Building and Environment 90 (2015) 136–145

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

# Methods to assess human occupancy and occupant activity in hospital patient rooms

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ARTICLE INFO

*Article history:*
Received 21 December 2014
Received in revised form
13 March 2015
Accepted 27 March 2015
Available online 4 April 2015

*Keywords:*
Healthcare environments
Carbon dioxide concentrations
Doorway beam-break sensors
Indoor microbiome
Room occupants

ABSTRACT

Human occupants have a profound influence on indoor environments, although there is limited information on means to cost-effectively assess occupant metrics in all types of buildings. Multiple measures of occupancy (i.e., the number of occupants and the duration of their presence) and occupant activity (i.e., the number of occupant movements through room doorways) were investigated in ten single-patient rooms in a new hospital in Chicago, Illinois as part of the Hospital Microbiome Project, with the overarching goal of determining occupant characteristics to inform an investigation of interactions between humans and microbial communities. Four relatively low-cost, non-invasive methods to estimate time-resolved occupancy and occupant activity were developed using data from (1) $CO_2$ concentration sensors installed in patient rooms and the supply air streams serving each room and (2) non-directional doorway beam-break sensors installed at each patient room doorway. A method that utilized data from both sensors produced the most accurate estimates and was used to characterize time-varying occupancy and occupant activity. Daily occupancy varied among rooms, with median values ranging from 0 to 3 persons per hour. Occupant activity exhibited less variation on average (approximately 8 doorway movements per hour), but reached high levels on certain days for some patient rooms. No consistent relationship was observed between estimated occupancy and occupant activity, indicating that one metric cannot be inferred from the other. This study shows that this dual-sensor methodology provides a relatively inexpensive, non-invasive, accurate approach to estimate occupancy and occupant activity in an environment with rigorous privacy and security limitations.



## 1. Introduction

Human occupants have a profound impact on the built environment, including building operation, energy consumption, and indoor environmental quality (IEQ). Building operational parameters, such as indoor temperature, relative humidity (RH), and lighting levels, are primarily governed by occupant comfort and preference [1] and a major component of building ventilation is based on occupancy [2]. Maintaining these conditions requires a substantial amount of energy; for example, in 2010, buildings accounted for 41% of total energy consumed in the United States [3]. Aside from energy consumption, human occupants have a significant impact on IEQ, particularly on indoor air quality (IAQ) and indoor microbial communities. Human activities such as cooking [4] and smoking [5] generate fine particles and other pollutants, while even simple movements such as walking result in particle resuspension [6]. Human occupants are also a prominent source of indoor bacteria [7–12], and indoor concentrations of airborne bacteria, including human-associated microflora and potentially harmful pathogens, have been shown to increase with occupancy [13].

The importance of occupants to the built environment has been widely recognized and investigated in existing studies [14]. Occupant information has been an essential component of these studies, and a number of strategies to attain such information have been

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http://dx.doi.org/10.1016/j.buildenv.2015.03.029
0360-1323/

explored, ranging from physical observations (e.g., [15]) to more sophisticated sensor-based methods (e.g., [16]). More intuitive approaches have detected occupants using vision sensors, including video camera, static camera, and/or passive infrared (PIR) sensor networks [17–23]. Alternatively, some studies have relied solely on $CO_2$ measurements and a steady state and/or dynamic mass balance [24–26], while other studies investigated correlations between occupancy and various environmental parameters, such as temperature, humidity, illumination, acoustics, and motion [25,27,28]. The use of less common indoor measurements has also been explored, including air velocity [29], and an air quality sensor network that monitored $CO_2$, total volatile organic compounds (TVOC), and particulate matter less than 2.5 μm in diameter ($PM_{2.5}$) [27]. Occupant detection methods designed specifically for office environments have been widely investigated. Examples include detecting occupant presence/absence with sonar-based hardware that exists in computers and other electronic devices [30]; utilizing chair pressure sensors, PIR sensors, and acoustic sensors (to detect keyboard and mouse sounds) [31]; and combining information from a variety of sensors, and employee badge and parking lot car counts [32].

Although a number of approaches have been analysed, there is still a gap in the literature. The majority of existing methods have focused on estimating occupancy (i.e., the number of people in a portion of a building and the duration of their presence), which could be a result of the importance placed on reducing energy consumption through building operation based on occupancy [33]. Much less attention has been given to detecting occupant activity (i.e., occupant movements), despite evidence indicating that such movements have a stronger effect than occupancy on certain aspects of IAQ, including increasing bioaerosol concentrations in residences [34] and undermining containment strategies in hospital isolation rooms [35,36]. The most relevant existing measures of occupant activity include identifying room-to-room occupant transitions [17,18,37], identifying high traffic areas [32], and characterizing various types of desk-based office work [30,31]. Furthermore, methods of occupancy or occupant activity detection have not been explored in a wide variety of buildings. Previously investigated buildings imposed few limitations on the employed detection methodologies, as most occurred in commercial office buildings and universities, where privacy/security restrictions and the level of invasiveness were not overwhelming concerns. This will not hold true in all indoor environments (such as hospitals), and there is a need to develop and evaluate methods to detect both occupancy and occupant activity in various types of buildings.

In response, we evaluated multiple methods for estimating both human occupancy and occupant activity in ten single-occupancy hospital patient rooms using data from multiple sensors as part of the Hospital Microbiome Project (www.hospitalmicrobiome.com). In this study, ‘occupancy’ is defined as a measure of the number of people in a patient room and the duration of their presence, and ‘occupant activity’ is defined as a measure of occupant movements through the patient room doorway (i.e., the number of entrances and exits, which provides insight on the occupant movements into and out of patient rooms but does not provide direct measurements of in-room activity). The results from this work (i.e., quantitative values of time-varying occupancy and occupant activity) will inform a future comparison to companion microbial data (when available) in order to determine potential interactions between human occupants and microbial communities in the studied environment. To accomplish this, we developed four low-cost, non-invasive methods to estimate both occupancy and occupant activity, which we analyse in this paper to provide methodological recommendations for occupancy and occupant activity detection in a type of building with several privacy and security restrictions, as well as valuable information regarding the levels of occupancy and occupant activity in this unique type of environment.

