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Research Article

Parametric Impacts of Metabolic Rate and Occupancy on Internal Thermal Gains in Buildings

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ABSTRACT

This study investigated the effects of varying metabolic rate (MR) and occupancy levels on indoor air temperature, interior surface temperatures, and internal thermal gains within a non-ventilated building model. The goal was to evaluate how these parameters influence thermal dynamics and determine which plays a more dominant role. Ventilation was intentionally excluded to isolate the thermal effects of occupants and eliminate external influences. The relative humidity generated by occupants accumulated, causing relative humidity to reach saturation in all scenarios. Since relative humidity showed no variation between cases, it was not included in the analysis. The results demonstrated that both MR and occupancy significantly impacted indoor thermal responses. Higher values of either parameter led to increased temperatures, though their relative influence varied. MR had a stronger effect under low-occupancy conditions, while its impact diminished as occupancy increased. For instance, in scenarios with 50 occupants, the indoor air temperature difference between MR values of 50 and 200 W/person reached 6.7ºC. Conversely, increasing occupancy led to more uniform total thermal gains due to expanded heat transfer surface area, especially with 200 occupants. The study concluded that both MR and occupancy need to be considered when modeling indoor thermal comfort and energy efficiency. Additionally, the results indicated that occupancy had a more significant influence on indoor temperature dynamics, particularly due to its role in heat transfer surface area expansion. These findings underscored the critical role of occupancy density in shaping indoor temperature profiles and highlighted the need to account for metabolic activity levels when designing energy-efficient and thermally comfortable building environments.

Introduction

Energy efficiency and indoor comfort are pivotal and continuously evolving research areas that form the foundation of sustainability-focused work in buildings [1], [2]. Achieving thermal comfort conditions often requires substantial energy consumption, primarily driven by heating, ventilation, and air conditioning (HVAC) systems [3]. These systems demand considerable energy to maintain indoor comfort parameters within ideal ranges, posing a significant challenge for energy efficiency, especially in buildings with high occupancy densities. In this context, reducing energy consumption while optimizing thermal comfort conditions is a fundamental objective in sustainable building design and operation [4].

Thermal comfort is a key determinant of occupant satisfaction in indoor environments [5]. It is influenced by environmental factors such as indoor temperature, relative humidity, air velocity, and mean radiant temperature, as well as personal factors like clothing insulation and metabolic rate (MR) [6]–[8]. Among these, MR refers to the amount of heat generated by the body in proportion to an individual's physical activity level [9]. Variations in metabolic activity can lead to differing thermal comfort perceptions under the same environmental conditions [10].

Numerous studies in the literature have addressed the consideration of MR to assess individual comfort [11]–[13]. Zhang et al. [14] examined the role of MR in thermal comfort evaluation, emphasizing the importance of accurate MR measurement for enhancing thermal index models. The study highlighted that dynamic MR changes are key human factors affecting thermal regulation and underscored the need for portable, affordable, and precise MR monitoring devices. Nomoto et al. [15] investigated MR values among Japanese individuals performing typical office activities, reporting significantly lower MR values (0.8–2.6 met) compared to international standards (1.0–3.0 met). This discrepancy, particularly pronounced among female participants, suggested potential inaccuracies in thermal comfort assessments and CO_2 generation estimations when applying global standards to specific populations. Jia et al. [16] evaluated the effectiveness of the standard effective temperature in thermal comfort studies across different MR levels. They found that the traditional model failed to maintain consistent thermal sensation across MR variations. Consequently, they proposed a new standard environment incorporating clothing insulation and convective heat transfer coefficients based on actual activity levels, ensuring a linear relationship between standard effective temperature and thermal sensation votes from 1.0 to 3.8 met.

International standards such as ASHRAE Standard 55-2020 [17] have been updated to better reflect the impact of occupant-related variables on indoor environmental quality. These standards emphasize the importance of accounting for dynamic human factors, such as activity level and occupant density, in the design and operation of HVAC systems. Accordingly, recent studies have begun integrating personalized inputs like MR and real-time occupancy levels into performance assessments, aiming to enhance comfort while optimizing energy use. Čulić et al. [18] reviewed advancements in monitoring technologies for personal thermal comfort and their implications for building energy performance. The review highlighted the significance of both environmental parameters (e.g., room temperature, humidity, mean radiant temperature) and personal factors (e.g., MR, skin temperature), with emerging technologies like wearable devices and connected sensors offering promising solutions for accurate data collection. Choi et al. [19] proposed a vision-based approach to estimate individual thermal comfort parameters, such as metabolic rate and clothing insulation, using indoor images in real time. Their intelligent model was designed to function in both single and multi-occupant spaces and achieved high accuracy through advanced computer vision techniques. The estimated parameters were integrated into a predicted mean vote (PMV) based control algorithm, which significantly improved thermal comfort compared to conventional methods. The study emphasized that using representative values for group scenarios offered a practical solution for real-time thermal regulation while maintaining energy efficiency. Yun et al. [20] developed an occupant-centric control strategy that utilizes real-time MR estimation to enhance thermal comfort and reduce energy use. Their approach combined pose classification and object interaction detection from indoor images to predict MR values, which were then integrated into a novel indoor thermal environment control algorithm. Experimental validation in real building settings demonstrated that this method significantly improved comfort levels, by up to 59% compared to fixed temperature control, and reduced energy consumption by as much as 88%. Jung et al. [21] introduced a semi-supervised multi-task learning model designed to estimate key occupant-specific parameters, namely MR and clothing insulation, for enhanced thermal comfort control. Leveraging both labeled and unlabeled image data, the proposed convolutional neural network model employed a dual-phase training method with pseudo labels to improve activity and clothing detection. Validation against existing models showed substantial accuracy gains, with a 15.8% increase in activity detection and a 25% improvement in clothing recognition. Zhang et al. [22] introduced a novel wearable sensor system designed to accurately estimate human MR, addressing the limitations of conventional bulky and intrusive measurement tools. Their model integrates physiological indicators such as heart rate, skin resistance, heat loss, and muscle composition to predict MR through a linear regression framework. Experimental validation involving various activity intensities and environmental conditions demonstrated strong agreement with reference equipment ($R^2 \approx 0.90$), achieving high accuracy and low uncertainty. Na et al. [23] proposed a deep learning-based approach to estimate individual MR for improved thermal comfort assessment. The study measured metabolic equivalents for eight common indoor activities in a diverse group of participants, analyzing the impact of gender and body mass index (BMI) on MR values. Their self-evaluation model achieved a low coefficient of variation, indicating reliable performance, while the third-party model demonstrated promising generalization across individuals. Notably, the results showed that MR values varied with both activity intensity and individual characteristics, highlighting the need for personalized comfort models in indoor environments. Yıldırım and Pekel [24] conducted a systematic review to explore how wearable sensors integrated with artificial intelligence (AI) can objectively assess physical activity levels, particularly among sedentary individuals. By screening 582 studies published between 2015 and 2024, they identified 17 relevant articles that examined AI-supported activity tracking using wearable technologies. Their findings highlighted the growing potential of such systems to monitor daily movement patterns, estimate MR, and support personalized interventions. The study emphasized that AI-enhanced wearable tools not only enable accurate and continuous activity assessment but also offer promising applications for promoting healthier behaviors in school-aged populations. Choi et al. [25] proposed a real-time MR and clothing insulation estimation method using deep learning and computer vision, alongside a comfort-focused temperature control strategy. Their system accurately predicted MR and clothing insulation with up to 100% accuracy and improved thermal comfort consistency, increasing the proportion of "no thermal change" votes by 17% compared to conventional set-point controls.

