Is There A "New Normal" For Building Occupancy? A Comparative Analysis of Pre- and Post-Lockdown Occupancy in A Library Building

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Abstract

A critical aspect to optimize the design and operation of buildings is to understand how occupants interact with them. The COVID-19 pandemic significantly altered post-lockdown occupancy patterns in the built environment, raising questions about whether building occupancy has returned to pre-lockdown levels. This study presents a comparative analysis of variations in occupancy patterns of an institutional building, for three distinct phases: pre-lockdown, during partial lockdown, and post-lockdown. The study enabled a comprehensive examination of occupancy trends with the imposed restrictions utilizing data from Wi-Fi connections and camera-based occupancy counts in a library building. A rigorous statistical analysis was performed to investigate fluctuations in the occupancy levels, variations in peak occupancy times, and temporal variations between both the data sources while transitioning from pre- to post-lockdown normal. The obtained results show an overall ~51 % drop in the daily peak post-lockdown occupancy levels. A slight shift in the peak occupancy times was observed – a delay of two hours on Mondays and one hour on Wednesdays, while other weekdays and weekends remained consistent. Additionally, the averaged post-lockdown occupancy conversion factors dropped by ~18 %. The outcome of this study highlights a considerable variation in the building occupancy levels pertaining to the imposed lockdown restrictions and serves as a guideline in providing key insights for the building operators to optimize buildings' system operation.

Introduction

The influence of occupant behaviour on energy consumption in buildings is seeking more attention as the overall energy demand of the buildings is substantially decreasing due to the highly ambitious energy performance requirements (Delzendeh et al., 2017). Occupants spend more than 85 % of the time indoors, thus incorporating the occupant dynamics into the building energy systems design and operation is just as crucial as the technological and policy dimensions (D'Oca et al., 2018), (Jia et al., 2017). The conventional occupancy schedules in building management systems or building simulation tools are incapable of capturing the dynamic nature of the building occupancy, ultimately resulting in unnecessary increase in the total energy consumption in buildings during non-working and unoccupied hours (Ding et al., 2021). However, a detailed investigation of occupancy patterns by considering the dynamic state of occupants i.e., arrival, presence in the space and departure can adequately alleviate the performance gap between the predicted and actual energy consumption in buildings. Moreover, the connection between occupants' movements and their behaviours have also been investigated by many researchers (Page et al., n.d.), (Rafsanjani & Ahn, 2016), (Page et al., 2008), (Yun & Steemers, 2008).

The unprecedented circumstances introduced by COVID-19 lockdown severely impacted the way occupants interact with the built environment. The daily life and behavioural patterns of the occupants were significantly affected under various restrictive measures imposed to tackle this pandemic. Moreover, several changes and challenges associated with office work culture arose, as many working professionals and students were encouraged to work and participate in different activities remotely. This resulted in a significant drop in the co-working space occupancy under imposed strict preventive measures.(Motuzienė et al., 2022). Various discussions claim that the hybrid-work culture, flexibility in the working schedules and locations has become a new normal and will never come back to the time of before Covid-19. Simultaneously, it's evident that the post-pandemic times have not only substantially changed occupancy patterns in the workspaces, but also introduced new challenges in predicting building occupancy levels, which has a direct impact on the design and operational phase of the buildings (Todeschi et al., 2022).

Numerous studies have previously emphasized the significance of occupant presence in buildings (Franco & Leccese, 2020), (Salimi et al., 2019) and the impact of their actions on building energy consumption (Happle et al., 2018),(Azar & Menassa, 2012), (Geraldi et al., 2021). Moreover, the outbreak of COVID-19 has significantly changed energy consumption in the built environment. Several studies reported that the total energy demand increases, whereas other studies have shown a decrease. These contradictory results are primarily due to a lack and exclusion of dynamic variation in the occupants' behaviour

