the average market value and set how much to reduce the value of the Abramavičiai Palace, to make it equally competitive in the market with the other heritage buildings under juxtaposition.

1.6.2.4. Hypothetical calculation of average market value for the Vilnius Basilian Monastery building

Market, investment, customer-perceived, hedonic, emotional, synergistic, and fair values stakeholders can calculate with the INVAR method. As an example, we will calculate a hypothetical average market value ($x_{1\ 2\ cycle\ e}$) for the Vilnius Basilian Monastery (a_2). This value had to let this heritage building to go up one position upper in its overall valuation, i.e., from third to second place in comparison to the other two heritage buildings (a_1 and a_3), while considering all the indicators under analysis. The calculations carried out show in Table 1.6.

Table 1.6. Hypothetical calculation of the average market value for the Vilnius Basilian Monastery.

Approximation cycles	Average market value, $x_{1\ 2\ cycle\ e}$	Vilnius Basilian Monastery (a_2), Utility degree (N_{2e})	Rank
0	4,581,000	81,13%	3
...	...	...	...
281	4,300,000	82,43%	3
...	...	...	...
1081	3,500,000	87,21%	3
...	...	...	...
1381	3,200,000	89,54%	2

The average market value for the Vilnius Basilian Monastery building was 4,581,000 euro ($x_{1\ 2\ cycle\ 0}$) based on expert valuations (see Tables 1.3 and 1.6). The Vilnius Basilian Monastery took third place in the overall valuation of the heritage buildings under analysis (a_1 and a_3). Table 1.6 shows that the Vilnius Basilian Monastery building stayed on in third place, even after 1081 approximation cycles. However, with a reduction in the average market value by 1,43 times (up to $x_{1\ 2\ cycle\ 1381}$ = 3,200,000 euro), the utility degree (N_{4e}) for the Vilnius Basilian Monastery comprises 89.54%. Now this heritage building rises to second from third place.

1.7. Summary and Conclusion

Constrained rationality was the concept announced by Nobel prize winner Simon, 1967, Simon, 1983, which began a new era in decision theory. The theory this author proposed in 1967 regarded the relation of motivation and emotional behavior to the information processing behavior of people. Later other scholars performed studies in the operational research fields of decision-making behavior and emotions (Hämäläinen et al., 2013, Koshkaki and Solhi, 2016, Arnott and Gao, 2019, Zhou et al., 2020). Additionally city planners analyze sustainability (Abubakar and Dano, 2020), land value (Aziz et al., 2020), pollution levels (Xing and Brimblecombe, 2020), security and crime rates (Yang, 2019), social equality (Meerow et al., 2019), trends in city management and planning as well as future projections (Das and Dahiya, 2020), optimizations of different planning alternatives (Natanian et al., 2019, Shu and Xiong, 2019, Yoon et al., 2019) as well as other aspects. These studies indicate that a good portion of decision-making depends on the emotional states of interested groups. In this same context, the authors developed ASP studies. Affective System for Researching Emotions in Public Spaces for Urban Planning (ASP System) was the application for collecting and analysis emotional circumstantial data in urban areas. This research added to science in the following eight ways.

Planners realize practical advantages by employing the ASP Method and System in the following eight directions (see 1.2 Planning practice by integrating an involved public, 1.3 Affective method for analyzing emotions in public spaces for urban planning, 1.4 Collective interest, objectives and e-democracy, 1.5 Affective system for researching emotions in public spaces for urban planning, 1.6 Case studies, Kaklauskas et al., 2018a, Kaklauskas et al., 2018b, Kaklauskas et al., 2019a, Kaklauskas et al., 2019b, Kaklauskas et al., 2020a, Kaklauskas et al., 2020b, Zavadskas et al., 2017a, Zavadskas et al., 2017b, Zavadskas et al., 2019):

1. The authors of this study developed the ASP Method by including multimodal, non-contact biometrics; recommenders; statistics such as logit, KNN and MBP and four multiple-criteria, decision analysis methods. The development of the ASP Method also involved use of the research by Kahneman pertinent to the results found in behavioral economics (Kahneman, 2003) and in the areas of psychology of judgment and decision-making (Kahneman, 2011) as well as the research results found by Simon (1997) in the areas of integration of emotions in decision-making and artificial intelligence. The key idea stated by Kahneman (2011) is noteworthy regarding the integration of two modes of thought ─ System 1 (emotional) and System 2 (more logical). Human emotional, affective and physiological states, arousal and valence (MAPS) data, which serve as the basis for drafting maps of the emotional and affective states of passersby as well as correlations and trends. Such a MAPS map creates a novel and advanced approach for the centric planning practices relevant to urban inhabitants. The ASP Method and System assist in analyzing planning processes more effectively and in reaching a rational decision.

2. MAPS data along with the results of their analysis can be quantitatively and qualitatively interpreted and applied in urban planning. Such results can include automatically submitted recommendations to city planners as well as calculated hedonic, customer perceived, integrated, hedonic-market and hedonic-investment values. Planners who employ the developed ASP Method and System can derive some 90% supplemental information for decision-making. They are also able to derive a good deal of more information by analyzing their own emotions and body languages as well as those of other interest groups

3. The eventual objective of the planning profession, as Chao et al. (2017) accentuate, is to develop a place, which humans can enjoy, as they foster their own well-being while facing a challenging tomorrow. Planners must always return to this objective over any others. Chao et al. (2017) undertook a review of planning history, which accentuated the idea of planning for well-being. These scholars went on to discuss the idea of a happy city. This provides a basis for considering compassion as an important, emotional state for planning (Lyles et al., 2018). Therapeutic approaches such as therapeutic planning, therapeutic outdoor spaces, therapeutic landscape design and therapeutic value of green spaces along with the MAPS data and ASP System can implement people-centric, urban design processes effectively. Since planning encompasses service for public wellbeing and a search for equity and social justice, compassion, as one example, substantiates and extends prominent organizing concepts such as planning for sustainable communities, as Lyles et al. (2018) proclaim.

4. By employing the MAPS data and ASP System, planners are able to use their personal, social and cultural competencies and intelligence for a significantly better understanding of public engagement in planning processes. Furthermore, with the aid of nonstop feedback from inhabitants, planners are able to supplement their assessments of city planning. Such indirect decision-making assistance also helps to achieve more competent conflict management for the improving sustainable urban planning practices.

5. Nobel Prize winners Kahneman (2011) and Simon (1997) integrated rational thought processes and emotions of interest groups. The key idea stated by Kahneman (2011) is noteworthy regarding the integration of two modes of thought ─ System 1 (emotional) and System 2 (more logical). The results of their research have practical applications in the profession of urban planning. Such applications can be employed along with MAPS data, neuro decision matrices, neuro correlations and the ASP System.

6. The goal for employing the ASP Method and System, when analyzing the emotional, affective and physiological states, arousal and valence (MAPS) of passersby, is a quantitative and qualitative understanding of people's feelings. Their feelings can be taken by gender, age and the biological circadian clock in static surroundings like green spaces and cultural monuments as well as in the dynamic environment made up of transportation flows, air and noise pollution and the seasons.

7. Development of Neuro Analysis Simulators was based on the proposed neuro decision-making table and applying the MCDM techniques (Kaklauskas, 1999, Kaklauskas, 2016) developed by the authors here. These Systems calculate priorities, utility grades, hedonic, customer-perceived, integrated, hedonic-market values, market, and hedonic-investment values (as an example, see Section 6.2.4).

8. Based on emotional, affective, and physiological maps, ASP gives urban planners tips on making the urban planning process further sustainable. For instance, the Recommender Model develops advice on increasing environmental quality (air and noise pollution).

The aforementioned Points 1, 2 and 4–8, constitute the research that has supplemented the knowledge on the science of urban planning worldwide.

Correlational analysis, five case studies, validation and verification approves our study hypothesis that "the human emotional, affective and physiological states, valence and arousal (MAPS), circadian rhythm, built environment, pollution and weather conditions in a city are all interrelated. These can be successfully used in the practice of city planning".

Implications pertinent to the "big picture" of the research appear in this article, which also illustrates the contributions of such research to this "big picture" in the field of the research under deliberation. Inhabitant centric urban planning policies constitute the first implication relevant to these integrated analyses. Such policies influence the wellbeing of their respective residents along with their MAPS (emotional, affective and physiological states, arousal and valence) data; meanwhile the residents themselves, based on their MAPS data, influence the respective urban planning policy. Furthermore this research apparently carries implications regarding the "big picture" about the effectiveness of an urban planning analysis. To assure significantly greater effectiveness, it is necessary for the analysis to include the life process of an urban planning, involved interest groups who have varying targets for implementation, MAPS and related data as well as the external micro-, meso- and macro-level environments. All of these must be analyzed thoroughly and treated as one object.

However, a validation of the results of this research requires many more studies in differing scientific fields. Here, for this research, the analysis only covers the built environment in one city, in Vilnius. Therefore, this investigation has certain particular, situation-reliant, MAPS and related data limitations as well as a structure of specific criteria and their significances. Assessments for future research of a built environment in different city contexts will require descriptions containing more variables with different significances. These research findings will not only be included in any upcoming study, but it would contain supplementary areas of study to confirm the results of this ASP Method. Such added examination would include a study and progress of urban strategic planning options, conflict examination, control, analysis of project variants, procurement, etc. Additional inclusions would be in the fields of manufacturing, agriculture, and services. An enlargement of the current Smart Database includes historical monuments and areas; structures in suburban zones with libraries, theaters, museums, open places, cultural festivals, shows, and concerts containing new MAPS and related data. The necessity of a complex analysis of MAPS and related data is shown in this study due to its potentially very serious implications in the aforementioned fields.

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

2.1. 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 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, Kaklauskas et al., 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, Kaklauskas et al., 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.

2.2. 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 (SpO2) and the like (Ding et al., 2020).

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

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

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

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

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

One monitoring technology used for measuring breathing and heart rates involves thermal imaging techniques (Hu et al., 2018). Others include breathing dynamics (Pereira et al., 2015) and respiration rate (Lewis et al., 2011). A recommendation offered by Jiang et al. (2020) involves use of a portable non-contact method. It is meant to screen the health conditions of people by analyzing respiratory characteristics even while people are wearing their face masks. This is possible with the application of a device mainly consisting of a FLIR one thermal camera and an Android phone. Its use includes monitoring possible COVID-19 patients by inspecting them in practical scenarios such as in hospitals or for pre-inspections at schools. Health screenings were performed by Jiang et al. (2020) by virtue of combining the RGB and thermal videos, which they acquired from the dual-mode camera and from deep learning architecture. A respiratory data capture technique was first accomplished by Jiang et al. (2020) on people wearing face masks by employing facial recognition. Next, they applied a bidirectional GRU neural network with an attention mechanism to the respiratory data to arrive at a final health screening result. Respiratory health status can be recognized to an 83.7% accuracy rate on the real-world dataset, as the results of validation experiments indicate regarding the Jiang et al. (2020) Model.

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

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

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

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

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

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

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

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

2.3. 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 statesS1. 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 (HChr=0.136, VChr = −0.078), the New Year (HNewYear=0.128, VNewYear = −0.096), the March 2–4, 2018 Kaziukas Fair (HKF=0.193, VKF = −0.09709), February 16 Restoration of Lithuania’s independence (HFeb16=0.140176, VFeb16 = −0.046), when the average monthly levels of happiness and valence were generally lower at the time (HDec=0.121, VDec = −0.10727, HJan=0.115, VJan = − = −0.1047, HFeb=0.135, VFeb = −0.136, HMarch=0.140 and VMarch = −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.

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 μ=0.1338 and the standard deviation was σ2 = 0.1603. During quarantine, the mean sadness was μ=0.1540 and the standard deviation was σ2 = 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.

2.4. 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 2.5 “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.

2.5. 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. 2.1 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, Kaklauskas et al., 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.

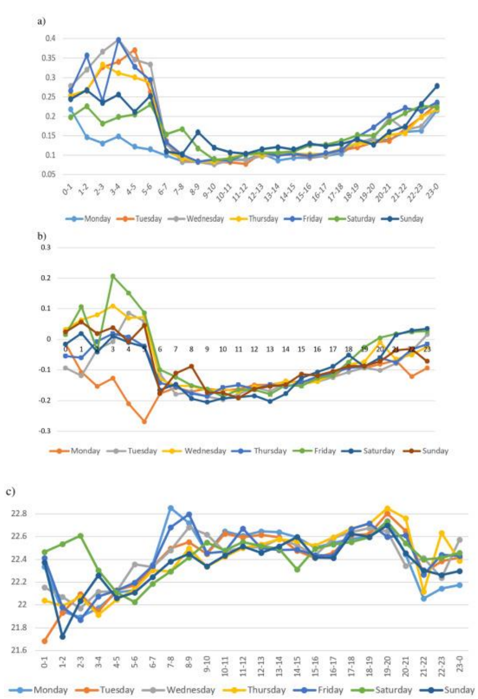


Fig. 2.1. Average happiness (a), valence (b) and temperature (c) values on weekdays, by hour. Recordings are gathered every hour about changes among Vilnius passers-by on the values of average (a) happiness, (b) valence and (c) temperature by Celsius degrees. Measurements of

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. 2.1 along with the derived results in comparison to studies from other parts of the world.

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. 2.1) 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 2.2). 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. 2.1).

Results of the correlation analysis appear in Table 2.2. 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. 2.2).

A total of 30,538,597 data entries on average diurnal sadness were made before the coronavirus crisis and 878,167 during the quarantine 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. 2.2b 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.

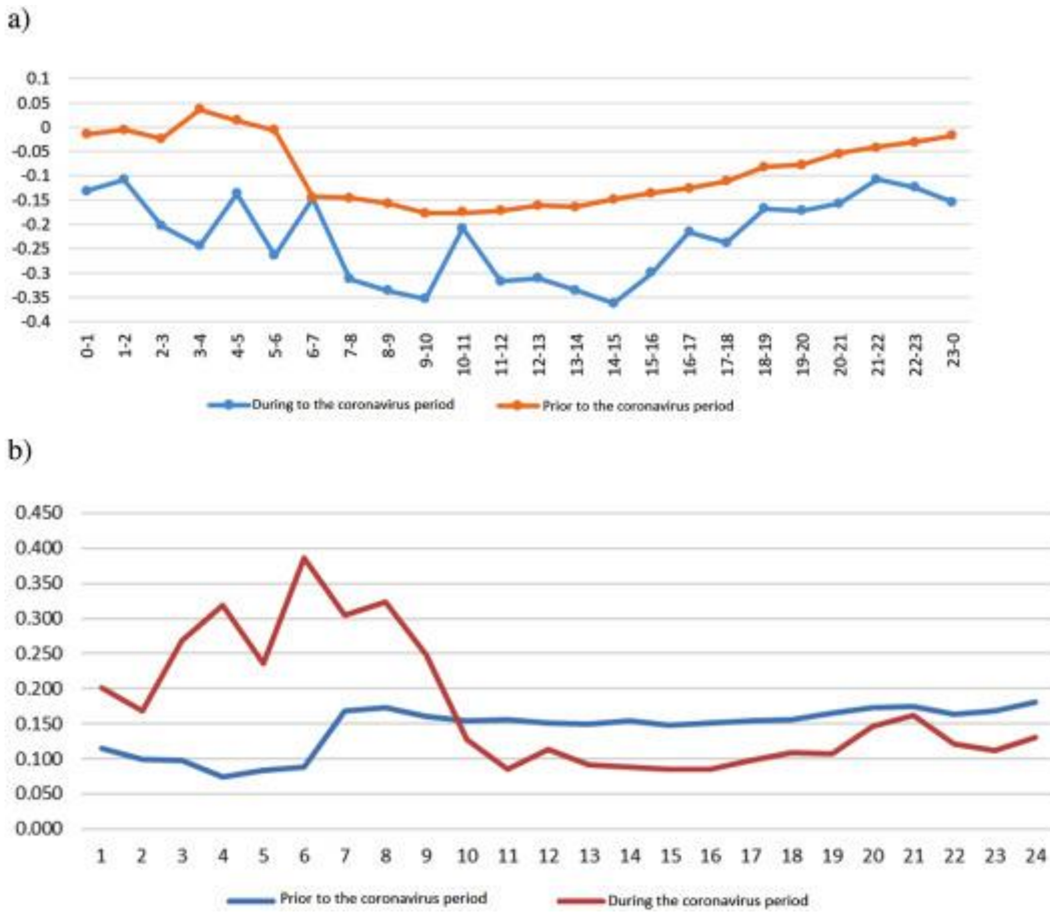


Fig. 2.2. Average diurnal patterns of valence (a) and sadness (b) over 24 h, before and during coronavirus quarantine. The average pattern of hourly changes in (a) valence and (b) sadness before and during the coronavirus period among passers-by in Vilnius as it appears when broken down by weekday at 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.

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 therefore focused on variances in happiness and valence among individuals as the days changed in length due to the season. Variations of happiness (Fig. 2.3a) and valence (Fig. 2.3a) 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

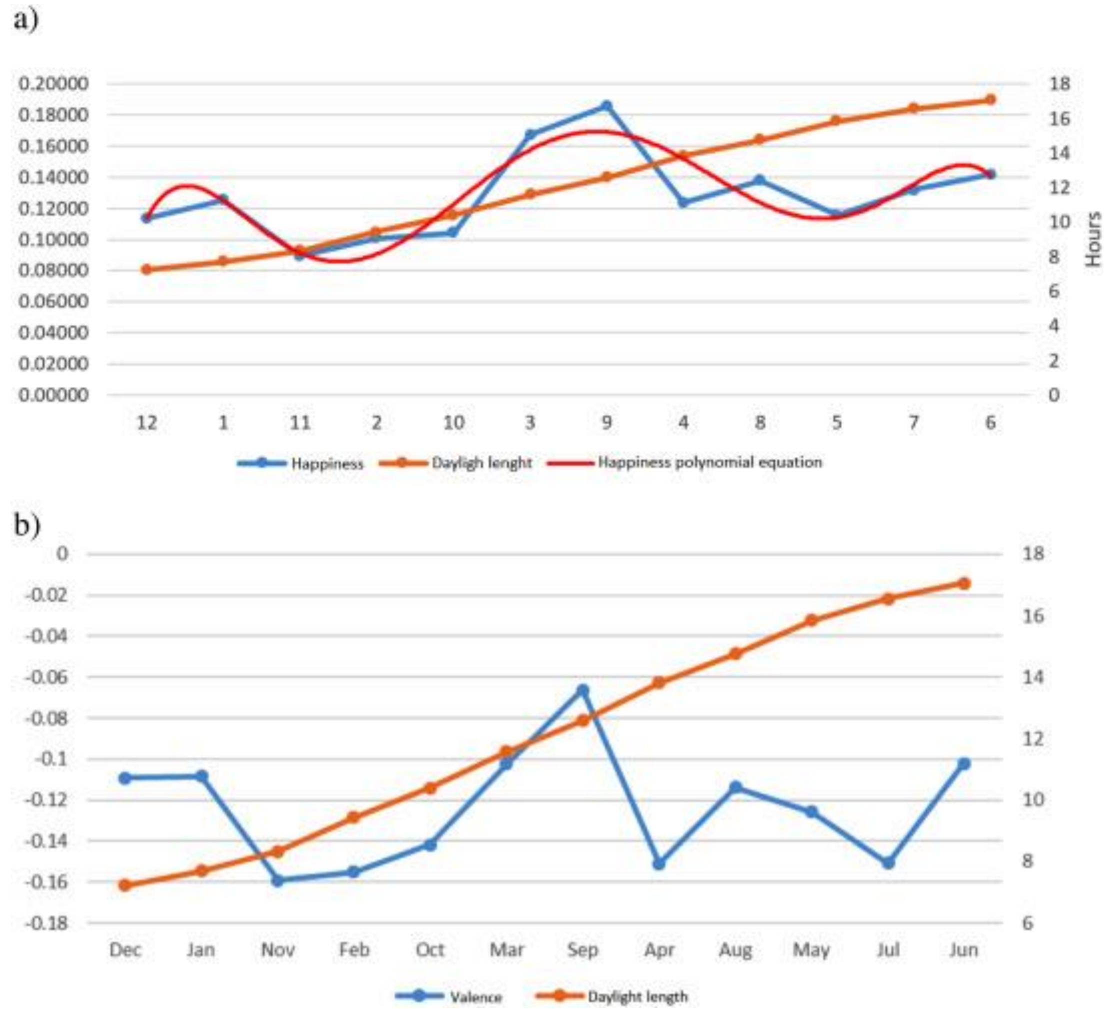


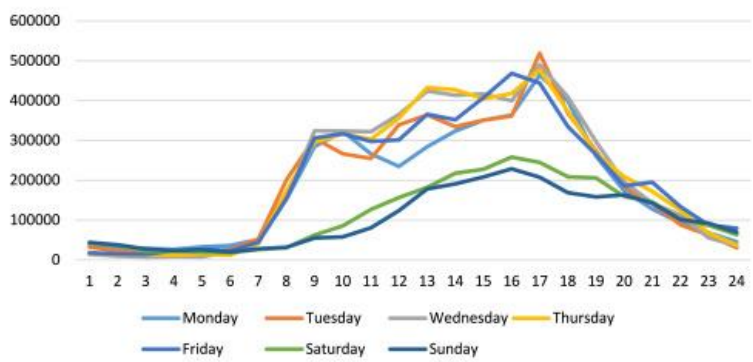
Fig. 2.3. Variations of (a) happiness and (b) valence relative to duration of daylight per month. Average values of (a) happiness and (b) valence among passers-by in Vilnius are examined by changes per monthly duration of daylight at 95% confidence intervals. The colors represent happiness (valence) 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. 2.3b).

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. 2.4) 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

a)



b)

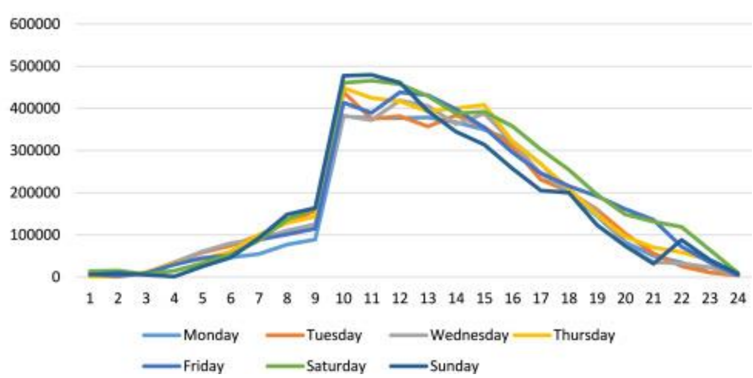


Fig. 2.4. Diurnal number of data on (a) happiness and (b) facial temperature. Changes in the diurnal number of data on (a) happiness and (b) facial temperature levels among Vilnius passersby appear on a per weekday basis, at 95% confidence intervals. The colors denote the weekdays. The hour of the measurement 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.

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

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 ($r = 0.719$, $p < 0.001$). Two daily peaks in valence can be seen, one at 4 a.m. and the other close to midnight.

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 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. 2.2).

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. 2.2).

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. 2.6).

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

Table 2. 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).

Table 2.2. 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 2.3. 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 2.4. 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).

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, Zenju et al., 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 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, Zenju et al., 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 2.3 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 2.4.

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 ($r_s = 0.983$), while the weakest, between variables AS and EU ($r_s = 0.858$).

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 2.5.

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:

$$\text{Temperature} = 21.002 - 0.622 \cdot LA - 0.165 \cdot NA + 1.646 \cdot EU + 1.459 \cdot OC + 0.008 \cdot AS \quad (3)$$

Table 2.5. 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

The Temperature values calculated according to the compiled regression equation and the measured Temperature values appear in Fig. 2.5.

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:

$$E = \beta \cdot \frac{\overline{x}}{\overline{y}} \quad (4)$$

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 2.6.