In indoor thermal environment studies, building simulations are often tailored to specific activity types to realistically assess internal heat gains and occupant comfort. The level of physical activity directly influences the MR, which in turn affects the thermal loads within space. Depending on the intended use of the building and the occupants' activity, various MR values have been utilized in literature to represent realistic internal conditions. For example, in [26], metabolic rates of 0.8, 1.0, and 1.2 met were used to represent low-activity conditions such as sitting or light movement, especially in residential settings. In [27], occupant activity was categorized into four levels, ranging from sedentary to intense, with corresponding MR values of 1.2, 2.4, 3.0, and 3.7 met, each phase lasting 20 minutes to assess the dynamic impact of different activity levels. In another study [4], thermal sensation was evaluated during sitting and two exercise conditions, associated with MR values of 1.0, 2.4, and 4.4 met. Further investigations, such as [28], simulated moderate indoor activities at 3.0, 3.5, and 4.5 met over 30-minute intervals.

In alignment with these studies, in this study, the simulation modeled a 100 m^2 space without ventilation. It varied occupancy levels (50 to 200 people) and metabolic rates (50 to 200 W/person) to reflect a range of indoor scenarios. These combinations correspond approximately to MR values ranging from sedentary office work to moderate activity, simulating indoor environments such as waiting areas, classrooms, or high-density public zones. This modeling strategy reflects diverse use cases found in the literature while enabling a controlled parametric evaluation of occupant-induced thermal impacts.

Studies focusing on continuous or intermittent building usage scenarios examine not only MR but also varying occupancy levels [29]–[31]. This is since occupancy rate significantly affects the total heat load within indoor spaces, thereby altering thermal balance and directly influencing the distribution of indoor temperatures [32]. Aparicio-Ruiz et al. [33] evaluated adaptive thermal comfort conditions in a primary school classroom with a floor area of 50 m^2 and a capacity of 25 students. A survey conducted with 67 students revealed inconsistencies between the thermal sensation vote (TSV) and the PMV. Kumar et al. [34] investigated thermal comfort in an engineering workshop occupied by approximately 15–20 students for over 20 minutes. Post-occupancy surveys indicated that female participants reported a comfort temperature approximately 1.5^{o}C higher than their male counterparts. Yang et al. [35] experimentally analyzed thermal comfort conditions in test rooms with floor areas of 6.3 m^2 and 17.6 m^2, each occupied by four individuals. The study found that female participants exposed to indoor temperatures of 14°C and 34°C reported feeling cooler and less comfortable at lower temperatures, whereas male participants felt warmer and less comfortable at higher temperatures. Reda et al. [36] examined thermal comfort and CO_2 concentrations in a mosque with a floor area of 1,000 m^2, accommodating 72 people during Friday prayers (1 hour), 72–117 people during Tarawih prayers (2 hours), and 20–50 people during daily noon and afternoon prayers (30 minutes). The results showed that CO_2 concentrations correlated with the duration of occupancy, reaching 480 ppm, 715 ppm, and 900 ppm for 30-minute, 1-hour, and 2-hour periods, respectively. Additionally, the predicted percentage of dissatisfied (PPD) values for these durations were 10, 41, and 28%, respectively.

MR and occupancy parameters play a pivotal role in ensuring thermal comfort and sustainable energy management, especially in high-occupancy buildings. While several studies have explored the thermal effects of MR and occupancy in buildings [4], these investigations typically focus on structures with varying floor areas, functions, and usage patterns. For instance, prior works have modeled occupant activities using a broad range of metabolic rates, such as 0.8–1.2 met for sedentary or elderly individuals, 1.2–3.7 met for staged activity simulations, and up to 5 met for higher-intensity activities under stable environmental conditions [26], [27]. These examples illustrate the relevance of MR variation across different indoor use cases and provide a foundation for selecting representative MR values in building simulations. Despite these efforts, a notable gap remains in understanding which of the two factors, MR or occupancy, has a more significant impact on indoor thermal gains. This study aims to address this gap by providing a comprehensive analysis of the effects of MR and occupancy on indoor environmental conditions. To achieve this objective, a building model was developed to simulate different activity levels and occupancy rates. In this context, internal heat gains of 50, 100, 150, and 200 W/person were used to represent metabolic activity levels ranging approximately from 0.85 to 3.4 met, in alignment with prior indoor environment research [4], [28]. The analysis focuses on variations in indoor air temperatures, interior surface temperatures, and internal thermal gains generated by occupants. The present study intentionally excluded humidity and ventilation effects to isolate the thermal gains due to occupancy alone, following the scope defined in the simulation framework. This approach allowed for controlled comparison of thermal loads arising directly from MR and occupancy density without confounding external climatic influences, despite the known importance of moisture in overall thermal comfort evaluations. The findings of this study are expected to offer critical insights into the interplay between MR and occupancy, contributing to the optimization of internal thermal gains and informing future energy efficiency strategies.

