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Space Use Efficiency through Occupancy Monitoring Technologies: A Case Study at KTH Royal Institute of Technology

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Space Use Efficiency through Occupancy Monitoring Technologies: A Case Study at KTH Royal Institute of Technology

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Abstract

Buildings account for approximately 40% of global greenhouse gas emissions, with a growing portion of these emissions stemming from the construction and production phases, particularly in countries with decarbonized energy systems such as Sweden. This thesis investigates the role of real-time occupancy monitoring technologies to improve space use efficiency as a sustainable alternative to new construction. The study focuses on a case within the Sustainable development environmental science and engineering (SEED) department at KTH Royal Institute of Technology, where space utilization was analyzed before and after downsizing from three floors to two.

By comparing sensor-based monitoring systems with manual counting methods, the study assesses the accuracy, reliability, and practical applications of ICT-based monitoring in office environments. Literature insights and empirical data are integrated to evaluate how real-time data influences spatial planning, energy management, and organizational decision-making. Key findings reveal that sensor data, when effectively calibrated and contextualized, enables informed space management decisions, supports passive desk-sharing strategies, and enhances energy efficiency through dynamic control of building systems.

The study also considers ethical implications of occupancy tracking, emphasizing transparency, user trust, and the balance between data utility and privacy. The conclusion provides recommendations for integrating sensor data with building management systems and aligning space utilization strategies with sustainability goals. Overall, this research contributes to both academic discourse and practical frameworks for sustainable office space management.

Sammanfattning

Byggnader står för cirka 40 % av de globala utsläppen av växthusgaser, och en växande andel av dessa utsläpp kommer från bygg- och produktionsfaserna, särskilt i länder med avkarboniserade energisystem som Sverige. Denna avhandling undersöker rollen för realtidsbaserade tekniker för närvaromätning i syfte att förbättra yteffektiviteten som ett hållbart alternativ till nybyggnation. Studien fokuserar på ett fall på institutionen för Hållbar utveckling, miljövetenskap och teknik (SEED) vid Kungliga Tekniska högskolan (KTH), där lokalutnyttjandet analyserades före och efter en omstrukturering från tre till två våningsplan.

Genom att jämföra sensorbaserade övervakningssystem med manuella räknemetoder utvärderas noggrannhet, tillförlitlighet och praktisk tillämpning av ICT-baserad övervakning i kontorsmiljöer. Litteraturstudier och empiriska data integreras för att undersöka hur realtidsdata påverkar rumsplanering, energihantering och organisatoriskt beslutsfattande. Centrala resultat visar att sensordata, när de kalibreras och tolkas korrekt, möjliggör informerade beslut om lokalhantering, stödjer passiva skrivbordsdelningsstrategier och förbättrar energieffektivitet genom dynamisk styrning av byggnadssystem.

Studien belyser även etiska aspekter av närvarospårning, med betoning på transparens, användarförtroende samt balansen mellan datanytta och integritet. Avslutningsvis ges rekommendationer för hur sensordata kan integreras med byggnadsstyrsystem och hur strategier för lokalutnyttjande kan anpassas till hållbarhetsmål. Sammantaget bidrar denna forskning till både den akademiska diskussionen och praktiska ramverk för hållbar hantering av kontorslokaler.

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1. Introduction

1.1 Background

Buildings are responsible for nearly 40% of global greenhouse gas emissions, a significant portion of which stems from the construction, production, and operational phases of buildings (Höjer *et al.*, 2024). In countries with highly decarbonized energy systems like Sweden, emissions related to building operations, such as energy use, are increasingly becoming less of a concern, with the construction and material production phases gaining more prominence (*IEA*, 2024). In response, there is a growing focus on improving space use efficiency in existing buildings, as an essential strategy for reducing the need for new construction and curbing emissions related to building material production.

In many modern office environments, the challenge of optimizing space use is compounded by a lack of accurate, real-time data on occupancy (Labeodan *et al.*, 2015). Many offices still rely on outdated or static space allocation models, which do not reflect actual usage patterns. Traditional methods, such as manual counting, are time-consuming and lack scalability, making them less suited to dynamic and evolving workspaces (Tagliaro, Zhou and Hua, 2021). This gap has led to the increased adoption of Information and Communication Technology (ICT)-based monitoring systems, such as sensor-based occupancy tracking, which offer the potential to provide real-time, data-driven insights for optimizing office space utilization (Chu *et al.*, 2022). However, questions remain regarding the accuracy, scalability, and practicality of these systems, especially when compared to manual counting methods (Labeodan *et al.*, 2015).