## 2. Methods

An opportunity to study human occupants in a hospital environment arose with the Hospital Microbiome Project, an investigation of microbial communities in a newly constructed hospital pavilion in Chicago, both before and after the hospital had opened to occupants [38,39]. Microbial samples were taken from a variety of surfaces, in air, and from various human sites, over the course of approximately one year. During this time, a number of sensors were also deployed to concurrently measure indoor environmental parameters, including temperature, RH, illuminance, room pressurization, ventilation rates, $CO_2$ concentrations, and doorway beam-breaks in the patient rooms [40]. The goal of this joint measurement campaign was to determine possible relationships between microbial communities and indoor environmental parameters.

One environmental parameter that was predicted to have a prominent effect on the microbial communities was human occupants [41]. Information regarding occupancy and occupant activity was therefore essential to the Hospital Microbiome Project, and so methods to estimate these occupant parameters (within reasonable cost constraints) in ten single-patient hospital rooms were developed. The rooms were all 33 $m^2$ (including a personal bathroom) and 2.9 m in height with large windows along the west-facing exterior walls. All rooms were designed and operated as neutral pressure rooms and at least one of the double doors typically remained closed. The five rooms on the 10th floor (referred to as rooms 201–205) were reserved for oncology patients, whereas the five rooms on the 9th floor (referred to as rooms 101–105) were reserved for patients with shorter stays. Although none of the sensors installed in these rooms provided a direct measurement of occupancy or occupant activity, values for these parameters for each room were estimated by processing data from select environmental sensors, which included both non-directional doorway infrared (IR) beam-break sensors (SenSource PC-TB12-R People Counters; accuracy not reported by the manufacturer; initial cost of ~$400 USD) and $CO_2$ sensors (PP Systems SBA-5 $CO_2$ Gas Analyzers; manufacturer-reported accuracy of ±20 ppm; initial cost of ~$2000 USD when combined with a data logger). The beam-break sensors were installed at each patient room doorway to record the number of times the beam was broken (i.e., the doorway threshold crossed by a person); however, the device provided no indication of the direction of movement. The $CO_2$ sensors were installed in each patient room and in the supply air streams that served the rooms, and recorded measurements to Onset Computing U12-013 data loggers. All sensors recorded data at 5-min intervals, however the measurement interval of the beam-break sensors could not be synchronized with that of the other devices. The data streams from these sensors were used to develop four methods of occupancy and occupant activity detection in each patient room, defined herein as the: (1) Beam-break, (2) $CO_2$, (3) Lagged $CO_2$, and (4) Combined methods. The approach that each method utilized to estimate: (1) occupancy and (2) occupant activity is described in the following section. The procedure used to validate each of the four methods is discussed later in Section 3.2.

### 2.1. Estimation of occupancy

#### 2.1.1. Beam-break method

The Beam-break method only utilized data from the beam-break sensors and estimated occupancy by applying an occupant movement pattern to the raw beam-break count. It was assumed that only the patient was present in each patient room at midnight (as the patient should be sleeping at this time), and occupancy fluctuated after this time based on the beam-break count. Each doorway beam-break was assumed to correspond to the movement of a single occupant and the direction of the beam-breaks was assumed to follow an alternating pattern, where 50% corresponded to patient room entrances, and the other 50% corresponded to patient room exits. This movement pattern was deemed appropriate for this environment as it was representative of the majority of occupant movements (i.e., over 90%) observed during periodic visual observations. The main challenges and error associated with this method stemmed from the beam-break sensors, particularly, the non-directionality of the measurements and the inability to determine the number of occupants associated with each beam-break (discussed further in Section 3.4).

The remaining three occupancy estimation methods differed from the Beam-break method in that their base estimate of occupancy was determined from a mass balance on $CO_2$ concentration data.

#### 2.1.2. $CO_2$ method

The $CO_2$ method utilized the basic form of this, as described by the following equation and assumptions:

$$C_{room} = \frac{Q_{sup}C_{sup} + E}{Q_{ex} + Q_{ret}} \tag{1}$$

where $C_{room}$ is the $CO_2$ concentration in the patient room (ppm/$10^6$), $Q_{sup}$ is the AHU supply air flow rate (L/min), $C_{sup}$ is the $CO_2$ concentration in the supply air stream for the patient room (ppm/$10^6$), $E$ is the $CO_2$ emission rate for a typical hospital occupant (L/min), $Q_{ex}$ is the AHU exhaust air flow rate (L/min), and $Q_{ret}$ is the AHU return air flow rate (L/min). $E$ was assumed to be 0.39 L/min based on the metabolic and respiratory rates for an average sized adult engaged in very light physical activity [2]. $Q_{sup}$, $Q_{ex}$, and $Q_{ret}$ were measured using a powered flow hood (with an estimated accuracy of 5%, as described further in Section 3.4). The device was most compatible in terms of register/grille geometry with the return and exhaust outlets, and therefore the measurements for $Q_{ex}$ and $Q_{ret}$ were deemed acceptable. However, the device did not fit well with the supply duct geometry (i.e., the slot diffuser) and so there was little confidence associated with the measurements for $Q_{sup}$. An alternate approach was taken to determine a representative value for $Q_{sup}$, which involved performing the steady-state mass balance (Equation (1)) during times of zero occupancy (defined as periods of five or more consecutive hours without a single beam-break) with the measured $Q_{ex}$ and $Q_{ret}$ values. Information from the building operations manager suggests that $Q_{sup}$ was constant, and so the median value from this analysis was used throughout this investigation.

Furthermore, it was assumed that patient rooms were under steady-state conditions at each 5-min measurement interval and that mixing was complete in each room. Design supply air flow rates ranged from 11,000–12,750 L/min for the patient rooms with volumes near 100,000 L, providing approximately 7–8 air changes per hour (ACH). This indicates that the time to reach 95% steady state ranges from approximately 20–25 min. The mixing assumption is supported in part by Wang et al.'s [25] observation of reasonably high levels of mixing in an office and a lecture hall with closed doors. Mixing was also investigated in the hospital before it opened by placing five $CO_2$ sensors in a single patient room [42]. The measurements showed that the air was reasonably well-mixed, and although there were no indoor sources of $CO_2$ (i.e., human occupants) at the time of this test, the large air flow rates relative to the patient room volumes should ensure reasonably thorough mixing when indoor sources of $CO_2$ are present. However the main issue with this method, and all those that incorporate this $CO_2$-based mass balance, is the error associated with using a generic value for $E$ (discussed further in Sections 3.4 and 3.5).