Material and Methods

Building upon the extensive literature addressing the significance of MR in assessing individual comfort [12], [13], [19], [37], this study employs EnergyPlus, a state-of-the-art building energy modeling tool, to further investigate these dynamics. EnergyPlus is a state-of-the-art building energy modeling tool developed by the U.S. Department of Energy. It is recognized for its ability to simulate various energy-related aspects of building performance, including thermal, lighting, and ventilation dynamics. The software provides a detailed analysis of energy flows, enabling simulations of both the building's energy consumption and the indoor environment. With its comprehensive set of features, EnergyPlus models the heat transfer within building materials, air movement, and internal heat gains from occupants and equipment. This makes it an ideal choice for evaluating how different levels of occupancy density and metabolic rates influence indoor temperatures and overall thermal dynamics. In this study, EnergyPlus software was employed to investigate the effects of varying MR and occupancy densities on indoor air temperatures and thermal dynamics.

The simulation was based on a 100 m^2 building model with a total volume of 300 m^3, specifically designed without natural ventilation, enabling a controlled and isolated assessment of internal thermal dynamics. Outdoor air conditions were defined using the "BSk" Koppen-Geiger climate classification, as shown in Fig. 1 [38]. This classification, which falls under the B (dry) climate group with S (steppe) indicating a semi-arid precipitation regime and k (cold) representing low mean annual temperatures, characterizes a cold semi-arid (steppe) climate. The building was assumed to be located within this BSk climate zone, exemplified by cities such as Denver, Colorado

(Latitude: 39.74°N, Longitude: 105.0°W), which experience semi-arid conditions with cold, dry winters and warm summers. The solar incidence angle in the modeled location varies throughout the day and year. At solar noon during the summer solstice, the sun reaches a maximum altitude of approximately 73°, resulting in a minimal incidence angle of about 17°. Conversely, during the winter solstice, the solar altitude at noon drops to around 27°, increasing the incidence angle to approximately 63°. This choice reflects the specific climate characteristics of the region where the modeled building is situated and ensures that the simulation results are relevant to realistic environmental conditions.

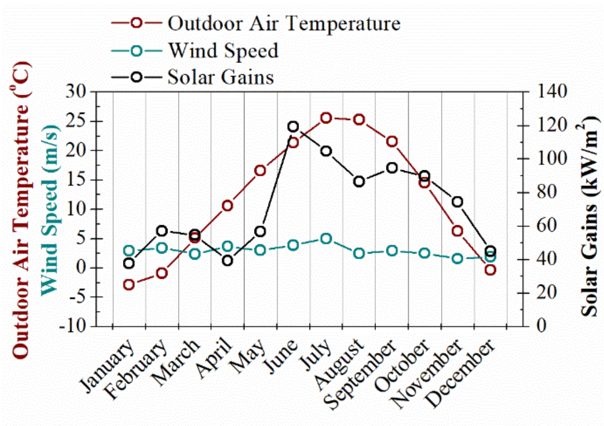

Figure 1. Monthly variations in outdoor air conditions for investigated BSk climate location.

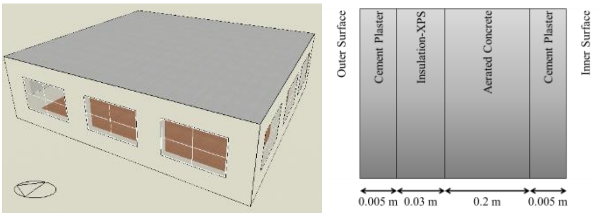

Figure 2. Building model and wall components.

The wall components of the building, as illustrated in Fig. 2 and Table 1, were constructed with materials that provided a U-value of 0.53 W/m^{2}K, ensuring a moderate level of thermal insulation. However, this U-value was relatively high compared to the values recommended in the latest national standards. According to the revised Turkish Thermal Insulation Standard TS825, the maximum allowable U-values for external walls vary regionally and range between 0.45 and 0.20 W/m^{2}K, depending on the severity of the local climate [39]. Although the selected U-value in the present study reflects older or less-insulated building stock still common in practice, this deviation from the latest recommendations was intentionally made to represent a more conservative and realistic scenario for thermal load analysis.

Additionally, all exterior walls were equipped with double-glazed windows, which accounted for 30% of the total wall surface area [40]. Each window used in the model was a standard double-glazing system, made up of two glass panes of 3 mm thickness, separated by a 13 mm air-filled cavity. These windows had a thermal transmittance of 2.7 W/m^{2}K. Their overall solar energy transmittance was 62%, with 54% of direct solar radiation passing through, and 62% of visible light being transmitted into space.

In the study, it was assumed that the indoor environment was not ventilated, and that no heat losses occurred other than through the building components. Additionally, the study did not include the effects of HVAC systems, as the primary focus was on investigating the impact of occupancy density and MR on internal thermal gains. It should be noted that ventilation was intentionally excluded in this simulation to isolate the effects of internal thermal gains caused solely by human metabolic activity and occupancy rate. The study was designed as a parametric analysis, in which the number of occupants and their metabolic rates were systematically varied to evaluate their direct impact on indoor thermal dynamics. Although such a non-ventilated and densely occupied environment does not reflect typical or safe real-world conditions, this modeling approach allows for a clearer understanding of the threshold points where internal gains begin to significantly influence thermal comfort.

