Occupancy Monitoring Approaches: Learnings from Literature and Current Research

MARINA TOPOUZI DPHIL
Environmental Change Institute, University of Oxford
marina.topouzi@ouce.ox.ac.uk

AMR SULIMAN PHD
Environmental Change Institute, University of Oxford
amr.suliman@ouce.ox.ac.uk

ZEYNEP DUYGU TEKLER PHD
Department of Engineering Science, University of Oxford
zeynep.tekler@eng.ox.ac.uk

Abstract

With evolving work patterns—especially in the post-COVID era, and with the rise of hybrid and remote work—understanding occupancy is more crucial than ever for managing building energy demand. These shifts have made predicting and optimising energy use more complex, highlighting the growing importance of occupancy monitoring in building energy management. The emergence of hybrid working arrangements in office spaces and 'working from home' has brought forward a novel challenge: periods of variable occupancy patterns leading to increased energy waste due to lack of building flexibility and demand response. Recognising that occupancy is an important factor in the flexibility and energy demand of buildings, this review exercise explores various techniques employed for monitoring occupancy in both domestic and office buildings. It examines quantitative and qualitative methods in literature and delves into changes in occupancy patterns and controlling building environments. Current challenges in understanding and capturing occupancy include the impact of hybrid working and the shift in work activities to employees' homes. This review also discusses the shortcomings of current data collection methods in adequately capturing occupancy at different environments as well as informing potential areas for future investigations. These summaries are supplemented by experiences from two distinct ongoing projects: a) An observatory of 2000 households in the UK, and b) Occupant perception of retrofits following the pandemic in a higher education building in Oxford, UK.

Keywords Occupancy, Occupancy Detection, Demand Response, Energy Waste, Low Energy Building

Introduction

Building occupancy patterns play a crucial role in determining the energy efficiency of buildings and serve as a key input for understanding buildings' performance. Occupants**'** interaction with systems and services like heating, cooling, lighting, and plug load usage is one of the key factors responsible for energy consumption in buildings (1). Accurately identifying and understanding occupancy patterns and profiles is essential for optimising building operating systems and can significantly contribute to reducing the performance gap between planned and actual energy usage. Despite this, occupancy patterns at the design stage of both domestic and non-domestic buildings still largely depend on "default" user profiles which often fail to reflect actual energy consumption during operation. Much of the existing literature on occupancy patterns relies on heuristic or modelling approaches, frequently lacking data-driven evidence (2).

Post-Occupancy-Evaluation and Building Performance Evaluation studies undertaken to a large extent both in residential and office buildings (3,4,5) significantly contribute on our understanding of buildings users' behaviours. Although occupant behaviour differs considerably between domestic and non-domestic sectors, occupancy data can inform **i**. systems settings with more precise HVAC scheduling and zoning; **ii.** adaptive lighting controls; **iii.** efficient management of plug loads that can allow more flexible patterns to respond to electricity grid peak demand; and **iv.** improve accuracy of energy demand predictions reducing performance gap between estimated and actual.

Incorporating detailed occupancy information into building management strategies, whether for facility managers or homeowners, can boost energy efficiency, improve occupant comfort, and potentially achieve substantial energy savings by eliminating unnecessary energy waste. This data-driven approach also enables more precise building performance simulations, leading to better-informed design decisions for new builds and retrofits. However, the COVID-19 pandemic has drastically reshaped work patterns and occupancy trends in both office and residential settings. The rise of hybrid and remote working has introduced new challenges for building management and energy efficiency, increasing variability in office occupancy while shifting energy demand from commercial to residential spaces. These changes complicate the task of accurately monitoring and predicting occupancy. As such, this paper explores the evolving landscape of occupancy monitoring, examining traditional methods alongside emerging techniques within the context of these new realities. This review also draws key learnings and reflections from two ongoing projects at Oxford each exploring occupancy in the built environment from different perspectives and settings.