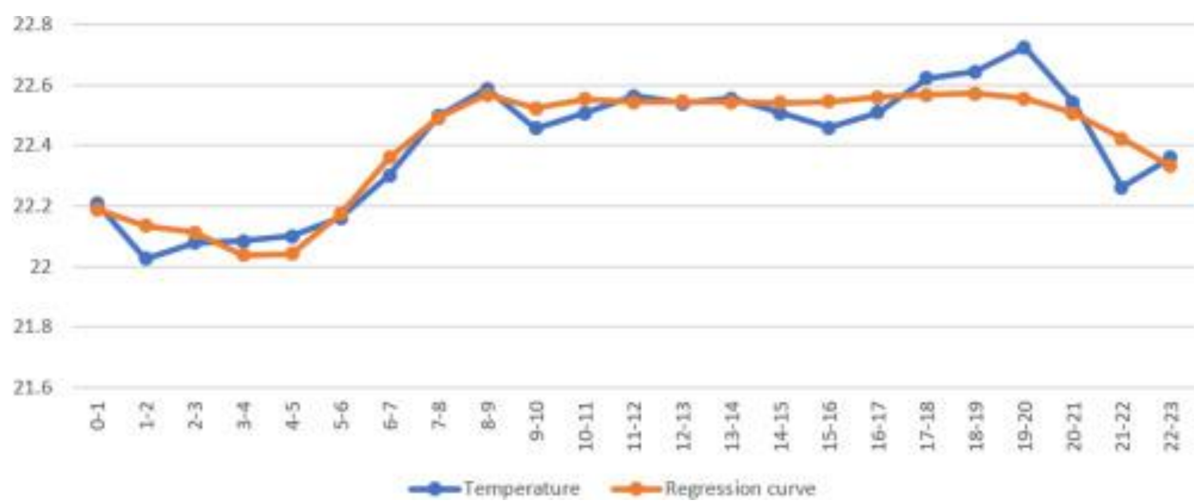


Fig. 2.5. Measured and calculated temperature for passers-by in Vilnius values.

Table 2.6. Elasticity coefficient calculations results.

	β	$\bar{x}$	$\bar{y}$	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

2.6. Summary and Conclusion

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 2.2).

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. 2.1a).

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, Kaklauskas et al., 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. 2.1c).

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 2.1).

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. 2.3a. 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. 2.3a). 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. 2.4). 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 $r_s = 0.950$. 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 $r_s = 0.983$. 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 duringCOVID-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, Kaklauskas, 2016).

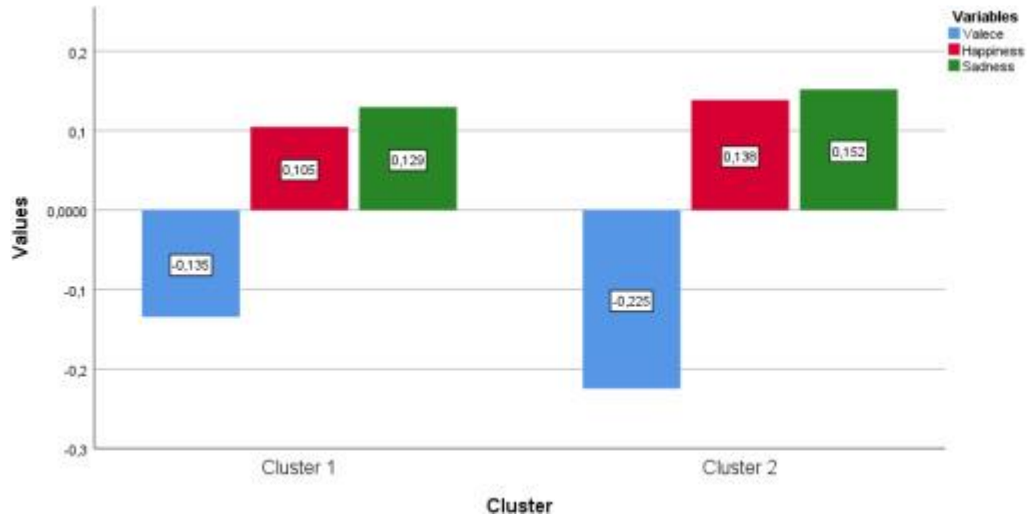


Fig. 6. Clusters analysis results and final cluster centers.

2.7. References

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3. A Review of AI Cloud and Edge Sensors, Methods, and Applications for the Recognition of Emotional, Affective and Physiological States

3.1. Introduction

Global research in the field of neuroscience and biometrics is shifting toward the widespread adoption of technology for the detection, processing, recognition, interpretation and imitation of human emotions and affective attitudes. Due to their ability to capture and analyze a wide range of human gestures, affective attitudes, emotions and physiological changes, these innovative research models could play a vital role in areas such as Industry 5.0, Society 5.0, the Internet of Things (IoT), and affective computing, among others.

For hundreds of years, researchers have been interested in human emotions. Reviews on the applications of affective neuroscience include numerous related topics, such as the mirror mechanism and its role in action and emotion [1], the neuroscience of under-standing emotions [2], consumer neuroscience [3], the role of positive emotions in education [4], mapping the brain as the basis of feelings and emotions [5], the neuroscience of positive emotions and affect [6], the cognitive neuroscience of music perception [7], and social cognition in schizophrenia [8]. Applications in neuroscience also include the analysis of cognitive neuroscience [9,10,11], and brain sensors [12,13], and works in the literature also discuss the recognition of basic emotions using brain sensors [14].

Studies of the applications of affective biometrics can be found in the literature in the fields of brain biometric analysis [15], predictive biometrics [16], keystroke dynamics [17], applications in education [18], consumer neuroscience [19], adaptive biometric systems [20], emotion recognition from gait analyses [21], ECG databases [22], and others. Several works on affective states have integrated multiple biometric and neuroscience methods, but none have included an integrated review of the application of neuroscience and biometrics and an analysis of all of the emotions and affective attitudes in Plutchik's wheel of emotions.

Scientists analyzed various brain and biometric sensors in the reviews [23,24,25,26]. Curtin et al. [23], for instance, state that both fNIRS and rTMS sensors have changed significantly over the past decade and have been improved (their hardware, neuronavigated targeting, sensors, and signal processing), thus clinicians and researchers now have more granular control over the stimulation systems they use. Krugliak and Clarke [26], da Silva [24], and Gramann et al. [27] analyzed the use of EEG and MEG sensors to measure functional and effective connectivity in the brain. Khushaba et al. [25] used brain and biometric sensors to integrate EEG and eye tracking for assessing the brain response. Other scientists [28,29,30,31,32,33] used the following biometric sensors in their studies: heart rate, pulse rate variability, odor, pupil dilation and contraction, skin temperature, face recognition, voice, signature, gestures, and others.

Indeed, the biometrics and neuroscience field has been the focus of studies by many researchers who have achieved significant results. A number of neuroscience studies have analyzed the detection and recognition of human arousal [34], valence [35,36], affective attitudes [36,37], emotional [38,39,40,41], and physiological [42] states (AFFECT) by capturing human signals.

Though most neuroimaging approaches disregard context, the hypothesis behind situated models of emotion is that emotions are honed for the current context [43]. According to the theory of constructed emotion, the construction of emotions should be holistic, as a complete phenomenon of brain and body in the context of the moment [44]. Barrett [45] argues that rather than being universal, emotions differ across cultures. Emotions are not triggered—they are created by the person who experiences them. The combination of the body's physical characteristics, the brain (which is flexible enough to adapt to whatever environment it is in), and the culture and upbringing that create that environment, is what causes emotions to surface [45]. Recently, there have been attempts in the academic community to supply contextual (from cultural and other circumstances) analysis [46,47].

Various theories and approaches (positive psychology [48,49,50], environmental psychology [51,52,53], ergonomics—human factors science [54,55,56], environment–behavior studies, environmental design [57,58,59], ecological psychology [60,61], person–environment–behavior [62], behavioral geography [63], and social ecology research [64] also emphasize emotion context sensitivity.

The objective of this research is to provide an overview of the sensors and methods used in AFFECT (affective, emotional, and physiological states) recognition, in order to outline studies that discuss trends in brain and biometric sensors, and give an integrated review of AFFECT recognition analysis using Plutchik's [65] wheel of emotions as the basis. Furthermore, the research aim is to review publications on how techniques that use brain and biometric sensors can be used for AFFECT recognition. In addition, this is a quantitative study to assess how the success of the 169 countries impacted the number of Web of Science articles on AFFECT recognition techniques that use brain and biometric sensors that were published in 2020 (or the latest figures available).

We identify the critical changes in this field over the past 32 years by applying text analytics to 21,397 articles indexed by Web of Science from 1990 to 2022. For this review, we examined 634 publications in detail. We have analyzed the global gap in the area of neuroscience and affective biometric sensors and have aimed to update the current big picture. The aforementioned research findings are the result of this work.

When emotions as well as affective and physiological states are determined by recognition sensors and methods—and, later, when such studies are put to practice—a number of issues arise, and we have addressed these issues in this review. Moreover, our research has filled several research gaps and contributes to the big picture as outlined below:

- A fairly large number of studies around the world apply biometric and neuroscience methods to determine and analyze AFFECT. However, there has been no integrated review of these studies.
- Another missing piece is a review of AFFECT recognition, classification, and analysis based on Plutchik's wheel of emotions theory. We have examined 30 emotions and affective states defined in the theory.
- Information on diversity attitudes, socioeconomic status, demographic and cultural background, and context is missing from many studies. We have therefore identified real-time context data and integrated them with AFFECT data. The correct assessment of AFFECT and predictions of imminent behavior are becoming very important in a highly competitive market.
- To demonstrate a few of the aforementioned new research areas in practice, we have developed our own metric, the Real-time Vilnius Happiness Index (Section 4), among

other tools. These studies have used integrated methods of biometrics and neuroscience, which are widely applied in various fields of human activity.

- In this research, we therefore examine a more complex problem than any prior studies.

3.2. Method

The research method we used can be broken down as follows: (1) formulating the research problem; (2) examining the most popular emotion models, identifying the best option among them for our research (Section 3.3), and creating the Big Picture for the model; (3) carrying out a review of publications in the field (Section 3.4); (4) raising and confirming two hypotheses; (5) collecting data; (6) using the INVAR method for multiple criteria analysis of 169 countries; (7) determining correlations; (8) developing three maps to illustrate the way the success of the 169 countries impacts the number of Web of Science articles on AFFECT (emotional, affective, and physiological states) recognition and their citation rates; (9) developing three regression models; and (10) consolidating the findings, providing a rationale for the current methods, comparing the effectiveness of existing methods, and quantifying how likely they are to address the issues and challenges in the field. The following ten steps of the method describe the proposed algorithm and its experimental evaluation in detail.

Furthermore, the research aim is to review publications on how techniques that use brain and biometric sensors can be used for AFFECT recognition, consolidate the findings, provide a rationale for the current methods, compare the effectiveness of existing methods, and quantify how likely they are to address the issues/challenges in the field (Step 1). We have analyzed the global gap in the area of neuroscience and affective biometric sensors and have set the goal of updating the current big picture. The findings of the research above framed the problem.

Step 2 of the research was to examine the most popular emotion models (Section 3.3) and identify the best option among them for our research. We have chosen the Plutchik’s wheel of emotions and one of the main reasons is that the model enables integrated analysis of human emotional, affective, and physiological states.

Step 3 was to review sensors, methods, and applications that can be used in the recognition of emotional, affective, and physiological states (Section 3.4). We have identified the major changes in the field over the past 32 years through a text analysis of 21,397 articles indexed by Web of Science from 1990 to 2022. We searched for keywords in three databases (Web of Science, ScienceDirect, Google Scholar) to identify studies investigating the use of both neuroscience and affective biometric sensors. A total of 634 studies that used both neuroscience and affective biometric sensor techniques in the study methodology were included, and no restrictions were placed on the date of publication. Studies which investigated any population group were at any age or gender were considered in this work.

A set of keywords related to biometric and neuroscience sensors were used for the above search of three databases. Two main sets of keywords “sensors + biometrics + emotions” and “sensors + neuroscience/brain + emotions” were used in our main search. More specific search terms related to biometrics (i.e., eye tracking, blinking, iris, odor, heart rate), neuroscience/brain techniques (i.e., EEG, MEG, TMS, NIRS, SST) and their components (i.e., algorithms, functionality, performance) were also used to refine the search. For each candidate article, the full text was accessed and reviewed to determine its eligibility. The primary results and article conclusions were identified, and discrepancies were resolved by way of discussion. The studies differed significantly in terms of protocol design, signal processing, stimulation methods, the equipment used, the study population, and statistical methods.

In Step 4, two central hypotheses were raised and confirmed:

Hypothesis 1

There is an interconnection between a country's success, its number of Web of Science articles published, and its citation frequency on AFFECT recognition. When there are changes in the country's success, its number of Web of Science articles published, and its citation times on AFFECT recognition, the countries' 7 cluster boundaries remain roughly the same (Section 3.6).

Hypothesis 2

Increases in a country's success usually go hand in hand with a jump in its number of Web of Science articles published and its citation times on AF-FECT recognition.

Next, in Step 5, we collected data. The determination of the success of 169 countries and the results obtained are described in detail in a study by Kaklauskas et al. [66]. This study used data [66] from the framework of variables taken from a number of databases and websites, such as the World Bank, Eurostat-OECD, the World Health Organization, Global Data, Global Finance, Transparency International, Freedom House, Knoema, Socioeconomic Data and Applications Center, Heritage, the Global Footprint Network, Climate Change Knowledge Portal (World Bank Group, Washington, DC, USA), the Institute for Economics and Peace, and Our World in Data; global and national statistics and publications were also used. We based our research calculations on publicly available data from 2020 (or the latest available).

We used the INVAR method [67] to conduct a multi-criteria examination of the 169 nations—the outcomes can be found in Section 3.6 (Step 6). This method determines a combined indicator for whole nation success. This combined indicator is in direct proportion to the corresponding impact of the values and significances of the specified indicators on a nation's success. The INVAR method was used to conduct multiple criteria analyzes of different groups of countries, such as the former Soviet Union [68], Asian countries [69], and the global analysis of 169 [66] and 173 [70] countries.

The study's 7th step presents the median values of the correlations for 169 countries, its publications, and citations (Section 3.6). It was found that the median correlation of the dependent variable of the Publications—Country Success model with the independent variables (0.6626) is higher than in the Times Cited—Country Success model (0.5331). Therefore, it can be concluded that the independent variables in the Publications—Country Success model are more closely related to the dependent variable than in the Times Cited—Country Success model.

In Step 8, we developed three maps that illustrate the way the success of the 169 countries impacts the number of Web of Science articles on AFFECT (emotional, affective, and physiological states) recognition and their citation rates. The Country's Success and AFFECT Recognition Publications (CSP) Maps of the World are a convenient way to illustrate how the three predominant CSP dimensions (a country's success, the numbers of publications, and the frequency of articles being cited) are interconnected for the 169 countries, while the CSP models allow for these connections to be statistically analyzed from various perspectives. It also allows for CSP dimensions to be forecast based on the country's success criteria. In other words, the CSP models give us a more detailed analysis of the CSP dimensions through statistical and multi-criteria analysis, while the CSP maps (Section 3.6) are more of a way to present the results in a visual manner. The amount of data available is gradually increasing, as is the knowledge gained from research conducted around the world. As a result, the CSP models are becoming better and better, and providing a clearer reflection of the actual picture. This means that they can effectively facilitate research and innovation policy decisions.

In Step 9, we created two regression models (Section 3.6). For the multiple linear regressions, we used IBM SPSS V.26 to build two regression models on 15 indicators of country success [66] and the three predominant CSP dimensions (Section 3.6). Step 9 entailed the construction of regression models for the number of publications and their citation rates, and the calculation of the effect size indicators describing them. Two dependent variables and 15 independent variables were analyzed to construct these regression models. The process was as follows:

- Construction of regression models for the numbers of publications and their citations.
- Calculation of statistical (Pearson correlation coefficient (r), standardized beta coefficient (β), coefficient of determination (R^2), standard deviation, *p*-values) and non-statistical (research context, practical benefit, indicators with low values) effect size indicators describing these regression models.

It was found that changes in the values of the Country Success variable explain the variance of the Publications variable by 89.5%, and the variance of the Times Cited variable by 54.0%. Additionally, when the value of the Country Success variable increases by 1%, the value of Publications increases by 1.962% and Times Cited—by 2.101%. As the success of a country increased by 1%, the numbers of Web of Science articles published and their citations grew by 1.962% and 2.101%, respectively. A reliability analysis of the compiled regression models allows us to conclude that the models are suitable for analysis ($p < 0.05$). The 15 country success indicators explained 69.4% and 51.18% of the number of Web of Science articles published and their citations, respectively.

Step 10 was to assess the biometric systems under analysis: the rationale behind the available biometric and brain approaches was outlined, the efficacy of existing methods compared, and their ability to address issues and challenges present in the field determined (Section 3.7).

3.3. Emotion Models

First, this chapter will discuss emotion models in more detail. Then, we will choose the best option for our research and look at the Big Picture, i.e., the links between the selected emotion model and biometric and brain sensors, and the trends.

Emotional responses are natural to humans, and evidence shows they influence thoughts, behavior, and actions. Emotions fall into different groups related to various affects, corresponding to the current situation that is being experienced [71]. People encounter complex interactions in real life, and respond to them with complex emotions that often can be blends [72]. Emotional responses are the way for our brain and body to deal with our environment, and that is why they are fluid and depend on the context around us [73].

Two fundamental viewpoints form the basis in approaches to the classification of emotions: (a) emotions are discrete constructs and they have fundamental differences, and (b) emotions can be grouped and characterized on a dimensional basis [74]. These classifications (emotions as discrete categories and dimensional models of emotion) are briefly analyzed next.

In word recognition, alternative models have so far received little interest, and one example is the discrete emotion theory [75]. This theory posits that there is a limited set of universal basic emotions hardwired through evolution, and that each of the wide variety of affective experiences can essentially be categorized into this limited set [76,77]. The discrete emotion theory states that many emotions can be distinguished on the basis of expressive, behavioral, physiological, and neural features [78]. The definition of emotions provided by Fox [79] states they are consistent and discrete responding processes that can include verbal, physiological, behavioral, and neural mechanisms. They are triggered and changed by external or internal stimuli or events and respond to the environment. Russell and Barrett [80] argue that, unlike the discrete emotion theory, their alternative models can account for the rich context-sensitivity and diversity of emotions. Emotion blends could be of three kinds: (a) Positive-blended emotions were blends of only positive emotions; (b) negative-blended emotions were blends of only negative emotions; and (c) mixed emotions were blends of both positive and negative emotions, as well as neutral ones. The way teachers have described blended emotions reflects that mathematics teaching involves many and complex tasks, where the teacher has to continuously keep gauging the level of progress [81].

Emotional dimensions represent the classes of emotion. Categorized emotions can be characterized in a dimensional form, with each emotion located in a different location in space, for example in 2D (the circumplex model, "consensual" model of emotion, and vector model) or 3D (the Lövheim cube, the pleasure–arousal–dominance (PAD) emotional state model, and Plutchik's model) [82].

The circumplex model [83] proposes that two independent neurophysiological systems: One of the systems is related to arousal (activated/deactivated) and to valence (a pleasure–displeasure continuum), and the other to valence (a continuum from pleasure to displeasure) and to arousal (activation–deactivation) [84]. Each emotion can be understood as having varying valence and arousal, and is a linear combination of these two dimensions, or as varying valence and arousal [83,85]. We already applied the Russel's circumplex model of emotions to perform a review of the human emotion recognition of sensors and methods [85].

The vector model comprises two vectors. The model holds that there is an underlying dimension of arousal with a binary choice of valence that determines direction, and an underlying dimension of arousal. This results in there being two vectors that, both starting at zero arousal and neutral valence and zero arousal, proceed as straight lines, one in a positive, and one in the direction of negative valence and the other in the direction of positive valence. Typically, the vector model uses direct scaling of the dimensions of each individual stimulus individually in this model [86,87].

The positive activation–negative activation (PANA) or "consensual" model of emotion, also known as positive activation/negative activation (PANA), assumes that there are two separate systems—positive affect and negative affect. In the PANA model, the vertical axis represents low to high positive affect, and the horizontal axis of this model represents low to high negative affect (low to high). The vertical axis represents positive affect (low to high) [88]. There are two uncorrelated and independent dimensions: Positive Affect (PA), represents the extent (from low to high) to which a person shows enthusiasm for life. The second factor is Negative Affect (NA), and NA represents the extent to which a person is feeling upset or unpleasantly aroused. Positive Affect and Negative Affect are independent and uncorrelated dimensions [89].

The Pleasure–Arousal–Dominance (PAD) Emotional-State Model, offers a general three-dimensional approach to measuring emotions [90]. This 3D model captures emotional response, and includes the three dimensions of pleasure–displeasure (P), arousal–nonarousal (A), and dominance–submissiveness (D) as basic factors of emotional response [91]. The initials PAD stand for pleasure, arousal, and dominance, which span different emotions. For instance, pleasure can be happy/unhappy, hopeful/despairing, satisfied/unsatisfied, pleased/annoyed, content/melancholic, and relaxed/bored. Arousal can be excited/calm, stimulated/relaxed, wide-awake/sleepy, jittery/dull, frenzied/sluggish, and aroused/unaroused. Dominance can be important/awed, dominant/submissive, influential/influenced, controlling/controlled, in control/cared-for, and autonomous/guided [92]. The neuro-decision and neuro-correlation tables, the inverted U-curve theory, the PAD emotional state model, neuro-decision making, and neuro-correlation tables are used to evaluate the impact of digital twin smart spaces (such as indoor air quality, a level of the lighting intensity and colors, learning materials, images, smells, music, pollution, and others) on users, and track their response dynamics in real time, and to then react to this response [93].

The PAD is composed of three different subscales, reflecting pleasure, arousal, and dominance. These can represent different emotions; for example, the pleasure states include happy (unhappy), pleased (annoyed), satisfied (unsatisfied), contented (melancholic), hopeful (despairing) and relaxed (bored), while the arousal states include stimulated (relaxed), excited (calm), frenzied (sluggish), jittery (dull), wide awake (sleepy) and aroused (unaroused), and the dominance states include controlling (controlled), influential (influenced), in control (cared for), important (awed), dominant (submissive), and autonomous (guided) [92]. The affective space model makes it possible to visualize the distribution of emotions along the two axes of valance (V) and arousal (A). Using this model, different emotions can be identified, such as happiness, calmness, fear, and sadness [94].

Swedish neurophysiologist Lövheim proposed that a cube of emotion is the direct relation between certain specific combinations of the levels of the three signal substances (serotonin, noradrenaline, and dopamine) and eight basic emotions [95]. A three-dimensional model, the Lövheim cube of emotion, was presented where there is a model with each of the signal substances of form represented as the axes of a coordinated system, and each corner of this 3D space holding one of the eight basic emotions is placed in the eight corners. In this model, anger is produced by the combination of high noradrenaline, high dopamine, and low serotonin [96].

The eight main categories of emotions defined by Robert Plutchik in 1980s include two equal groups opposite to each other: half are positive emotions and the other half are negative ones [97]. To visualize eight primary emotion dimensions, which are fear, trust, surprise, anticipation, anger, joy, disgust and sadness, eight sectors have been isolated [98]. The Emotion Wheel shows each of the eight basic emotions highlighted with a recognizable color [99]. When we add another dimension, the Wheel of Emotions becomes a cone with its vertical dimension representing intensity. Moving from the outside towards the wheel's center emotions intensify and this fact is highlighted by the indicator color. The intensity of emotions is decreasing towards the outer edge and the color, correspondingly, becomes less intense [98,99]. When feelings intensify one feeling can turn into another: annoyance into rage, serenity into ecstasy, interest into vigilance, apprehension into terror, acceptance into admiration, pensiveness into grief, distraction into amazement, and, if left unchecked, boredom can become loathing [98]. Some emotions have no color marking. They are a mix of two primary emotions [98,99]. Joy and anticipation, for instance, combine to become optimism. When anticipation combines with anger it becomes aggressiveness. The combination of trust and fear is submission, joy and trust combine to become love, surprise and fear become awe, the pair of disgust and anger becomes contempt, sadness and disgust combine to become remorse, and surprise and sadness become disapproval [100].

After the analysis of the said emotion models, we have made the decision to choose Plutchik's wheel of emotions for our research. The ability to analyze human emotional, affective, and physiological states in an integrated manner offered by this model is one of the main reasons of our choice. The wheel is briefly discussed below.