Internal thermal gains can be defined as the thermal energy generated by the activities of individuals present in the environment and the devices used. These gains generally include the heat produced by human metabolic activities, the operation of electrical devices, indoor heaters, various activities within the building, and other internal energy sources. Metabolic gains refer to the thermal energy produced by individuals because of their physical activities, while the occupancy rate represents the number of people and their activity level within the building. In the presented study, MR and occupancy rate were considered the primary factors influencing internal thermal gains. Other potential internal heat gain sources such as equipment and lighting were intentionally excluded to ensure that the effects of occupants' sensible heat contributions could be assessed in isolation. This approach allowed for a focused analysis of how MR and occupancy influence indoor thermal dynamics in the absence of external or non-human internal loads. Four MR values were evaluated: 50, 100, 150, and 200 W/person, representing different activity levels. Occupancy levels were varied as 50, 100, 150, and 200 occupants, resulting in total internal heat gains ranging from 2,500 W (50 occupants × 50 W) to 40,000 W (200 occupants × 200 W). This approach allowed for a focused and quantifiable analysis of how MR and occupancy influence indoor thermal dynamics under controlled internal gain conditions. The study was designed to represent a broad range of human activities, covering both low and high activity levels. Activities such as sleeping, which are associated with a metabolic rate of 0.7–0.8 met or 45–55 W/person, were considered alongside more physically demanding activities, such as heavy physical labor, which generate a higher metabolic rate of 2.5–3.5 met or 200–300 W/person. Moreover, the proportion of sensible and latent heat gains varies depending on both activity level and ambient temperature. According to ASHRAE Standard 55-2020 [17], [41], at an ambient temperature of 26°C, approximately 42% of the total metabolic heat generated by a resting individual is sensible, while the remaining 58% is latent. This ratio can shift depending on the activity level, with higher-intensity activities leading to increased latent heat production due to elevated perspiration and respiration rates. For example, in activities exceeding 2.5 met (e.g., heavy manual labor), latent heat can surpass sensible heat gains [42]. Although this study does not separate these components explicitly in the simulation, the total metabolic rates (e.g., 200 W/person) implicitly include both latent and sensible portions as estimated by EnergyPlus's internal algorithms. In EnergyPlus, internal gains from people are specified using the "People" object, where the activity level represents the total metabolic rate. This total is then internally divided into sensible and latent heat gains based on predefined algorithms, which rely on ambient temperature and activity level. Specifically, EnergyPlus uses empirical correlations, derived from ASHRAE Standard 55-2020, to partition the total metabolic heat into dry (sensible) and moist (latent) components. Sensible heat further contributes to convective and radiative heat transfer within space, while latent heat contributes to moisture gains through respiration and perspiration. Although users do not manually enter these fractions, EnergyPlus dynamically calculates them during simulations to ensure realistic thermal and moisture load estimations under various environmental and metabolic conditions.

Table 1. Thermophysical properties of building materials.

	Material	Thickness (m)	Density (kg/m^3)	Thermal Conductivity (W/m.K)	Specific heat (J/kg.K)
Wall	Outer cement plaster	0.005	1760	0.72	840
	XPS insulation	0.03	35	0.034	1400
	Aerated concrete	0.2	750	0.24	1000
	Inner cement plaster	0.005	1760	0.72	840
Roof	Roof brick	0.1	1000	0.3	840
	Roofing felt	0.02	960	0.19	837
	Roof insulation	0.06	20	0.035	1100
Floor	Aerated concrete	0.1	750	0.24	1000
	Flooring block	0.14	650	0.14	1200

The values used in the simulations (up to 200 W/person) correspond to activities such as moderate walking, manual work, or physically active standing tasks, which might occur in emergency response centers, temporary shelters, or crowded healthcare environments during intense or stressful periods. These activities were selected to reflect not routine conditions, but highly loaded emergency-like scenarios. Additionally, the study considered a range of occupancy densities from 0.5 to 2 people/m^2 to evaluate the effects of varying population densities on thermal performance. Although these values are significantly higher than the typical standards defined by ASHRAE Standard 55-2020 [17] (5-100 m^2 per person), they were deliberately selected to simulate high-density occupancy scenarios beyond normal conditions. The simulated building was intended to represent public-use spaces such as primary healthcare waiting areas, temporary shelters, or emergency response centers, where elevated occupancy levels may temporarily occur. However, it is acknowledged that the upper-bound internal load condition (e.g., 2 people/m^2 combined with high metabolic activity leading to 200 W/m^2) exceeds the typical operational range of such facilities. This scenario does not represent passive activities like sitting or standing quietly, but rather a hypothetical worst-case scenario involving moderately active occupants (e.g., moving, queueing, or interacting) densely packed in a confined space. The goal was not to reflect average or routine usage but to explore how the indoor thermal environment responds to extreme internal load conditions. In all scenarios, occupants were assumed to be uniformly distributed throughout the 100 m^2 indoor space, ensuring consistent internal heat gain distribution. This modeling approach allowed for a comprehensive assessment of system performance under stressful conditions that could arise in overcrowded environments such as emergency shelters or waiting rooms during peak hours. Besides, it was assumed that both MR and occupancy remained constant throughout the year, maintaining steady values 24 hours a day, 7 days a week. This simplification allowed for a focused analysis, free from the complicating factors of fluctuating occupancy patterns or seasonal variations in activity levels. However, to reflect real-world conditions more accurately, clothing insulation values were assumed to vary seasonally, with different values applied for summer, transitional, and winter months. The clothing insulation was set at 0.5 clo for summer, 1.0 clo for transitional months, and 1.5 clo for winter months, corresponding to the typical clothing insulation levels expected for each season.

Validation of Simulation Model

To validate the reliability of the developed EnergyPlus-based simulation model, indoor air temperature outputs were compared with real-world data reported by Alonso et al. [43]. In reference study [43], the thermal performance of classrooms in southern Spain was monitored under specific HVAC protocols during January 2020 (pre-pandemic) and

January 2021 (pandemic period with altered ventilation strategies).

For the North Class (A6) with 100 m^2 floor area, which was selected for validation purposes, mechanical ventilation and heating were active from 7:30 a.m. to 2:00 p.m. with no manual airing in January 2020. During January 2021, the protocol changed to manual airing through one window (11:30 a.m. to 2:00 p.m.), with no mechanical ventilation and only heating being applied. These HVAC protocols were incorporated solely for model validation. In the remainder of the study, the building was modeled as a naturally non-ventilated space with no mechanical ventilation, representing a controlled scenario for investigating the impact of internal heat gains and occupancy patterns. The MR and occupancy ratio were 1.4 met and 3.85 m^2/person, respectively.

The reference study [43] reported average indoor air temperatures of 21.9°C and 18.0°C for January 2020 and January 2021, respectively. The simulated values under corresponding HVAC conditions were 22.8°C and 18.7°C. The maximum deviation was 0.9°C and 0.7°C, which fell within the acceptable range for thermal modeling [44]. Simulated temperature ranges also aligned closely with measured field data. These results confirmed that the simulation model could capture indoor thermal behavior under real-world HVAC strategies, supporting its validity for further use in thermal comfort and energy performance analysis of buildings.

Table 2. Comparison of average indoor air temperatures between the reference [43] and present study.