under the imposed lockdown restriction (Motuzienė et al., 2022). Due to the interruption caused by COVID-19, pre-pandemic occupancy schedules are no longer reliable in forecasting the post-pandemic energy demands. In a study conducted by (Xie et al., 2021), the impact of lockdown restrictions on the occupant' behaviour was investigated. Another similar analysis (Todeschi et al., 2022) highlighted the challenges posed in using pre-pandemic occupancy data to train machine learning algorithms for energy demand forecasting. The results suggested that incorporating detailed pre-, partial, and post-pandemic occupancy scenarios improved the energy demand forecasting model performance by 10 %. (Motuzienė et al., 2022) analysed the pre- and post-occupancy patterns in a small office building consisting of two offices. The overall drop in post-lockdown occupancy levels in both offices never exceeded 20 % of the pre-lockdown occupancy. Moreover, a significant drop in the post-occupancy levels in an institutional building was reported by (Fu et al., 2021). A comparative analysis of the variation in pre- and post-lockdown pandemic occupancy schedules in US-residential buildings was performed by (Mitra et al., 2022). It was found that pandemics substantially impacted the occupancy schedules in residential sector with a 45 % rise, observed in 2020.

The literature review suggests that various investigations has been carried out to study the interruption caused by COVID-19 on building energy consumption. Since the energy trends and demand have evidently changed, however, there is still lack of work pertaining to the analysis of how significantly the variation in occupancy trends changed after this transition, which is one of the most critical factors in energy performance of buildings. To the authors best of knowledge, there is no clear evidence reported in literature on to what extent building occupancy has changed post-lockdown, raising critical questions about whether it has returned to pre-lockdown levels or not. To this end, this study focuses on evaluating transitions in occupancy patterns during pre, partial, and post-lockdown periods. The analysis is based on the long-term monitoring of occupancy profiles in an institutional building, located in Montreal, Canada. Wi-Fi connections and camera-based occupancy counts were used to produce the occupancy data and the main objectives of this study include (i)- analysing hourly and weekly variation in the occupancy levels (ii)- identification of the discrepancies in the occurrence of peak occupancy times and (iii)- investigating the relationship between both the data-sources (Wi-Fi connections and camera-based occupancy counts) during pre, partial, and post-lockdown period.

Methodology

The proposed methodology entailed two steps which are discussed in this section.

1. Data Collection and Preparation

The datasets used in the present study have been collected from two sources (i.e., Wi-Fi connection counts and camera-based occupancy counts) for a total of nine weeks (i.e., Jan 13th till March 12th) spanning three distinct periods. The selection of this particular time interval is based on the exclusive availability of occupancy records for pre-lockdown phase, which refers to the period before COVID-19 in 2020. During this period, library functioned normally and was actively used by the staff and students. Following the outbreak, the university subsequently reopened under COVID-19 guidelines in 2021, marking the partial lockdown phase. The post-lockdown period, commencing in 2022, corresponds to the full lifting of lockdown restrictions.

The total number of devices connected to the Wi-Fi access points were retrieved from the Wi-Fi network administration. In order to avoid any privacy concerns, the adopted data collection approach is only limited to the aggregated connection counts and doesn't reveal any additional information including users' connection history and *MAC* addresses of the connected devices. Two cameras installed at the main entrance/exit of the library were used to generate the ground truth data. It is pertinent to mention that collecting ground truth data in this study doesn't involve facial recognition. Instead, it utilizes the concept of head image recognition and only provides total number of people entering and/or leaving the library. Furthermore, the outliers for hourly values in both the datasets were identified using the Interquartile Range (IQR) method. This approach defines outliers as values exceeding 1.5 times the IQR, which is the difference between the third quartile (Q3) and the first quartile (Q1), either below Q1 or above Q3. These detected hourly outliers were subsequently substituted with the corresponding hour's mean or median value. Lastly, both the Wi-Fi and camera-based occupancy counts were cleaned, synchronized, and transformed to a proper format for further analyses.