Literature Review

A comprehensive review of existing literature reveals a range of approaches for occupancy monitoring. Table 1 provides a snapshot of studies that gather different sensor data information to monitor occupancy presence and count in both office spaces and residential spaces. As illustrated in table 1, the collection of occupancy data has proven invaluable across various building applications. Some of the most common occupancy applications include building controls for HVAC (6), lighting (7), and plug loads (8) as well as maintenance operations of building maintenance (9) and points of interest identification (10) for high performance buildings. Occupancy information in both sectors can be gathered at varying levels of detail concerning spatial scale (such as building, floor, zone, or room), temporal scale (including hours, minutes, or seconds), and types of occupancy (like presence, count, identity, or activity).

The complexity of data collection and the requirements for sensing increase with the desired resolution of occupancy data, factoring in sensor costs, their purpose, and the intrusiveness of these detection techniques to occupants. Tekler et al (11) categorise occupancy sensing methods into two groups: terminal-based (active) and non-terminal-based (passive) approaches. Active approaches rely on technologies like wearables and smartphones to collect occupancy data within buildings. However, despite their benefits, they also have limitations due to the necessity of deploying specific sensors and software (e.g., Wi-Fi access points, mobile apps), which increases costs, disrupts occupants' schedules, and raises privacy issues. Passive approaches, on the contrary, rely on passive sensing technologies including sound and ultrasonic sensors, Passive Infrared (PIR) sensors, surveillance cameras and smart meters to obtain occupancy data for specific zones within buildings indirectly. Although passive sensing approaches are generally less invasive compared to active approaches, the resulting occupancy monitoring systems often have limitations in terms of accuracy and resolution. It is essential to carefully consider the advantages and limitations of each approach when selecting the most appropriate occupancy sensing technology for the specific needs and applications. This ensures that the chosen technology effectively meets the objectives while minimising potential drawbacks.

Making use of pre-existing infrastructure has been an approach which has been explored across literature, for example a study compared data obtained from Wi-Fi, swipe cards and security data in an open office space to estimate occupancy. Using a combination of statistical analysis and machine learning approaches, the authors found that these approaches were able to estimate arrival time accuracy by 94%, departure time accuracy by 72% and a peak occupancy time accuracy of 45% (12). In the context of residential buildings, researchers (13) were able to develop a tool modelling occupancy profile using data from motion-detection measurements and data collected by PIR sensors connected to the smart thermostat of the household.

Table 1 Summaries of Studies Performing Occupancy Monitoring

Occupancy Resolution	**Sensor Type**	**Sensor Data**	**Space Types**	**Study**
Presence	Single-faceted	Motion	Office	(14)
Presence	Multi-faceted	CO_2, Pressure, Air Temp, Humidity	Office	(15)
Presence	Single-faceted	Plug load energy consumption	Office	(16)
Presence	Single-faceted	Electricity Consumption	Residential	(17)
Presence	Single-faceted	Thermostat	Residential	(18)
Presence	Multi-faceted	Passive infrared (PIR) motion sensors, Questionnaires & interviews	Residential	(4)

Presence	Single-faceted	Water-metering data loggers	Residential	(19)
Count	Multi-faceted	Bluetooth, MAC address	Office	(20)
Count	Multi-faceted	CO_2, Pressure, Air Temp, Humidity	Office	(21)
Count	Multi-faceted	CO_2, Air Temp, Humidity, illuminance, motion, energy consumption of lighting, plug loads, HVAC	Office	(22)
Count	Multi-faceted	CO_2, Air Temp, Humidity, MAC Address	Office	(23)
Count	Multi-faceted	CO_2, Air Temp, Humidity, illuminance, motion	Office	(24)
Count	Multi-faceted	CO_2, Air Temp, Humidity, MAC Address	Office	(25)
Count	Multi-faceted	CO_2, indoor air temp, humidity, motion, indoor acoustic, VOC, outside temperature, dew point, $PM_{2.5}$, lighting	Office	(26)
Count	Multi-faceted	CO_2, pressure, air temperature, humidity	Office	(27)
Count	Multi-faceted	Humidity, air temperature, pressure,	Residential	(28)
Count	Multi-faceted	Wi-Fi, occupancy count, security data, computer activity	Office	(12)
Count	Multi-faceted	Passive Infrared (PIR), Motion Detection	Residential	(13)