	Average indoor air temperatures (°C)	
	January 2020	January 2021
Reference Study [43]	21.9°C (range: 14.5-26.8)	18.0°C (range: 14.0-20.0)
Present Study (Simulation)	22.8°C (range: 14.0-27.5)	18.7°C (range: 14.5-21.2)
Difference (ΔT)	0.9°C	0.7°C

Model Limitations

In this study, mechanical ventilation and HVAC systems were intentionally excluded from the simulation model after the validation phase, with the aim of developing a simplified framework that isolates the effects of internal heat gains, occupancy rates, and metabolic activity on thermal conditions. This approach allows for a more focused analysis of thermal comfort dynamics that are often overshadowed by HVAC operation in fully conditioned spaces. However, it is important to acknowledge that the exclusion of ventilation inherently limits the model's ability to capture certain environmental parameters, such as CO_2 concentration and indoor air quality metrics. In real buildings, especially those with continuous or dense occupancy, ventilation plays a vital role in maintaining acceptable air quality and regulating humidity. The current model, by design, does not simulate these aspects, as its primary objective is to examine the thermal response of the indoor environment under passive or emergency-like conditions where ventilation may be reduced or temporarily unavailable. While scenarios involving extended high occupancy without ventilation are not intended to reflect standard operating conditions, they serve to highlight the thermal consequences and internal load behaviors in the absence of mechanical systems. Therefore, the findings should be interpreted as representing a boundary case that contributes to a better understanding of how internal factors influence thermal comfort when HVAC support is limited or selectively deactivated.

Results and Discussion

The variations in monthly average outdoor and indoor air temperatures, as well as interior surface temperatures for different occupancy and MR values, are presented in Fig. 3. As expected, an increase in MR or occupancy led to an increase in indoor air temperature and interior surface temperatures. In scenarios with 50 occupants, the impact of increasing MR on temperatures was more pronounced. However, in scenarios with 100 or more occupants, the effect of MR on monthly average indoor air and wall surface temperatures remained limited. For the case with 50 occupants, the difference between the maximum and minimum indoor temperatures was 16.8°C for MR of 50 W/person and 10.1°C for MR of 200 W/person. For 200 occupants, these values were determined as 4.4°C and 4.1°C, respectively. Additionally, with every increment of 50 people, the average indoor air temperatures increased by 3.7, 1.2, and 0.6°C, while the average interior surface temperatures increased by 2.9, 0.9, and 0.5°C, respectively. The reduction in temperature differences with increasing occupancy highlighted that the contribution of thermal gains from occupants to the total heat load was significant, making these effects more noticeable at lower occupancy levels.

On the other hand, an increase in MR significantly influenced indoor temperatures, and it was observed that at an MR value of 200 W/person, indoor air temperatures remained higher regardless of the number of occupants. This result clearly highlighted the dominant role of metabolic activity in shaping internal thermal conditions, especially under low occupancy scenarios. This indicated that the increase in heat production per person elevated the total internal heat gain, consequently raising indoor temperatures as expected. Each 50 W/person increase in MR raised the average indoor air temperatures by 5.4, 0.7, and 0.6°C for an occupancy of 50 people, and by 0.1, 0.1, and 0.2°C for an occupancy of 200 people. This non-linear trend suggested that as the internal thermal load increased, the relative impact of additional metabolic heat generation diminished, indicating a saturation effect in enclosed environments. Therefore, it was determined that the influence of MR diminished in conditions where high internal thermal gains and temperatures were achieved. Additionally, as outdoor temperatures increased, indoor temperatures reached maximum levels, indicating a potential rise in cooling loads. Although the interior surface temperatures followed a trend parallel to indoor air temperatures, they exhibited more limited variations in response to increases in MR and occupancy. For 50 occupants and an MR of 50 W/person, the difference between the average indoor air and interior surface temperatures was 1.8ºC, which increased to 3.1ºC with rising MR and occupancy. In the study by Calvaresi et al. [45], an increase of approximately 50 W/person in metabolic rate during the winter months was noted to cause a rise in air temperature of up to 3ºC for occupancy level of 10 people. In the present study, this increase corresponded to average temperature rises of 2.1, 0.6, 0.3, and 0.1ºC for occupancy levels of 50, 100, 150, and 200 people during January, February, and December. This was attributed to the slower response of wall surfaces to heat transfer processes and the influence of thermal mass. Additionally, these findings underscored the buffering role of building envelope materials in mitigating rapid indoor temperature changes, which could be strategically utilized in passive design approaches. Kumar et al. [34] evaluated thermal comfort conditions in a university workshop located in a "Cwa" climate zone based on the Koppen–Geiger classification, involving students with an estimated metabolic rate of approximately 100 W/person. Although the floor area per person was not specified, the average indoor air temperatures during autumn, winter, and the overall experimental period were reported as 25.1ºC, 18.1ºC, and 20.8ºC, respectively. In the present study, under a comparable metabolic rate (100 W/person) and an occupancy level of 50 individuals, the corresponding values were calculated as 30.8ºC, 24.9ºC, and 27.9ºC. This notable difference was likely attributed to variations in building envelope configurations and regional climate characteristics. Furthermore, other factors such as differences in solar exposure levels or internal heat gains from equipment might also have contributed to the observed temperature discrepancies. These findings demonstrated that, even under similar metabolic loads, indoor thermal conditions could differ significantly depending on building and environmental parameters.

On the other hand, when MR values were kept constant and occupancy varied, the differences observed in indoor air and interior surface temperatures were more pronounced compared to scenarios where occupancy was kept constant and MR varied. This was because the increase in the heat transfer surface area associated with the number of occupants had a more significant effect than individual heat gains resulting from metabolic density. In other words, the spatial distribution and density of heat sources (people) had a greater influence on the thermal environment than the intensity of each source. Particularly, as the number of occupants increased, the heat transfer surface area of the indoor environment expanded, which led to a higher potential for heat insulation or heat loss. Consequently, it was concluded that occupancy had a much stronger impact on indoor temperature dynamics compared to MR. This conclusion aligned with the fundamental principles of internal heat gain modeling, emphasizing that both occupant density and distribution significantly affect thermal comfort outcomes.

In Fig. 4, the variation of monthly internal thermal gains from occupants (total metabolic gains) according to MR and the number of occupants is presented. It was determined that total internal thermal gains reached minimum levels during the summer months and maximum values during the winter months. This indicated that the thermal balance of the indoor environment was related to outdoor temperatures. Additionally, it was identified that due to the high outdoor temperatures in the summer, heat production from occupants had a limited impact. However, the increase in internal thermal gains during the winter months (January, February, December) was identified as a significant factor contributing to the maintenance of indoor temperatures.