2. Examining the relationship between the Wi-Fi connection and Camera based occupancy counts

Investigating the relationship between the hourly variation in the Wi-Fi connections and camera-based occupancy counts spanning over three distinct periods was performed into two steps. The initial step entailed the identification of all the Wi-Fi connected devices that are not the representants of the occupant's presence, including printers and servers etc., termed as stationary devices. The minimum estimated number of stationary devices varied significantly on weekdays and weekends, i.e., 13, 1 and 7 during weekends and 17, 2 and 8 on weekdays for the pre-, partial-, and post lockdown periods, respectively. These identified stationary devices were subtracted from Wi-Fi connection counts of the pre-, partial- and post lockdown period. The second step entailed examining the temporal variations between both the data sources. A timeseries indicating the ratio of the Wi-Fi connections and camera-based occupancy counts has been generated for the pre-, and post lockdown period. The dynamism of these conversion factors

throughout the day as well as between different days was then investigated using statistical analysis techniques.

3. Peak Occupancy Analysis

In order to estimate the occurrence time of peak occupancy during weekdays and weekends of the pre- and post-lockdown period, the cumulative relative frequency distribution of the occurrence of daily maximum Wi-Fi connections have been estimated by aggregating the frequencies with the corresponding time intervals of the peak occupancy. This method resulted in identifying the probability of occupancy peak occurrence at different times of the day, for both the weekdays and weekends. It serves as a guideline in providing key insights for the building operators to optimize buildings' system operation in accordance with post-lockdown peak occupancy patterns.

Case study

The case study building is a four-storey building located in Montreal, Canada. The building covers a total of 19,180 m^2 area, allocated for various purposes i.e., 14 % of the area is dedicated for staff offices, while 40 % is allocated for lecture rooms, group study, reading and discussion rooms. The rest of the space is covered by lobbies, collection areas and corridors. The library was operated under standard conditions and students were allowed access to the library premises 24/7 before the lockdown, whereas the operational hours were then changed under the restrictions imposed by lockdown. However, after lockdown, the library has resumed its normal operating schedule and is accessible for the students and staff 24/7. It is pertinent to mention that the multi-spaces dedicated for students were actively utilized during both the weekdays and weekends, however, the staff offices were occupied during the working hours and only on weekdays.

The library was continuously monitored during the pre, partial and post-lockdown periods and the occupancy profiles of the users were extracted from two data sources

(i.e., Wi-Fi connection counts and camera-based occupancy counts) for a total of nine weeks (i.e., Jan 12th till March 12th) spanning three distinct periods. Two cameras (one optical and other thermal) covering the main entrance/exit of the library were installed on the first floors. The granularity of the occupancy counts generated by the camera counts is 5 mins time interval, which were the continuous source of ground truth data. The inaccuracy of both the cameras in producing the occupancy data has been investigated in a previous study (Alishahi et al., 2022). Moreover, a total of 152 APs (Cisco Aironet AIR-CAP3702I and Cisco Aironet 2802I), covering all the floors were providing the Wi-Fi connection counts at a 3 mins time interval, without revealing any additional information including users' connection history and MAC addresses of the connected devices. The data generated from both sources was inconsistent, therefore, was then hourly aggregated to produce the occupancy counts. It is worth mentioning that the availability of the multi-occupant's spaces in the case study building is of great significance to clearly interpret and understand the dynamics variation in the pre- and post-lockdown occupancy patterns.

Results and Discussion

In order to better understand and interpret the variation in occupancy patterns statistical analysis has been performed on the dataset collected for three distinct periods and the obtained results are detailed as follows.

1. Descriptive Analytics and Occupancy Profiles

The hourly variation of the Wi-Fi connection and camera-based occupancy counts during the pre-lockdown, partial lockdown, and post-lockdown periods are delineated in Figs. 1(a) and 1(b), respectively. The weekly occupancy profiles follow a similar pattern, however, the overall total number of occupants during the first two weeks were relatively less in comparison to other weeks of the partial and post-lockdown. Also, a drop in the overall occupancy levels was observed during the seventh week, referring to the university's mid-term break, which is consistent for all the time periods under observation. However, it is pertinent to note that during partial lockdown, this drop in total occupancy counts during mid-term break is not considerable which is attributed to overall low occupancy counts observed during this time as compared to pre- and post-lockdown periods. Overall, the results of Fig. 1 highlight the significance of imposed lockdown restrictions, resulting in an overall ~96 % and ~51 % drop in the peak daily occupancy levels during the partial and post lockdown times, respectively, in comparison to the pre-lockdown.