#### 2.1.3. Lagged $CO_2$ method

The basic mass balance approach in Section 2.1.2 was then built upon by the remaining two methods. The Lagged $CO_2$ method also utilized Equation (1) and the same assumptions described above, but differed in that it incorporated a 20-min time delay on $C_{room}$. This accounted for the time it takes to achieve near steady-state conditions in each patient room for a $CO_2$ measurement at a specific instant in time.

#### 2.1.4. Combined method

Finally, the time-lagged mass balance from Section 2.1.3 was built upon by the Combined method, which included the addition of beam-break sensor data to reflect dynamic short-term changes in occupancy. The time-lagged mass balance served as a base estimate of occupancy, and the total was allowed to fluctuate based on the beam-break activity. These fluctuations were informed by findings from the visual observations (as explained in Section 2.1.1) and were based on the following assumptions: (1) there was no change in occupancy if no beam-breaks were recorded in a measurement interval, (2) an even number of beam-breaks in a measurement interval resulted in a change in occupancy (dependent upon the number of measured beam-breaks) in that time interval only (i.e., an even number of entrances and exits resulted in no residual change in occupancy), and (3) an odd number of beam-breaks within a measurement interval equated to a change in occupancy during the interval (dependent upon the number of measured beam-breaks) as well as a residual change of one occupant (assuming that the occupants associated with other recorded beam-breaks measured in that time interval had exited). The direction of the beam-break movement (i.e., an entrance or exit) was informed by the difference between the $CO_2$ concentration in the supply air stream and patient room air between consecutive time intervals (e.g., an increase in this difference represented an occupant entering and a decrease represented an occupant exiting). This approach was made possible through the use of $CO_2$ sensors with a high accuracy and low response time (manufacturer-reported response time of 1.6 s).

### 2.2. Estimation of occupant activity

Once the four methods to estimate occupancy were established, each method was also used to estimate occupant activity (i.e., the number of doorway movements) using one of two approaches. The first approach used the raw beam-break count as the value for occupant activity, since it is a direct measure of doorway movements and should capture every movement occurring within each 5-min measurement interval. The methods that incorporated beam-break data (i.e., the Beam-break method and the Combined method) adopted this strategy. The second main approach applied to the methods that relied solely on $CO_2$ data: the $CO_2$ method and Lagged $CO_2$ method. The $CO_2$ sensors do not provide a direct measure of doorway movements, and so occupant activity was inferred from the occupancy estimates. The $CO_2$ method and Lagged $CO_2$ method assumed that a change in direction and magnitude of the respective occupancy estimates between consecutive time intervals indicated a doorway movement.

### 2.3. Visual observations of occupancy and occupant activity

Occupancy and occupant activity were also measured in the patient rooms through periodic visual observations, which involved a single investigator physically monitoring occupancy and occupant activity in multiple patient rooms on the same floor over the course of five consecutive hours on two separate occasions. This manual count data was intended to provide true values of occupancy and occupant activity, however this was not realized at all times for both parameters (if for example, the observer was unable to capture a doorway movement for a patient room). This manual count data was assumed to be the most accurate measure of occupancy (since occupancy, or the number of people in a room, was simple to monitor and could be verified at any time by the observer), and so the occupancy estimates made with all four methods were compared to the manual count values. However unlike occupancy, the manual count data for occupant *activity* was deemed less accurate because it was difficult for one observer to record every doorway movement occurring in multiple rooms simultaneously (the doorway movements were much more dynamic and could not be verified after the fact). The beam-break sensor data was assumed to be the most accurate indicator of occupant activity since the sensors are more reliable than one observer at capturing all doorway movements. Accordingly, the occupant activity estimates were evaluated through a comparison to the beam-break sensor data.

## 3. Results and discussion

### 3.1. Estimates of occupancy and occupant activity

The Beam-break, $CO_2$, Lagged $CO_2$, and Combined methods were used to estimate daily occupancy and daily occupant activity using approximately six months of reliable sensor data (July 2013–January 2014). The occupancy estimates were converted into units of person·hours by accounting for the duration of each state of constant occupancy, since both the number of occupants in the patient rooms and the duration that they were present were of interest to this study. The number of occupants can also be inferred by dividing the number of person·hours by the number of hours in the defined period, which is 24 h for the daily period discussed below. The occupant activity estimates were expressed as the total number of beam-breaks occurring each day. Sample occupancy and occupant activity estimates for a single patient room (Room 105)

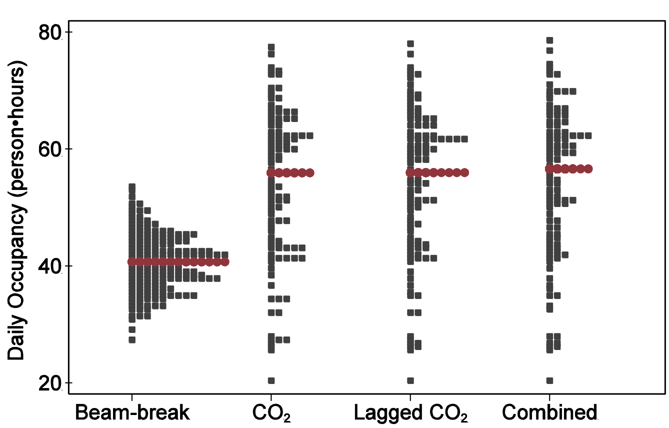


**Fig. 1.** Sample occupancy estimates for patient room 105 using each of the four methods. The vertical histograms show values of daily occupancy (i.e., the number of person·hours over a 24- period) for the six month measurement period. Complementary plots for all rooms are available in the Supplementary Data.