Several ways to classify emotions have been proposed in the field of psychology. For that purpose, the basic emotions are first identified and then they allow clustering with any other more complex emotion [101]. Plutchik [65] proposed a classification scheme based on eight basic emotions arranged in a wheel of emotions, similar to a color wheel. Just like complementary colors, this setup allows the conceptualization of primary emotions by placing similar emotions next to each other and opposites 180 degree apart. Plutchik's wheel of emotions classifies these eight basic emotions grounded on the physiological aim [102]. Emotions are coordinated with the body's physiological responses. For example, when you are scared, your heart rate typically increases and your palms become sweaty. There is ample empirical evidence that suggests that physiological responses accompany emotion [103]. Another parallel with colors is the fact that some emotions are primary emotions and other emotions are derived by combining these primary emotions. The two models share important similarities, and such modelling can also serve as an analytical tool to understand personality. In this case, a third dimension has been added to the circumplex model to represent the intensity of emotions. The structural model of emotions is, therefore, shaped like a cone [104]. Figure 3.1 demonstrates Plutchik's wheel of emotions, biometrics and brain sensors, and trends and interdependence in this Big Picture stage. At the center of the circles is Plutchik's wheel of emotions. Plutchik's wheel of emotions also includes affective attitudes (interest, boredom). Plutchik [65] notes that the same instinctual source of energy is discharged as part of the emotion felt and the underlying peripheral physiological process. Emotions can be of various levels of arousal or degrees of intensity [105]. Looking at the intensity of Plutchik's eight basic emotions, Kušen et al. [106] identified variations in emotional valence. The first circle, therefore, analyses, directly or indirectly, human arousal, valence, affective attitudes, and emotional and physiological states (AFFECT). Human AFFECT can be measured by means of neuroscience and biometric techniques. The market and global trends are a constant force affecting neuroscience and biometric technologies and their improvement. Based on the analysis of global sources [107,108,109,110] and our experience, Figure 3.1 presents brain and biometric sensors, as well as technique trends. Sensors will be able to integrate more and more new technologies and collect a greater variety of data, as they will become more accurate, more flexible, cheaper, smaller, greener, and more energy-efficient [108,109,110]. Network neuroscience, a new explicitly integrative approach towards brain structure and function, seeks new ways to record, map, model, and analyze what constitutes neurobiological systems and what interactions happen inside them. The computational tools and theoretical framework of modern network science, as well as the availability of new empirical tools to map extensively and record the way shifting patterns link molecules, neurons, brain areas and social systems, are two trends enabling and driving this approach [107].

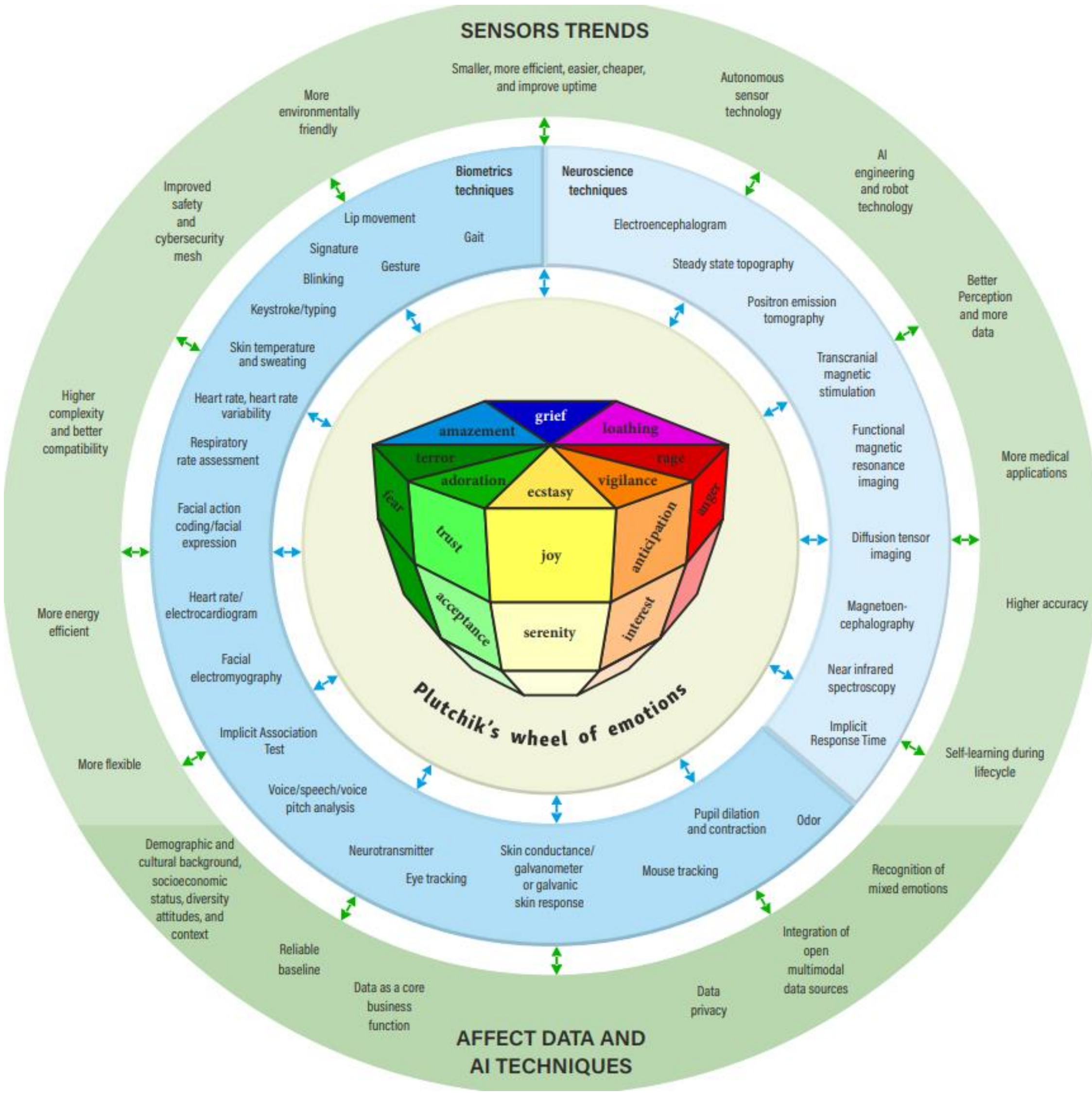


Figure 3.1. Plutchik's wheel of emotions, biometrics and neuroscience sensors, and trends.

Figure 3.2 shows numerous sciences and areas in which neuroscience and biometrics analyze the AFFECT. According to Sebastian [111], neuroeconomics is the study of the effect of anticipating money decisions on our brain. It has solidified as an entirely academic and unifying field that ventures to describe the techniques of the decision-making process; and reiterates economic behavior and decision-making process with economic disposition. The procedure of neuroeconomics involves the integration of behavioral experiments and brain imaging in order to more clearly appreciate the workings behind individual and collective decision-making [112]. Serra [113] reported that neuroeconomics researchers utilize neuroimaging devices such as functional magnetic resonance imaging (fMRI), magnetic resonance imaging (MRI), transcranial magnetic stimulation (rTMS), and transcranial direct-current stimulation (tDCS), positron emission tomography (PET) and electroencephalography (EEG). The majority of challenges probed by neuroeconomics researchers are basically similar to the problems a marketing researcher would acknowledge as aspects of their functional domain [114]. Kenning and Plassmann [115] has also defined neuroeconomics as the implementation of neuroscientific methods in the evaluation and appreciation of economically significant behavior.

Figure 3.2. Neuroscience and biometric branches analyzing AFFECT in various sciences and fields.

According to Wirdayanti and Ghoni [116], neuromanagement entails psychology, the biological aspect of humans for decision-making in management sciences. As stated Teacu Parincu et al. [117], neuromanagement is targeted at investigating the acts of the human brain and mental performances whenever people are confronted with management challenges, using cognitive neuroscience, in addition to other scientific disciplines and technology, to evaluate economic and managerial problems. Its focal point is on neurological activities that are related to decision-making and develops personal as well as organizational intelligence (team intelligence). It also centers on the planning and management of people (for example, selection, training, group interaction and leadership) [118].

Neuro-Information Science can be defined as the science that observes neurophysiological reactions that are connected with the peripheral nervous system; that is then connected to conventional cognitive activities. Michalczyk et al. [119] stated that neuro-information-systems research has developed into a conventional approach in the information systems (IS) discipline for evaluating and appreciating user behavior. Riedl et al. [120] and Michalczyk et al. [119] concluded that Neuro-information-systems comprise studies that are centered on all types of neurophysiological techniques, such as functional magnetic resonance imaging (fMRI), electroencephalograhy (EEG), fNIRS (functional near-infrared spectroscopy), electromyography (EMG), hormone studies, or skin conductance and heart rate evaluations, as well as magnetoencephalography (MEG) and eye-tracking (ET).

Neuro-Industrial Engineering brought about by the synergy between neuroscience and industrial engineering has afforded resolutions centered on the physiological status of people. Ma et al. [121] reported that NeuroIE secures its objective and real data by analyzing human brain and physiological indexes with advanced brain AFFECT devices and biofeedback technology, evaluating the data, adding neural activities as well as physiological status in the process of evaluation; as new constituents of operations management, and finally understanding better human–machine integration by modifying work environment and production system in line with people’s reaction to the system, preventing mishaps and enhancing efficiency and quality. According to Ma et al. [121], Neuro-Industrial Engineering is centered on humans and lays hold of human physiological status data (e.g., EEG, EMG, GSR and Temp). Zev Rymer [122] also stated that the application of Neuro-Industrial Engineering is multidisciplinary in that it cuts across the neurological sciences (particularly neurology and neurobiology) in addition to different fields of engineering disciplines such as simulation, systems modeling, robotics, signal processing, material sciences, and computer sciences. The area encompasses a range of topics and applications; for example, neurorobotics, neuroinformatics, neuroimaging, neural tissue engineering, and brain–computer interfaces.

As soon as a user contacts an insurer, a bank or any other call center, a version of Cogito’s software known as Dialog could be active in the background, assisting the client service agent to deal with the client. Should the user become upset or angry, the client service agent can ensure that necessary actions are taken to satisfy the client. According to Cogito, this service is known as “digital intuition”. Its usefulness in call centers cannot be overemphasized as it can give feedback about real-time communications. The speed at which speeches are made by the callers as well as the dynamic range of their voices can also be analyzed by the software. For example, significant variations in pitch and stresses in caller’s tones could signify excitement or anger. Less significant dynamism, a monotonous flat tone, could imply a lack of interest or unconcern. Some companies make use of the software to assist their employees engage new patients for healthcare projects that help control health challenges such as obesity or asthma. Cogito is among recent profit-based research companies whose focus are on the evaluation of signals subconsciously given off by people which exposes their mindset. The evaluation of these kinds of social-signals is beneficial beyond call centers and meeting rooms. According to Hodson [123], keeping track of conversations during surgeries or plane cockpits could assist surgeons and pilots to be aware of whether their colleagues are really attentive to their directives, possibly preserving lives.

Several areas where we can apply the technology of recognizing emotions from speech include human–computer interactions and call centers [124].

3.4. Brain and Biometric AFFECT Sensors

3.4.1. Classifications

Globally, several classifications of biometric and neuroscience methods and technologies are used. Our research focuses on neuroscience methods that are non-invasive. The use of non-invasive brain stimulation is widespread in studies of neuroscience [125]. The non-invasive neuroscience methods are: transcranial magnetic stimulation (TMS), electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), near infrared spectroscopy (NIRS), diffusion tensor imaging (DTI), steady-state topography (SST), and others [126,127,128,129,130,131,132,133,134]. These non-invasive neuroscience methods are described in detail in Section 3. In the future, the authors of this article plan to analyze invasive neuroscience methods, too.

Biometrics can be physical or behavioral. In the first case, emotions can be identified by their physical features, including face, and in the second case by their behavioral characteristics, including gait, voice, signature, and typing patterns [135]. Various sensors can measure physiological signals, known as biometrics, capturing the response of bodily systems to things that are experienced through our senses, but also things imagined, by tracking sleep architecture, heart rate variability (HRV), respiratory rate (RR), and heart rate (RHR) [136].

Scientific literature classifies biometrics into certain types. Stephen and Reddy [137] and Banirostam et al. [138], for instance, classify biometrics into three categories: physiological, behavioral, and chemical/biological. Yang et al. [139] distinguish physiological and behavior traits. Kodituwakku [140] believes biometric technology can be classified into two general categories: physiological biometric techniques and behavioral biometric techniques. Jain et al. [141] and Choudhary and Naik [142] also classify biometrics into two categories: physiological and behavioral. In the literature, not only signature, voice, and gait are considered behavioral biometric features, but also ECG, EMG, and EEG [143], while other authors distinguish cognitive biometrics [144,145], including electroencephalography (EEG), electrocardiography (ECG), electrodermal response (EDR), blood pulse volume (BVP), near-infrared spectroscopy (NIR), electromyography (EMG), eye trackers (pupillometry), hemoencephalography (HEG), and related technologies [145]. Some scientific sources claim that eye tracking is a behavioral biometric [146], while others claim that it is a measurement in physiological computing [147]. Physiological biometrics measures the physiological signals to determine identity as well as authenticating and analyzing users emotions. Respiration, perspiration, heartbeat, eye-reactions to light, brain activity, emotions, and even body odor can be measured for numerous purposes, including physical and logical access control, payments, health monitoring, liveness detection, and neuromarketing among them [136].

Scientists identify the following AFFECT biometric types [139,140,141,142,148,149,150]:

- Physiological features: facial patterns, odor, pupil dilation and contraction, skin conductance, heart rate, respiratory rate, temperature, blood volume pulse, and others.
- Behavioral features: gait, keystroke, mouse tracking, signature, handwriting, speech/voice, and others.
- The authors of this article have used the classification of biometrics proposed by the abovementioned authors (physiological and behavioral features).

Biometric technologies are usually divided into those of first and second generation [151]. First-generation biometrics can confirm a person’s identity in a quick and reliable way, or authenticate them in different contexts, and law enforcement is one of the areas where such solutions are employed in practice [152]. The primary purpose of first-generation biometrics is identity verification, such as facial recognition, and the technology is built around simple sensors that capture physical features and store them for later use [153]. Second-generation biometrics can also be used to detect emotions, with electro-physiologic and behavioral biometrics (e.g., based on ECG, EEG, and EMG) as examples of such technologies [154]. Second-generation biometrics measure individual patterns of learned behavior or physiological processes, rather than physical traits, and are also known as behavioral biometrics [155]. Second-generation biometrics usage has the ability to analyze/evaluate emotions and detect intentions [156]. The use of second-generation biometrics enables wireless data collection regarding the body. The data can then be used to infer an individual's intent and emotions, as well as emotion tracking across spaces [151,157]. We examine only physiological effects affected by emotional reactions (i.e., second-generation biometrics), and the use of biometric patterns for the identification of individuals is not discussed in this study.

A diverse range of AI algorithms have been applied for AFFECT recognition, for example machine learning, artificial neural networks, search algorithms, expert systems, evolutionary computing, natural language processing, metaheuristics, fuzzy logic, genetic algorithms, and others. Some of the most important supervised (classification, regression), unsupervised (clustering), and reinforcement learning algorithms of machine learning are common as tools in biometrics or neuroscience research to detect emotions and affective attitudes, and are listed below:

- Among classification algorithms the most common choices are: naïve Bayes [158,159,160], Decision Tree [161,162,163], Random Forest [164,165,166], Support Vector Machines [167,168,169], and K Nearest Neighbors [170,171,172].
- Among regression algorithms the usual choices are: linear regression [173,174,175], Lasso Regression [176,177], Logistic Regression [178,179,180], Multivariate Regression [181,182], and Multiple Regression Algorithm [183,184].
- Among clustering algorithms the most common choices in biometrics or neuroscience research are: K-Means Clustering [185,186,187], Fuzzy C-means Algorithm [188,189], Expectation-Maximization (EM) Algorithm [190], and Hierarchical Clustering Algorithm [188,191,192].
- Among reinforcement learning algorithms the most common choices are: deep reinforcement learning [193,194,195] and inverse reinforcement learning [196].

3.4.2. Brain AFFECT Devices and Sensors

Neuroscience is associated with multiple fields of science, for example chemistry, computation, psychology, philosophy, and linguistics. Various research areas of neuroscience include behavioral, molecular, operative, evolutionary, cellular, and therapeutic features of the neurotic system. The neuroscience market encompasses technology (electrophysiology, neuro-microscopy, whole-brain imaging, neuroproteomics analysis, animal behavior analysis, neuro-functional study, etc.), components (services, instrument, and software) and end-users (healthcare centers, research institutions and academic, diagnostic laboratories, etc.) [197]. Global Industry Analysts Inc. (San Jose, CA, USA) [197] has previously grouped the global neuroscience market into instrument, software, and services based on components.

Neuroscience provides valuable perceptions concerning the structural design of the brain and neurological, physical, and psychological activities. It helps neurologists to appreciate the various components of the brain that can assist in the development of medications and techniques to handle and avoid many neurological anomalies. The rising death rate as a result of several neurological disorders, such as Parkinson's disease, Alzheimer's, schizophrenia, and other brain-related health challenges, represents the basic factor controlling the neuroscience market growth [198]. According to Neuroscience Market [198], the increasing request for neuroimaging devices and the progressive brain mapping research and evaluation projects are other crucial growth-inducing factors.

Neuroscience covers a whole range of branches, such as, neuroevolution, neuroanatomy, developmental neuroscience, neuroimmunology, cellular neuroscience, neuropharmacology, clinical neuroscience, cognitive neuroscience, nanoneuroscience, molecular neuroscience, neurogenetics, neuroethology, neurochemistry, neurophysics, paleoneurobiology, neurology, and neuro-ophthalmology.

Other branches of neuroscience analyze AFFECT in various related sciences and fields, such as affective neuroscience [199,200], neuroinformatics [201,202], neuroimaging [203,204], systems neuroscience [205,206], computational neuroscience [207,208], neurophysiology [51,209], behavioral neuroscience [210,211], neural engineering [212,213], neuroeconomics [214,215], neurolinguistics [216,217], neuropsychology [218,219,220], neurophilosophy [221,222,223], neuroaesthetics [224,225,226], neurotheology [227,228,229], neuropolitics [230,231,232], neurolaw [233,234,235], social neuroscience [236,237], cultural neuroscience [238,239], neuroliterature [240,241,242], neurocinema [243,244,245], neuromusicology [246,247,248], and neurogastronomy [249,250].

For example, Lim [251] identifies the following neuroscientific techniques for neuromarketing:

- Electromagnetic methods, including magnetoencephalography (MEG), electroencephalography (EEG), and steady-state topography (SST). MEG involves the magnetic fields produced by the brain (its natural electrical currents) and is used to track the changes that occur when participants see or interact with various presentation outputs. EEG is related to the ways in which brainwaves change and is used to detect changes when participant see or interact with various promoting outputs (an electrode band or helmet is used for this purpose). SST measures a steady-state visually evoked potential, and is used to determine how brain activities change depending on the task;
- Metabolic methods, including positron emission tomography (PET) and functional magnetic resonance imaging (fMRI). PET is used to examine the metabolism of glucose within the brain with great accuracy by tracing radiation pulses, while fMRI is used to measure blood flow in the brain to determine changes in brain activity;
- Electrocardiography (ECG), which uses external skin electrodes to measure electrical changes related to cardiac cycles;
- Facial electromyography (fEMG), which amplifies tiny electrical impulses to record the physiological properties of the facial muscles;
- Transcranial Magnetic Stimulation (TMS), which is used to observe the effects of promoting output on behavior by temporarily disrupting specific brain activities. TMS is a non-invasive, safe brain stimulation method. By means of a strong electromagnet, this technique momentarily generates a short-lived virtual lesion, i.e., disrupts information

processing in one of brain regions. If stimulation interferes with performing a certain task, the affected brain region is, then, necessary for normal performance of the task [252].

Table 3.1 demonstrates traditional non-invasive neuroscience methods.

Table 3.1. Traditional non-invasive neuroscience methods.

Methods	Author(s)	Description
Electroencephalography (EEG)	[111,253–266]	EEGs capture brainwave variations, using recorded amplitudes to monitor mental states that include alpha waves (relaxation), beta waves (wakefulness), delta waves (sleep), and theta waves (calmness) [255]. An EEG signal comprises five brain waves and measuring the activity of certain brain areas can reveal the state of the subject's cortical activation. Each wave is characterized by different amplitudes and frequencies, and corresponds to distinct cognitive states [265].
Magnetoencephalography (MEG)	[111,253–256,259,260,267]	Using magnetic potentials, an MEG records brain activity at the scalp level. A helmet with sensitive detectors is placed on the subject's head to track the signal [255], and the MEG detects the magnetic fields produced by electromagnetic fields [111].
Transcranial Magnetic Stimulation (TMS) (Figure 3)	[111,251,253,255,258,260,267]	TMS modulates the activity of certain brain areas located 1–2 cm below the skull, without reaching the neocortex, using magnetic induction [255]. When TMS is used, short electromagnetic impulses are applied at the scalp level. This instrument can stimulate or inhibit a particular cortical area [111].
Near Infrared Spectroscopy (NIRS)	[267–269]	NIRS measures hemodynamic alterations accompanying brain activation and is a simple bedside technique [269]. NIRS makes use of the near-infrared region of the electromagnetic spectrum (about 700–2500 nm). Measurements are taken of light scattered from the surface of and through a sample, and NIR reflectance spectra can give rapid insight into the properties of a material without altering the sample [268].
Steady-State Topography (SST)	[251,253,255,256,260]	SST can be applied to track high-speed changes and measure the activity of the human brain. This tool is very commonly used in neuromarketing research and cognitive neuroscience [255].
Functional Magnetic Resonance Imaging (fMRI) (Figure 4)	[111,251,253–256,258–261,263,264,266,267]	fMRI is suitable for use within neuromarketing studies, as brain activity can be measured in subjects performing certain tasks or experiencing marketing stimuli. It allows for the observation of deep brain structures, and hence can reveal patterns [255]. fMRI can also measure increases in oxygen levels in the blood flow to the brain and can detect the active cortical regions [111].
Positron Emission Tomography (PET) (Figure 4)	[111,251,253,254,256,259–261,267]	The subject is injected with a radioactive substance, and the flow of the substance is then measured. Significant increases in the flow are seen in activated areas [111].
Diffusion Tensor Imaging (DTI) (Figure 5)	[267,270,271]	This is an MRI-based neuroimaging technique that allows the user to estimate the location, anisotropy and orientation of the brain's white matter tracts [271]. DTI makes it possible to visualize and characterize white matter fasciculi in two and three dimensions [270].

For clarity, several descriptions of traditional neuroscience methods are presented below.

Wearable healthcare devices store a lot of sensitive personal information which makes the security of these devices very essential. Sun et al. [272] proposed an acceleration-based gait recognition method to improve gait-based elderly recognition. Gait is also a good indicator in health assessment, Majumder et al. [273] created a simple wearable gait analyzer for the elderly to support healthcare needs.

Lim [251] states that neuroscientific methods and tools include those that track, chart, and record the activity of a person's neural system and brain in relation to a certain behavior, and neurological representations of this activity can then be generated to shed light on how an individual's brain and nervous system respond when the person is exposed to a stimulus. In this way, neuroscientists can observe the neural processes as they happen in real time. There are three main types of neuroscientific method: those that track what is happening inside the brain (metabolic and electromagnetic activity); those that track what is happening at the neural level outside the brain; and those that can influence neural activity (Table 3.1, Figure 3.1).

Non-invasive neuroscience technical information is provided in detail in various research literature about the origin of the measured signal and the engineering/physical principle of the sensors for EEG [274,275,276], MEG [277,278,279], TMS [280,281,282], etc.

Gannouni et al. [283] have proposed a new approach with EEG signals used in emotion recognition. To achieve better emotion recognition using brain signals, Gannouni et al. [283] applied a novel adaptive channel selection method. The basis of this method is the acknowledgment that different persons have unique brain activity that also differs from one emotional state to another. Gannouni et al. [283] argue that emotion recognition using EEG signals needs a multi-disciplinary approach, encompassing areas such as psychology, engineering, neuroscience, and computer science. With the aim of improving the reproducibility of emotion measurement based on EEG, Apicella et al. [35] have proposed an emotional valence detection method for a system based on EEG, and their experiments proved an accuracy of 80.2% in cross-subject analysis and 96.1% in within-subject analysis. Dixson et al. [284] have pointed out that facial hair may interfere with detection of emotional expressions in a visual search. However, facial hair may also interfere with the detection of happy expressions within the face in the crowd paradigm, rather than facilitating an effect of anger superiority as a potential system for threat detection.

Wang et al. [285] introduced an EEG-based emotion recognition system to classify four emotion states (joy, sadness, fear, and relaxed). Their experiments used movie elicitation to acquire EEG signals from their subjects [285]. The way in which meditation influences emotional response was investigated via EEG functional connectivity of selected brain regions as the subjects experienced happiness, anger, sadness or were relaxed, before and after meditation.

Neurometrics is a quantitative EEG method. Looking at individual records, this method provides a reproducible, precise estimate of deviations from normal. Only sufficient amount of good quality raw data transformed for Gaussian distributions, correlated with age, and corrected taking into account intercorrelations among measures ensure meaningful and reliable results [286]. Businesses, government agencies, and individuals use neurometric information when they need timely and profitable decisions. Techniques based on neurometric information are applied to make profitable business decisions. These techniques are based on biometric information, eye tracking, facial action coding and implicit response testing, and are used to understand and record human sentiments and other related feedback [161].

The fronto-striatal network is involved in a range of cognitive, emotional, and motor processes, such as decision-making, working memory, emotion regulation, and spatial attention. Practice shows that intermittent theta burst transcranial magnetic stimulation (iTBS) modulates the functional connectivity of brain networks. Treatments of mood disorders usually involve high stimulation intensities and long stimulation intervals in transcranial magnetic stimulation (TMS) (Figure 3.3) therapy [287].