The variation in daily occupancy profiles was quite similar for both the Wi-Fi connections and camera- based occupancy counts during the weekdays except the partial lockdown period. Fig. 2 shows daily variation in camera-based occupancy counts for the pre, partial and post-

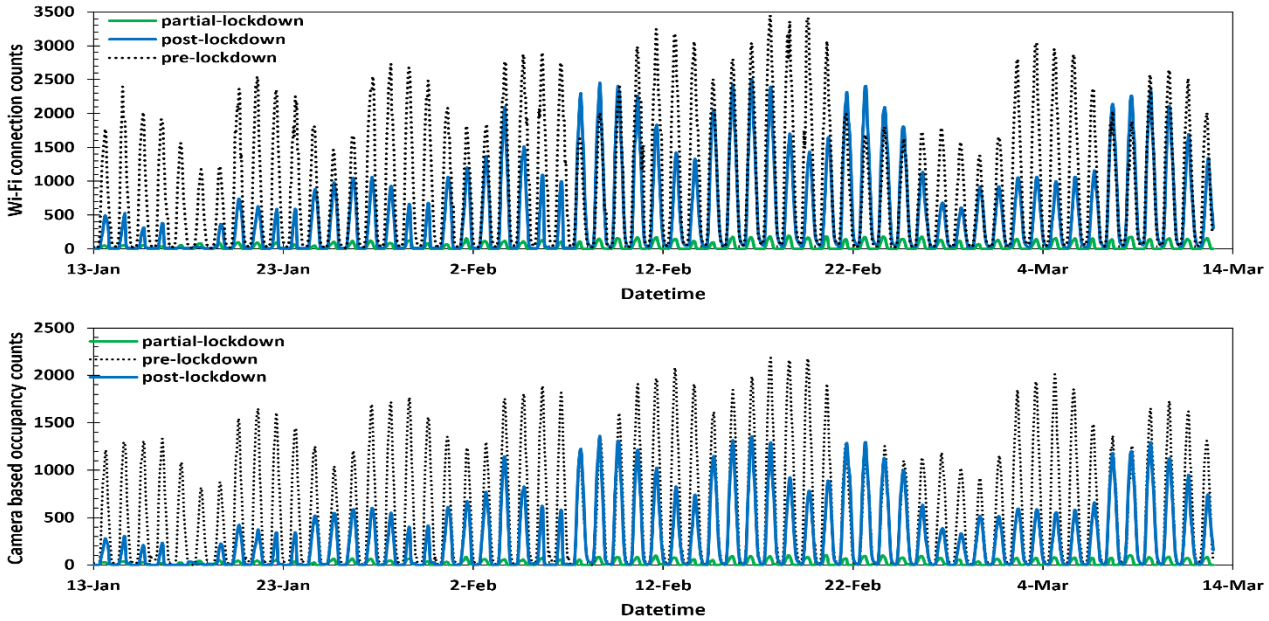

Figure 1. Weekly profiles of the (a)- Wi-Fi based connection counts (b)- camera based occupancy count during pre-, partial- and post-lockdown periods (i.e., Jan 13 – March 12)

lockdown period. The occupancy levels start increasing gradually at 9 am, which then peaks around 03:00 – 04:00 pm and gradually drops around 10:00 pm, whereas this drop is observed at 7:30 pm during the partial lockdown (due to reduced operational hours i.e., 08:30 am - 7:30 pm). Pre-lockdown weekends follow a similar pattern as weekdays; however, the occupancy increase was observed at 10:00 am, which then steps down at 05:30 after peaking around 4 pm. This peculiar behaviour of the daily occupancy profiles is due to the varying operational schedules over the pre- and post-lockdown weekends. Moreover, the overall peak occupancy of the library during post-lockdown dropped by 31 % (as compared to the pre-lockdown), indicating a new normal in the building occupancy dynamics with more unoccupied spaces. This eminent drop in the post-lockdown occupancy evidently signifies a critical need to re-align the mechanical schedules, owing to substantial dynamic transition in the building occupancy patterns.