The scatter plot visualisation in Figure 1, facilitates a comparison of various monitoring methods based on their impact on privacy and financial feasibility. It illustrates that, with the exception of visual methods (such as cameras, thermal cameras and PIR sensors), the majority of other data collection techniques—such as ambient sensors, transmitted signals, and self-reported methods—tend to have medium to low costs and levels of intrusiveness. Additionally, it highlights the need for specific tools that can be applied to certain buildings to provide meaningful occupancy data. For example, water meter loggers are suitable for domestic buildings, while card-swipe systems are appropriate for non-domestic office environments where occupancy access may need to be controlled. The cost of occupancy detection tools based on transmitted signals is relatively low, as the necessary equipment often already exists to service other user activities but can raise data privacy issues depending on the different environments (e.g. swipe card data, CCTV Cameras). Selecting a combination of occupancy tools is crucial, taking into account the frequency of occupancy data collection. For instance, qualitative methods like surveys and interviews can provide rich contextual data on occupancy and activities. While they tend to be one-off or seasonal and lack the granularity of daily occupancy data, they remain critical to providing insights in terms of some of the background and behaviours behind variable occupancy (29). Similarly, integrating passive monitoring tools with user-reported data can help refine insights into not just when a space is occupied but also why and under what conditions.

It is essential to carefully evaluate the advantages and limitations of each approach when selecting the most suitable occupancy sensor technology or combination of technologies for specific needs and applications. Different combinations of methods must be considered to ensure that the chosen technology effectively meets objectives while minimising potential drawbacks.