A noticeable increase in thermal gains was observed with the rise in occupancy when the MR was kept constant and the number of occupants varied. This trend was particularly evident in the scenario with 200 occupants, where the total internal heat gain in January and December was significantly higher than in other scenarios. These findings emphasized the substantial impact of occupant density on indoor heat accumulation, even when individual metabolic contributions remained unchanged. This highlighted the influence of per capita metabolic heat on total thermal gains.

Internal thermal gains increased as the MR rose when the number of occupants was kept constant and the MR varied. For instance, in the scenario with 50 occupants, thermal gains generated by individuals with a MR of 200 W/person showed a significant increase compared to those with a MR of 50 W/person. This showed a saturation point where the relative contribution of additional metabolic energy per person becomes less significant in environments with already high internal heat loads.

In the findings presented thus far in this study, the increases in indoor air temperatures, interior surface temperatures, and internal thermal gains from occupants due to the rise in MR or the number of occupants were expected outcomes. However, determining which factor (MR or occupancy) had a greater influence on internal thermal gains was significant, particularly for improving energy efficiency and thermal comfort in buildings. Therefore, scenarios with different combinations of MR and the number of occupants, where the total metabolic thermal gains (MR × number of occupants) were equal, were analyzed to determine their impacts on indoor air temperature, interior surface temperature, and internal thermal gains from occupants, as shown in Fig. 5.

Despite having the same total metabolic heat production (e.g., MR: 50 W/person with 100 occupants and MR: 100 W/person with 50 occupants), notable differences in indoor air and wall surface temperatures were observed, especially during winter and transitional seasons. In scenarios with a higher number of occupants and lower MR, indoor air and surface temperatures tended to be slightly higher due to more homogeneous heat distribution and reduced local temperature gradients. Conversely, in scenarios with fewer occupants and higher MR, heat was concentrated around fewer individuals, reducing distribution efficiency and resulting in lower average indoor temperatures.

Furthermore, while sharp peaks in thermal gains were observed in scenarios with higher MR but fewer occupants, the total thermal contribution remained limited due to local heat losses and inefficient air mixing. In contrast, scenarios with lower MR and more occupants exhibited more stable and balanced thermal gains, contributing to the stability of indoor temperatures. Notably, scenarios with a higher number of occupants demonstrated greater internal thermal gains even when the total metabolic heat production was the same, highlighting the importance of heat distribution dynamics.

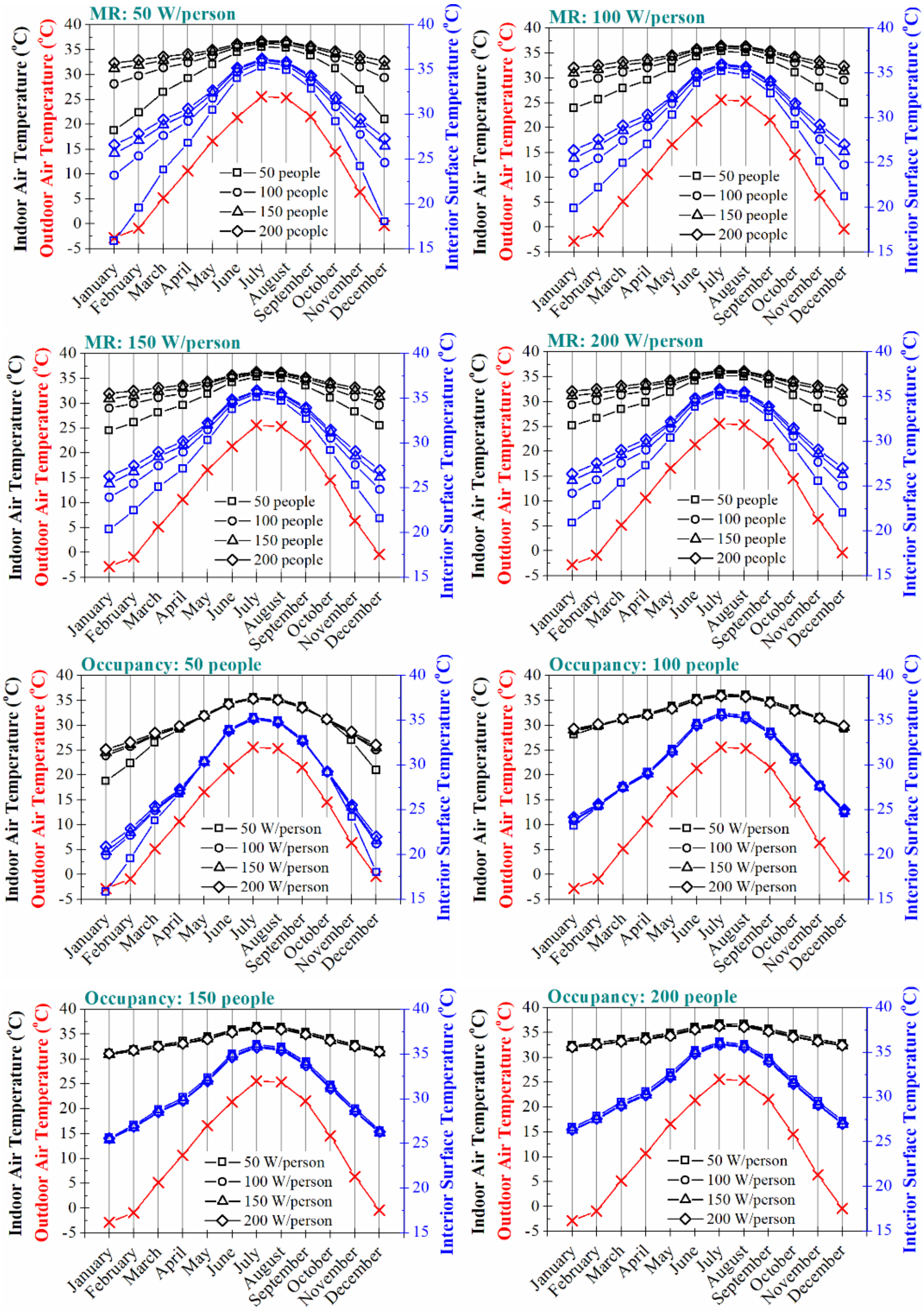

Figure 3. Indoor air and interior surface temperatures for different occupancy and MR values.