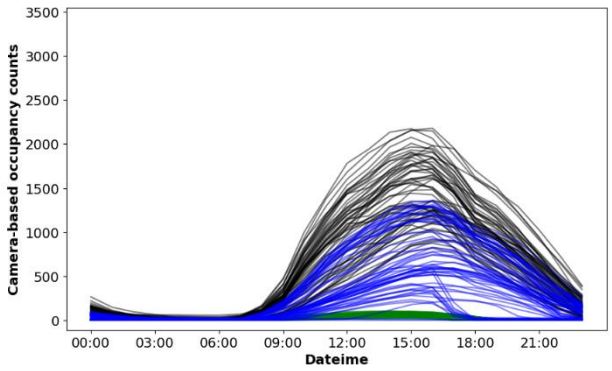

Figure 2. Daily profiles of the camera-based occupancy count during pre-, partial- and post-lockdown periods

A noticeable difference in pre-, partial, and post-lockdown occupancy patterns during the weekdays and weekends was observed for both Wi-Fi connection counts and camera-based occupancy counts. The pre-lockdown period, characterized by unconstrained access to the library, exhibited robust occupancy figures, with camera-based occupancy counts peaking at a median of ~1000 occupants per hours, and Wi-Fi connection counts mirroring this trend, averaging ~1600 connections per hour during on weekdays and weekends, respectively. The partial lockdown period experienced consistently lower occupancy levels and no significant differences between the weekends and weekends were observed. Post lockdown phase follows similar trends as pre-lockdown. Despite significant drop in the pre- and post-lockdown occupancy, the occupancy patterns also follow an inconsistent trend across the days of the week. The deviation in pre- and post-lockdown occupancy levels is more pronounced on weekends, followed by Fridays, whereas Mondays and Wednesdays, on the other hand experienced a more pronounced increase in both camera-based occupancy counts and Wi-Fi connections relative to other weekdays, during the post-lockdown phase. These observations collectively highlight substantial deviation in the post-lockdown occupancy dynamics, not merely reverting to pre-pandemic patterns. Moreover, it is pertinent to mention that in the wake of this new occupancy normal, pre-lockdown occupancy schedules are no longer reliable in forecasting the post-pandemic energy demands.

Besides these intuitive insights demonstrated by the daily and weekly profiles, Kruskal-Wallis H test was also performed to further quantify if there exist any noticeable statistical differences in both the Wi-Fi connection counts

and camera-based occupancy accounts recorded during the pre-, partial- and post-lockdown period. The obtained p-values ranged between 3.30×10^{-269} - 2.97×10^{-66} were significantly lower ($p < 0.05$), thus suggesting significant statistical differences in the pre- and post-lockdown occupancy patterns of the library building. Table. 1 presents the descriptive statistics of both the Wi-Fi connection counts and camera-based occupancy counts for three distinct periods i.e., pre, partial and post-lockdown.

Table 1. Descriptive statistics of the Wi-Fi connections and camera-based occupancy counts

Descriptive statistics	Pre-lockdown (Jan 12th – Mar 13th, 2020)		Partial lockdown (Jan 12th – Mar 13th, 2021)		Post-lockdown (Jan 12th – Mar 13th, 2022)	
	camera counts	Wi-Fi counts	camera counts	Wi-Fi counts	camera counts	Wi-Fi counts
Min	44	126	0	2	0	7
Max	2180	3449	104	194	1357	2502
Median	911.5	1413	30	50.5	369.5	666
Mean +- SD	(931.16, 492.98)	(1466, 746.5)	(33.36, 28.37)	(62.61, 52.67)	(438.28, 346.8)	(796.33, 638.2)

It is important to mention that the partial-lockdown period, characterized as a brief transitional phase, is excluded from further analysis due to the low probability of similar circumstances reoccurring in the future.