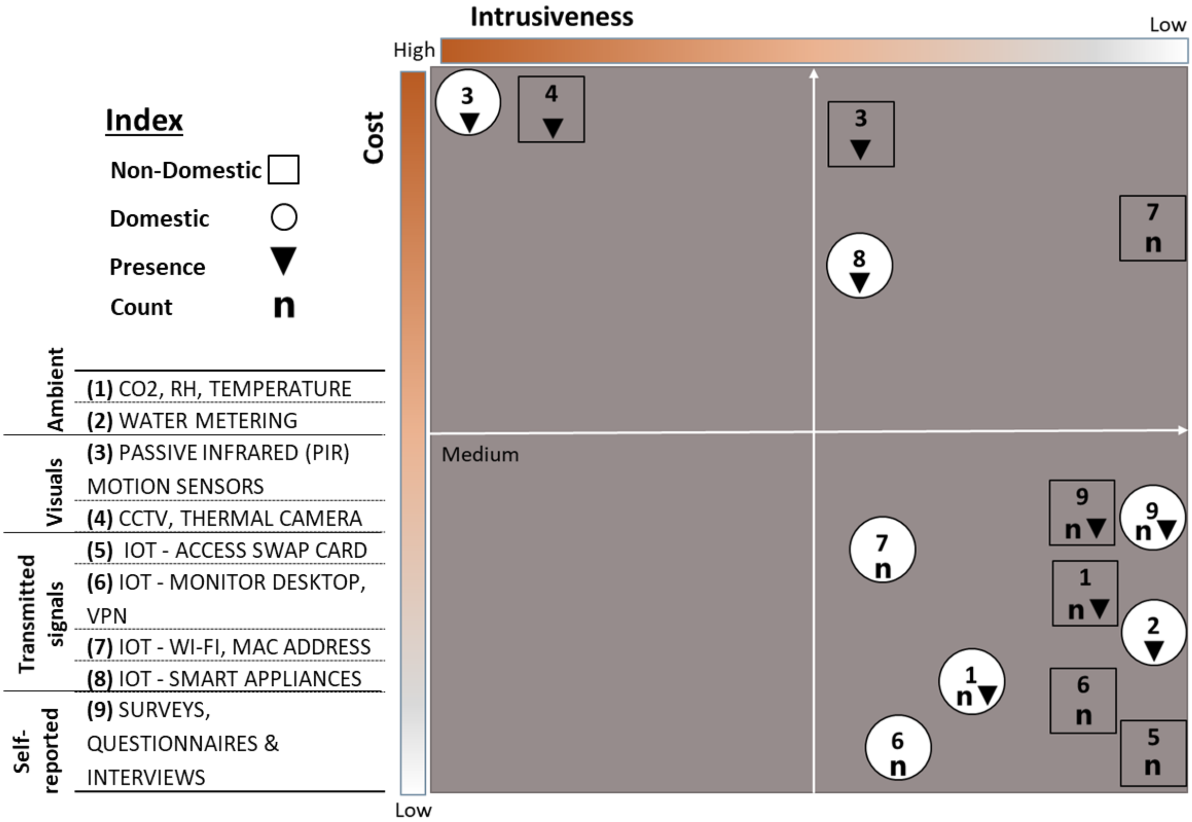

Figure 1 - Comparison of occupancy techniques for domestic and non-domestic buildings with respect to data collection type, resolution, cost, intrusiveness, and type of occupancy data. Axes X and Y show the level of intrusiveness and cost, ranging from high to low. Symbols (squares and circles) indicate whether the sensor is used in non-domestic or domestic settings, and presence and count are indicated by triangles for presence, "n" for count.

Current Challenges and Emerging Norms in Occupancy

Inefficient energy use related to occupancy often occurs in homes when services and controls, such as heating, are left ON while the house is unoccupied (2, 30). However, occupancy, especially in the home environment, is changing as the digitalisation of activities and automation of appliances can occur even when no real occupants are present (31). This is where the concept of the 'invisible occupant' arises, where automated systems perform tasks and respond to demand flexibility events when the building is unoccupied by real people. While this provides greater flexibility from a demand-response perspective, it can also lead to misleading data regarding actual occupancy and user activities. This is especially problematic and biases our understanding when the data is used for modelling and optimising smart energy management systems that learn user behaviour, comfort preferences, and indoor environmental conditions, which may not reflect the reality of actual users. The digitalisation of activities and smart controls also means that energy consumption may not always correlate with physical presence. This could raise significant concerns, as it widens the gap in our understanding of whether decision-making and preferences are driven by the user or by an 'invisible' automated system acting as the occupant.

Challenges in understanding occupancy patterns have intensified post-pandemic due to the shifting balance between workplace and home environments. As more people work from home, residential energy use patterns have changed, often going untracked or unmonitored. This shift impacts also office buildings’ building energy management systems (BEMS), which may over perform to meet users' indoor environmental quality (IEQ) needs or struggle to learn and adapt to real user’s demand. The number of occupants and space requirements often no longer reflect actual usage, leading to biases in decision-making and system operations, ultimately increasing energy consumption when demand is low or non-existent (29). Initial finding from a current ongoing survey in a higher education building found that IEQ and retrofits have a significant impact in hybrid working decisions. With occupants in non-retrofitted spaces are likely to find the indoor environment as a big influence on their decision to work from home. It highlights how other factors, such as indoor environmental quality and lifestyle practices, can influence the decision to occupy one space over another, especially now that more flexible ways of working are becoming the norm. Therefore, occupancy decisions are quite complex and are influenced by many factors (even built environment related factors).

Key Points of Discussions and Opportunities

The review of occupancy studies as summarised in table 1 highlights that most research primarily focuses on office environments, with only a limited number of studies addressing residential buildings, where occupancy patterns and behaviours are significantly more variable and less predictable.