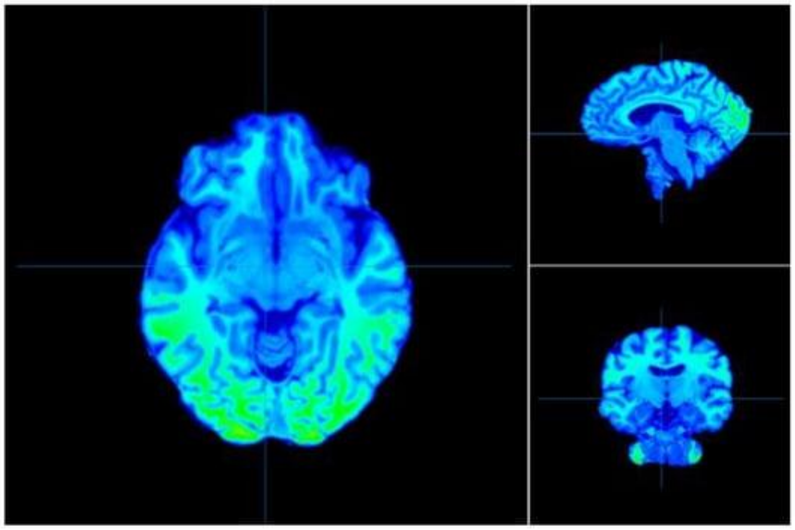


Figure 3.3. Resting state TMS brain scan image [287].

One of imaging techniques is FDG-PET/fMRI (simultaneous [18F]-fluorodeoxyglucose positron emission tomography and functional magnetic resonance imaging). This technique makes it possible to image the cerebrovascular hemodynamic response and cerebral glucose uptake. These two sources of energy dynamics in the brain can provide useful information. Another greatly useful technique for characterizing interactions between distributed brain regions in humans has been resting-state fMRI connectivity, while metabolic connectivity can be a complementary measure to investigate the dynamics of the brain network. Functional PET (fPET), a new approach with high temporal resolution, can be used to measure fluoro-d-glucose (FDG) uptake and looks like a promising method to assess the dynamics of neural metabolism [288]. Figure 3.4 shows raw images of signal intensity variation across the brain for one individual subject.

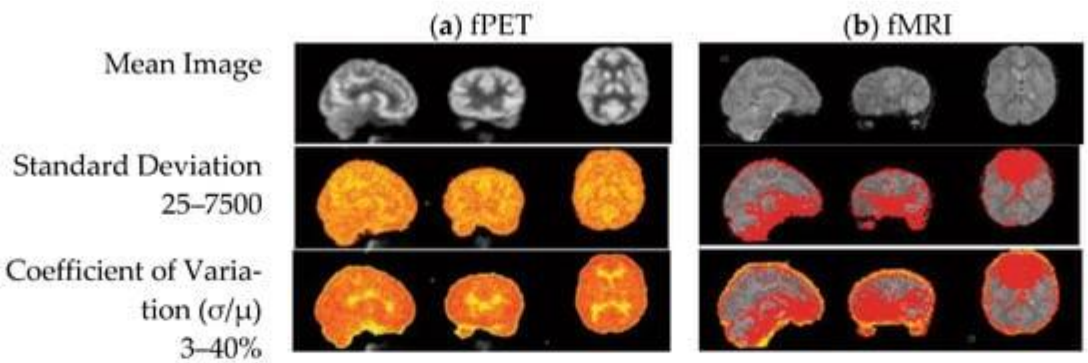


Figure 3.4. Raw images of fPET and fMRI scans [288].

Many biological tissues comprised of fibers, which are groups of cells aligned in a uniform direction, have anisotropic properties. In the human brain, for instance, within its white matte regions, axons usually form complex fiber tracts that enable anatomical communication and connectivity. Non-invasive tools can show the groups of axonal fibers visually. One of them is diffusion tensor magnetic resonance medical imaging (DTI), which is one particular method or application of the broader Diffusion-Weighted Imaging (DWI). The basic principle behind this technique is that water diffuses more slowly as it moves perpendicular to the preferred direction, whereas in the direction aligned with the internal structure the diffusion is more rapid. The DTI outputs can be further used to compute diffusion anisotropy measures such as the fractional anisotropy (FA). The principal direction of the diffusion tensor can also be used to obtain estimates related to the white matter connectivity in the brain. Figure 3.5 shows an example of DTI tractography, or visualization of the white matter connectivity [289].

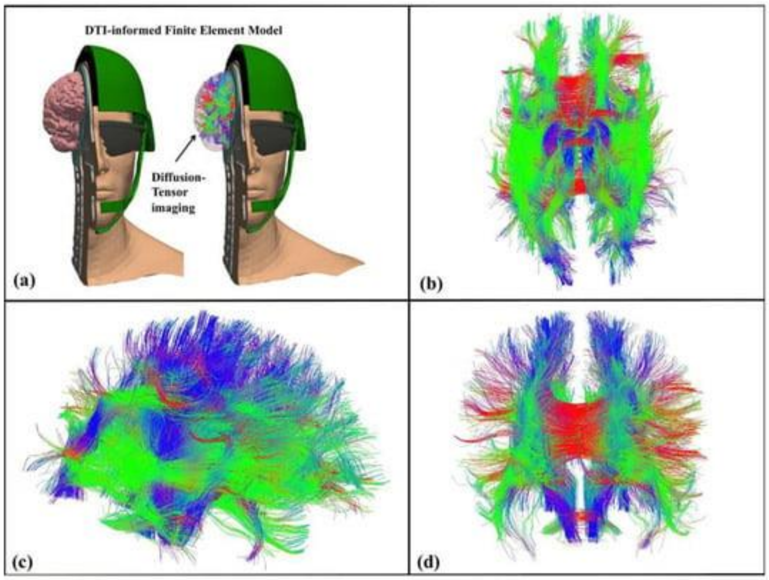


Figure 3.5. DTI can be used to construct a transversely isotropic model by overlaying axonal fiber tractography on a finite element mesh: (a) DTI-informed Finite Element Model; tractography shows complex fibers from (b) the dorsal view, (c) the right lateral side view, and (d) the posterior view. Cartography of the tracts' position, direction by color: red for right-left, blue for foot-head, green for anterior-posterior [289].

3.4.3. Physiological and Behavioral Biometrics

Physiological biometrics (as opposed to behavioral biometrics) is a category of approaches that refers to physical measurements of the human body, including face, pupil constriction and dilation [290]. When a recognition system is based on physiological characteristics it can ensure a comparatively high accuracy [291]. The ubiquity of electronics such as cell phones and computers, and evolving sensor technology offer human beings new possibilities to track their behavioral and physiological features and evaluate the associated biometric results. Advances in mobile devices mean they now have many efficient and complex sensors. Biometric technology often contributes to mobile application growth, including online transaction efficiency, mobile banking, and voting. The global market for biometric systems is wide and comprises many different segments such as healthcare, transportation and logistics, security, military and defense, government, consumer electronics, and banking and finance [292].

Table 3.2 presents widely used physiological and behavioral biometrics.

Table 3.2. Physiological and behavioral biometrics.

Technique	Author(s)	Description
		Physical/Physiological Features
Eye Tracking (ET) (Figure 6)	[111,251,253–261,264–267]	ET determines the areas at which the subject is looking and for how long, and also tracks the movement of the subject's eyes and changes in pupil dilation while the subject looks at stimuli. With this technique, behavior and cognition can be studied without measuring brain activity [255]. By measuring eye movements and visual attention, an eye tracker determines the point of regard [265].
Blinking	[261,264,293]	Eye blinking forms the basis of the new biometric emotions identifier proposed by Abo-Zahhad et al. [293]. These authors outline where eye blinking signals come from and give an overview of the features of the EOG signals from which the eye blinking waveform is extracted.
Iris characteristics		User-oriented examinations were applied to find the relationships between personality and three common iris characteristics: pigment dots, crypts ,and contraction furrows [294]. Dark-eyed individuals typically have higher scores for neuroticism and extraversion [295], sociability [296], and ease of emotional arousal [297].
Facial Action Coding (FC)/Facial Expression Analysis Surveys (Figure 7)	[253–258,260,261,263–265,298]	FC uses a video camera to track micro-expressions that correspond to certain subconscious reactions. The activity of the facial muscles is tracked [255]. Scientists and practitioners have developed various open data datasets (KaoKore Dataset, CelebFaces At-tributes Dataset, etc.) and applied elicitation techniques (gamification, virtual reality) in practice.
Facial Electromyography (fEMG) (Figure 8)	[251,253–256,259–263,298,299]	fEMG is used in measuring and evaluating the physiological properties of facial muscles [255].
Odor	[300]	This a method of emotion recognition based on an individual's odor [300]. An emotional mood, for example a period of depression, may affect body odor [301].
Keystroke dynamics and mouse movements (Figure 9)	[302]	AFFECT states can be determined by how a person moves a computer mouse while sitting at a computer.
Skin Conductance (SC)/Galvanometer or Galvanic Skin Response (GSR)	[111,251,253,255,256,258,260–262,264,265,267]	SC is highly correlated with the rate of perspiration, and is often linked to stress as well as to the processes happening in the nervous system [261]. SC methods measure arousal based on tiny changes in conductance that occur when something activates the autonomic nervous system [255]. The sympathetic branch of the autonomic nervous system controls the skin's sweat glands, and the activity of the glands determines the galvanic skin response [265].
Heart rate (HR)/Electrocardiogram (ECG)	[19,111,251,256,261,303]	An ECG is used to measure the electrical activity of the heart [261]. An ECG relies on cardiac electrical activity and measures the electrical impulses that travel through the heart with each beat, causing the heart muscle to pump blood. In ECGs of a normal heartbeat, the timing of the lower and top chambers of the heart is charted [303].

Respiratory Rate Assessment (RRA)	[111,261,304]	Respiratory rate, one of fundamental vital signs, is sensitive to various pathological situations (clinical deterioration, pneumonia, adverse cardiac events, etc.), as well as stressors [304].
Skin temperature (SKT)	[305]	SKT data can be used to measure the thermal responses of human skin. SKT depends on the complex relationship between blood perfusion in the skin layers, heat exchange with the environment, and the central warmer regions of the skin [305]
Photoplethysmography (PPG) or Blood volume pulse (BVP)	[305]	Changes in the amplitudes of PPG signals are related to the level of tension in a human being. PPG is a simple, non-invasive method of taking measurements of the cardiac synchronous changes in the blood volume [305].
Trapezium electromyogram	[306]	EMG is a technique that can be used to evaluate and record the electrical activity generated by skeletal muscle [306], for example the trapezius muscle [307].
Neurotransmitter (NT)	[251,308]	Brain neurotransmitters are particular chemical substances that act as messengers in chemical synaptic transmissions and can transmit emotive information. They have excitability and inhibitive abilities [308].
Voice/Speech/Voice Pitch Analysis (VPA)	[263,267,300,309,310]	This is a method of emotion recognition that relies on the person's voice.
Implicit Association Test (IAT)	[255,264,311]	IAT measures individual behavior and experience by assessing the reaction times of subjects to determine their inner attitudes. The subjects are given two cognitive tasks, and measurements are taken of the speed at which they associate two distinct concepts (brands, advertisements, etc.) with two distinct assessed features. IATs can be used to identify hierarchies of products by means of comparisons [255].
Mouse Tracking (MT)	[257,312]	Recognition of a user's emotions is possible based on their mouse movements. Users can be classified by extracting features from raw data on mouse movements and employing complex machine learning techniques (e.g., a support vector machine (SVM)) and basic machine learning techniques (e.g., k-nearest neighbor) [312].
Signature (Figure 9)	[298–300,309]	Emotions can be identified by their handwriting style, and in particular their signature.
Gait (Figure 9)	[298–300,309]	This method allows for emotions recognition based on a person's walking style or gait [300].
Lip Movement	[299]	Lip movement measurements are a recently developed form of biometric emotions recognition that is very similar to the way a deaf person determines what is being said by tracking lip movements [299].
Gesture	[298,309]	Gesture recognition is used to identify emotions rather than a person, and gestures are grouped into certain categories [298].
Keystroke/Typing Recognition (Figure 9)	[169,300]	In this method, the unique characteristics of a person's typing style are used for emotions identification purposes [300].

Most of today's eye tracking systems are video-based, with an eye video camera and infrared illumination. Eye tracking systems can be categorized as tower-mounted, mobile, or remote based on how they interface with the environment and the user (Figure 6) and different video-based eye tracking systems are required depending on the experiment, the environment, and the type of activity to be studied [313]. Researchers have used eye-tracking for behavioral research.

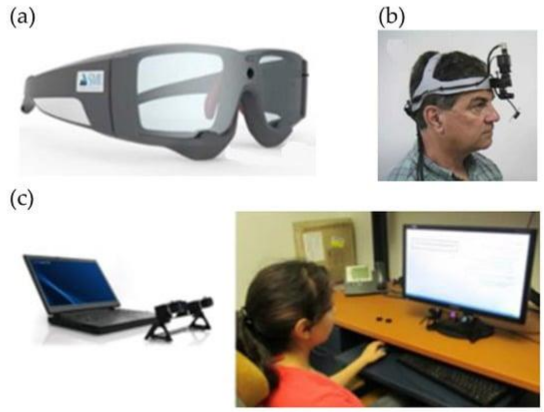


Figure 3.6. Sample of various kinds of eye-tracking tools: (a) eye-tracking glasses [314]; (b) helmet-mounted [315]; (c) remote or table [316].

The left image in Figure 3.7 shows the last frame of an expression showing surprise on a sample face from Cohn–Kanade database and highlights the trajectories (the bright lines that change color from darker to brighter from their start to end) followed by each tracked feature point. Figure 3.7. The application of the dense flow method (right) and the result of applying the feature optical flow on the subset of 15 points (left) [317].

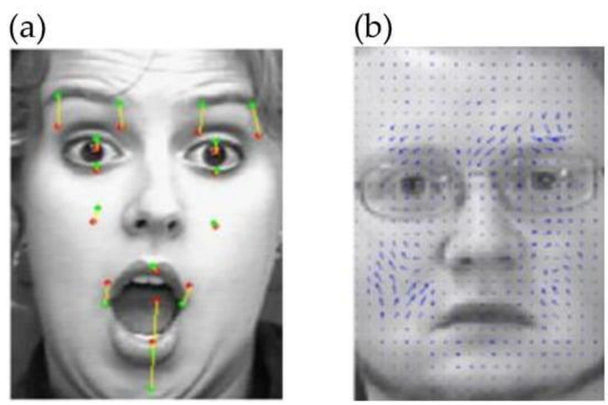


Figure 3.7. Facial expression recognition: (a) feature point tracking; (b) dense flow tracking [317].

A group of participants were tested to record the facial EMG (fEMG) activity. Following the guidelines for fEMG placement recommended by Fridlund and Cacioppo, two 4-mm bipolar miniature silver/silver chloride (Ag/AgCl) skin electrodes were placed on their left corrugator supercilii and zygomaticus major muscle regions (Figure 3.7) [318]. To avoid bad signals or other unwanted influences, the BioTrace software (on NeXus-32) was used to visualize and, if necessary, correct the biosignals before each recording. Figure 3.8 shows the arrangement of fEMG electrodes on the M. zygomaticus major and M. corrugator supercilii. An example of a filtered electromyography (EMG) signal is shown on the right side [319].

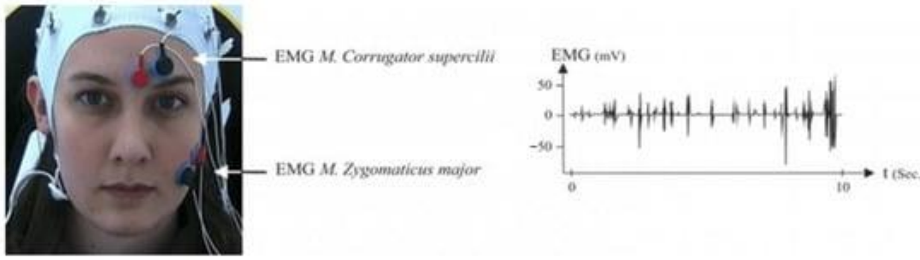


Figure 3.8. Placement of fEMG electrodes and a sample of a filtered EMG signal [319].

Humans have a range of biometric traits that can be a basis for various biometric recognition systems (Figure 3.9). The other biometrics traits are iris, face thermogram, gait, keystroke pattern, voice, face, and signature. They can have different significance. For example, iris scan has high accuracy, medium long term stability and medium security level, while voice recognition has low accuracy, low long term stability and low security level [320]. The choice of the biometric traits, however, invariably depends on the availability of the dataset's samples, the application, the value of tolerance accepted, and the level of complexities [150].

Figure 3.9. Other examples of biometric traits.

Biometric sensors are transducers that change the biometric traits of a person, such as face, voice, and other characteristics, into an electrical signal. These sensors read or measure speed, temperature, electrical capacity, light, and other types of energy. Different technologies are available with digital cameras, sensor networks, and complex combinations. One type of sensor is required in every biometric device, and biometric sensors are a key feature of emotions recognition technology. Biometrics can be used in a microphone for voice capture or in a high-definition camera for facial recognition [321].

Jain et al. [141] state that enrolment and emotions recognition are two main phases in biometric emotions recognition systems. The enrolment phase means acquiring an individual's biometric data to be stored in the database along with the emotions recognition details. The recognition phase uses the stored data to compare the data with the re-acquired biometric data of the same individual, to determine emotions. A biometric system is, therefore, a pattern recognition system consisting of a database, sensors, a feature extractor, and a matcher.

Loaiza [322] states that overall physiological effects related to emotional reactions depend on three types of autonomic variables: (1) the cardiac system, including blood pressure, cardiac cycles, and heart rate variability; (2) respiration, including amplitude, respiration period, and respiratory cycles; and (3) electrodermal activity, including resistance, responses, and skin conductance levels. Ekman [77] report that different emotions can have very different autonomic variables. For instance, in contrast to someone in a happy state, an angry person had a higher heart rate and temperature. Furthermore, the feeling of fear was also accompanied by higher heart rate. Pace-Schott et al. [323] argue that the ability to regulate physiological state and regulation of emotion are two inseparable features. Physiological feelings contribute to emotion regulation, reproduction, and survival.

Many works have focused on emotion detection using different techniques [35,283,284,324,325,326,327]. Specific tasks (e.g., WASSA-2017, SemEval) have also included emotion detection tasks that cover four categories of emotions (anger, fear, sadness, and joy) [320]. According to Saganowski et al. [326], the most common approach to the use of physiological signals in emotion recognition is to (1) collect and clean data; (2) to preprocess, synchronize, and integrate signal; (3) to extract and select features; and (4) to train and validate machine learning models.

Signals are a natural expression of the human body; they can be used with great success in the classification of emotional states. EEGs, temperature measurements, or electrocardiograms (ECGs) are examples of such physiological signals. They can help us to classify emotional states such as anger, sadness, or happiness, and can be captured by different sensors to identify individual differences. The goal of all of these physiological methods is to evaluate consumer attention and to obtain a particular message noticed, and their performance in this area is commendable. The advantages of these techniques include their creative and versatile placement, the stimulation of interest through novel means that capture attention, the ability to directly target and personalize messages, and lower implementation costs [328]. To study marketing trends, Singh et al. [328] recommend avoiding costly research methods such as fMRI and EEG, and instead using smaller and cheaper galvanic readings and eye tracking (ET) to investigate brain responses. These authors also propose a fuzzy rule-based algorithm to anticipate consumer behavior by detecting six facial expressions from still images.

Various organizations are contributing to the progress of biometric standards, such as international standards organizations (International Electrotechnical Commission, ISO-JTC1/SC37, London, UK), national standards bodies (American National Standards Institute, New

York, NY, USA), standards-developing organizations (International Committee for Information Technology Standards, American National Institute of Standards and Technology, Information Technology Laboratory), and other related organizations (International Biometrics and Identification Association, International Biometric Group, Biometric Consortium, Biometric Center of Excellence) [329]. De Angel et al. [330] give rise to numerous recommendations to begin improving the generalizability of the research and generating a more standardized approach to sensing in depression.

- Sample recommendations include reporting on recruitment strategies, sampling frames and participation rates; increasing the diversity of the study population by enrolling participants of different ages and ethnicities; reporting basic demographic data such as age, gender, ethnicity, and comorbidities; and measuring and reporting participant engagement and acceptability in terms of attrition rates, missing data, and/or qualitative data.
- Furthermore, in machine learning models—describing the model selection strategy, performance metrics and parameter estimates in the model with confidence intervals or nonparametric equivalents.
- Recommendations for data collection and analysis include using established and validated scales for depression assessment; presenting any available evidence on the validity and reliability of the sensor or device used; describing in sufficient detail so as to enable replication, data processing and feature construction; and providing a definition and description of how missing data is handled.
- Recommendations for data sharing include making the code used for feature extraction available within an open science framework and sharing anonymized datasets in data repositories.
- The key recommendation is recognizing the need for consistent reporting in this area. The fact that many studies—especially in the field of computer science—fail to report basic demographic information. A common framework should be developed that has standardized assessment and analysis tools and reliable feature extraction and missing data descriptions, and has been tested in more representative populations.

Neuromarketing, neuroeconomics, neuromanagement, neuro-information systems, neuro-industrial engineering, products, services, call centers studies use various instruments and techniques to measure user psychological states. Some of these tools are more complex than others, and the results that are produced can vary widely [331]. They fall into three major categories: the first two contain tools used for neuroimaging (medical devices offering in vivo information on the nervous system) and use techniques that measure brain electrical activity and neuronal metabolism, while the third contains tools used to evaluate neurophysiological indicators of the mental states of an individual. Leading neuroimaging tools such as fMRI and PET fall into the first category, while EEG, MEG, and other less invasive and cheaper neuroimaging devices that measure electrical activity in the brain [332] fall into the second category, and tools that track and record individual signals of broader physiological reaction and response measurements (e.g., electro-dermal activity, ET, etc.) fall into the third category.

Next, we overview the literature and examine the various types of arousal, valence, affective attitudes, and emotional and physiological states (AFFECT) recognition methods in more detail. A summary of the outcomes is provided in Table 3.3.

Table 3.3. An overview of studies on arousal, valence, affective attitudes, and emotional and physiological states (AFFECT) recognition.