2. Relationship between Wi-Fi and camera-based occupancy counts

To further interpret and understand the temporal variations between both the data sources, a timeseries indicating ratio of the Wi-Fi connections and camera-based occupancy counts (terms as *CW* conversion factors) has been generated for the pre-, and post lockdown period. The influence of occupancy levels and time on the estimated conversion factors have been observed and obtained results are delineated in Figs. 3 and 4. It is worth mentioning that this analysis is primarily focused on the standard operational hours (i.e., 9 am till 10 pm), during which library is actively occupied with an overall occupancy level greater than 10 %. This assumption is held valid due to the fact that the occupancy-based HVAC controls in institutional buildings are practiced only for the standard operational hours during the day.

Fig. 3 demonstrates the hourly variation in CW conversion factors with camera-based occupancy counts during the pre, and post-lockdown periods. At lower value of camera-based occupancy counts, both the pre- and post-lockdown conversion factors experienced significant variations. This is attributed to the high disparities between the camera-based occupancy counts and Wi-Fi connections at lower levels of occupancy. Moreover, it can be inferred from the findings of Fig. 3, the variation in post-lockdown CW conversion factors is less pronounced as compared to the pre-lockdown CW conversion factors. Nonetheless, with increasing levels of the camera-based occupancy counts towards peak level, both the pre- and post-lockdown conversion factors starts converging, suggesting that both camera-based occupancy counts and the corresponding wi-fi connections got closer at higher levels of occupancy. The convergence of the post-lockdown conversion factors is considerably higher than the pre-lockdown conversion factors, the former achieving a steady state convergence of 0.56 (when the corresponding occupancy are 500), while the corresponding camera-based occupancy counts for the pre-lockdown convergence factors is 1250, to attain a steady state conversion factor of 0.68. This suggests that the discrepancies in both the data sources have reduced over

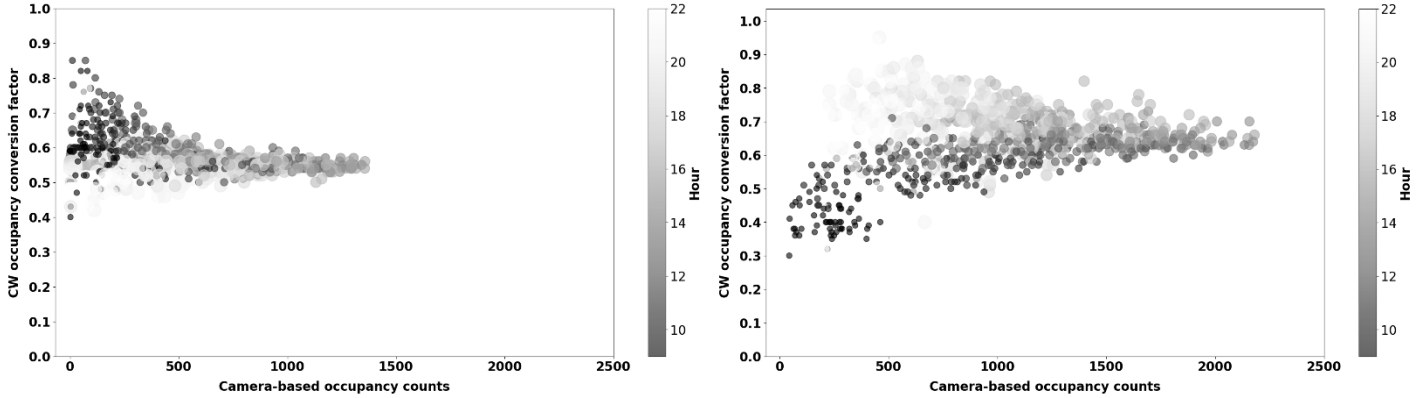

Figure 3. Hourly variation in the relationship between Wi-Fi connection and camera-based occupancy counts for (a)- pre-lockdown and (b)-post-lockdown

time while transitioning from pre-lockdown to the post-lockdown period. This might be a consequence of the improvements in the library's Wi-Fi network management platform system with time.