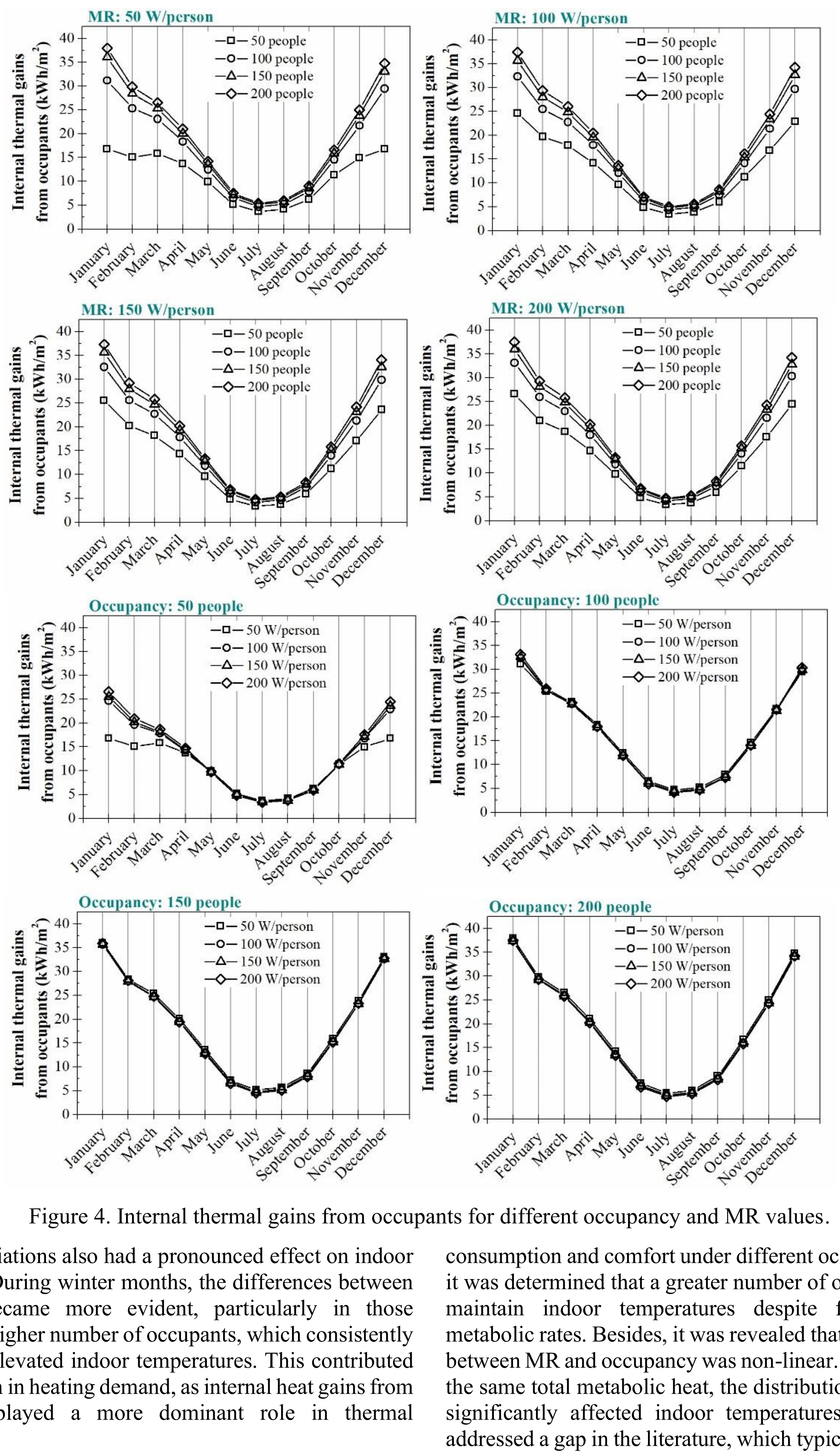

Figure 4. Internal thermal gains from occupants for different occupancy and MR values.

Seasonal variations also had a pronounced effect on indoor conditions. During winter months, the differences between scenarios became more evident, particularly in those involving a higher number of occupants, which consistently maintained elevated indoor temperatures. This contributed to a reduction in heating demand, as internal heat gains from occupancy played a more dominant role in thermal regulation.

In the summer, due to high outdoor temperatures, the influence of metabolic thermal gains diminished; however, a large number of occupants could marginally increase indoor temperatures, potentially impacting cooling loads. As in studies such as [46], which examined energy consumption and comfort under different occupancy levels, it was determined that a greater number of occupants could maintain indoor temperatures despite fluctuations in metabolic rates. Besides, it was revealed that the interaction between MR and occupancy was non-linear. Despite having the same total metabolic heat, the distribution of occupants significantly affected indoor temperatures. This finding addressed a gap in the literature, which typically focused on total heat output while overlooking the effects of spatial distribution and air mixing. Additionally, seasonal analyses highlighted the variable impacts of internal thermal gains under different climatic conditions, emphasizing the importance of context-specific strategies in building energy design. In conclusion, even when total metabolic heat remained constant across different MR-occupancy scenarios, indoor conditions were influenced by factors such as heat distribution efficiency and occupant density. These findings contributed to a deeper understanding of thermal comfort modeling and building energy consumption, offering valuable insights for the development of more responsive and adaptive HVAC strategies.