1.2 Problem Statement

Despite the increasing adoption of ICT-based monitoring systems for tracking office space utilization, organizations still encounter challenges in effectively interpreting and applying occupancy data for space improvements. One key issue is the reliability and accuracy of the data collected by sensors, particularly when compared to traditional manual counting methods (Labeodan *et al.*, 2015). The accuracy of sensor data is crucial for ensuring that space utilization decisions are based on reliable information. However, the effectiveness of sensor-based monitoring in real-world office settings has yet to be thoroughly validated, raising concerns about the practical implications of relying solely on this technology (Chu *et al.*, 2022).

Moreover, there is limited insight into how real-time occupancy data can directly influence decision-making processes aimed at improving office space allocation and utilization. Occupancy data has the potential to inform decisions related to space use, resource allocation, and energy consumption, organizations may struggle to fully harness this data without a clear understanding of its practical applications (Abdullah *et al.*, 2015).

The lack of accurate and actionable data could lead to inefficient resource allocation, underutilized office spaces, and unnecessary energy consumption (Abdullah *et al.*, 2015). This not only undermines operational efficiency but also hinders efforts to achieve sustainability goals. Without a clear understanding of how occupancy data can be effectively leveraged, organizations may miss the opportunity to optimize space and reduce environmental impacts.

1.3 Research Objectives

This study aims to address the challenges outlined in the problem statement by focusing on three research objectives. First, it seeks to identify and demonstrate effective strategies for enabling data driven decision making to improve space use efficiency, including exploring the role of real-time occupancy data in influencing space allocation, energy management, and overall office planning. Second, it aims to understand the role of ICT-based monitoring systems in promoting long term sustainability within office environments and how these systems can inform space utilization decisions in practice. Third, it explores the relationship between real-time occupancy data and organizational practices related to workspace management, highlighting how data can improve both the efficiency of space use and energy management. By addressing these objectives, the study seeks to bridge the gap between the theoretical benefits of ICT-based monitoring systems and their practical application in real-world office settings.

1.4 Research Questions

To address the objectives and the challenges identified in the problem statement, this study will explore the following research questions:

1. **How accurate are ICT-based monitoring systems in capturing and analyzing space utilization data when compared to manual counting methods?**
2. **How can ICT-generated data be leveraged for effective space utilization analysis and improvement?**
3. **How does the downsizing from three floors to two impact space utilization metrics?**

By answering these questions, the study will provide valuable insights into the practical application of occupancy monitoring technologies. Furthermore, it will offer guidance on how to harness these technologies for improving office space efficiency, enhancing sustainability efforts, and improving resource allocation.

2. Literature Review

The efficient and adaptive use of space has become a pressing concern in both office and academic environments, driven by sustainability targets, cost containment, and evolving work practices such as hybrid and flexible working (*IEA*, 2024). A growing body of literature highlights how digital technologies, particularly ICT-based systems and real-time sensor tools can transform static workplaces into responsive, data-driven environments. This review critically examines these systems across several domains technical validation, practical implementation, and strategic application while identifying the gaps that remain in bridging technical capacity with organizational outcomes and long-term spatial planning.

2.1 ICT-Based Systems and Space Efficiency

ICT-based systems, particularly those leveraging Internet of Things (IoT) technologies, are widely regarded as key enablers of spatial efficiency in an era of increasing urban density and constrained resources (Azizi *et al.*, 2021). These systems support a hierarchical strategy for space optimization: reducing demand, intensifying usage, repurposing space, and constructing new facilities only as a last resort (Aghemo *et al.*, 2013; Höjer and Mjörnell, 2018). Tools such as reservation platforms and occupancy dashboards enable shared use models and dynamic adjustments based on real-time conditions.

However, despite the theoretical robustness of such frameworks, real-world applications often face obstacles not addressed in literature. Regulatory systems still rely heavily on outdated performance indicators (e.g., energy per square meter), inadvertently penalizing high-occupancy or shared-use spaces (Höjer and Mjörnell, 2018). Moreover, most existing studies focus on environmental and operational metrics, with limited analysis of user behavior, institutional culture, or the political dimensions of space allocation. As such, the potential of ICT tools to contribute to broader institutional transformation remains underexplored.