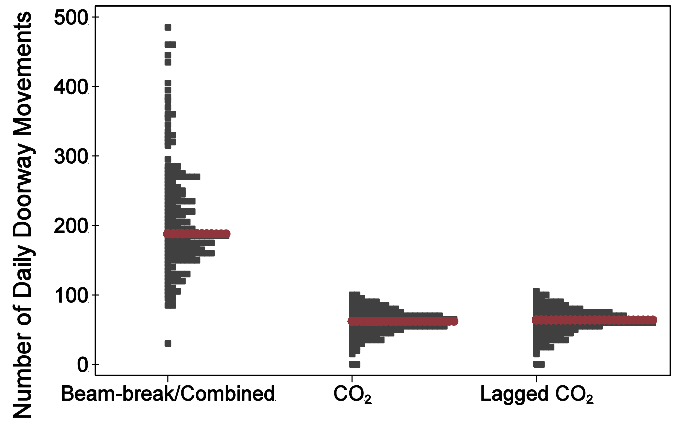


**Fig. 2.** Sample occupant activity estimates for patient room 105 using each of the four methods (the Beam-break method and the Combined method are expressed by the same distribution, since these methods produce equal estimates of occupant activity). The vertical histograms show daily values of occupant activity (i.e., the total number of doorway movements occurring over a day) for the six month measurement period. Complementary plots for all rooms are available in the Supplementary Data.

using the six months of data are shown in Figs. 1 and 2, respectively (complementary figures for all patient rooms are included in the Supplementary Data). Fig. 1 shows that the methods that incorporate $CO_2$ data produce occupancy estimates that appear similar in terms of both range and median (i.e., 1–3 persons and approximately 2 persons, respectively), but exhibit a small number of minor differences in the frequency of certain values of occupancy. In general, the Beam-break method occupancy estimates fall within a smaller range of values compared to the estimates produced by methods that incorporate $CO_2$ data (i.e., 1–2 persons vs. 1–3 persons, respectively). There is no general trend in regards to the median values, as these varied between methods depending on the room (Fig. 1 shows sample values for room 105 only). Fig. 2 shows that the occupant activity estimates based solely on beam-break data entail a higher median value and wider range than those made solely with $CO_2$ data (which is true for all rooms). Distinct differences are apparent for both parameters, and so a method of validation for both the occupancy and occupant activity estimates was required.

### 3.2. Evaluation of estimates

The estimates were evaluated by comparing the results to the most accurate values available for both occupancy and occupant activity (discussed previously in Section 2.3). The most accurate method(s) to predict occupancy and also occupant activity were then identified (as discussed below). Following this evaluation, the one method that provided the most accurate estimates of both occupant parameters was determined.

#### 3.2.1. Occupancy

The method estimates for occupancy were evaluated first by a comparison to the visual observations. Fig. 3 shows the cumulative deviation of the occupancy estimates made at 5-min intervals from the manual observational count value of occupancy over 4-h periods for multiple patient rooms (i.e., there are 48 data points per 4-h period for eight different combinations of patient room and time of monitoring).

These results for occupancy show that each of the methods produce an equally accurate long-term estimate of occupancy, as the deviations of the occupancy estimates produced by each of the four methods were not statistically significant from each other (*t*-

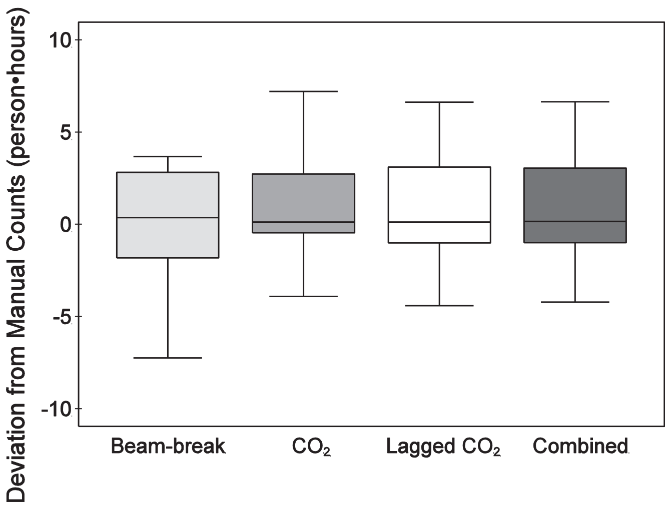


**Fig. 3.** Cumulative deviation of occupancy estimates from the manual count value (represented by 0 on the *y*-axis) over 4-h periods for various patient rooms that were monitored at different times. Positive values indicate an overestimation with respect to the manual count value, and negative values correspond to an underestimation. A deviation of zero indicates agreement with the manual count value.

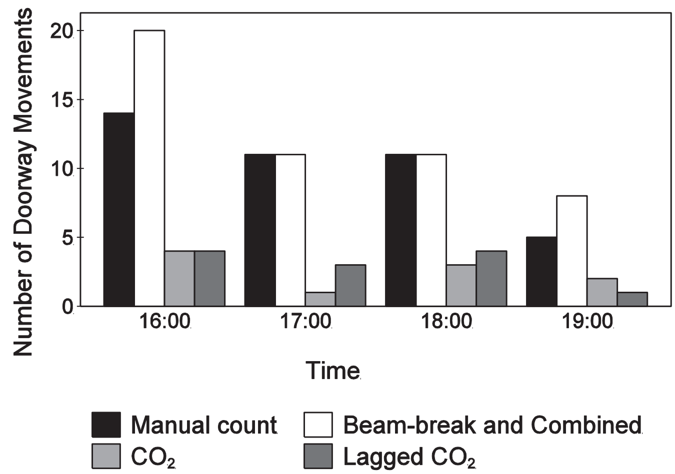


**Fig. 4.** Comparison of occupant activity estimates for four consecutive 1-h periods. The Beam-break method and the Combined method estimates are represented by the same bar, as these methods produce equal estimates of occupant activity using the same procedure. Bars show the number of doorway movements occurring each hour for patient room 105 as an example.