Secondly, questions remain over identifying the most effective combination of parameters to measure occupancy, as many existing studies rely on predefined sensor data without testing different combinations in real-world settings to assess their accuracy. Occupancy patterns vary significantly between residential and office environments, requiring tailored measurement approaches. In office spaces, occupancy is typically structured around work hours, making sensor-based monitoring—such as CO_2 levels, motion detectors, or Wi-Fi signals—more effective for detecting presence and density. In contrast, residential occupancy is far more irregular, influenced by lifestyle, remote work, and personal habits. Traditional sensors alone may struggle to capture this complexity, requiring an additional combination of ambient monitoring and qualitative insights to contextualize occupancy patterns accurately. However, each of these methods come with varying levels of intrusiveness, cost, and privacy concerns. Striking a balance between efficient monitoring and minimizing both intrusiveness and cost, while respecting privacy, is essential to make these systems practical and ethically sound.

Thirdly, there is a lack of research coupling qualitative (visuals and self-reported) and quantitative (ambient and transmitted signals) methods to understand occupancy in spaces. Surveys and post-occupancy evaluations are able to provide insights regarding space use patterns and hybrid working practices following the pandemic. The challenges discussed also emphasises the need to not only collect data on occupancy to understand the real energy demand of buildings but also to combine monitoring tools that can cross-check whether occupancy is due to actual or ‘invisible’ occupants. It also highlights those different types of buildings and uses require tailored occupancy sensors. The literature review suggests that data collection can lead to over deployment of sensors, resulting in an overload of data without the capacity or mechanisms to effectively analyse it. This can hinder meaningful decision-making and turn the data into 'data waste,' failing to provide valuable input for optimisation models to address current occupancy challenges.

Future research should concentrate on developing innovative, low-cost occupancy monitoring tools tailored for various building environments. These tools need to be less intrusive while maintaining high levels of user data privacy. Additionally, there is a need for innovative applications of AI to synthesise data from different sources. This is to help distinguish automated patterns from genuine user behaviours, allowing for a better understanding of actual energy demands and preventing the supply of services to unoccupied spaces. Future research should also utilise social science approaches, in addition to pure quantitative mathematical approaches, simply because contextualising the problem provides more depth and reasoning behind why occupants have variable occupancy. These responses allow for targeted interventions to take place and provide a more in depth understanding of occupancy in spaces.

Insights from Current Ongoing Research

Current efforts are underway to address existing gaps and inform the design of data collection for both current and future analyses of occupancy and household energy use behaviours through the Energy Demand Observatory Laboratory (EDOL) program. This initiative aims to establish a world-class observatory comprising 2,000 representative UK homes, equipped to collect high-resolution, longitudinal technical and social data using ambient, transmitted, and self-reported tools for tracking occupancy. This approach will provide evidence on the methodological aspects and challenges discussed above, while also enhancing our understanding of occupancy and household energy consumption patterns, and how these may shift to other building environments. A recent study within this program has explored the feasibility of Wi-Fi-based approaches to capture occupancy trends by identifying unique devices connected to a household network. While this approach has seen success in office spaces, its application in residential environments remains an open gap and presents additional challenges. Specifically, identifying the household network in a non-intrusive manner is difficult due to interference from neighbouring networks. Residential networks tend to consist of more diverse devices and less restricted with fluctuating network data. Preliminary results of this study have shown that Wi-Fi-based tracking can be feasible to identify the number of devices in households as a proxy for occupancy; however, accuracy can be compromised by overlapping signals from neighbouring networks, device mobility within households, and fluctuating signal strength. This challenge underscores the need for advanced filtering techniques and robust algorithms that can accurately separate household network data from external signals, ultimately identifying device types, their activity patterns and household occupancy. Addressing this gap will significantly advance the development of innovative, non-intrusive, low-cost occupancy detection methods for residential settings.