Stimulus	AFFECT	Methods	Reference
Recording of dances, video	Anger, fear, grief, and joy	GSR, eye movement (Figure 3.6)	[334]
Neurophysiological research from 2009 to 2016	Overview of the existing works in emotion	EEG	[335]
Affective stimuli	Surprise, disgust, anger, fear, happiness, and sadness	EEG	[336]
The visual stimuli, black and white photographs of 10 different models	Happy, sad	MEG	[337]
20 face actors, each displaying happy, neutral, and fearful facial expressions	Happy, neutral, fearful	MEG	[338]
Task-irrelevant emotional and neutral pictures	Pleasant, unpleasant	TMS	[339]
A subset of music videos from the Dataset for Emotions Analysis using Physiological signals (DEAP) dataset	Valence, arousal	fNIRS, EEG	[340]
Emotional faces for the emotion perception test	Pleasant, unpleasant, neutral	fMRI	[341]
-	Stress	PET	[342]
Video	Happiness, sadness, disgust, anxiety, pleasant, unpleasant, neutral	PET	[343]
Facial Emotion Selection Test (FEST)	Positive, negative	DTI	[344]
Real time biometric-emotional data collection from depersonalized passersby	Neutral, happiness, sadness, surprised, anger, scared, valence, arousal, disgust, interest, confusion, boredom	Emotional, Affective and Biometrical States Analytics of the Built Environment Method	[345]
Real time data collection	Happy, sad, angry, surprised, scared, disgusted, valence, arousal	Method of an Affective Analytics of Demonstration Sites	[346]
Scanning a human-centered built environment, real time data collection	Sadness, disgust Happiness, anger, fear surprise, boredom, neutral, arousal, valence, confusion, and interest	Affect-Based Built Environment Video Analytics	[347]
Remote real time data	Happiness, arousal, valence	Video Neuro-advertising Method	[93,348]
Smelling strips	Happy, radiant, well-being, soothed, energized, romantic, sophisticated, sensual, adventurous, comforted, amused, interested, nostalgic, revitalized, self-confident, surprised, free, desirable, daring, excited	IRT	[349]
Text	Positive and negative valence	Eye tracking (ET)	[350]
21 video fragments	High/low arousal, high/moderate/low valence	Eye tracking (ET)	[351]
Crypts	Feelings, tendermindedness, warmth, trust and positive emotions	Iris	[294]
The simulation environment	Wellness/malaise, relaxation/tension, fatigue/excitement	Retina	[352]
Colors	Surprise, Happiness, Disgust, Anger, Sadness and Fear	Blinking, heart rate	[353]
HSV color space	Fear, disgust, surprise, joy, anticipation, sadness, anger, trust	Blinking	[354]
Review of existing novel facial expression recognition systems	Anger, disgust, fear, happiness, sadness, surprise and neutral	Facial expression recognition	[355]
Destination promotional videos	Pleasure, arousal	Skin conductance, facial electromyography	[355]

Games scenario between a human user and a 3D humanoid agent	Arousal, valence, fear, frustrated, relaxed, joyful, excited	Electromyography, skin conductance	[356]
Dramatic film	Real-time emotion estimation	EEG, Heart Rate, Galvanic Skin Response	[357]
Emotional state of a driver while in an automobile	Happy, anger	Electrocardiogram (ECG)	[358]
Music	Pleasure, unpleasure	Heart and respiratory rates	[359]
Trier Social Stress Test	Stress, relax	Respiratory rate and heart rate	[360]
Voice- and speech-pattern analysis	Normal, angry, panic	Voice, speech	[361]
Implicit anxiety-related self-concept	Shame, guilt proneness, anxiety, anger-hostility	Implicit Association Test	[362]
Case studies	Self-control, happiness, anger, fear, sadness, surprise, and anxiety	Mouse Tracking	[302]
Academic study website	Neutral, positive, negative	Mouse Tracking	[363]
Motor improvisation task	Joy, sadness, and a neutral control emotion	Signature	[364]
-	Neutral, joy, anger, sadness	Gait	[365]
Text	Neutral, joy, surprise, fear, anger, disgust, sadness	Lip Movement	[366]
Dataset	Anger, disgust, fear, happiness, sadness, and surprise	Keystroke dynamics	[367]
Recall of past emotional life episodes	Valence, arousal	EEG	[368]
Physiological emotional database for real participants	Valence, arousal	Peripheral signals, EEG	[369]
Data from wearable sensors on subject's skin	High/neutral/low arousal and valence	ECG, EEG, electromyography (EMG)	[370]
Real time heartbeat rate and skin conductance	High/low arousal and valence	GSR, temperature, breathing rate, blood pressure, EEG	[371]
Multimedia contents based on IPTV, mobile social network service, and blog service	Pleasant, unpleasant	GSR, skin temperature, heart rate	[372]
Stress stimuli	High/low valence, high/low arousal	GSR, heart rate, ECG	[373]
CCD-capture human face, measure user's physiological data	Pleasant, unpleasant	GSR, photoplethysmogram (PPG), skin temperature	[374]
Music videos	High/low arousal, high/low valence	EEG	[375]
Detect the current mood of subjects	High/low arousal, high/low valence	EEG	[376]
DEAP database	Joy, fear, sadness, relaxation	EEG, back-propagation neural network	[377]
Hjorth features, statistics features, high order crossing features	Happy, calm, sad, scared	EEG, CNN, LSTM recurrent neural networks	[378]
Thirty film clips	Serenity, hope, joy, awe, love, gratitude, amusement, interest, pride, inspiration	EEG	[379]
Transcendental meditation	Ecstasy	EEG	[380]
Ultimatum game	Acceptance	EEG	[381]
Driving a car equipped	Trust	EEG, GSR	[382]
12 prototypes that were designed based on the framework of diachronic opposite emotions	Amazement, happiness	EEG, SD tests	[383]
Audio-visual emotion database	Pleasure, irritation, sorrow, amazement, disgust, and panic	-	[384]
Sleep measures	Grief	EEG	[385]
Real episodes from subjects' lives	Grief, anger	EEG	[386]

Virtual environment consisting of three types of cues	Pensiveness relaxation, non-arousal, stress	EEG	[387]
Patient with dramatic, episodic, seizure-related rage and violence	Rage and aggression	Video-EEG recording	[388]
DEAP database	Rage	EEG, multiclass-common spatial patterns	[389]
Brainstem auditory evoked potentials	Rage and self-injurious behavior	EEG, brainstem evoked potentials (BAEPs)	[390]
Acoustic annoyance	Annoyance	EEG	[391]
70 dBA white noise and pure tones at 160 Hz, 500 Hz and 4000 Hz	Annoyance	EEG	[392]
30 pictures from International Affective Picture System	Neutral, joy, sadness anger, surprise, valence (positive and negative), contempt, fear, disgust	EEG	[393]
Movie clips	Anger, fear, anxiety, disgust, contempt, joy, happiness	EEG	[394]
Emotional factor	Aggressiveness	EEG	[395]
Buss–Durkee questionnaire	Aggressiveness	EEG	[396,397]
Reward anticipation	Anticipation	EEG	[398]
Structured Clinical Interview for DSM-IV	Anticipation	EEG, fMRI	[399]
DEAP database	High/low valence and arousal	EEG	[400–405]
Reading and reflection task about Muslims	Disapproval	EEG, ANOVA	[406]
Simulated train driving	Fatigue and distraction	EEG, Multi-type feature extraction, CatB-FS algorithm	[407]
Faces (the participant’s own face, the face of a stranger, and a celebrity’s face)	Admiration	EEG, 18-Items Narcissistic Admiration and Rivalry Questionnaire	[408]
Presentation of 12 virtual agents	Acceptance	EEG and the virtual agent’s acceptance questionnaire (VAAQ)	[409]
English prosocial and opposite antisocial words in a sentence	Approval and disapproval	EEG, ANOVA	[410]
Data from Facebook comments	Enjoyment (peace and ecstasy), sadness (disappointment and despair), fear (anxiety and terror), anger (annoyance and fury), disgust (dislike and loathing) surprise, other (neutral)	Natural language processing (NLP); convolutional neural network (CNN) and long short-term memory (LSTM); Random Forest and support vector machine (SVM), standard Vietnamese social media emotion corpus (UIT-VSMEC)	[411]
Video clips	Pride, love, amusement, joy, inspiration, gratitude, awe, serenity, interest, hope	fNIRS	[412]
User’s interaction with a web page	Arousal/valence anxiety and aggressiveness	Facial expressions, Facial Action Coding System, specialized questionnaires	[413]
An investment game that uses artificial agents	Trust	EEG	[285]
Simulated autonomous system	Trust	EEG and GSR	[382]
The iCV-MEFED dataset. For each subject in the iCV-MEFED dataset, five sample images were captured.	Neutral, angry, contempt, happy, happily surprised, surprisingly fearful, surprised	Facial emotion recognition (Figure 3.7),	[414]

		CNN; Inception-V3 network	
Dynamic emotional facial expressions were generated by using FACSGen	Contempt, disgust, sadness, neutral	ANOVA, Participants completed emotion scales	[415]
Film clips	Pride, love, amusement, joy, inspiration, gratitude, awe, serenity, interest, hope	EEG, multidimensional scaling (MDS), intra-class correlation coefficients (ICCs)	[379]
Simulated driving system	Vigilance	EEG and forehead electrooculogram (EOG), eye tracking (Figure 3.6)	[416]
DEAP dataset	Optimism, pessimism, calm	EEG, CNN	[166]
Music	Relaxing-calm, sad-lonely, amazed-surprised, quiet-still, angry-fearful, happy-pleased	Binary relevance (BR), label powerset (LP), random k-label sets (RAKEL), SVM	[417]
Music	Happiness, love, anger and sadness	EEG, SVM, Multi-Layer Perceptron (MLP), and K-nearest Neighbor (K-NN)	[418]
Three sets of pictures	Anticipation	Facial emotions (Figure 3.7), action observation network (AON), two-alternative forced-choice procedure, Reaction times (RT), ANOVA	[419]
Individuals enacted aggressive actions, angry facial expressions and other non-aggressive emotional gestures	Aggressive actions and anger	Kinect infrared sensor camera: hand movement, body posture, head gesture, face (Figure 3.9), and speech. SVM and the rule-based features	[420]
Images of faces from the Ekman and Friesen series of Pictures of Facial Affect	Grief	Facial Expression of Emotion Test (Figure 3.7)	[421]
Music	Soothing, engaging, annoying and boring	FBS fusion of three-channel forehead biosignals, ECG	[422]
Films	Amusement, anger, grief, and fear	Fingertip blood oxygen saturation (OXY), GSR, HR	[423]
Polish emotional database, database consists of 12 emotional states	Rage, anger, annoyance, grief, sadness, pensiveness, ecstasy, joy, serenity, terror, fear, apprehension	Speech, KNN Algorithm	[424]
Video	Nonverbal behaviors signaling dominance and submissiveness	Implicit association test, body language, MANOVA	[425]
Music	High/low valence, high/low arousal	EMG, EEG, HRV, GSR	[426]
The external auditory canal is warmed or cooled with water or air	High and low arousal	Electrodermal activity (EDA), HRV, activity tracker, EMG, SKT	[427]
After-image experiments, direct visual observation, photography of the eyes, recording of the corneal reflex	High/low valence, high/low arousal	GSR, EMG	[428]
Assessment of emotional states experienced by racing drivers	Sadness, fear, anger, surprise, happiness, and disgust	ECG, EMG, respiratory rate, GSR	[429]

Dataset of standardized facial expressions	Happiness, sadness, anger, disgust, fear, and surprise	Facial Action Coding (FC)	[430]
Neighbor sounds	Arousal, valence	fEMG, heart rate (HR), electrodermal activity (EDA)	[431]
Audio visual stimuli	Joy, sadness, anger, fear	ECG	[432]
Playing with the infant to elicit laughter	Joy	Skin temperature (SKT)	[433]
Two different kinds of video inducing happiness and sadness	Happiness, sadness	Photoplethysmography (PPG), skin temperature (SKT)	[434]
International Affecting Picture System (IAPS) pictures	Joy, sadness, fear, disgust, neutrality, amusement	Electromyogram signal (EMG), respiratory volume (RV), skin temperature (SKT), skin conductance (SKC), blood volume pulse (BVP), heart rate (HR)	[435]
Movie and music video clips	Arousal, valence	Electrooculogram (EOG), electrocardiogram (EEG) trapezium electromyogram (EMG)	[436]
Audio/visual	Anger, happiness, sadness, pleasure	GSR, EMG, respiratory rate, ECG	[437]

The combination of several different approaches to the recognition and classification of emotional state (also known as multimodal emotion recognition) is currently a research area of great interest, especially since the use of different physiological signals can provide huge amounts of data. Since each physiological can make a significant impact on the ability to classify emotions [333]. Table 3.3 presents an overview of studies related to the recognition of valence, arousal, emotional states, physiological states, and affective attitudes (affect). A brief overview of some of these studies follows.

Many scientists and practitioners have earned acclaim and honor for their research in areas such as diagnostics, large-scale screening, analysis, monitoring, and categorizations of people by COVID-19 symptoms. Their work relied on early warning systems, wearable technologies, the Internet of Medical Things, IoT based systems, biometric monitoring technologies, and other tools that can assist in the COVID-19 pandemic. Javaid et al. [438] review how different industry 4.0 technologies (e.g., AI, IoT, Big data, Virtual Reality, etc.) can help reduce the spread of disease. Kalhori et al. [439] and Rahman et al. [440] discuss the digital health tools to fight COVID-19. Various sensors and mobile devices to detect the disease, reduce its spread, and measure different symptoms are also widely discussed. Rajeesh Kumar et al. [441] propose a system to identify asymptotic patients using IoT-based sensors, measuring blood oxygen level, body temperature, blood pressure, and heartbeat. Stojanović et al. [442] propose a phone headset to collect information about respiratory rate and cough, Xian et al. [443] present a portable biosensor to test saliva. Chamberlain et al. [444] presented distributed networks of Smart thermometers track COVID-19 transmission epicenters in real-time.

Neurotransmitters (NT) are billions of molecules constantly needed to keep human brains functioning. They are chemical messengers that carry, balance, and boost signals travelling between nerve cells (neurons) and other cells in the body. Many different psychological and physical functions can be affected by these chemical messengers, including fear, appetite, mood, sleep, heart rate, breathing rate, concentration and learning [445]. Lim [251] has also outlined new ways of exploiting neuromarketing research to achieve a better understanding of the brain and neural activity and hence advance marketing science. Lim [251] highlighted three main aspects: (i) antecedents (such as the product, physical evidence, the price of the product, the place where everything is happening, promotion, the process involved, people); (ii) the process; and (iii) the consequences for the target market (behavioral outcomes before, during and after the act of buying) and the marketing organization (visits, sales, awareness, equity). Agarwal and Xavier [253] described the most popular neuromarketing tools, including event-related potential (ERP) (P300), EEG, and fMRI, and explained how these tools could be applied in marketing. A business and marketing article [256] lists the three categories of neuroscientific techniques that are applied in business and advertising research (Table 3.1 and Table 3.2, Figure 3.1) as follows:

1. Methods that monitor what is happening in the brain (i.e., the physiological activity of the CNS);
2. Methods that record what is happening elsewhere in the body (i.e., the physiological activity of the PNS);
3. Other techniques for tracking behavior and conduct.

Ganapathy [260] groups neuromarketing tools into three categories (Table 3.1 and Table 3.2). Farnsworth [258] gives information that can be essential when deciding on the best neuromarketing method or technique to help stakeholders understand research methods relating to human behavior at a glance, while Saltini [264] gives a short list of neuromarketing tools (Table 3.1 and Table 3.2). A system developed by CoolTool [257] allows several neuromarketing tools to be used separately or combined.

Although individual neuroscientific tools for neuromarketing, neuroeconomics, neuromanagement, neuro-information systems, neuro-industrial engineering, products, services, call centers have been developed by many researchers (for example [111,251,253,254,255,256,257,258,259,260,261,262,263,264,265,266,267,268,269,270,293,298, 299,300,303,309,311,312,328,446,447,448], a review and analysis of the complete range of tools used in neuromarketing, neuroeconomics, neuromanagement, neuro-information systems, neuro-industrial engineering, products, services, call centers research has not yet been carried out. Thorough examinations of the range of research tool alternatives that are available for neuroscience are also often missing from research in this area. We have therefore compiled a complete list of neuroscience techniques for neuromarketing, neuroeconomics, neuromanagement, neuro-information systems, neuro-industrial engineering, products, services, call centers. Humans experience emotions and their associated feelings (e.g., gratitude, curiosity, fear, sadness, disgust, happiness, and pride) on a daily basis. Yet, in case of affective disorders such as depression and anxiety, emotions can become destructive. Thus the focus on understanding emotional responsiveness is not surprising in neuroscience and psychological science [449]. So neuroscience techniques analyze emotional, affective and physiological states tracking neural/electrical activity [335,336,337,338,339,340,450,451] or neural/metabolic activity [341,342,343,344,349,447,452,453] within the brain. This is also presented in Table 3.3.

For example, neuromarketing techniques can complement business decisions and make them more profitable, using the automated mining of opinions, attitudes, emotions and expressions from speech, text, emotions, neuron activity and other database-fed sources. Advertisements that are adjusted based on such information can engage the target audience more effectively and make a better impact on the audience, and this may translate into better sales and higher margins. In an attempt to enhance corporate branding and advertising routines, various factors have been studied, such as emotional appeal and sensory branding, to ensure that companies deliver the right message and that customers perceive the right message [171].

Affect recognition is widely used in gaming to create affect-aware video games and other software. Alhargan et al. [454] present affect recognition in an interactive gaming environment using eye-tracking. Szwoch and Szwoch [455] give a review of automatic multimodal affect recognition of facial expressions and emotions. Krol et al. [456] combined eye-tracking and brain–computer interface (BCI) and created a completely hands-free game Tetris clone where traditional actions (i.e., block manipulation) are performed using gaze control. Elor et al. [457] measure heart rate and galvanic skin response (GSR) with Immersive Virtual Reality (iVR) Head-Mounted Display (HMD) systems paired with exercise games to show how exercise games can positively affect physical rehabilitation.

Stress is a relevant health problem among students, so Tiwari, Agarwal [458] present a stress analysis system to detect stressful conditions of the student, including measurement of GSR and electrocardiogram (ECG) data. Nakayama et al. [459] suggest measuring heart rate variability as a method to evaluate nursing students stress during simulation to provide a better way to learn.

A literature review can reveal the most popular types of traditional and non-traditional neuromarketing methods. According to Sebastian [111], focus groups are one of the more traditional marketing methods, while various neuroscience techniques have also been applied to record the metabolic activity of the body and the electrical activity of the brain (transcranial magnetic stimulation (TMS), electroencephalography (EEG), functional magnetic resonance imaging, magnetoencephalography (MEG), and positron-emission tomography (PET)).

Electronic platforms are not the only possibility for non-traditional marketing, and Tautchin and Dussome [460] believe that traditional media can also be reimagined in new forms, such as guerrilla marketing, local displays, vehicle wraps, scaffolding, and even bubble cloud ads or aerial banners. In addition to giving high-quality feedback data, non-traditional techniques can also help in the evaluation of business decisions and conclusions [328].

Based on factors such as skin texture, gender, and SC, wearable biometric GSR sensors could be used to identify whether a person is in a sad, neutral, or happy emotional state. To understand marketing strategies better and to improve ads, other biometric sensors such as pulse oximeters and health bands could be used in the future to make automated predictions of emotions [461]. The galvanic skin response (GSR) method has an important limitation—it does not provide information on valence. The usual way to address this issue is to use other emotion recognition methods. They provide additional details and thus enable detailed analysis. Table 3.3 lists studies where GSR is used to measure emotions.

Eye tracking (ET) is used to record the frequencies of choices; sensor features are extracted and matched with certain preference labels to determine mutual dependences and to discover which brain regions are active when a certain choice task is performed. High values for alpha, beta and theta waves have been reported in the occipital and frontal brain regions, with a high degree of synchronization. A hidden Markov model is a popular tool for time-series data modeling, and researchers have successfully used this approach to build brain–computer-interface tools with EEG signals, counting mental task classification, medical applications and eye movement tracking [462].

A classification model based on SVM architecture, developed by Lakhan et al. [463], can predict the level of arousal and valence in recorded EEG data. Its core is a feature extraction algorithm based on power spectral density (PSD).

Multimodal frameworks that combine several modalities to improve results have recently become popular in the domain of human–computer interaction. A combination of modalities can give a more efficient user experience since the strengths of one modality can offset the weaknesses of another and the usability can be increased. These systems recognize and combine different inputs, taking into account certain contextual and temporal constraints and thus facilitating interpretation. Kong et al. [464] created a way of using two different sensors and calibrating them to achieve simultaneous gesture recording. Hidden Markov Model (HMM) was used for all single- and double-handed gesture recognition. Multimodality means that several unimodal solutions are combined into a system, meaning that multiple solutions can be combined into a single best solution using optimization algorithms [464].

The automatic emotion recognition system proposed by El-Amir et al. [465] uses a combination of four fractal dimensions and detrended fluctuation analysis, and is based on three bio-signals, GSR, EMG, and EEG. Using two emotional dimensions, the signals were passed to three supervised classifiers and assigned to three different emotional groups, with a maximum accuracy for the valence dimension of 94.3% and a maximum accuracy for the arousal dimension of 94%. This approach is based on external signals such as facial expressions and speech recognition, which means that it is simple and that no special equipment is required. The limitations of this approach are that emotions can be faked, and that these types of recognition methods fail with disabled people and people with certain diseases. Other approaches are based on electromyography, ECGs, SC, EEGs, and other physiological signals that are spontaneous and cannot be consciously controlled [465].

Plassmann et al. [466] as well as Perrachione and Perrachhione [467] carried out exciting studies in an attempt to determine how marketing stimuli lead to buying decisions. They applied neurosciences to marketing in order to create better models and to understand of how a buyer's brain and emotions operate. Gruter [468] states that a wide range of techniques and tools are used to measure consumer responses and behavior. Three approaches that are used in neuromarketing can give access to the brain: input and output models, internal reflexes, and external reflexes.

Leon et al. [469] present a real-time recognition and classification method based on physiological signals to track and detect changes in emotions from a neutral state to either a positive or negative (i.e., non-neutral) state. They used the residual values of auto-associative neural networks and the statistical probability ratio test in their approach. When the proposed methodology was implemented to process a recognition level of 71.4% was achieved [469]. Monajati et al. [470] also investigated the recognition of negative emotional states, using the three physiological signals of galvanic skin response, respiratory rate and heart rate. Fuzzy-ART was applied to analyze the physiological responses and to recognize negative emotions. An overall accuracy of 94% was achieved in determining which emotions were negative as opposed to neutral [470].

Andrew et al. [471] described investigations of brain responses to modern outdoor advertising, focusing on memorability, visual attention, desirability, and emotional intensity. They also described ways in which the latest imaging tools and methods could be applied to monitor subconscious emotional responses to outdoor media in many forms, from multisensory advertising screens to simple paper posters. Andrew et al. [471] explained the cognitive processes behind their success, not solely in the context of the advertising to which people are typically exposed outside their homes, but also in the broader digital world. Andrew et al. findings have fundamental implications for media campaign planning, design, and development, identifying the possible role of outdoor advertising compared to other media, and possible ways of combining different media platforms and making them work for the benefit of advertisers.

Kaklauskas et al. [472] integrated Damasio's somatic marker hypothesis with biometric systems, multi-criteria analysis techniques, statistical investigation, a neuro-questionnaire, and intelligent systems to produce the INVAR neuromarketing system and method. INVAR can measure the efficiency of both a complete video advertisement and its separate frames. This system can also determine which frames make viewers interested, confused, disgusted, happy, scared, surprised, angry, sad, bored, or confused; can identify the utmost positive or negative video advertisement; measure the consequence of a video advertisement on long-term and short-term memory; and perform other functions.

Lajante and Ladhari [473] applied peripheral psychophysiology measures in their research, based on the assumption that measures of emotion and cognition such as SC responses and facial EMGs could make a significant contribution to new ideas about consumer decision making, judgments and behaviors. These authors believe that their approach can help in applying affective neuroscience to the field of consumer services and retailing.

Michael et al. [474] aimed to understand the ways in which unconscious and direct cognitive and emotional responses underlie preferences for particular travel destinations. A 3×5 factorial design was run in order to better understand the unconscious responses of consumers to possible travel destinations. The factors considered in this study were the type of stimulus (videos, printed names, and images) and the travel destination (New York, London, Hong Kong, Abu Dhabi, and Dubai). ET can provide reliable tracking of cognitive and emotional responses over time. The authors suggested that decisions on travel destinations have both a direct and an unconscious component, which may affect or drive overt preferences and actual choices.

Harris et al. [448] investigated ways of measuring the effectiveness of social ads of the emotion/action type, and then of making these ads more effective using consumer neuroscience. Their research offers insights into changes in behavioral intent brought about by effective ads and gives an improved understanding of ways of making good use of social messages regarding a certain action, challenge or emotion that may be needed to help save lives. It can also reduce spending on social marketing campaigns that end up being ineffectual.

Libert and Van Hulle [475] argue that the development of economically practicable solutions involving human–machine interactions (HMI) and mental state monitoring, and neuromarketing that can benefit severely disabled patients has put brain–computer interfacing (BCI) in the spotlight. The monitoring of a customer’s mental state in response to watching an ad is interesting, at least from the perspective of neuromarketing managers. The authors propose a method of monitoring EEGs and predicting whether a viewer will show interest in watching a video trailer or will show no interest, skipping it prematurely. They also trained a k-nearest neighbor (kNN), a support vector machine (SVM), and a random forest (RF) classifier to carry out the prediction task. The average single-subject classification accuracy of the model was as follows: 73.3% for viewer interest and 75.803% for skipping using SVM; 78.333% for viewer interest and 82.223% for skipping using kNN; and 75.555% for interest and 80.003% for skipping using RF.

Jiménez-Marín et al. [476] showed that sensory marketing tends to accumulate user experiences and then exploit them to bring the users closer to the product they are evaluating, thus motivating the final purchase. However, several issues need to be considered when these techniques are applied to reach the desired outcomes, and it is important to be aware of recent advances in neuroscience. The authors explore the concept of sensory marketing, pointing out its possibilities for application and its various typologies.

Cherubino et al. [477] highlighted the new technological advances that have been achieved over the last decade, which mean that research settings are now not the only scenarios in which neurophysiological measures can be employed and that it is possible to study human behavior in everyday situations. Their review aimed to discover effective ways to employ neuroscience technologies to gain better insights into human behavior related to decision making in real-life situations, and to determine whether such applications are possible.

Monica et al. [478] explored the cognitive understanding and usability of banking web pages. They reviewed the theoretical literature on user experience in online banking services research, with a focus on ET as a research tool, and then selected two Romanian banking websites to study consumer attention, while consumers were navigating the sites, and memory, after their visits. The research findings showed that the layout and information display can make web pages more or less usable and can have an effect on cognitive understanding.