test $p > 0.05$) and the median value for each method was very close to the manual count value (i.e., a deviation from the manual count near 0, ranging from 0.13–0.36 person·hours over 4-h periods, as shown in Fig. 3). However, the methods do differ in terms of their variability. The coefficient of variation (i.e., standard deviation over mean) for the deviation of the Beam-Break, $CO_2$, Lagged $CO_2$, and Combined estimates from the manual count estimate was approximately −33, 3, 4, and 4, respectively. These values indicate that the inclusion of $CO_2$ data produced more consistent estimates of occupancy at each instant in time over longer periods of time, whereas beam-break sensor data on its own is more likely to produce a more variable estimate of occupancy at a specific instant in time. Furthermore, although the Beam-break method is more likely to overestimate occupancy (as its median is slightly greater than zero), it also produces underestimates in occupancy that are much larger than those of the other methods. The number of occupants in each patient room often exceeded one just before midnight for the Beam-break method estimates (however 90% of estimates still remained below four occupants for each room at this time), which means that either upper boundaries need to be applied in order to satisfy the initial assumptions, or that days with a high and unreasonable number of residual occupants should be disregarded. The number of occupants just before midnight was lower on average for the methods that incorporated $CO_2$ data, which also do not include the assumption of a single occupant at midnight, and so the above remedies are not needed for these methods. For these reasons, the three methods that incorporate $CO_2$ data (i.e., the $CO_2$, Lagged $CO_2$, and Combined methods) are the preferred methods to estimate occupancy of the four methods under analysis.

### 3.2.2. Occupant activity

Fig. 4 provides a sample comparison (for patient room 105) of the occupant activity estimates to the beam-break sensor count over four 1-h periods. The Beam-break and Combined methods are expressed by a single bar in Fig. 4 because they utilize the same approach (i.e., the use of beam-break sensor data directly) and therefore produce the same estimate for occupant activity.

The sample results in Fig. 4 show a trend in method accuracy that is similar to the other patient rooms, albeit with some differences in magnitude. In general, the manual count data is most similar to the beam-break data (the benchmark dataset for occupant activity, as explained in Section 2.3), but it does not capture every movement. On average, the manual count data missed 5–6 beam-breaks per hour (equating to an average relative error of approximately 43%) during the periods of visual observations. The methods based solely on $CO_2$ sensor data (i.e., the $CO_2$ and Lagged $CO_2$ methods) provide even less information, as the $CO_2$ sensors have difficulty detecting dynamic short-term, and in some instances, smaller, changes in occupancy (e.g., activities occurring within a 5-min interval). Both $CO_2$-based methods failed to detect an average of 8–9 doorway movements per hour compared to the beam-break sensor measurements (equating to a relative error of close to 70%) during the periods when visual observations took place (the validation exercise was limited to these time periods so that all measurement methods could be compared). Therefore the preferred methods to estimate occupant activity are those that utilize beam-break sensor data: the Beam-break method and the Combined method.

### 3.2.3. Interpretation of results

Based on these collective results, the Combined method appears to be the preferred way to estimate both occupancy and occupant activity, as it produced the most accurate estimates of both parameters. Several studies support this finding, as they have identified a strong correlation between $CO_2$ concentrations and human occupancy [27,43]. However, other investigations that estimated occupancy using only $CO_2$ concentrations in a mass balance noted delays in the estimates [22] and difficulties detecting low levels of occupancy [43] and minor changes in occupancy (e.g., two to three persons) [24,25]. The Combined method overcomes such difficulties by utilizing $CO_2$ sensors with a high accuracy to achieve improved estimates during low occupancy periods, accounting for the time delay in the $CO_2$ sensor measurements, and also by supplementing the mass balance on $CO_2$ concentration data with beam-break sensor data to capture small changes in occupancy. The beam-break data also provides a robust measure of occupant activity, which has not been widely explored [34]. Furthermore, the error and labour-intensiveness associated with the visual observations justifies the need for an alternative method to estimate these occupant parameters. The Combined method provides an improved approach to attain occupant information in buildings that are more difficult to characterize (accordingly, the following results and discussion pertain to the Combined method).

### 3.3. Occupant characteristics and implications in hospital patient rooms

The occupancy and occupant activity estimates provide insight on the occupant behaviours occurring in the patient rooms. The results for daily occupancy and occupant activity using the six months of data (Figs. 5 and 6, respectively) show variation both within the patient rooms over time and among patient rooms. Occupancy was noticeably higher in rooms 103 and 105 (median person·hour values equate to roughly 3 and 2 persons, respectively) and noticeably lower in rooms 101 and 202 (median person·hour values equate to 0 persons for both). These differences could be attributed to varying numbers of visitors/staff, varying unoccupied periods, or the use of an unrepresentative value of $E$ (discussed further in Section 3.5). In general, occupancy was slightly higher on the 9th floor (rooms 101–105), whereas occupant activity was higher (in terms of the median and maximum) in rooms on the 10th floor (rooms 201–205), which could be a result of patient condition (e.g., 10th floor rooms were occupied by oncology patients, who typically had longer stays than patients on the 9th floor).

The median value for occupant activity implies an average of approximately 8 beam-breaks each hour, with more extreme cases exceeding 17 beam-breaks per hour on average (Fig. 6). These median and extreme values exhibit less variation than those for occupancy, which is an important point of distinction because it implies that occupancy and occupant activity might not be as closely related as one might think. This hypothesis was confirmed by calculating Spearman correlation coefficients with Bonferonni correction, which yielded only low to moderate positive correlations (ranging from 0.24 to 0.51) in each patient room, which implies that there is no strong or consistent correlation between occupancy and occupant activity in this investigation. While there is limited data on occupant activity (i.e., doorway movements) in hospitals, a previous study recorded anywhere from 10 to 60 persons entering/exiting a single hospital operating theatre within 30-min periods [37], which serves to illustrate that occupant activity can be unexpectedly high in hospitals, due to various medical procedures and patient needs, in otherwise relatively low-occupancy areas.