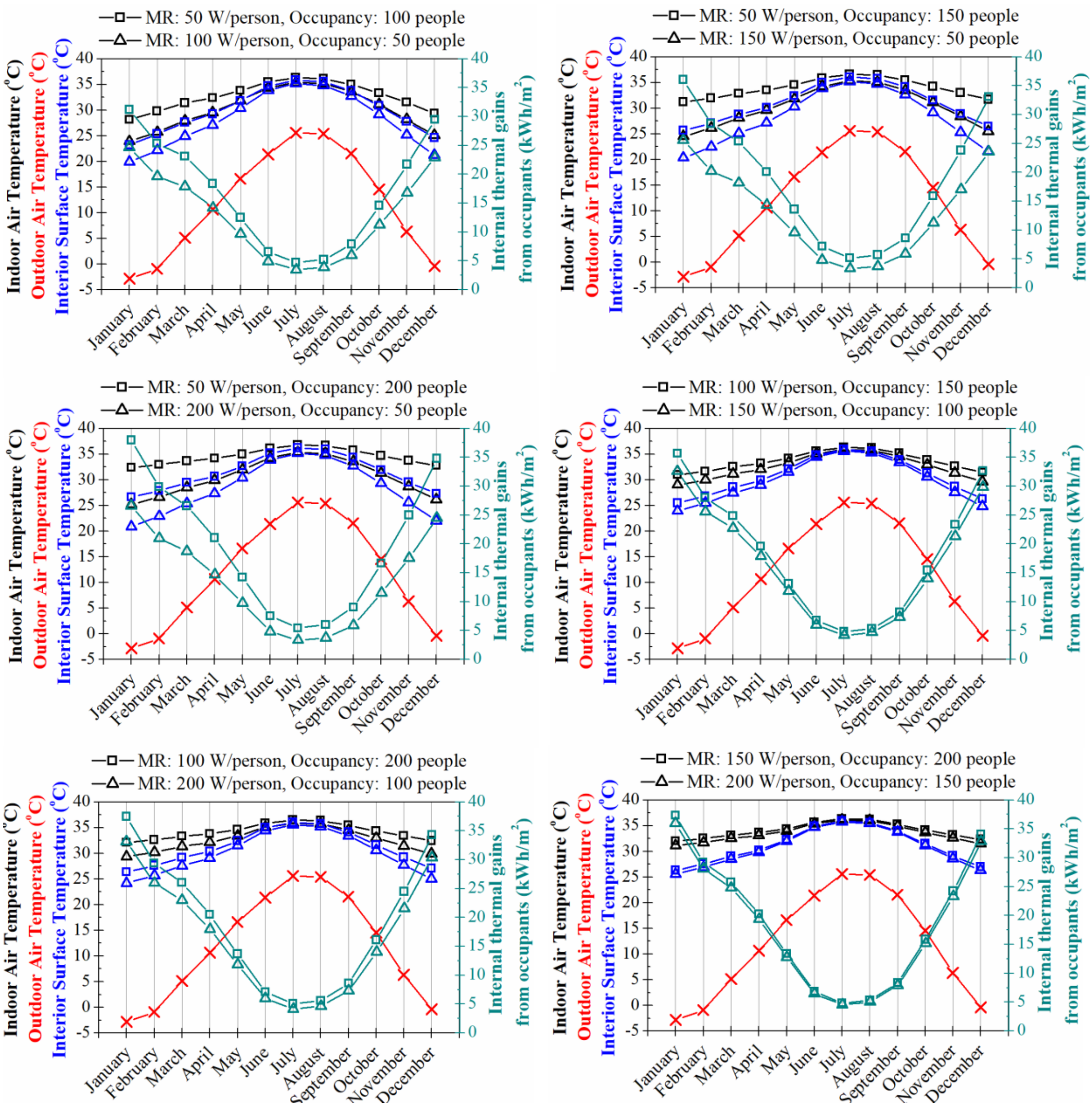

Figure 5. Monthly mean temperatures and internal thermal gains for different occupancy and MR combinations.

Conclusion

In this study, a simulation-based parametric analysis was conducted to examine the effects of different combinations of MR and occupancy on indoor air temperature, interior surface temperature, and internal thermal gains from occupants. Unlike previous studies that primarily investigated thermal effects in buildings with diverse functions, floor areas, and usage scenarios, this research specifically isolated the influence of MR and occupancy in a controlled non-ventilated building model. By systematically varying these parameters, the study provided a novel perspective on their relative impact on temperature distribution and thermal dynamics. The findings contributed to bridging the existing knowledge gap by clarifying which factor (MR or occupancy) played a more dominant role in shaping indoor thermal conditions. These insights served as a foundation for optimizing internal thermal gains and advancing energy-efficient design strategies. To eliminate external influences and isolate the thermal effects of occupants, ventilation was intentionally excluded from the simulation model. Consequently, the humidity released by occupants accumulated over time, causing indoor relative humidity to reach saturation (100%) in all cases. Since relative humidity remained saturated and showed no variation across scenarios, it was not included in the comparative analysis.

This modeling approach is particularly relevant for temporary or transitional indoor environments where ventilation may be limited or intentionally suspended. Examples include temporary emergency shelters, high-density waiting areas (e.g., during crises or vaccination campaigns), or enclosed public spaces used for short-term occupancy, such as modular field hospitals or relief centers. In such contexts, understanding the thermal effects of occupancy and metabolic activity is critical for ensuring occupant safety, thermal resilience, and energy resource planning. By identifying the dominant role of occupant density in shaping indoor temperatures, even under conditions of constant metabolic heat, the study provides actionable insights for energy load forecasting and passive design strategies in these special-use environments.

The key findings revealed that both MR and occupancy significantly impacted indoor thermal conditions, but their effects differed depending on the scenario. While an increase in MR or occupancy generally led to higher indoor air and wall surface temperatures, the influence of MR diminished in scenarios with high occupancy. Conversely, occupancy had a stronger effect on indoor temperature dynamics, particularly due to its role in expanding the heat transfer surface area. Notably, even when total metabolic heat production was constant, scenarios with a higher number of occupants demonstrated greater internal thermal gains due to more homogeneous heat distribution. Seasonal variations played a critical role, with the impact of metabolic thermal gains being more pronounced during the winter months, thereby reducing heating demands, whereas in the summer, their influence was limited due to dominant outdoor temperatures.

In conclusion, even when total metabolic heat remained constant across different MR-occupancy scenarios, indoor conditions were influenced by factors such as heat distribution efficiency and occupant density. These findings contributed to a deeper understanding of thermal comfort modeling and building energy consumption.

In future work, it would be valuable to explore how different heating and cooling strategies, beyond traditional HVAC systems, influence the relationship between MR, occupancy, and indoor thermal conditions. Moreover, it may be beneficial to investigate the impact of smart building technologies, such as automated shading or adaptive lighting systems, on the interplay between MR, occupancy, and indoor thermal comfort. Expanding the scope of such modeling to include emergency-use scenarios and adaptive ventilation schemes may further enhance its relevance and practical applicability. This could provide insights into how responsive systems can optimize energy use while maintaining occupant comfort under varying conditions.

Ethics committee approval and conflict of interest statement

There is no need to obtain permission from the ethics committee for the article prepared.

There is no conflict of interest with any person / institution in the article prepared.

Authors' Contributions

Yüksel A.: Study conception and design, acquisition of data, analysis and interpretation of data, drafting of manuscript, and critical revision

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