Thermal Comfort Indices Through Room Occupancy Prediction

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Room occupancy prediction based on indoor environmental quality may be the breakthrough to ensure energy efficiency and establish an interior ambience tailored to each user. Identifying whether temperature, humidity, lighting, and CO_2 levels may be used as efficient predictors of room occupancy accuracy is needed to help designers better utilize the readings and data collected in order to improve interior design, in an effort to better suit users. It also aims to help in energy efficiency and saving in an ever-increasing energy crisis and dangerous levels of climate change.

Keywords: smart buildings ; sustainability ; room occupancy ; thermal comfort

1. Introduction

It is no secret that by 2050, almost 70% of the world's population will be situated in urban areas [1][2]. The urbanization rate is astounding and shows no signs of slowing down. Thus, the best option concerned individuals and policymakers have is to adapt to the current situation instead of mitigating its side effects [3][4]. To decrease the massive threats that urbanization will have on the environment, technology has been utilized to help diagnose, interfere with, solve, and maintain these adverse effects; these can be either standalone initiatives or more integrated ones in the form of a smart city. The smart city initiative aimed to put welfare and well-being of citizens and inhabitants at the center of technology [5], and with its progress, many schemes were developed to ensure health and well-being [6]. Although only recently defined, the initiative targeted city management and technology as separate entities, not as parts of a whole [7]. However, several other components have been integrated into smart city principles that aim to achieve holistic urban parameters such as infrastructure [1], livability and improvement of environmental factors [8], as well as energy and buildings [9]. These may be achieved through embedded sensors and data collectors that may be deemed as essential to the main components of smart cities and smart buildings, aiming at improving building design through data collection and diagnosis [10][11]; these systems can be implemented at both the city and national levels to improve resource usage efficiently. In 2016, [12] stated that smart cities aim to use digital technologies to enhance performance, reduce costs and resource consumption, and engage more effectively and actively with their citizens, ultimately leading to their citizens' well-being.

2. The Sustainable Development Goals (SDGs) and Smart Cities

The rich discussion on the existence of healthy cities and the SDG 11 goal is prominent and cannot be ignored; scientists, technologists, and academics have all thoroughly contributed to this massive growth of literature that is evident and abundant today [13][14][15][16][17][18]. Implementing these strategies into smart cities means preparing existing buildings to better adapt to the evolving environmental or sociological crises [19][20]. To help remedy some of these occurrences, the building sector is expected to overcome its adverse effect on the environment (more than 70% of all greenhouse gases emitted lie in that sole sector). That is why delving into what aids a building in giving back to the environment is an essential route that should be foremost for academics and scientists today.

In 2017, implementation tactics were proposed to tackle existing strategies defined by the SDG 11 goal. One of these strategies for achieving resilience in smart cities, focusing on climate change, is to help improve eco-efficiency and aim for climate-resilient infrastructure and buildings [7][21].

3. Thermal Comfort Indices as an Adjunct to User Experience

Through the focus on buildings and to better aid designers in designing better indoor environments for end-users, the utmost goal of building designers, an emphasis on comfort and aesthetics as well as overall pleasure and leisure is becoming more and more explicit and inevitable to ensure a better user experience in a growing competitive environment.

Designers today focus on integrated and holistic design aimed to bring together more than one discipline to better aid the user in achieving the best results, whether through embedding innovative services (infrastructure, sensors and so on) or through computations that support and facilitate the design by utilizing machine-based learning and artificial intelligence. This hype is now in full force. However, understanding the factors that affect occupants' perception and thermal comfort is mandatory to ensure the safety and comfort of any interior space and promote occupants' health and well-being.

Thermal comfort has a set of physiological and environmental factors which pertain to each individual. While the usual average of thermal comfort is an 80% percentile in contrast to the normalized 50% [22], it ensures that the design at hand suits more people and is better fitted to the vast majority than the obsolete average. Perceiving thermal comfort should always bear in mind the physical characteristics of the inhabitants of the space at hand; factors such as weight, age, fitness level, and gender all have an impact on the sense of comfort of an individual; although the environmental factors may all stay the same, these factors all contribute to the metabolic rate and effect of heat on each individual.

Of the main environmental thermal comfort indices, relative humidity and temperature are the most common parameters addressed when designing an indoor environment. The design's less common parameters are the overall air change rate followed by CO_2 levels and volatile organic compounds levels. These independent, or combined, parameters affect the overall user experience and perception of the space as well as comfort level, and may ultimately affect physical and mental well-being [23], as well as productivity [24][25].

4. Importance of Linking Thermal Comfort with Energy-Saving and Efficiency

With evident climate change and with the stress placed on the importance of decreasing the impact the building sector has on the world to ensure sustainable development, energy efficiency is now a top priority to most establishments and businesses worldwide; the complete awareness of the global energy crisis is leading more and more people to investigate cleaner options and healthier substitutes for non-renewable fuels, ultimately leading to both better and more efficient consumption, and use of renewable energy sources. However, even with the enforcement of adaptation, mitigation in areas where renewable energy plans may have a higher initial cost, especially in places where the funds are not readily located, should inevitably investigate embedding new technologies and techniques to ensure energy-efficient usage and costs.