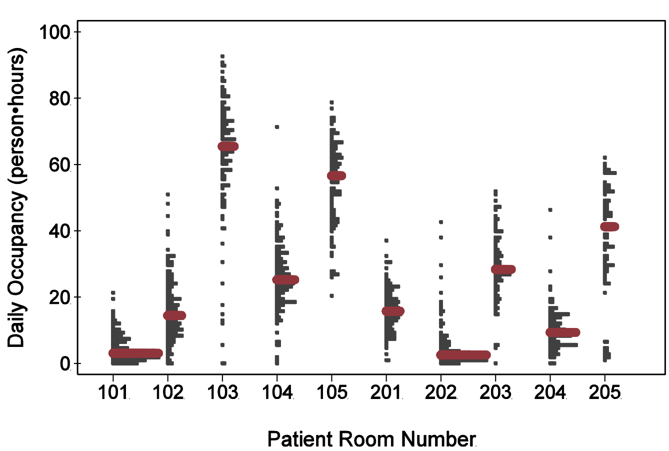


**Fig. 5.** Estimates of daily occupancy (i.e., the total number of person·hours occurring over 24 h) for each of the ten patient rooms using the Combined method and the six months of measured data.

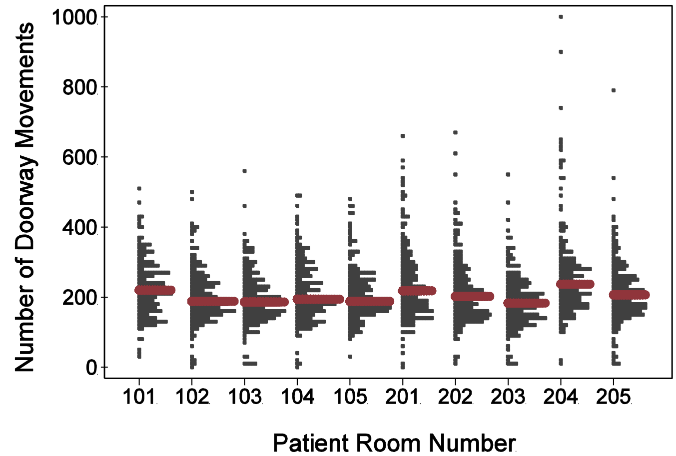


**Fig. 6.** Estimates of daily occupant activity (i.e., the total number of doorway movements occurring over a day) for each of the ten patient rooms using the Combined method and the six months of measured data.

For the purposes of the Hospital Microbiome Project (i.e., determining interactions between microbial communities, indoor environmental parameters, and occupant characteristics), it is ideal to estimate occupancy and occupant activity, since they both have significance to the built environment and to the ongoing microbial analysis. It has been shown that human occupants have a dominant effect on indoor bacterial bioaerosols [45,46] and bacteria from human skin, hair, and nostrils have been shown to leave a distinct human mark on indoor air during periods of occupancy [8,46,47]. Additionally, each human sustains a unique microbiome, which will rapidly colonize an indoor environment [11]. In the Home Microbiome study, it was found that the microbial communities associated with an initial occupant were replaced by those of a new occupant in less than a day [11]. The succession of microbial communities in the patient rooms under investigation will likely differ due to a rigorous cleaning procedure prior to the admission of a new patient. Greene et al. [37] found higher airborne bacterial counts in hospitals during periods of high occupancy and activity compared to times immediately following a thorough cleaning and with fewer occupants. Therefore in this study, it is likely that periods with distinct microbial communities (associated with specific admitted patients) will be separated by periods with disrupted microbial ecology due to patient room cleaning. This can provide insight pertaining to the microbes associated with certain patients and/or rooms, which can be coupled with the Combined method estimates to identify areas of high occupancy and/or occupant activity, which could potentially represent areas with elevated levels of certain airborne particles [48].

### 3.4. Combined method uncertainty

In order to determine such occupant characterizations, it is important to understand the associated uncertainty and error in the method used herein. To do so, the propagated uncertainty was determined for the occupancy estimates made with the Combined method. The uncertainty associated with $C_{room}$ and $C_{sup}$ was taken as 20 ppm, the manufacturer reported uncertainty associated with the $CO_2$ sensors (for a measurement range of 0–2000 ppm). The uncertainty associated with the air flow measurements made with the powered flow hood varies depending on the measurement scenario; however a 5% measurement uncertainty was deemed reasonable for the $Q_{ret}$ and $Q_{ex}$ measurements in this study [44,49–51]. The uncertainty associated with $Q_{sup}$ was then determined by calculating the propagated uncertainty associated with the mass balance on $CO_2$ during times of zero occupancy. Finally, the uncertainty associated with $E$ was taken as the standard deviation of a distribution of possible values for $E$ (described further in Section 3.5).

There was no manufacturer-reported uncertainty with the beam-break sensors, but there was uncertainty associated with the direction of the beam-breaks and also with the number of occupants that moved through the doorway during each beam-break. It was assumed that 50% of the beam-breaks corresponded to entrances, while the other 50% corresponded to exits. The manual count data reveals that there were slightly more exits than entrances (due to the number of persons associated with each doorway movement), with the most extreme ratio consisting of approximately 43% entrances and 57% exits. On average, there was 2.6% error associated with the initial 50% assumption. Furthermore, it was assumed that each doorway beam-break corresponded to the movement of a single occupant. However, the manual count data indicates that approximately 90% of the total observed beam-breaks corresponded to the movement of a single occupant. Approximately 7.5%, 1.5%, and 1% of the total observed beam-breaks corresponded to the movements of two, three, and four occupants, respectively (movements involving more than four occupants were not observed). This supports the assumption that a beam-break likely corresponds to the movement of one occupant, but also implies that there is approximately 10% estimated uncertainty associated with this assumption.

The above values were used to determine the level of uncertainty associated with the occupancy estimates, which was approximately 1.3 person·hours for a 1-h period. This is a reasonably small amount of uncertainty compared to previous studies due to the high accuracy of the $CO_2$ sensors used (i.e., $\pm$20 ppm for 0–2000 ppm compared to past studies that used less accurate $CO_2$ sensors with $\pm$5% or $\pm$75 ppm for 0–2000 ppm) [25]. This uncertainty should still be accounted for because it has a proportionally larger effect in hospital patient rooms, which have lower occupancies than other types of buildings (e.g., an uncertainty of 1.0 person·hour in the estimate could equate to an error of 100%, or a doubling of the actual occupancy, in patient rooms devoted to a single patient). Furthermore the uncertainty associated with the beam-break sensors does not affect the estimates of occupant activity, since this parameter is a measure of the number of doorway movements only, and does not consider the number or direction of occupants associated with each movement. However these factors are significant to the indoor environment in terms of the magnitude of resuspension and the locations where it occurs, and so these factors should be considered in addition to, and independently of, the total beam-break count. Although the uncertainty in this study is small, reducing it further can improve the confidence associated with the estimates.