The second on-going project at the University of Oxford looks into occupancy behaviour and space performance in retrofitted and non-retrofitted office spaces following the pandemic. In this investigation it was apparent that to understand the energy performance of the space, it was critical to collate occupant response (Post-Occupancy Evaluations) and understand occupancy patterns. In this project, CO_2 sensors were used to gauge occupancy in the space, however it was found to be obsolete in open plan office and medium size offices, and more effective in small or single occupied offices. This project found that space sensors and IT infrastructure (Wifi, computer data and access data) is critical to the detection of occupants especially in large or open plan spaces as it provides a higher resolution data with the infrastructure already available.

Furthermore, the occupant questionnaires and surveys found that the indoor environmental quality plays a key role in influencing decisions to work from home or from offices (especially following the COVID-19 pandemic), which has been noted as a key (and sometimes the most important factor) in the decision to work from the usual place of work or from home. This relationship can be reflected in figure 2, where occupants were asked **“Does the air quality in your usual place of work have an impact on your work performance?”** in a retrofitted and non-retrofitted space in the same high educational building. The results show that 57% of the respondents in the non-retrofitted spaces felt either negatively or very negatively about the air quality, while only 7% negatively or very negatively in the retrofitted space. From figure 3, when the same group of occupants were asked, **“To what extent has the building environment impacted your decision to work in your usual place of work?”** 57% of the respondents in the non-retrofitted space stated the building indoor environment had an impact in deciding to work away from the usual place of work, with one occupant stating it is the most important factor in deciding to work away from the usual place of work. While for the retrofitted, only 13% stated that the building environment has an impact in deciding to work away from the usual place of work, with 40% stating no impact and 47% stating some impact in their decision to work away from the usual place of work.

This work acknowledges that following the pandemic The dynamic between occupancy and building use has significantly changed. Especially when traditional occupancy patterns no longer exist and building energy system controls and management remained unchanged, leading to prolonged periods of empty or low occupancy spaces being conditioned unnecessarily. Furthermore, with the emergence of hybrid working the indoor environment has become a significant influencer in prompting occupants to use the space, with areas with poor indoor air quality and comfort becoming more vacant and less utilised increasing energy waste. Overall, this work observed that the problem of energy waste has become more apparent due to the sudden change of occupancy behaviour post-pandemic and calls for a need for occupant-centric control for building energy management.