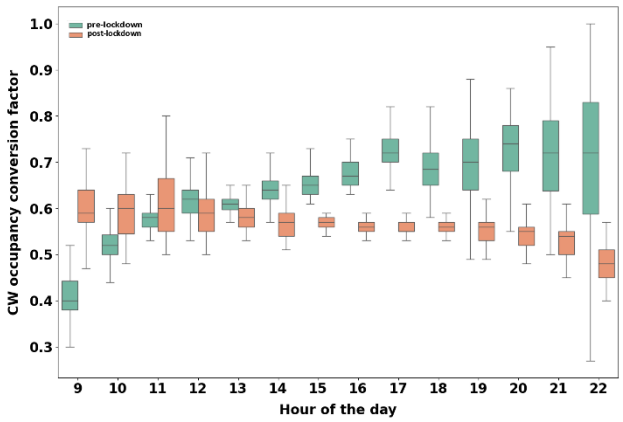

Figure 4. Range of hourly CW occupancy conversion factors during pre-, and post-lockdown period

The lingering effect in the occupancy levels is also evident in the post-lockdown conversion factors. The results presented in Fig. 4 indicate a notable difference in conversion factors between pre-lockdown and post-lockdown periods. During the post-lockdown phase, these factors were higher as the day progressed, particularly noticeable between 09:00 and 10:00 am. However, their difference reached a minimum from 11:00 am to 1:00 pm. In contrast, the pre-lockdown conversion factors were dominant, and the disparity between the pre- and post-lockdown values widened over time, particularly from 2:00 pm to 10:00 pm. The pre-lockdown conversion factors exhibited a progressively increasing trend and continued to rise till the end of the day, suggesting a reduced discrepancy between the wi-fi connections and camera-based occupancy counts. On the other hand, a gradual decline observed in the post-lockdown conversation factors highlights a slightly increased inconsistency between both the data sources, which is more prominent particularly during late evening hours. Overall, the post-lockdown factors were more consistent, with a standard deviation of less than 0.08, in contrast to the pre-lockdown period, where the standard deviation was less than 0.2. The diversified trends observed in pre- and post-lockdown conversion factors implies that the relationship between both the data sources has changed significantly in comparison to what was observed before the lockdown.

Variation in peak occupancy times

The transition in the probable occurrence of pre- and post-lockdown peak occupancy has been analysed separately for weekdays and weekends and the obtained results are presented in Fig. 5. During weekdays, the probabilities of pre- and post-lockdown peak occupancy were predominantly concentrated on Tuesday, Thursdays, and Fridays, experiencing a pronounced peak occupancy at 04:00 pm. Conversely, Mondays and Wednesdays experienced the most significant temporal variation in the probable occurrence of peak occupancy time. On both days, pre-lockdown occupancy gradually increases and peaks during early evening hours i.e., at 6 pm and 5 pm, respectively, on Mondays and Wednesdays. However, during the post-lockdown period, the peak occupancy on both of these days was observed at 4 pm. This forward shift (by 2 hours on Mondays and one hour on Wednesdays) in the possible occurrence of post-lockdown peak occupancy times underscores a behavioural adaptation to the post-lockdown occupancy patterns, possibly reflecting an inclination for earlier library use to avoid denser crowds later in the day. However, the occurrence of pre- and post-lockdown peak occupancy times remains unchanged over the weekends.