### 3.5. Influence of occupant $CO_2$ emission rate

One approach to reduce the uncertainty is to improve the accuracy of model inputs and assumptions. This was investigated for the per-person emission rate, $E$, because it contributed a high degree of uncertainty to the estimates. The value for $E$ was assumed to be constant across all patient rooms, but will vary in reality between individuals and throughout the course of the day for specific individuals [52] based on a number of factors, such as age, weight, gender, activity level, and the proportion of consumed macronutrients. The effect of these variations was investigated by performing a sensitivity analysis on $E$. A distribution of values for $E$ was generated based on the literature (Table 1). Percentile values from this generated distribution along with 10% variations from the selected value (Table 2) were used to generate alternate estimates of occupancy using the Combined method (time-series sample shown in Fig. 7).

The results show that varying the value of $E$ to any of the alternative values presented in Table 2 produced a statistically significant difference ($t$-test $p < 0.05$). This is apparent when examining Fig. 7, as there are noticeable differences between the occupancy estimates made with the selected emission rate (represented by the dashed line in Fig. 7) and the estimates made with the alternative emission rates. The majority of values for $E$ produced occupancy estimates that were within a reasonably close range, with the exception of the lowest value for $E$, which produced a much higher estimate of occupancy. These estimates frequently exceeded 200 person·hours, and on some days, exceeded 400 person·hours, which correspond to average occupancies of approximately eight and sixteen persons, respectively. Although it is possible that patient rooms contained visitors and staff members in addition to the patients, these levels of occupancy are highly unlikely in hospital patient rooms and were not observed during the manual counts. Since the results from a much lower value for $E$ are unrealistic (and those cited in the literature are from much older studies that do not provide details of the assumed occupant characteristics), the value for $E$ for hospital occupants should be selected from the smaller range of larger values described in this section (i.e., 0.36–0.44 L/min). These are also similar to values from recent studies of human $CO_2$ emission rates involving similar activity levels [58]. Consideration should be given to this selection, as the value for $E$ is highly variable and can cause a significant difference in the results.

One approach to reduce this error is to select a customized value of $E$ for each occupant. To investigate this, patient characteristics (i.e., weight, age, gender, and duration of room occupancy) were used to select unique values for $E$ following procedures outlined in ASTM D6245 [59] and recommendations from the EPA Exposures Handbook [60]. Estimates were generated using the Combined method, and were compared to the manual count estimates, as well as the Combined method estimates using the generic value of $E$. Due to a limited amount of patient information, there was only one 4-h period where the customized Combined method estimates could be compared to the other two estimates. This one comparison revealed that incorporating an emission rate based on occupant characteristics improved the estimate accuracy by approximately 0.5 person·hours over a 4-h estimation period. This approach could therefore potentially improve occupancy estimates over both short and long-term periods, although it requires detailed information on occupant characteristics that may not be available in all environments at all times (as was the case in this study).

### 3.6. Other potential surrogates for occupancy

Another approach to overcome the error associated with $E$ (and a potential lack of information on occupant characteristics) is to use other indoor environmental parameters as a surrogate for occupancy. Patient room temperature and relative humidity were selected since they should theoretically be affected by human occupants. Both parameters were measured at 5-min intervals in each patient room with an Onset U12-012 data logger (temperature accuracy of $\pm$0.4 °C at 25 °C and RH accuracy of $\pm$2.5% from 10% to 90% RH). Both datasets were used to conduct a mass balance on moisture content in the air (in a similar approach to Equation (1), but with the humidity ratio instead of $CO_2$). Temperature, RH, and the calculated humidity ratio were then compared to the manual count data to determine potential relationships. Correlation coefficients with Bonferroni correction ranged from low negative to moderately high positive values indicating no strong or consistent

**Table 1**
Potential values for $E$ from the literature.

| $E$ (L/min) | Occupant description | Source |
|---|---|---|
| 0.15 | Quiet adult sleeper | [53] |
| 0.17 | Child engaged in very light activity (1.2 met) | [54] |
| 0.20 | Average sized adult seated/sleeping quietly | [2] |
| 0.25 | Restless adult sleeper | [53] |
| 0.30 | Average sized adult engaged in office work | [2] |
| 0.31 | Average sized adult engaged in light office work (1.2 met) | [54] |
| 0.31 | Typical office worker | [55] |
| 0.32 | Typical office worker | [55] |
| 0.35 | Typical University library occupant | [56] |
| 0.39 | Upper end of "very light" activity (~1.3 met) | [2] |
| 0.47 | Bar occupants | [57] |
| 0.60 | Average sized adult engaged in office work (upper end at 2 met) | [54] |

**Table 2**
Alternate values of $E$ for comparison.

| $E$ (L/min) | Description of value |
|---|---|
| 0.086 | 10th percentile value from distribution (based on values from the literature) |
| 0.27 | Mean value from distribution (based on values in the literature) |
| 0.36 | 10% less than the chosen value |
| 0.39 | Selected value for this investigation (based on [2]) |
| 0.43 | 10% more than the chosen value |
| 0.44 | 90th percentile value from distribution (based on values from the literature) |

relationship in all cases. A linear regression analysis further supported this, as the $R^2$ values were close to zero for each parameter in each room, indicating no linear relationship. Finally, a Wilcoxon matched-pairs signed rank test and equality of matched pairs of observations test further supported this, by identifying offsets between data pairs and unequal distributions for all comparisons. These tests were also performed on the six months of occupancy data produced with the Combined method to observe potential correlations over a longer period of time; however results were similar to those using the manual count data.

Evidently, patient room temperature, RH, and humidity ratio are not suitable indicators of occupancy in this study, and were also not useful for estimating occupant activity. This is likely a result of the very small changes in each of these parameters (caused by low levels of occupancy), as well as the homogenizing effect of the hospital HVAC system in this relatively tightly controlled environment [40]. However, previous studies have identified strong correlations between occupancy and $CO_2$ concentration and acoustic measurements in an office environment [27]. Another study installed a number of environmental sensors in a university office to detect low levels of occupancy, and found that features extracted from humidity, $CO_2$, and acoustic sensor data exhibited high correlations to human occupants, while features extracted from temperature sensor data showed weak correlations to occupants [28]. So although indoor temperature and RH were not suitable surrogates for occupancy in this tightly controlled hospital, this does not discount their use in other built environments and investigations.