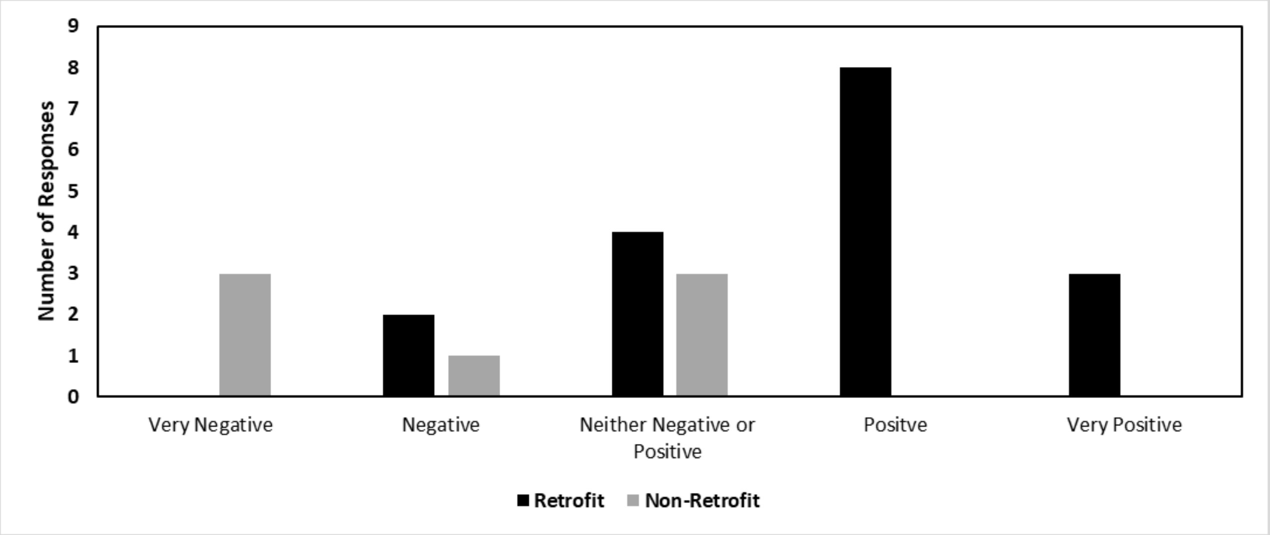

Figure 2 – Occupant response in a retrofitted and non-retrofitted space during the winter period when asked if "Does the air quality in your usual place of work have an impact on your work performance?"

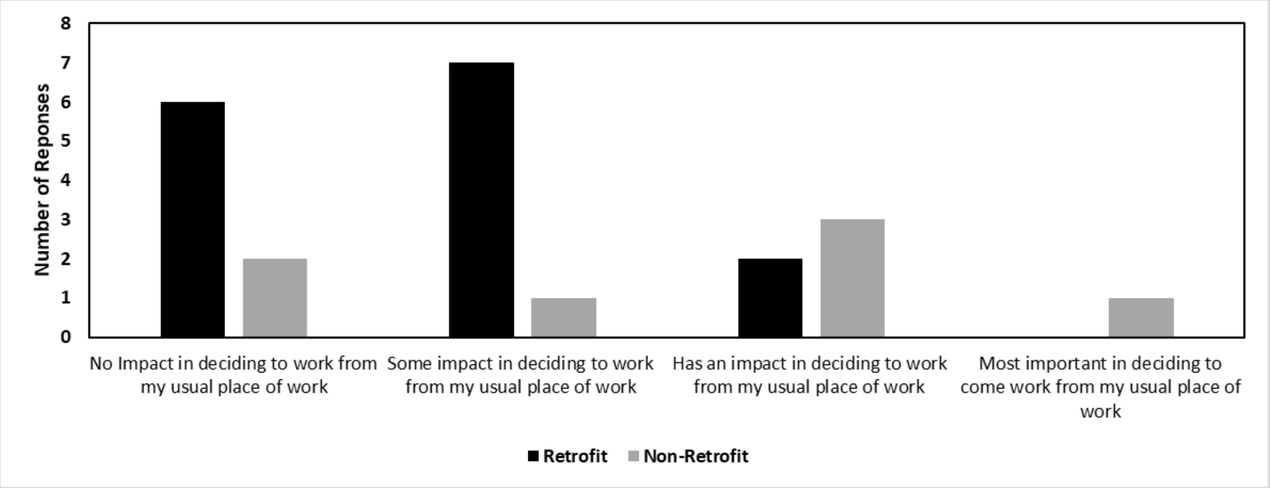

Figure 3 – Occupant response in a retrofitted and non-retrofitted space during the winter period when asked if "To what extent has the building environment impacted your decision to work in your usual place of work?"

Conclusions

Overall, this review was successfully able to highlight some of the key approaches used to detect and count occupancy currently found at both residential and office spaces. The review was also able to highlight some of the limitations associated with occupancy detection methodology as well as the complex dynamic between the occupants, the building and the building systems. This review stresses that occupancy should not just be a count and that qualitative approaches are also needed to contextualise the reasons behind the measured occupancy in the space. Finally, this review touches on learnings and reflections from projects currently in progress at the University of Oxford addressing occupancy and how these projects aim to address some of the limitations presented in regard to occupancy in office and residential spaces with insights presented in some of the initial findings from both.

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