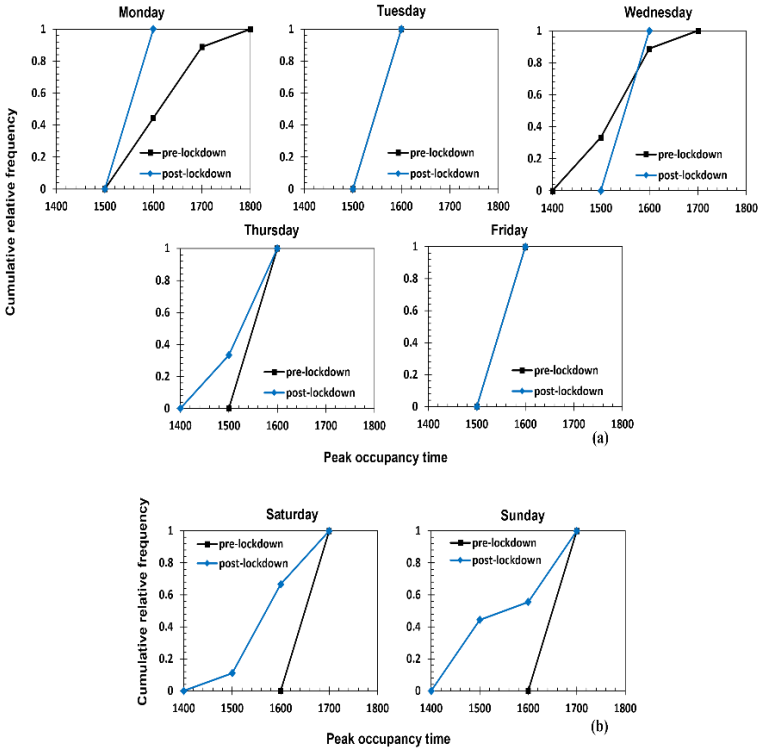

Figure 5. Variation in probable occurrence of pre- and post-lockdown peak occupancy times (a)- weekdays (b)- weekends

Conclusion

The unprecedented circumstances introduced by COVID-19 lockdown significantly impacted the daily occupancy patterns in the institutional buildings due to hybrid-work culture, flexibility in the working schedules and locations. Several studies reported that the total energy demand increases, whereas several other studies have shown a decrease. These contradictory results are primarily due to a lack of dynamic variation in the occupants' behavior under

the imposed lockdown restriction. To fill this gap, this study presented a comparative analysis of variations in occupancy patterns of an institutional building, for three distinct phases: pre-lockdown, during partial lockdown, and post-lockdown. A rigorous statistical analysis was performed to investigate key influential factors such as fluctuations in the occupancy levels, variations in peak occupancy times, and temporal variations between both the data sources while transitioning from pre- to post-lockdown normal.

1. The variation in the daily occupancy patterns indicated ~51 % drop in the peak post-lockdown occupancy levels. The analysis was extended for each day of the week and the obtained results suggested that Mondays and Wednesdays, on the other hand experienced a more pronounced increase in both camera-based occupancy counts and Wi-Fi connections relative to other weekdays. Moreover, the temporal variation in the conversion factors evidently signified that building's occupancy no longer follows the pre-lockdown pattern, thus adequately implying a paradigm shift in the density of post-occupancy levels (from before to after peak hours).
2. The cumulative relative frequency analysis was performed to estimate the temporal probability of peak occupancy occurrence at different times of the day, for both pre- and post-lockdown period. A slight shift in the possible occurrence of peak occupancy times was observed – a delay of two hours on Mondays and one hour on Wednesdays. This indicates a behavioral adaptation to the post-lockdown occupancy patterns, possibly reflecting an inclination for earlier library use to avoid denser crowds later in the day, while other weekdays and weekends remained consistent.

The outcome of this study highlights a considerable variation in the building occupancy levels pertaining to the imposed lockdown restrictions. The performed analysis is of great significance and can serve as a guideline in providing key insights for the building operators to optimize buildings' system operation. Moreover, the notable variation observed between pre- and post-lockdown occupancy patterns indicate that the pre-lockdown occupancy schedules are no longer reliable in forecasting the post-pandemic energy demands accurately. Although the proposed approach highlighted how the building occupancy has changed, it is equally important to acknowledge and address certain limitations to be addressed in future. The findings of this study are based on a limited time period spanning ~ 9 weeks of data and it primarily serves as a proof of concept for identifying the noticeable variations in pre- and post-lockdown occupancy patterns. Future work should focus on developing models to precisely forecast post-lockdown occupancy counts and finally their integration into the building operation system. Moreover, the analysis should be extended at room or zone-level to estimate occupancy-based indicators e.g., space type and utilization, earliest arrival and departures etc. Nevertheless, to comprehensively capture these variations and validate the accuracy of the results, it is essential to extend data collection beyond this study's timeframe, ideally for a minimum of one year. It is also pertinent to mention that the applicability of the results is only limited to the case study building that requires extensive investigation for their applicability to other similar and/or different single or multi-occupant spaces, owing to unique occupancy patterns.

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