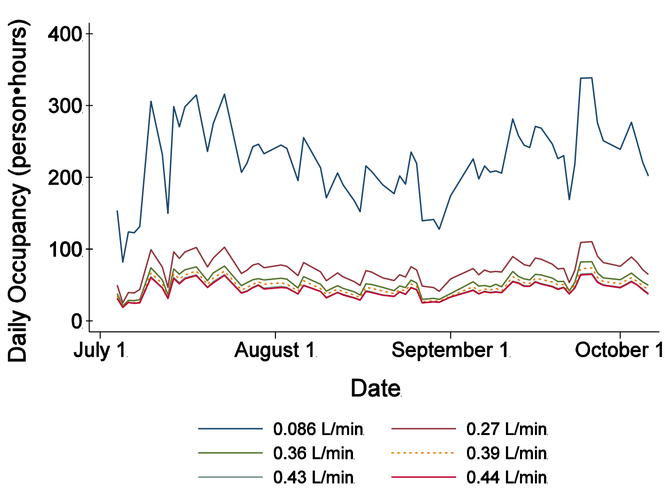


**Fig. 7.** Daily occupancy estimates (i.e., the number of person·hours over the course of a day) using the Combined method and various values of $E$ to show the effect of the occupant $CO_2$ emission rate on the occupancy estimates. The dashed line represents the generic value used in this study and the solid lines represent plausible alternatives. Estimates are shown for patient room 105 as an example.

### 3.7. Influence of data logging frequency

Of the sensors deployed, the beam-break and $CO_2$ sensors were most useful in determining occupant parameters and are recommended for similar investigations with similar resources. The 5-min measurement interval produced an abundance of data, but also entailed maintenance and time (data logger storage reached capacity within 10 days), which may not be feasible in other investigations. To determine if such a frequent measurement interval was necessary, data points from the beam-break and $CO_2$ concentration datasets were eliminated to simulate 10-, 20-, 30-, and 60-min measurement intervals. These new datasets were used to estimate occupancy using the Combined method (the time lag applied to $C_{room}$ increased to 30 and 60 min for those simulated measurement intervals, respectively), and the results were compared to the estimates using the original dataset with 5-min measurement intervals (a time-series sample is shown in Fig. 8).

Increasing the measurement interval produced a statistically significant difference ($t$-test $p < 0.05$) in the estimates in some, but not all, instances. This is evident in Fig. 8, as there are distinct differences between various estimates on some days, while the estimates appear very similar on others. The median percent change across all rooms ranged from 1.5–89.0%, 0.5–110.0%, 0.1–147.0%, and 1.7–224.0% for the 10-, 20-, 30-, and 60-min measurement intervals, respectively, indicating that an increase

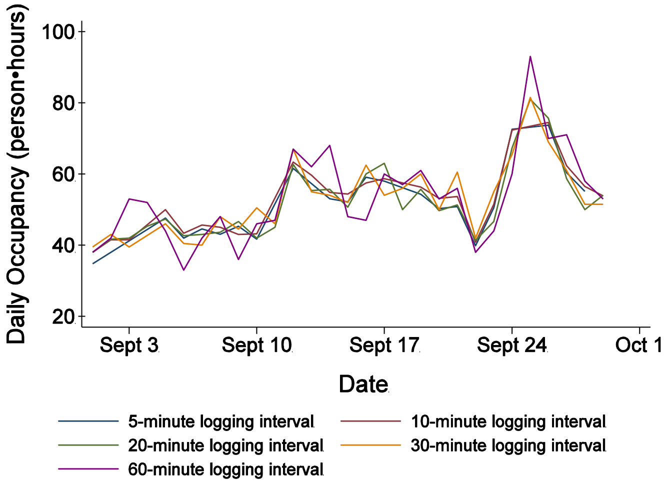


**Fig. 8.** Daily occupancy estimates (i.e., the number of person·hours over the course of a day) using the Combined method and various data logging intervals. Estimates for patient room 105 are shown as an example.

in the measurement interval is likely to cause an increase in the occupancy estimates. Although some of these increases seem large, they have a proportionally smaller absolute effect in the context of single-patient rooms, where a 200% increase could equate to the addition of 2 persons. A smaller/shorter data logging interval is recommended for estimating occupancy in hospital patient rooms in order to detect changes in occupancy that are small in magnitude and short in duration, as observed in this study. Occupant dynamics will differ in other indoor environments however, and so the data logging interval should be investigated in different buildings to determine an appropriate measurement rate, especially since the data logging interval was observed to affect results (in this study) and there is no standard measurement interval currently in use [17,28].

## 4. Conclusions

The cumulative analytical and methodological results from this investigation address a gap in the literature by examining methods of detection that estimated both occupancy and occupant activity in hospital patient rooms. A combined method, which incorporated both $CO_2$ and non-directional single IR beam-break sensor data, was found to produce the most accurate estimates of both parameters. Sources of error and uncertainty in this method (e.g., input assumptions, environmental measurements, and the data logging interval) were determined to be reasonably small, while strategies to further reduce this error were also explored. The resulting occupant information can be used to identify areas of high occupancy and/or occupant activity within the hospital that may have influenced the IEQ. This occupant information can later be compared to the companion microbial data to determine potential interactions between the human and microbial communities. These cumulative findings can be used to better understand occupant behaviours and their effect on the indoor air and surface parameters in a hospital environment.

## Acknowledgements

The authors would like to thank the Alfred P. Sloan Foundation for funding the Hospital Microbiome Project (Grant No. 2012-10-04). We also thank the hospital and facilities staff at the University of Chicago Hospital, as well as Tiffanie Ramos, Pahram Azimi, Laurit Dide, Daniel Smith, and Kristen Starkey for their help in data collection.

## Appendix A. Supplementary material

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.buildenv.2015.03.029.

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