Singh et al. [328] discussed various methods of feature extraction for facial emotion detection. The algorithm they proposed could detect a total of six facial emotions, using a fuzzy rule-based system. During their experiment, neurometrics were recorded using a system comprising MegaMatcher software, Grove-GSR Sensor V1.2, and a 12-megapixel Hikvision IP camera. The participants were asked to watch a set of video ads for a range of well-known cosmetic products and wore SC sensors and sat in front of a camera that monitored their responses. Singh et al. [328] analyzed the cognitive processes of university students in relation to advertising and compliance with the code of self-regulation. A quantitative and qualitative methodology based on facial expressions, ET techniques and focus groups was used for this purpose. The results suggested that online game operators could be clearly identified. A high interaction of the public within the exhibition of supposed skills of the successful player and welcome bonuses also exists, and there was shown to be a lack of knowledge of the visual elements of awareness, a trivialization of compulsive gambling, and sexist attitudes towards women attracting public attention. A positive public attitude towards gaming was also observed by Singh et al. [328]; it was seen as a healthy form of leisure that was compatible with family and social relationships.

Goyal and Singh [461] proposed the use of research-based approaches for the automatic recognition of human affective facial expressions. These authors created an intelligent neural network-based system for the classification of expressions from extracted facial images. Several basic and specialized neural networks for the detection of facial expressions were used for image extraction.

Electromyography measures and assesses electric potentials in muscle cells. In medical settings, this method is used to identify nerve and muscle lesions, while in emotion recognition this method is used to look for correlations between emotions and physiological responses. Most EMG-based studies examine facial expressions drawing on the hypothesis that facial expressions take part in emotional responses to various stimuli. The hypothesis was first proposed by Ekman and Friesen in 1978; they described the relationships between basic emotions, facial muscles, and the actions they trigger. Morillo et al. [479] used low-cost EEG headsets and applied discrete classification techniques to analyze scores given by subjects to individual TV ads, using artificial neural networks, the C4.5 algorithm and the Ameva discretization algorithm. A sample of 1400 effective advertising campaigns was studied by Pringle et al. [480], who determined that promotions with exclusively emotional content achieved around double (31% vs. 16%) success as those with only rational content, while compared to campaigns with mixed emotional and rational content, the exclusively emotional campaigns performed only slightly better (31% vs. 26%).

According to Takahashi [481] some of the available emotion recognition systems in facial expressions or speech look at several emotional states such as fear, teasing, sadness, joy, surprise, anger, disgust, and neutral. Takahashi [481] investigated emotion recognition based on five emotional states (fear, anger, sadness, joy, and relaxed).

The authors [353,355,356,357,359,360,371,372,373,374] carried out an in-depth analysis of how blood pressure, SC, heart rate and body temperature depend on stress and emotions. Figures suggest that work-related stress costs the EU countries at least EUR 20 billion annually. Stress experienced at work can cause anxiety, depression, heart disease and increased chronic fatigue which can have a considerable negative impact on creativity, competitiveness and work productivity.

Research worldwide shows that people exposed to stress can experience higher blood pressure and heart rate. Light et al. [482] analyzed cases of daily elevated stress levels and looked at the effects on fluctuations in systolic and diastolic blood pressure. Gray et al. [483] investigated how systolic and diastolic blood pressure can be affected by psychological stress, while Adrogué and Madias [484] described the effects of chronic, emotional and psychological stress on blood pressure. The unanimous conclusion of research in this area is that diastolic and systolic blood pressure and heart rate depend on stress and can increase depending on the level of stress.

Blair et al. [485] analyzed the effect of stress on heart rate and concluded that heart rate rises sharply within three minutes of the onset of stress and starts to fall only after another five to six minutes. Gasperin et al. [486] concluded that high blood pressure was affected by chronic stress. A number of studies have shown that patients with heart rates higher than 70 beats per minute are more likely to develop cardiovascular diseases and to die from them; tests show that a rapid heartbeat increases the risk of heart attack by 46%, heart insufficiency by 56% and death by 34%.

Sun et al. [487] proposed an activity-aware detection scheme for mental stress. Twenty participants took part in their experiment, and galvanic skin response, ECG, and accelerometer data were recorded while they were sitting, standing, and walking. Baseline physiological measurements were first taken for each activity, and then for participants exposed to mental stressors. The accelerometer was used to track activity, and the data gave a classification accuracy between subjects of 80.9%, while the 10-fold cross-validation accuracy for the classification of mental stress reached 92.4%. This study focused on physiological signals for example photoplethysmography and galvanic skin response. The neural network configurations (both recurrent and feed forward) were examined and a comprehensive performance analysis showed that the best option for stress level detection was layer recurrent neural networks. For a sample of 19 automotive drivers, this evaluation achieved an average sensitivity of 88.83%, a precision of 89.23% and a specificity of 94.92% [488].

Palacios et al. [489] applied a new process involving two databases containing utterances under stress by men and women. Four classification methods were used to identify these utterances and to organize them into groups. The methods were then compared in terms of their final scores and quality performance.

Fever occurs when the body's thermoregulatory set point increases, and many findings suggest that the rise in core temperature induced by psychological stress can be seen as fever. A fever of psychological origin in humans might then be a result of this mechanism [490].

Wu and Liang [491] presented a training and testing procedure for emotion recognition based on semantic labels, acoustic prosodic information and personality traits. A recognition process based on semantic labels was applied, using a speech recognizer to identify word sequences, and HowNet, a Chinese knowledge base, was used as the source for deriving the semantic word sequence labels. The emotion association rules (EARs) of the word sequences were then mined by applying a text-based mining method, and the relationships between the EARs and emotional states were characterized using the MaxEnt model. In a second approach based on acoustic prosodic information, emotional salient segments (ESSs) were detected in utterances and their prosodic and acoustic features were extracted, including pitch-related, formant, and spectrum attributes. The next step was the construction of base-level classifiers using SVM, gaussian mixture models (GMM) and MLP, which were then combined (using MDT) by selecting the most promising option for emotion recognition based on acoustic prosodic information. The process ended when the final emotional state was determined. A weighted product fusion method was applied to combine the outputs produced by the two types of recognizers. The personality traits of the specific speaker, as determined from the Eysenck personality questionnaire, were then taken into consideration to examine their impact and personalize the emotion recognition scheme [491].

A hybrid analysis method for online reviews proposed by Nilashi et al. [492] allows for the ranking of factors affecting the decisions of travelers in their choice of green hotels with spa services. This method combined text mining, predictive learning techniques and multiple criteria decision-making methods, and was proposed for the first time in the context of hospitality and tourism, with an emphasis on green hotel customer grouping based on online customer feedback. Nilashi et al. [492] used the latent Dirichlet analysis method to analyze textual reviews, a self-organizing map for cluster analysis, the neuro-fuzzy method to measure customer satisfaction, and the TOPSIS method to rank the features of hotels. The proposed method was tested by analyzing travelers' reviews of 152 Malaysian hotels. The findings of this research offer an important method of hotel selection by travelers, by means of user-generated content (UGC), while hotel managers can use this approach to improve their marketing strategies and service quality.

A neuromarketing method for green, energy-efficient and multisensory homes, proposed by Kaklauskas et al. [493], can be used to determine the conditions that are required. The multisensory dataset (physiological and emotional states) collected as part of this research contained about 200 million data points, and the analysis also included noise pollution and outdoor air pollution (volatile organic compounds, CO, NO2, and PM10). This article discussed specific case studies of energy-efficient and green buildings as a demonstration of the proposed method. The results matched findings from both current and previous studies, showing that the correlation between age and environmental responsiveness has an inverse U shape and that age is an important factor affecting interest in eco-friendly, energy-efficient homes.

The VINERS method and biometric techniques developed by Kaklauskas et al. [494] for the analysis of emotional states, physiological reactions and affective attitudes were used to determine which locations are the best choice and then to show neuro ads of available homes offered for sale. Homebuyers were grouped into rational segments, taking into account consumer psychographics and behavior (happy, angry or sad, and valence and heart rate) and their demographic profiles (age, gender, marital status, children or no children, education, main source of income). A rational video ad for the respective rational segment was then selected. This study aimed to combine the somatic marker hypothesis, neuromarketing, biometrics and the COPRAS method, and to develop the VINERS method for use with multi-criteria analysis and the neuromarketing of the best places to live. The case study presented in the article demonstrated the VINERS method in practice.

Etzold et al. [495] examined the case of users booking appointments online, and the ways in which they interacted with the webpage interface and visualizations. The main point was to determine whether a new interface for online booking was easy to navigate and successful in attracting user attention. In this study, the authors particularly wanted to determine whether a new, more expensive customer website was seen as more user-friendly and supportive than the older, cheaper alternative. An empirical study was carried out by tracking users eye movements as they were navigating the existing website of Mercedes-Benz, a car manufacturer, and then a new, updated version of the same company's website. A total of 20 people were observed, and evaluations of their ET data suggested that the new service appointment booking interface could be further improved. Scan-paths and heatmaps demonstrated that the old website was superior [495].

In recent years, many different emotional values, such as the net emotional value (NEV), the service encounter emotional value (SEEVal), and others, have been analyzed. Attempts have been also made to put them into practice [496,497,498,499,500,501,502,503]. These studies are overviewed below. To calculate NEV, the average score for negative emotions (stressed, dissatisfied, frustrated, unhappy, irritated, hurried, disappointed, neglected) is subtracted from the average score for positive emotions (cared for, stimulated, happy, pleased, trusting, valued, focused, safe, interested, indulgent, energetic, exploratory). The average score obtained this way can be used to characterize a client's feelings about a service or a product [499]. A higher value of NEV indicates that the relationships forged by a business are more reliable. One advantage of the NEV is that it characterizes the total balance of a consumer's feelings related to products or services, and thus reveals the value drivers. The relationship between NEV and client satisfaction is linear [500].

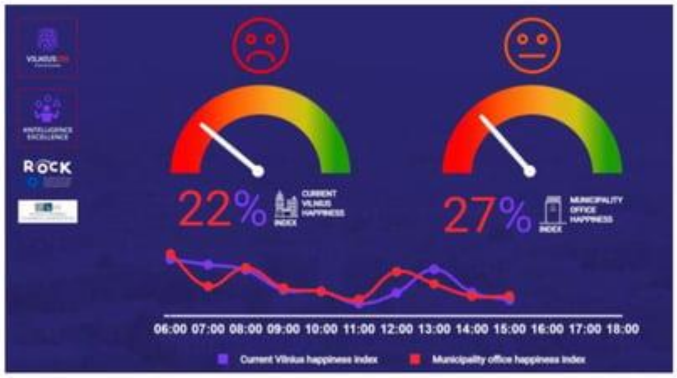
The NEV can be used to highlight both aspects that need to be improved, and those that are positive. Since the NEV is calculated based on a subtraction, the result may be either a negative or a positive number. The overall score can indicate what is happening with the client at an emotional level, and suggest ways to use this to gain competitive advantage [501].

The SEEVal is another measure proposed by Bailey et al. [504], and is the sum of the NEV experienced by the client and the NEV experienced by the product or service provider's employee. The client's end results linked to SEEVal are typically loyalty, satisfaction, pleasure, and voluntary benevolence [504]. The IGI Global Dictionary defines an emotional value as a set of positive moods (feeling good or being happy) resulting from products or services and contained in the value gain from the customers' emotional states or feelings when using the products or services (IGI Global Dictionary). Emotional value acts as a moderator, and has significant effects on the roles of social, functional, epistemic, conditional and environmental values [497].

Zavadskas et al. [505] examined data on potential buyers to analyze the hedonic value in one-to-one marketing situations. They used the neutrosophic PROMETHEE technique to examine arousal, valence, affective attitudes, emotional and physiological states (AFFECT), and argued that hedonic value is tied to several factors including customers' social and psychological data, client satisfaction, criteria of attractiveness, aesthetics, and economy, the sales site rental price, emotional factors, and indicators of the purchasing process. Their research showed that an analysis of the aforementioned data on potential buyers can make an important contribution to more effective one-to-one marketing. The case study cited in this work concerned two sites in Vilnius and intended to calculate the hedonic value of these sites during the Kaziukas Fair.

The ROCK Video Neuroanalytics and associated e-infrastructure were established as part of the H2020 ROCK project. This project tracked passers-by at ten locations across Vilnius. One of our outputs is the real-time Vilnius Happiness Index (Figure 3.10 and https://api.vilnius.lt/happiness-index, accessed on 5 September 2022). The project also involved a number of additional actions (https://Vilnius.lt/en/category/rock-project/, accessed on 5 September 2022).

(a)



(b)

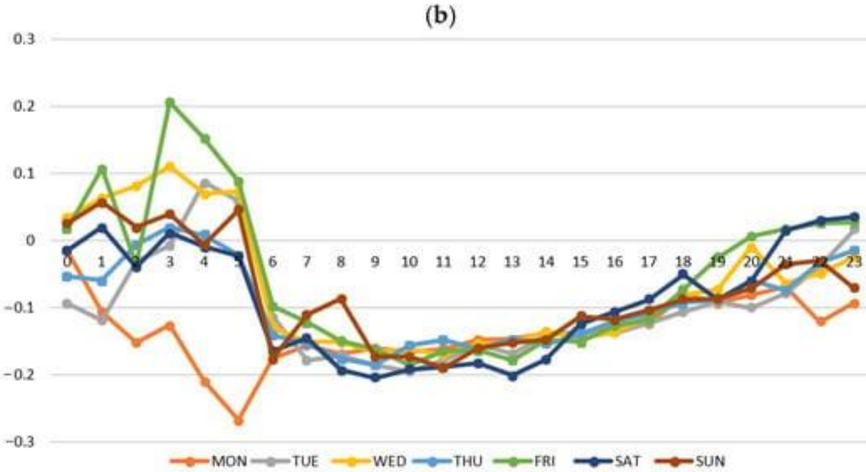


Figure 3.10. Real-time Vilnius Happiness Index (a) and the mean magnitudes of valence, by the hour, on weekdays (b).

The intensity of the most intense negative emotion (scared, disgusted, sad, angry) subtracted from the intensity of "happiness" equals valence [430]. This way the single score of valence combines both positive and negative emotions. Our pool of data comprised 208 million data points analyzed using SPSS Statistics, a statistical software suite. Figure 3.10b presents the average values of valence per hour on weekdays. Every hour, the changes of average valence among Vilnius passers-by were recorded. Valence was measured every second and these values were accumulated by weekdays (marked in the chart with specific colors) at 95% confidence intervals. The y-axis shows the average values of valence (which fluctuates between −1 to 1) for each full day, for seven days, and the x-axis shows the hour starting at midnight [348].

3.5. Users' Demographic and Cultural Background, Socioeconomic Status, Diversity Attitudes, and Context

Emotions are a means to engage in a relationship with others: Anger means that the person refuses to accept a specific treatment from others and expresses that they feel entitled to something more. Anger is expressed with the aim of influencing, controlling, and fixing the behavior of others [506].

Through emotions, people can adaptively respond to opportunities and demands they face around them [507,508,509]. When people face everyday stressors, stressful transitions, ongoing challenges, and acute crises, the adaptive function of emotions is evident in all of these situations. Emotions also depend on context [510]. This means that emotions are most effective when people express them in the situational contexts for which the emotions most likely evolved. In addition, they are specifically most likely to promote adaptation in such scenarios. The experience of anger, for instance, is adaptive because it motivates the focus of energies and the mobilization of resources toward an effective response. When a person expresses anger, adaptive mechanisms are also at work because it shows the person's willingness, and perhaps even ability, to defend themselves. Emotional responses are sensitive to contexts, and are therefore, an integral part of our ways to adapt to daily life and the environment [511].

The ability to modify emotion responses according to changing context may be an important element of psychological adjustment [510]. An individual's capacity to modify emotion responses taking into account the demands of changing contexts (i.e., environmental or interpersonal) is particularly relevant. This mechanism is known as emotion context sensitivity [511].

Cultural and gender differences in emotional experiences have been identified in previous research [512]. For instance, these authors used the Granger causality test to establish how a person's cultural background and situation affect emotion. The conclusions drawn by [513] propose a top-down mechanism where gender and age can impact the brain mechanisms behind emotive imagery, either directly or by interacting with bottom-up stimuli.

Cultural neuroscientists are studying how cultural traits such as values, beliefs, and practices shape human affective, emotional, and physiological states (AFFECT) and behavior. Hampton and Varnum [514] have reviewed theoretical accounts on how culture impacts internal experiences and outward expressions of emotion, as well as how people opt to regulate them. They also analyze cultural neuroscience research that investigates how emotion regulation varies in different cultural groups.

Thus far, differences between nations have largely been the focus in studies of culture in social neuroscience. Culture impacts more than just our behavior—it also plays a role in how we see and interpret the world [515]. For instance, socioeconomic factors such as education, occupation, and income have a significant impact on how a person thinks. In one study, working-class Americans were shown to exhibit a more context-dependent thought process, similar to the collectivist patterns seen in other countries. Individuals of a lower social class in terms of their socio-economic status agreed with contextual explanations of economic trends, broad social outcomes, and emotions [516].

Gallo and Matthews [517] looked at the indirect evidence that socioeconomic status is associated with negative emotions and cognition, and that negative emotions and cognition are associated with target health status. They also proposed a general framework for understanding the roles of cognitive–emotional factors, arguing that low socioeconomic status causes stress, and impairs a person's reserve capacity for managing it, thus heightening emotional and cognitive vulnerability.

Choudhury et al. [518] explore critical neuroscience, a field of inquiry that probes the social, cultural, political, and economic contexts and assumptions that form the basis for behavioral and brain science research.

Numerous studies have illustrated that depending on the specific demographic background, there are major differences between users' emotions, behavior, and perceived usability. According to Goldfarb and Brown [519], scientific research is characterized by racial, cultural, and socioeconomic prejudices, which lead to demographic homogeneity in participation. This in turn spurs inaccurate representations of neurological normalcy and leads to poor replication and generalization.

According to Freud, the unconscious is a depository for socially unacceptable ideas, wishes or desires, traumatic memories, and painful emotions that psychological repression had pushed out of consciousness [520]. HireVue, which is a global front-runner in AI technologies, is one of the top emotional AI companies that is now turning to biosensors that read non-conscious data in lieu of facial coding methods to measure emotions [521].

The ideas of what it means to have good relationships and to be a good person differ in different cultural contexts [522]. People's emotional lives are closely related to these different ideas of how people see themselves and their relationships: Emotions usually match the cultural model [523,524]. Therefore, rather than being random, cultural variation in emotions matches the cultural ideals of ways to be a good person and to maintain good relationships with other people [506].

Aside from being biologically driven, emotion is also influenced by environment, as well as cultural or social situations. Culture can constrain or enhance the way emotions are felt and are expressed in different cultural contexts, and it can influence emotions in other ways. Studies have consistently shown cross-cultural differences in the levels of emotional arousal. Eastern culture, for instance, is related to low arousal emotions, whereas Western culture is related to high arousal emotions [525]. Many findings in cross-cultural research suggest that decoding rules and cultural norms influence the perception of anger [526]. Scollon et al. [527] look at five cultures (Asian American, European American, Hispanic, Indian, and Japanese) to assesses the way emotions are experienced in these cultures. Pride shows the greatest cultural differences [527]. As emotions are fundamentally genetically determined, different ones are perceived in similar ways throughout most nations or cultures [528].

3.6. Results

The present article aims to bridge the affective biometrics and neuroscience gap in existing knowledge, in order to contribute to the overall knowledge in this area. We also aim to provide information on the knowledge gaps in this area and to chart directions for future research.

We conclude this review by discussing unanswered questions related to the next generation of AFFECT detection techniques that use brain and biometric sensors.

By performing text analytics of 21,397 articles that were indexed by Web of Science from 1990 to 2022, we examined the key changes in this area within the last 32 years. Scientific output relating to AFFECT detection techniques using brain and biometric sensors is steadily increasing. As this trend suggests, there has been continuous growth in the number of papers published in the field, with the total number of articles appearing between 2015 and 2021 nearing the total number of articles published over the previous 25 years (1990 to 2014). In light of the increasing commercial and political interest in brain and biometric sensor applications, this trend is likely to continue.

With ground-breaking emerging technologies and the growing spread of Industry 5.0 and Society 5.0, AFFECT should be analyzed by taking into account demographic and cultural background, socioeconomic status, diversity attitudes, and context. Advanced computational models will be needed for this approach.

Quite a few biometric and neuroscience studies have been performed in the world, where AFFECT detection takes into account demographic and cultural background (age, gender, ethnicity, race, major diagnoses, and major medical history); socioeconomic status (education, income, and occupation); diversity attitudes; and context. Yet, to the best of our knowledge, none of the technologies available in the world offer AFFECT detection that incorporates political views, personality traits, gender, race, diversity attitudes, and cross-cultural differences in emotion.

Sometimes confusion exists in the spirit of some research about physiological effects due to emotional reactions and biometric patterns with regard to individual identification. To resolve this confusion, we analyze only physiological effects caused by emotional reactions (i.e., second generation biometrics; Section 3.3) in the part of the review discussing biometrics. Biometric patterns for individual identification are not analyzed in this research.

Human emotions can be determined by physiological signals, facial expressions, speech, and physical clues, such as posture and gestures. However, social masking—when people either consciously or unconsciously hide their true emotions—often renders the latter three ineffective. Physiological signals are therefore often a more accurate and objective gauge of emotions [529]. For instance, researchers [530,531] performed many studies to analyze physiological signals and unconscious emotion recognition. Nonetheless, our years of research experience have proven that in public spaces, facial expressions, speech, and physical clues, such as posture and gestures, are much more convenient and effective.

Emotion recognition can be more accurate when human expressions are analyzed looking at multimodal sources such as texts, physiological signals, videos, or audio content [532]. Integrated information from signals such as gestures, body movements, speech, and facial expressions helps detect various emotion types [533]. Statistical methods, knowledge-based techniques, and hybrid approaches are three main emotion classification approaches in emotion recognition [534].

The emotional dimensions follow the approach of representing the emotion classes. Categorized emotions can be represented in a dimensional form with each emotion placed in a distinct position in space: either 2D (Circumplex model, "Consensual" Model of Emotion, Vector Model,) or 3D (Lövheim Cube, Pleasure-Arousal-Dominance [PAD] Emotional-State Model, Plutchik's model, PAD Emotional-State Model), with each emotion occupying a distinct position in space. Most dimensional models have dimensions of valence and arousal or intensity or arousal dimensions: Valence dimension indicates how much and to what degree an emotion is pleasant or unpleasant, whereas arousal dimension differentiates between showing its state, either that of activation or deactivation [82]. The objectives of our study were most in line with Plutchik's 'wheel of emotions' model, which we used in this research.

The use of artificial intelligence to recognize emotions and affective attitudes is a comparatively promising field of investigation. To make the most of artificial intelligence, multiple modalities in context should be generally used. Artificial intelligence has enabled biometric recognition and the efficient unpacking of human emotions and affective and physiological responses and has contributed considerably to advances in the field of pattern recognition in biometrics, emotions, and affective attitudes. Many different AI algorithms are used in the world, such as machine learning, artificial neural networks [535,536,537], search algorithms [166,538,539], expert systems [540,541], evolutionary computing [542,543], natural language processing [544,545], metaheuristics, fuzzy logic [546,547,548], genetic algorithm [549,550,551], and others.

Based on our review, presented in Section 3.1, Section 3.2, Section 3.3, Section 3.4 and Section 3.5, we find that investigators should develop procedures to guarantee that AI models are appropriately used and that their specifications and results are reported consistently. There is a need to create innovative AI and machine learning techniques.

Based on the review (Section 3.1, Section 3.2, Section 3.3, Section 3.4 and Section 3.5), investigators should develop procedures to guarantee that AI models are appropriately used and that their specifications and results are reported consistently. There is a necessity to create innovative AI and machine learning techniques.

The existing emotion recognition approaches all need data, but the training of machine learning algorithms requires annotated data, and obtaining such data is usually a challenge [552]. The use of AI models may become less complex, and AI algorithms faster when certain database techniques are applied. These techniques can also provide AI capability inside databases. Supporting AI training inside databases is a challenging task. One of the challenges is to store a model in databases, so that its parallel training is possible with multiple tenants involved in its training and use, at the same that security and privacy issues are taken care of. Another challenge is to update a model, especially in case of dynamic data updates [553]. The following datasets can help with the task of classifying different emotion types from multimodal sources such as physiological signals, audio content, or videos: BED [554], MuSe [555], MELD [544,556], UIT-VSMEC [411] HUMAINE [557], IEMOCAP [558], Belfast database [559], SEMAINE [560], DEAP [561], eNTERFACE [384], and DREAMER [562]. Github [563], for instance, provides a list of all public EEG-datasets such as High-Gamma Dataset (128-electrode dataset from 14 healthy subjects with about 1000 four-second trials of executed movements, 13 runs per subject), Motor Movement/Imagery Dataset (2 baseline tasks, 64 electrodes, 109 volunteers), and Left/Right Hand MI (52 subjects).