The thermal comfort index is one of the most relevant in human biometeorology [26]; it is an interaction between physiological, psychological, physical (environmental), social, and cultural factors as the architecture of the space and its urban context. Spatial thermal comfort is a massive key player in the design process of buildings today; it affects usability and comfort and has a standing effect on the resale and equity of the space itself. Designing for comfort comes in all shapes and forms, from orientation and sun/wind relationship into the area to scenic landscapes and integration of natural elements; designers are equipped to make users feel as comfortable and satisfied as possible. Understanding that thermal comfort and interior ambience affect user perception of space and usability is a top priority among designers today. However, sometimes ideal ambient temperatures and parameters cannot be met due to environmental factors like noise, pollution, and drastic temperature fluctuation due to climate change, which may inhibit the existing site analysis and lead to user irritability, an opportune environment for embedding the role of artificial intelligence and machine learning, where AI has a much broader scope than ML, though they are both multifaceted. AI creates intelligence that stimulates human thinking, interaction, and behavior, often leading to new "human made thinking power". It does not need to be pre-programmed but rather depends on algorithms that, once utilized, devise their own form of "thinking" and intelligence. ML, a subset of AI, teaches machines the concept of learning from existing data and building upon it to reach new solutions through predictions. Hence, utilizing ML may help create a moderated interior climate that caters to the indices of each living space, whether at work or home, and tailoring the space to accommodate each person and not treating the building as a whole creates a unique and detailed user experience that brings in more people whilst marketing the space to sell at a higher rate [27].

Previous research has tackled the idea of different standalone thermal comfort parameters to determine occupancy. Indices such as CO_2, [28], relative humidity [29], and ambient temperature, if measured independent of HVAC and mechanical systems [30], have been targeted to determine whether or not the space is occupied; however, the correlation between the different parameters remains rich material for investigation, especially in light of tailored user experience and individual differences.

5. Tailored Comfort and Occupancy

Spaces designed with user comfort at their core are more likely to sell faster and at a higher rate than spaces designed to be generic for all [31]. Evidence shows that more and more clients are using expert interior designers and tailored spaces designed specifically for their needs, to personalize their individual spaces and make them more comfortable [32]. This also encompasses issues such as controlled interior atmosphere and ambience. Factors such as mood and stress levels and psychological states of mind [33] affect interior spatial design and comfort since these measures affect the physiological state (one of the basic parameters of thermal comfort). Thus, regulating mood and stress factors, in turn, needs to be integrated into the design process of interior ambient design and quality; this can be achieved through the utilization of sensors and machine learning to aid in accurate data collection over a longer period, yielding better results.

6. AI Relationships in Room Occupancy

The effect of AI today is seen in the integration with the technology used by the many industry domains, to help owners assess their data, deliver positive results, and impact their guest relationships (e.g., hospitality industry). AI algorithms are becoming very efficient in assisting owners to save money, enhance service, and improve operations. ML analyzes data from prominent sources and assimilates them into patterns to help administrators uncover meaningful and actionable decision-making insights. ML is enhancing the in-room experience by integrating smart technology into the room amenities, and AI can reduce workloads while speeding up responses and much more.

The prediction of occupancy in a room environment requires evolving sensor design and the implementation of ML in the indoor environment to enhance user experience and aid in a user-centered atmosphere, affecting room occupancy. The presence of sensors to monitor indoor environmental conditions may assist designers and decision-makers on room occupancy rates and ways to increase or decrease these rates. It may also bring forward decisions relating to heating and cooling, which directly affect energy consumption, thus leading to an overall energy-efficient building and a user enhanced experience. It was highlighted that the importance of utilizing indoor environmental data to efficiently diagnose whether the room is occupied or vacant and regulate energy usage following user-centered design to achieve a combined dual effect of indoor comfort and energy efficiency.

The prediction of occupancy in a room environment using data from light, temperature, humidity, and CO_2 sensors was tested using several machine learning classification models. It has lately been predicted that the accurate estimation of occupancy detection in the building could save energy from 30% to 42% [34][35][36]. If the occupancy room dataset was applied as an input for HVAC control algorithms, practical measurements indicated energy savings of 37% in [36] and between 29% to 80% in [37][38] shown through an experiment using data from a CO_2 sensor in an office building and additional synthetic data acquired via a simulation method for CO_2 dynamics with randomized occupant behavior. It combines a convolutional network with a deep bidirectional long short-term memory to detect occupancy (DBLSTM). Deep neural networks, Rpart logistic regression, and Random Forest with variable reduction techniques were used to generate prediction models of specific energy usage in Croatian public sector buildings [39], ML algorithms to detect occupant presence in space by measuring interior air-conditioning were also used [40], while [41] compared 36 ML algorithms for predicting interior temperature in a smart building.

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