The findings also suggest that the development of more powerful algorithms cannot address the perception, reading, and evaluation of the complexity of human emotions, by making an integrated analysis of users' demographic and cultural background (age, gender, ethnicity, race, major diagnoses, and major medical history); socioeconomic status (education, income, and occupation); diversity attitudes; and context. We can only hope that the future will bring further research to address this issue and help to develop more advanced AFFECT technologies that can better cope with issues such as demographic and cultural background (age, gender, ethnicity, race, major diagnoses and major medical history); socioeconomic status (education, income and occupation); diversity attitudes; and context (weather conditions, pollution, etc.).

Worldwide research has yet to resolve several problems, and additional research areas have arisen, such as missing data analysis, potential bias reduction, a lack of stringent data collection and privacy laws, application of elicitation techniques in practice, open data and other data-related issues. Olivas et al. [564] for instance, analyze various methods for handling missing data:

- Missing data imputation techniques: analysis of the variable containing missing data (Mean, Regression, Hot Deck, Multiply Imputation) and analysis of relationships between variables for a case containing missing data (Imputation based on Machine Learning: Neural Network, Self-organizing map, K-NN, Multilayer perceptron);
- Case deletion (Listwise Deletion (Complete-case), Pairwise Deletion);
- Approaches that take into account data distributions (Bayesian methods, Model-based likelihood, Maximum Likelihood with EM).

It was found that the median correlation of the dependent variable of the Publications—Country Success model with the independent variables (0.6626) is higher than in the Times Cited—Country Success model (0.5331). Therefore, it can be concluded that the independent variables in the Publications—Country Success model are more closely related to the dependent variable than in the Times Cited—Country Success model (Figure 3.11).

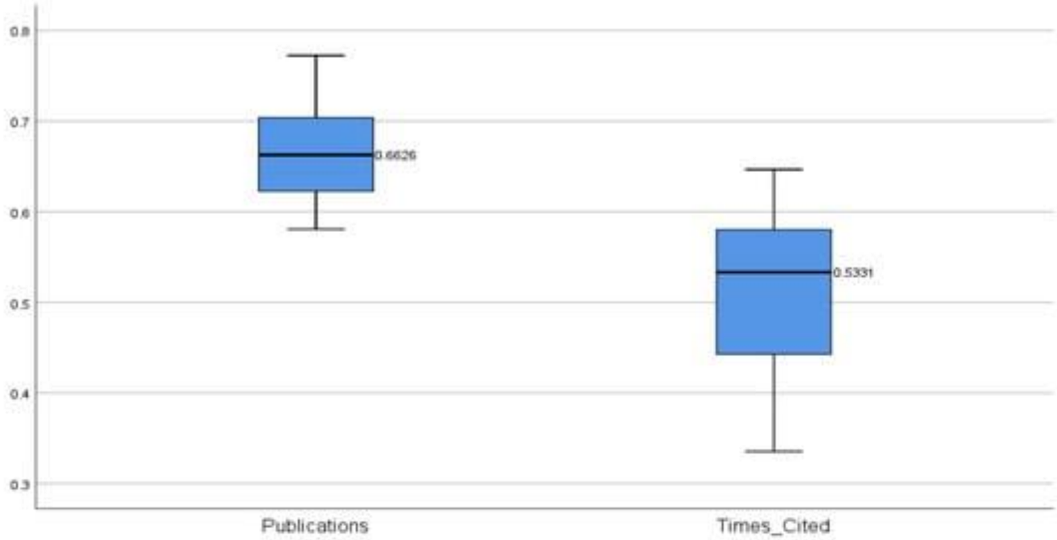


Figure 3.11. Distribution of correlations based on 15 criteria applied to 169 countries, their publications, and citations, as a CSP map.

The CSP maps of the world that have been compiled for this research provide a visualization of two aspects. A country's success (x-axis) is one of the aspects, while the publications dimensions (CSPN and CSPC; y-axis) are the other (Figure 3.12 and Figure 3.13). The publications (x-axis) are one of the aspects, while the publications times cited dimensions (y-axis) are the other in Figure 3.14. The CSP maps group the countries into the same eight clusters as the Inglehart–Welzel 2020 Cultural Map of the World (English-speaking, Catholic Europe, Protestant Europe, Orthodox Europe, West and South Asia, African-Islamic, Confucian, and Latin America) [565]. Two clusters—English-speaking and Protestant Europe—have been merged into one because of their shared history, religion, cultures, and degree of economic development. The parallels between the two aforementioned clusters have been confirmed by numerous studies [566]. The Inglehart–Welzel 2020 Cultural Map of the World includes many institutional, technological, psychological, and economic variables that demonstrate strong perceptible correlations [567]. The country success indicators in the CSP maps can be characterized as a large set of variables within the criteria system, such as politics, human development and well-being, the environment, macroeconomics, quality of life, and values based.

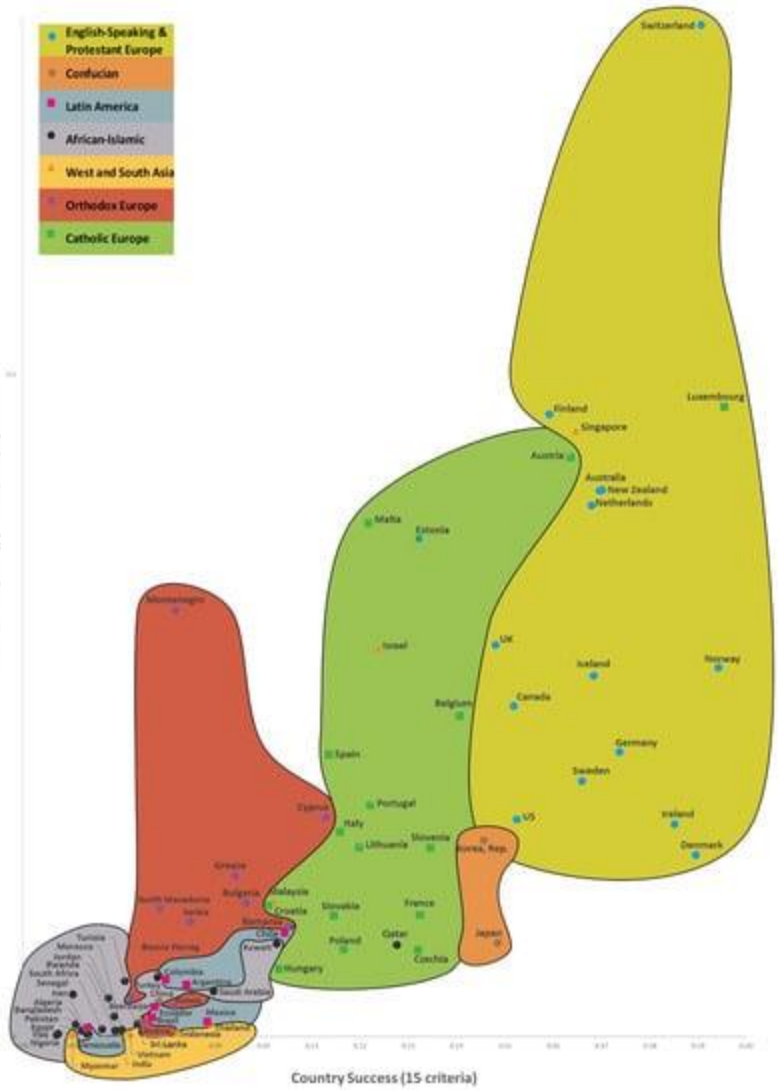


Figure 3.12. CSP map showing the success of countries in terms of the numbers of publications on AFFECT recognition (CSPN) in Web of Science journals with impact factor.

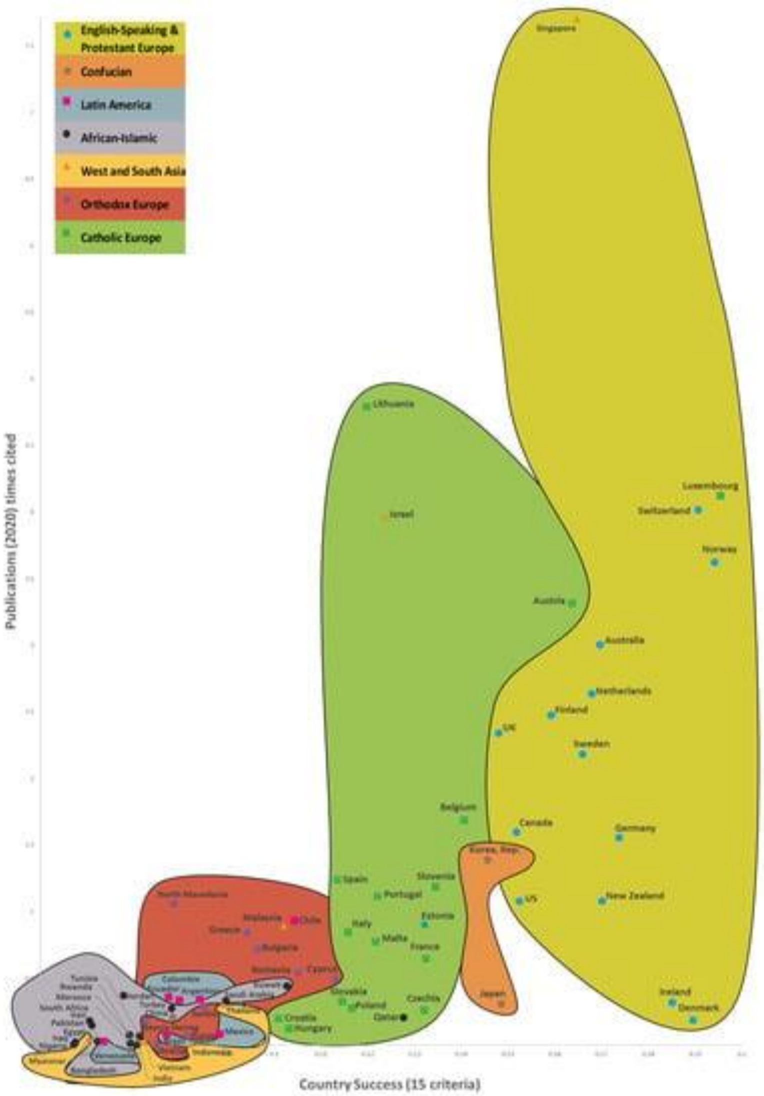


Figure 3.13. CSP map showing the success of countries in terms of the number of citations of their publications on AFFECT recognition (CSPC) in Web of Science journals with impact factor.

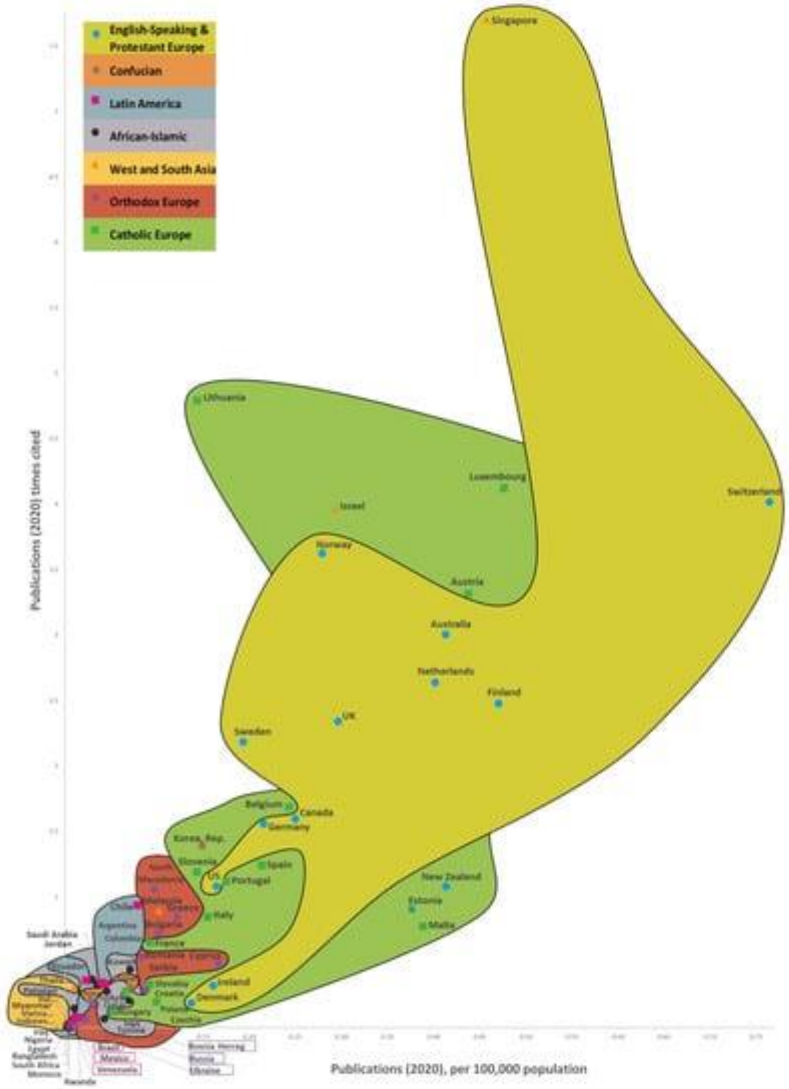


Figure 3.14. CSP map showing the number of articles on AFFECT recognition and the numbers of citations in Web of Science journals with impact factor.

In addition, this is a quantitative study to assess how the success of the 169 countries impacted the number of Web of Science articles published in 2020 on AFFECT recognition techniques that use brain and biometric sensors (or the latest figures available).

For the multiple linear regressions, we used IBM SPSS V.26 to build two regression models on 15 indicators of country success and the two predominant CSP dimensions. Two CSP regression models were developed based on an analysis of 15 independent variables and two dependent variables. The 15 independent variables and the two regression models are summarized in Table 3.4, Table 3.5, Table 3.6, Table 3.7 and Table 3.8. Table 3.4 contains descriptive statistics for two of the CSP models. The minimum and maximum values indicate the value range for each variable in the set of values that the variable in question can take. The average value of the full range that each variable can take is the mean and is usually equal to the arithmetical average. The standard deviation is a measure of the dispersion in the values of the variable in relation to the mean. Kurtosis is a measure of whether the values are heavy-tailed or light-tailed relative to the center of the distribution, whereas skewness is a measure of the symmetry of the distribution of the values. Acceptable values are considered to be between −3 and +3 for skewness, and between −10 and +10 for kurtosis. When the skewness is close to zero and kurtosis is close to three, the distribution of the values of the variable within the specified value range is in line with a normal distribution.

Table 3.4. Descriptive statistics for the dependent variables of two models.

Descriptive Statistics	**Descriptive statistics of 2 Models Dependent Variables**	
	Publications—Country Success	**Times Cited—Country Success**
	Model 1 (CSPN)	**Model 2 (CSPC)**
Mean	0.1354	0.9279
Median	0.0785	0.3297
Maximum	0.7642	7.7034
Minimum	0.0015	0.0000
Standard Deviation	0.1557	1.3893
Skewness	1.5533	2.4316
Kurtosis	5.3614	9.8641
Observations	166	165

Table 3.5. Goodness-of-fit testing for two models.

Independent Variables	**Dependent Variables**	
	Publications—Country Success	**Times Cited—Country Success**
	Model 1 (CSPN)	**Model 2 (CSPC)**
GDP per capita	0.7725 *** (1.2062)	0.6368 *** (7.1524)
GDP per capita in PPP	0.6975 *** (8.4298)	0.6467 *** (7.3418)
Ease of doing business ranking	−0.4821 *** (−4.7652)	−0.4390 *** (−4.2317)
Corruption perceptions index	0.7624 *** (1.5319)	0.6341 *** (7.1014)
Human development index	0.6717 *** (7.8530)	0.5347 *** (5.4799)
Global gender gap	0.4797 *** (4.7348)	0.3354 *** (3.0834)
Happiness index	0.7037 *** (8.5774)	0.5315 *** (5.4340)
Environmental performance index	0.6939 *** (8.3444)	0.5166 *** (5.2256)
Freedom and control	−0.5808 *** (−6.1782)	−0.3832 *** (−3.5932)
Economic freedom	0.6535 *** (7.4765)	0.5801 *** (6.1681)
Democracy Index	0.6227 *** (6.8912)	0.4429 *** (4.2777)
Unemployment rate	−0.1860 (−1.6398)	−0.1642 (−1.4412)
Healthy life expectancy	0.6312 *** (7.0471)	0.5194 *** (5.2635)
Fragile state index	−0.7229 *** (−9.0606)	−0.5405 *** (−5.5634)
Economic decline index	−0.6358 ***	−0.5597 ***

	(−7.1339)	(−5.8487)

Table 3.6. Descriptive statistics for two models.

Descriptive Statistics	Descriptive Statistics of 2 Models	
	Publications—Country Success	**Times Cited—Country Success**
	Model 1 (CSPN)	**Model 2 (CSPC)**
Pearson's correlation coefficient (|r|)	0.6272	0.5142
Coefficient of determination (R^2)	0.6943	0.5114
Adjusted R^2	0.6191	0.3912
Standard deviation	0.1557	1.3693
p values (probability level)	0.0000	0.0000
F	9.2356	4.2570

Table 3.7. Standardized beta coefficient values of the dependent variables.

Independent Variables	Standardized Beta Coefficient Values of the Dependent Variables	
	Publications—Country Success	**Times Cited—Country Success**
	Model 1 (CSPN)	**Model 2 (CSPC)**
GDP per capita	0.7735 **	−0.0853
GDP per capita in PPP	−0.5123 *	0.5304 *
Ease of doing business ranking	0.2535	0.1599
Corruption perceptions index	0.2392	0.3633
Human development index	0.1697	−0.1836
Global gender gap	−0.0228	0.0703
Happiness index	0.0800	−0.0916
Environmental performance index	−0.0601 **/	0.1819
Freedom and control	−0.0299	0.0846
Economic freedom	0.4558	0.3239
Democracy Index	−0.1524	0.0577
Unemployment rate	0.0353	0.0552
Healthy life expectancy	0.0047	0.0696
Fragile state index	−0.0008	0.0246
Economic decline index	0.0147	−0.0301

Table 3.8. How country success and its factors influence the two indicators.

Publications—Country Success	**Times Cited—Country Success**
Model 1 (CSPN)	**Model 2 (CSPC)**
When a country's success increases by 1%, the indicator improves by	
1.962%	2.101%
The 17 independent variables explain the dependent variable under analysis by	
89.5%	54.0%

Step 9 entailed the construction of regression models for the number of publications and their citation rates, and the calculation of the ES indicators describing them. Two dependent variables and 15 independent variables were analyzed to construct these regression models. The process was as follows:

- Construction of regression models for the numbers of publications and their citations.

- Calculation of statistical effect size (ES) indicators describing these regression models. ES is a value used in statistics to measure the strength of the relationship between two variables, or to calculate a sample-size estimate of that amount [568]. An ES may reflect the regression coefficient in a regression, the correlation between two variables, the mean difference, or the risk of a specific event occurring [569]. Guidelines developed by Durlak [570] provide advice on the ESs to use in research, and how to calculate and interpret them. We used these guidelines, and applied the following five measures of ES, as these indicators are crucial for meta-analysis and could be computed from our measurements:
    - Pearson correlation coefficient (r): Beta weights and structure coefficients r are the two sets of coefficients that can provide a more perceptive stereoscopic view of the dynamics of the data [571]. Interpretation may be also improved through the use of other results (e.g., [572]).
    - Standardized beta coefficient (β): Theoretically, the highest-ranking variable is the one with the largest total effect, since β is a measure of the total effect of the predictor variables [573].
    - Coefficient of determination (R^2): This is a measurement of the accuracy of a CSP model. The outcome is represented by the dependent variables of the model. The closer the coefficient of determination to one, the more variability the model explains. R^2 can therefore be used to determine the proportion of the variation in the dependent variable that can be predicted by examining the independent variables [573].
    - Standard deviation: If this is too high, it will render the measurement virtually meaningless [574].
    - *p*-values. There is no direct relationship between the *p*-value and the size, and a small *p*-value may be associated with a small, medium, or large effect. There is also no direct relationship between the ES and its practical or clinical significance: a lower ES for one outcome may be more important than a higher ES for another outcome, depending on the circumstances [570].
- Calculation of non-statistical ES measures, which may better indicate the significance of the relationships between pairs of variables in our two models:
    - Research context: Durlak [570] argues that ESs must be interpreted in the context of other research.
    - Practical benefit: As this is an intuitive measure, practical benefit can allow stakeholders to make more accurate assessments of whether the research findings published can significantly improve their ongoing projects [575].
    - Indicators with low values: These are usually easier to improve than indicators with high values.

Based on the results of descriptive statistics, it can be concluded that the values of the dependent variables of the models used in the study demonstrate normal distribution (skewness < 10 and kurtosis < 10), which allows for the use of parametric analysis methods in the analysis.

A correlation analysis found that the strongest relationship in the Publications—Country Success model is between the dependent variable Publications and the independent variable GDP per Capita. Meanwhile, in the Times Cited—Country Success model, the strongest relationship is between the variables of Times Cited and GDP per Capita in PPP. It was also found that in both models, the relationships between the dependent variables and the independent variables are statistically significant ($p < 0.001$), except for the relationships between the dependent variables and the Unemployment Rate variable.

A reliability analysis of the compiled regression models allows us to conclude that the models are suitable for analysis ($p < 0.05$). It was also found that the changes in the values of the independent variables used in the models explain the variance of the Publications variable by 69.4%, and the variance of the Times Cited variable by 51.1%.

An analysis of the standardized coefficients of the model allows us to conclude that changes in the GDP per Capita variable have the biggest impact on changes in the Publications variable. The GDP per Capita in PPP variable also have a significant impact. Meanwhile, the Times Cited variable is most affected by the GDP per Capita in PPP variable, which has a statistically significant effect on the dependent variable.

To confirm Hypothesis 1, we built two CSP models, which are formal representations of the CSP maps. These models demonstrate that on average, an increase of 1% in a country's success leads to an average improvement by 0.203% in the country's two CSPN and CSPC dimensions. As the success of a country increased by 1%, the numbers of Web of Science articles published and their citations grew by 1.962% and 2.101%, respectively. Figure 3.12 and Figure 3.13 also illustrate that an increase in a country's success goes hand in hand with a jump in its CSPN and CSPC dimensions, thus confirming Hypothesis 1.

Hypothesis 2 was based on the results of the analysis pertinent to the CSP models, as well as on the correlations found between the 169 countries and the 15 indicators [66]. A clear visual confirmation of Hypotheses 1 and 2 are also provided by Figure 3.12 and Figure 3.13, which show the specific groupings of countries in the seven clusters examined in this study. These models may be of major significance for policy makers, R&D legislators, businesses, and communities.

3.7. Evaluation of Biometric Systems

In this chapter, we outline the rationale behind the current biometrics and brain approaches, compare the efficacy of existing methods, and determine whether or not they are capable of addressing the kinds of issues and challenges associated with the field (with figures). Biometric systems have several drawbacks in terms of their precision, acceptability, quality, and security. They are generally evaluated based on aspects such as (1) data quality; (2) usability; (3) security; (4) efficiency; (5) effectiveness; (6) user acceptance and satisfaction; (7) privacy; and (8) performance.

Data quality measures the quality of biometric raw data [576,577]. This type of assessment is generally used to quantify biometric sensors and can also be used to enhance the system performance. According to the International Organization for Standardization ISO 13407:1999 [578], usability is defined as "[t]he extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use" [579]:

- In this context, efficiency means that users must be able to accomplish the tasks easily and in a timely manner. It is generally measured as task time;
- Here, effectiveness means that users are able to complete the desired tasks without excessive effort. This is generally measured by common metrics such as the completion rate and number of errors, for example the failure-to-enroll rate (FTE) [580];
- User satisfaction measures the user's acceptance of and satisfaction with the system. It is generally measured by looking at a number of characteristics, such as ease of use and trust in the

system. Even if the performance of one biometric system exceeds that of another in terms of performance, this will not necessarily mean that it will be more operational or acceptable.

Security measures the robustness of a biometric system (including algorithms, architectures, and devices) against attack. The International Organization for Standardization ISO/IEC FCD 19792 [581] specifically addresses processes for evaluating the security of such systems [579].

Unlike traditional methods, biometric systems do not provide a 100% reliable answer, and it is almost impossible to obtain such a response. In a secure biometric system, there is a trade-off between recognition performance and protection performance (security and privacy). The reason behind this trade-off arises from the unclear concept of security, which requires a more standardized framework for evaluation purposes. If this gap can be closed, an algorithm could be developed that would jointly reduce both of them. ISO 19795 contained standards for performance metrics and evaluation methodologies for traditional biometric systems. In addition to performance testing, it provided metrics related to the storage and processing of biometric information [582]. ISO/IEC 24745 specifies that, unlike privacy, security is delivered at the system level. In general, the ability of a system to maintain the confidentiality of information with the use of the provided countermeasures (such as access control, integrity of biometric references, renewability, and revocability) is referred as its security factor. When seeking to bypass the security of a biometric system, an invader may impersonate a genuine user to gain access to and control over various services and sensitive data. Privacy refers to secrecy at the information level. The following criteria were proposed in ISO/IEC 24745 for the purpose of evaluating the privacy offered by biometric protection algorithms: irreversibility, unlinkability, and confidentiality [583].

The discriminating powers of all biometric technologies rely on the extent of entropy, with the following used as performance indicators for biometric systems [584,585,586,587]: False match rate (FMR); False non-match rate (FNMR); Relative operating characteristic or receiver operating characteristic (ROC); Crossover error rate or equal error rate (CER or EER); Failure to enroll rate (FER or FTE), and Failure to capture rate (FTC).

Specific advantages and disadvantages are characteristic to each biometric technology. Table 3.9 shows these comparisons.

Table 3.9. Benefits and limitations of biometric technologies.

Tool	Benefits	Limitations
Electroencephalography (EEG)	Can be used to measure rapid changes in neural activity by the millisecond [588] Minimally invasive and/or commercial research packages are available [588] Participants can move around and benefit from enriched/social environments [588] Uses portable instruments and natural environments; there is long tradition of well-controlled experiments; measurement processes requiring several hours are possible in practice [589]	It is difficult to pinpoint neural signals from particular brain areas (poor spatial resolution) [588] Measurements from structures deep within the brain (e.g., nucleus accumbens) are not possible [588] Published studies on biometrics based on this signal have used high-cost medical equipment [590] Subjects have reported discomfort since it is necessary to apply scalp neck gel to improve conduction between electrodes [590]
Functional magnetic resonance imaging (fMRI)	Has the ability to observe activity in small structures [588] Differentiates signal from neighboring areas [588] Measurements of the whole brain are possible [588]	Physically restrictive; participants lie on their back in the scanner and cannot move around [588]

		Expensive, and equipment is in high demand [588] Equipment cannot be removed from the laboratory; the sequence of the activities is difficult to monitor [589]
MEG (magnetoencephalography)	Some MEG study protocols are quite well suited for design studies; there is a long tradition of well-controlled experiments based on EEG; optimal space-time-resolution [589]	Equipment cannot be removed from the laboratory; the location of existing brain activity is relatively difficult to determine [589]
Electrocardiogram (ECG)	Highly reliable source providing precise features of the electrical and physiological activity taking place with an individual; high performance has been noted in prior research on this signal [591]; it can easily be fused with other signals [592]	One of the great difficulties listed in the literature is a lack of user acceptance, as its implementation at the physical level makes it fairly uncomfortable [593]; body posture can also affect cardiac signals [594]
MRI (magnetic resonance imaging) [589]	Good for studies comparing groups of people	Equipment cannot be removed from the laboratory
PET (positron emission tomography) [589]	Good for comparing groups of people or natural tasks	Radioactive tracer is injected into participants; equipment cannot be removed from the laboratory
Eye tracking [588]	Offers strong nuanced data on visual attention and gaze pathways, and can be integrated with pupillometry	Does not measure inferences, the valence of the response, thoughts, or emotions
Iris [595]	Unique data; input is stable throughout lifetime; non-intrusive	Large data template; images are frequently improperly focused; single-source; high cost
NIRS (near-infrared spectroscopy) [589]	Uses portable instruments and natural environments; some NIRS study protocols are well suited for design studies; measurement processes requiring several hours are possible in practice	Difficulties in determining the location of brain activity; few groups are using NIRS for cognitive studies as yet
Transcranial magnetic stimulation (TMS/tDCS) [588]	Can be used to show causality	Limited to investigating the function of brain surface areas Can generally only lessen (TMS/tDCS) or increase (tDCS) neural activity in a general sense; cannot test for specific levels of activity or influence specific circuits
Forehead electrooculogram (EOG)	These signals are low cost, and are not invasive [596]	Electrodes used for the acquisition of the signals can present instability to eye flicker [597]; signals are highly affected by noises in the immediate vicinity [596]
Skin conductance response (SCR), heart rate, pupil dilation [588]	Simple; well validated Unobtrusive equipment; allows for more natural interactions with the environment	Cannot distinguish between positive and negative arousal

Lips [598]	Easy acquisition and lip characteristics; it is possible to extract the outline even if the person has a beard or a moustache	An image of the lips cannot be acquired when they are moving
Facial electromyography (fEMG), facial affective coding [599]	This is a precise and sensitive method for measuring emotional expression Unlike self-reports, fEMG does not depend on language and does not require cognitive effort or memory Yields large amounts of data and is continuous and scalable (hence more credible) Dynamic tracking of emotional (potentially unconscious) responses to ongoing stimuli/information Can measure facial muscle activities for the sake of balancing weakly evocative emotional stimuli Less intrusive than other physiological measures such as fMRI and EEG Automatic facial encoding software/algorithms are available	The technique is intrusive and may alter natural expression The number of muscles that can be triggered is limited by how many electrodes can be attached to the face Requires electrodes to be directly attached to the face (in a lab) Certain medicines that act on the nervous system, such as muscle relaxants and anticholinergics, can impact the final electromyography (EMG) result
Gait	Convenient and non-intrusive (2D); subjects can be evaluated covertly, without their knowledge [595]	During the assessment stage, light affects the results; clothing may affect detection [46] Data may alter throughout a lifetime (injuries, training, footwear); specialist personnel required for data processing; large data template [595]
Body motion [595]	Unique and various sources of data, small template size	Time consuming; subject must cooperate with reader; specialist personnel required for data processing

Upon completing the literature analysis, we then compared biometric technologies looking at the following seven parameters: universality, distinctiveness/uniqueness, permanence, collectability, performance, acceptability, and circumvention (Table 3.10). Another set of comparisons was the strengths and weaknesses characteristic to biometric technologies and related to their ease of use, error incidence, accuracy, user acceptance, long term stability, cost, template sizes, security, social acceptability, popularity, speed, and whether or not they have been socially introduced (Table 3.11). The working characteristics of various biometrics differ, as does their accuracy, and depend on the design of their operation. The level of security and the kinds of possible errors are also different in each biometric approach; the denial of access to the biometric sample holders is possible caused by various factors such as aging, cold, weather conditions, physical damages, and so on [600,601]. Other researchers also look at FAR, FRR, CER, and FTE in their comparisons of biometric technologies (Table 3.12).

Table 3.10. Comparison of biometric technologies by seven characteristics (traits).

	Universality	**Uniqueness or Distinctiveness**	**Permanence**	**Collectability**	**Performance**	**Acceptability**	**Circumvention**
Iris/pupil	High [141, 602–606]	High [141, 602–606]	High [141, 602–606]	Medium [141, 602–606]	High [141, 602–606]	Low [141, 602,604–606]	High [141,602]

						Medium [603]	Low [603–606]
Face	High [141, 602–606]	Low [141, 602,604–606] Medium [603]	Medium [141, 602–606]	High [141, 602–606]	Low [141, 602–606]	High [141, 602–606]	Low [141,602] High [603–606]
Odor	High [602, 603–606]	High [602, 603–606]	High [602, 603–606]	Low [602, 603–606]	High [602,603] Low [604–606]	Low [602] Medium [603–606]	Low [602, 603–606]
Keystroke dynamics and mouse movements, Mouse Tracking	Low [141, 602,604–606]	Low [141, 602,604–606]	Low [141, 602,604–606]	Medium [141, 602,604–606]	Low [141, 602,604–606]	Medium [141, 602,604–606]	Medium [141, 602,604–606]
Skin temperature - thermogram	High [141,604–606]	High [141,604–606]	Low [141,604–606]	High [141,604–606]	Medium [141,604–606]	High [141,604–606]	High [141] Low [604–606]
Voice/Speech /Voice Pitch Analysis (VPA)	Medium [141, 602, 604–606]	Low [141, 602, 604–606]	Low [141, 602, 604–606]	Medium [141, 602, 604–606]	Low [141, 602, 604–606]	High [141, 602, 604–606]	Low [141, 602] High [604–606]
Signature	Low [141, 602–606]	Low [141, 602–606]	Low [141, 602–606]	High [141, 602–606]	Low [141, 602, 604–606] Medium [606]	High [141, 602–606]	Low [141, 602] High [603–606]
Gait	Medium [602, 604–606] High [603]	Low [141, 604–606] Medium [603]	Low [141, 604–606] Medium [603]	High [602,603–606]	Low [602,603–606]	High [602,604–606] Medium [603]	Medium [602,603–606]

Table 3.11. Comparison of biometric technologies by various attributes.

	Easy of Use	Error Incidence	Accuracy	User Acceptance	Long Term Stability	Cost	Size of Template	Security	Socially Introduced	Social Acceptability	Popularity	Speed
Eye Tracking (ET)			0.5°–1° [607]			Low-High [608]						
Iris/pupil	Medium [602,603, 609]	Lighting [602,609] Lighting, glasses [603]	Very High [602,609] High [320,603,610,611]	Medium [602,609]	High [602,609,610] Medium [320,603]	High [320,603, 611]	Small [320]	Medium [320] High [603] Very high [609]	1995 [603]	Medium-Low [610,611]	Medium [603]	Medium [603]
Face	Medium [602,609] High	Lighting, age glasses, hair [602,603,609]	High [602,609]	Medium [602,609]	Medium [602,609] Low [320,602]	High [320]	Large [320]	Low [320] Medium [602,610,611]	2000 [603]	High [610,611]	High [603]	Medium [603]

	[603]		Low [320, 602] Medium-Low [610,611]			Medium [602,610, 611]						
Keystroke dynamics and mouse movements, Mouse Tracking	Low [602]	Device, weather [602]	Low [602]		Low [602]	Medium [602]		Low [602]	2005 [603]		Low [603]	Medium [603]
Voice/Speech/ Voice Pitch Analysis (VPA)	High [602,603, 609]	Noise, colds [602,603,609]	High [602,609] Low [320,603] Medium [610,611]	High [602,609]	Medium [602,603, 609] Low [320]	Medium [320,610, 611] Low [603]	Small [320]	Low [320] High [603] Medium [609]	1998 [603]	High [610,611]	High [603]	High [603]
Signature	High [602,603, 609]	Changing signature [602,603,609]	High [602,609] Medium [320, 603] Low [610,611]	High [602] Very High [609]	Medium [602,609] Low [320,603]	Low [320] Medium [603, 610,611]	Medium [320]	Low [320] High [603] Medium [609]	1970 [603]	High [610,611]	High [603]	High [603]
Gait			Medium [610]			Medium [610]				Low [610]		
Lip Movement			Medium [603]		Medium [603]	Medium [603]	Small [603]	High [603]				
Gesture			Low [612]									

Table 3.12. Comparison of performance metrics for biometric technologies by various authors.

	FAR	**FRR**	**CER**	**FTE**
Iris/pupil	0.94% [603] 0.0001–0.94 [613] 2.4649% [614]	0.99% [603] 0.99–0.91 [613] 2.4614% [614]	0.01% [603]	0.50% [603]
Face	1% [603] 16% [614]	10% [603] 16% [614]		3.1% [615]
Keystroke dynamics and mouse movements, Mouse Tracking	7% [603] 0.01% [614]	0.10% [603] 4% [614]	1.80% [603]	
Voice/Speech/Voice Pitch Analysis (VPA)	2% [603,613] 7% [614]	10% [603, 613] 7% [614]	6% [603]	0.5% [615]

Multimodal biometric systems take advantage of multiple sensors or biometrics to remove the restrictions of unimodal biometric systems [616]. While unimodal biometric systems are restricted by the integrity of their identifier, the change of several unimodal systems having the same restrictions is low [617]. Multimodal biometric systems can fuse these unimodal systems sequentially, simultaneously, both ways, or in series, meaning sequential, parallel, hierarchical, and serial integration modes, respectively. For instance, final results of decision level fusion of multiple classifiers are joined using methods such as majority voting [616]. This multimodal analysis will assist in identifying the actual reasons of such issues with the current biometrics and brain approaches, as well as the restrictions of the existing state-of-the-art approaches and technologies.

An efficient way to combine multiple classifiers Is needed when an array of classifiers outputs is developed. Various architectures and schemes have been proposed for joining multiple classifiers. The most popular methods are majority vote and weighted majority vote. In majority vote, the right class is the one most selected by various classifiers. If all the classifiers show different classes or in the event of a tie, then the one with the highest overall output is chosen to be the right class. Vote averaging method averages the separate classifier outputs confidence for every class over the entire ensemble. The class output with the highest average value is selected to be the right class [618]. The vote averaging method has been used to measure the efficacy of existing biometrics methods (Table 3.10 and Table 3.11). In our case, High (Very High) was assigned 3 points, Medium was assigned 2, and Low was assigned 1. The calculations did not evaluate some qualitative indicators, such as error incidence and socially introduced. Additionally, not all biometrics technologies had data on the analyzed indicators. As a result, eye tracking we not evaluated in this case due to a lack of data. The highest average number of points was collected by Skin temperature-thermogram (2.57), Iris/pupil (2.43), Face (2.30), and Signature (2.09). Many of the metrics for biometric technologies in Table 3.9, Table 3.10, Table 3.11 and Table 3.12 are analyzed in detail throughout the article.

3.8. Summary and Conclusion

Nevertheless, there are still unanswered questions that need to be addressed. We evaluated the evidence available to find a relationship between brain and biometric sensor data and AFFECT in order to determine the primary digital signals for AFFECT. The multidisciplinary literature used was from the disciplines of engineering, computer science, neuroscience, physiology, psychology, mathematical modeling, and cognitive science. The distinct conventions of these disciplines resulted in certain variegations, depending on the features and characteristics of the research results being focused on. The literature under analysis has small sample sizes, short follow-up times, and significant differences in the quality of the reports, which limits the interpretability of the pooled results. On average, the current AFFECT detection techniques that use brain and biometric sensors achieved a classification accuracy greater than 70%, which seems sufficient for practical applications. As part of this review, several issues that need to be addressed were identified, as well as numerous recommendations and directions for future AFFECT detection and recognition research being suggested. They are listed below:

- Many studies fail to report information on demographic and cultural background, socioeconomic status, diversity attitudes, and context, and AFFECT papers often have limited descriptions of feature extraction and analysis. This has a significant impact on the interpretation of their findings. Sample recommendations include reporting on participant enrolment and selection approaches and analysis of demographic and cultural background (age, gender, ethnicity, race, major diagnoses, and major medical history); socioeconomic status (education, income and occupation), diversity attitudes, and context. In order to improve the ability of researchers to assess the strength of evidence, one of the first steps should be the development of this kind of consistent reporting.

- Behavioral traits (e.g., gesture, keystroke, voice) change over time, and therefore are less stable. Multiple interactions are typically required to set a reliable baseline. Injury, illness, age, and stress can also cause changes in behavioral traits. Many of the studies on AFFECT recognition examined brain and biometric data under different AFFECT while overlooking the baseline (spontaneous) brain and biometric data.
- The literature did not contain brain and biometric sensor-based AFFECT recognition of mixed emotions (parallel involvement of negative and positive emotions). We study the 30 primary, secondary, and tertiary dyads of Plutchik's wheel of emotions, creating mixed emotions.
- Researchers need a set of guidelines to ensure AI models (artificial neural networks, evolutionary computing, natural language processing; metaheuristics, fuzzy logic, genetic algorithm) are correctly applied, and that their specifications and results are consistently reported (the model selection strategy, parameter estimates in the model with confidence intervals, performance metrics, etc.). There is also a need to further develop advanced AI and machine learning techniques (multi-modal learning, neuroscience-based deep learning, automated machine learning, self-supervised deep learning, Quantum ML, Tiny ML, System 2 deep learning).
- More results are also needed to identify which of the elicitation techniques applied in practice are effective, and in which cases they work best, taking into account the type of information obtained, the stakeholders' (developers, end-users, etc.) characteristics, the context, and other factors. More data sets need to be created that use active elicitation techniques, such as various games, as these are better at mimicking real-life experiences and bringing about emotions. Gamification is a current trend that uses game methods for real-life AFFECT elicitation.
- Recommendations also state that the two sources of potential bias (AFFECT interpretation algorithmic biases, data sources and input) in multi-feature studies should be reduced, and a wider variety of multimodal samples should be used.
- Missing data analysis has some gaps, for example missing data descriptions and how missing data is handled, and most appropriate methods should be applied in AFFECT recognition. As far as missing data goes, the literature had major shortcomings.
- As algorithms improve, accuracy is growing, but this significantly depends on the data sets used. Some gaps and a lack of discussion have also been noted concerning the question of whether the integrated brain and biometric sensors used in this research are reliable and appropriate for AFFECT detection.
- A trend related to emotional AI businesses (Realeyes, Affectiva, etc.) that expand their global operations in regions with less stringent data collection and privacy laws has not been sufficiently examined globally.
- The recommendations for open science include the proposal to share and reuse open multimodal AFFECT data, information, knowledge, and science practices (publications and software) by preparing a Data Management Plan that would address any important aspects of making data findable, accessible, interoperable, and reusable, or FAIR. Open data analysis should also include recognized and validated scales for AFFECT evaluation; any accessible confirmation on the reliability and validity of the AFFECT device and sensor applied should be presented. The open datasets have usually sought to obtain higher accuracy by using different sets of stimuli and groups of participants.

Emotional acculturation, happens when people, on contact with a different culture, learn new ways to express their emotions [619], incorporate new cultural values in their existing set, and then adjust their emotions to suit these new values [620,621,622,623]. This may be a research area in affective computing that needs more studies and focus. With growing global integration, emotional acculturation will become increasingly important, and advanced computational models will be needed to simulate the related processes. M.-T. Ho et al. [624] believe that this may be a key thematic change in the decades to come. The findings also suggest that developing more powerful algorithms cannot solve the perception, reading and evaluation of the complexity of human emotions. Instead, the complex modulators that affective and emotional states stem from need to be better understood by the scientific community. We can only hope that the future will bring further research that will remedy this and help develop more advanced technologies that can better cope with issues such as gender, race, diversity attitudes, and cross-cultural differences in emotion [624].

The substantial improvements in the development of affordable and simple to utilize sensors for recognizing AFFECT have resulted in numerous studies being conducted. For this review, we studied in detail 634 articles. We focused on recent state-of-the-art AFFECT detection techniques. We also took existing data sets into account. As this review illustrates, exploring the relationship between brain and biometric signals and AFFECT is a formidable undertaking, and novel approaches and implementations are continually being expanded.

The evaluation of the intensity of human AFFECT is a complex process which requires the use of a multidirectional approach. The main difficulties of this process include variations in the nature of human beings, social aspects, etc., due to these methods, which fits for average evaluation of customers majority, but shows poor results in personalized cases and vice versa. Moreover, the reliability of evaluations of human emotions strongly depends on the number of biometric parameters used, and the measurement methods and sensors applied. It is well known that a higher reliability of recognition can be achieved by increasing the number of parameters, but this will also increase the need for certain equipment and will slow down the evaluation process. The selection of measurement methods and sensors is no less important in the successful recognition of emotions. Contact measurement methods give the most reliable results, but their implementation is relatively complicated and may even be frightening for potential customers. The best solution in this case is non-contact measurement methods, that is, contact methods which do not require special preparation and allow measurements to be taken without the knowledge of the customer.

Future research possibly could focus on areas of reaction to emotion development stage, while sensing and evaluation became faster than emotion recognition by person itself.

This research has addressed the various issues that emerge when affective and physiological states, as well as emotions, are determined by recognition methods and sensors and when such studies are later applied in practice. The manuscript presents the key results on the contribution of this research to the big picture. These results are summarized below:

- Many studies around the world apply neuroscience and biometric methods to identify and analyze human valence, arousal, emotional and physiological states, and affective attitudes (AFFECT). An integrated review of these studies is, however, yet missing.
- In view of the fact that no reviews of AFFECT recognition, classification and analysis based on Plutchik’s wheel of emotions theory are available, our study has examined the full spectrum of thirty affective states and emotions defined in the theory.

- We have demonstrated the identification and integration of contextual (pollution, weather conditions, economic, social, environmental, and cultural heritage) [342] and macro-environmental [568] data with data on AFFECT states.
- The authors of the article have presented their own Real-time Vilnius Happiness Index (Figure 3.10a) and other systems and outputs to demonstrate several of the aforementioned new research areas in practice.

Information on diversity attitudes, socioeconomic status, demographic and cultural background, and context is missing in many studies. In this study, we have identified real-time context [347] data and have integrated them with AFFECT data. For example, the ROCK Video Neuroanalytics system and associated e-infrastructure were established as part of the H2020 ROCK project, in which passers-by were tracked at 10 locations across Vilnius [348]. One of the outputs was the real-time Vilnius Happiness Index (Figure 10 and https://api.vilnius.lt/happiness-index, accessed on 5 September 2022), and the project also involved a number of additional activities (https://Vilnius.lt/en/category/rock-project/, accessed on 5 September 2022) [625,626].

The analysis of the global gap In the area of affective biometric and brain sensors presented in this study and our aim of contributing to the current state of research in this area have led to the aforementioned research results.

Based on the evaluation of biometric systems performed in Section 7 and the conclusions presented in Chapter 8, future AFFECT biometrics and neuroscience development directions and guidelines are visible. We performed the above analysis by extensively discussing biometric and neuroscience methods and domains in the article.

Additionally, Section 3.2 and Section 3.6 present statistical and multiple criteria analysis across 169 nations, our outcomes demonstrate a connection between a nation's success, its number of Web of Science articles published, and its frequency of citation on AFFECT recognition. This analysis demonstrates which country's success metrics significantly influence future AFFECT biometrics and neuroscience development.

Advancements in the development of biometric and neuroscience sensors and their applications are summarized in this review. Regardless of the encouraging progress and new applications, the lack of replicated work and the widely divergent methodological approaches suggest the need for further research. The interpretation of current research directions, the technical challenges of integrated neuroscience and affective biometric sensors, and recommendations for future works are discussed. The reviewed literature revealed a host of traditional and recent challenges in the field, which were examined in this article and are presented below.

Biometric research aims to provide computers with advanced intelligence so that they can automatically detect, capture, process, analyze, and identify digital biometric signals—in other words, so they can "see and hear". In addition to being one of the basic functions of machine intelligence, this is also one of the most significant challenges that we face in theoretical and applied research [627].

There are still many challenging issues in terms of improving the accuracy, efficiency, and usability of EEG-based biometric systems. There are also problems concerning the design, development and deployment of new security-related BCI applications, such as personal authentication for mobile devices, augmented and virtual reality, headsets and the Internet [628]. Albuquerque et al. [628] have presented the recent advances of EEG-based biometrics and addressed the challenges in developing EEG-based biometry systems for various practical applications. They have also put forth new ideas and directions for future development, such as signal processing and machine learning techniques; data multimodal (EEG, EMG, ECG, and other biosignals) biometrics; pattern recognition techniques; preprocessing, feature extraction, recognition and matching; protocols, standards and interfaces; cancellable EEG biometrics; security and privacy; and information fusion for biometrics involving EEG data, virtual environment applications, stimuli sets and passive BCI technology.

Some of these challenges (accuracy, efficiency, usability, etc.) are analyzed in the article. Each of these features can be examined in more detail. For example, Fierrez et al. [629] analyzed five challenges in multiple classifiers in biometrics: design of robust algorithms from uncooperative users in unconstrained and varying scenarios; better understanding about the nature of biometrics; understanding and improving the security; integration with end applications; understanding and improving the usability. “Design of robust algorithms from uncooperative users in unconstrained and varying scenarios” is a challenge that has been a major focus of biometrics research for the past 50 years [2], but the performance level for many biometric applications in realistic scenarios is still not adequate [629].

Recently, new challenges in the field have been appearing; some of which are presented below as an example. Sivaraman [630] argues that in the age of AI and machine learning, cyberattacks are more powerful and are sometimes able to crack biometric systems. Additionally, these attacks will become more frequent. Multimodal biometrics are increasingly important, where a combination of biometrics is used for greater security. The pandemic has resulted in changes to the biometric algorithm of various modalities. Facial recognition algorithms have been improved to recognize people wearing masks and cosmetics. Updates like these may improve the accuracy of biometrics systems. Biometric devices will take web and cloud-based applications to the next level, as many organizations will continue to operate remotely [630].

Furthermore, a few problems have not been solved, and additional research fields have emerged, namely: biometric and neuroscience technologies lack privacy, are invasive and persons do not like to share their personal data and be identified; lack of protection from hacking; lack of accuracy; a quite expensive life cycle (brief, design, development, set up, running, operation, etc.); lack of capability to read some human features; customer satisfaction is not always guaranteed; human figure form recognition and examination of figure fragments, examination of head vibrations, and human electrical fields are inefficient.

3.9. References

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