The literature also tends to assume seamless integration into existing infrastructure, yet older buildings pose technical and financial barriers that require careful planning. Although low-cost, off-the-shelf sensor technologies offer promise (Aghemo *et al.*, 2013), few studies examine the lifecycle costs or governance models required for long-term deployment, particularly in public institutions.

Expanding beyond corporate offices, recent work by Valks et al. (2020) provides a valuable case study on the application of smart space tools in university settings. Through the implementation of real-time monitoring at TU Delft, the authors demonstrate how smart campus tools can inform strategic decisions across four domains: strategic, tactical, operational, and user experience.

Notably, Valks et al. identify significant mismatches between scheduled and actual use of teaching spaces, allowing the university to reallocate resources and avoid unnecessary new construction. Their work confirms many of the technical claims made elsewhere in the literature such as improved scheduling and reduced energy use but uniquely positions these tools within institutional planning processes.

However, while the study successfully illustrates the practical potential of sensor data, it also reveals persistent implementation challenges. Organizational silos, data governance concerns, and limited user involvement hinder the full integration of these tools into long-term strategy. Importantly, the study stops short of evaluating long-term user satisfaction or educational outcomes, suggesting that more interdisciplinary and longitudinal research is needed to fully assess the impact of smart campus systems (Valks *et al.*, 2018).

2.2 Sensor Technology and Its Limitations

Occupancy sensors form the backbone of smart building systems, yet their effectiveness depends on both technological accuracy and contextual suitability. Commonly deployed sensors such as Passive Infrared (PIR) offer low-cost monitoring solutions but are limited in low-motion environments, such as seated workstations (Chu *et al.*, 2022). Multimodal sensor networks integrating PIR, ultrasonic, and CO_2 sensors have been proposed to increase detection fidelity (Amuta *et al.*, 2024).

The PIR sensors detect movement by picking up changes in heat from people or animals as they move across a space (Amuta *et al.*, 2024). When a warm body passes in front of the sensor, it senses the difference and triggers a response (Amuta *et al.*, 2024). PIR sensor was able to reliably detect motion under different conditions, including various angles, distances, and sensitivity levels (Amuta *et al.*, 2024). Its low cost and energy efficiency make it a practical choice for many motion-detection systems (Chu *et al.*, 2022).

Validation studies report high accuracy and F1 scores under controlled conditions, suggesting these systems are reliable for desk booking, heating ventilation air conditioning(HVAC) control, and space analytics (Chu *et al.*, 2022). However, these findings often lack longitudinal data or real-world validation in complex organizational settings. Few studies critically examine how sensor accuracy degrades over time, or how false positives/negatives influence decision-making.

Moreover, the focus on technical performance obscures broader ethical and operational questions. Issues of privacy, data governance, and user trust especially in sensitive environments like universities remain under-theorized in the literature. Without robust anonymization protocols and transparent data use policies, sensor deployment risks undermining institutional legitimacy and user acceptance.

2.3 Comparing Sensor Data with Manual Observation

Sensor-based monitoring offers clear advantages over manual counting, particularly in terms of temporal resolution, accuracy, and scalability. Automated systems can detect nuanced usage patterns such as dwell times, peak flows, and space frequency that human observation methods typically miss (Tagliaro, Zhou and Hua, 2021). This granularity enables predictive modeling and dynamic system control, where HVAC and lighting systems adjust in anticipation of demand (Taboada-Orozco, Yetongnon and Nicolle, 2024).

Yet, the literature generally portrays this shift from manual to automated data collection as unproblematic. While sensor data reduces subjectivity and labor costs, it may also strip out important qualitative context such as user intent, comfort, or satisfaction that is more readily captured through ethnographic or observational methods. This raises the risk of making planning decisions that are technically efficient but experientially inadequate.

In addition, there is a lack of critical evaluation regarding data quality over time, especially in high-traffic or flexible-use environments. Real-world deployments may encounter issues such as sensor drift, maintenance gaps, or spatial blind spots, which are rarely acknowledged in technical validation studies.

2.4 Sensor-Driven Strategies for space improvement

Once validated, sensor systems offer a foundation for data-informed interventions in workplace design and policy. Strategies such as passive desk-sharing and dynamic space allocation have demonstrated the potential to reduce spatial requirements by up to 40% without degrading user access (Einola and Dooley, 2025). Similarly, adaptive planning based on real-time usage data can reallocate underused zones, enhancing both efficiency and user satisfaction(Genel, Heijer and Arkesteijn, 2024).

Nonetheless, the literature tends to emphasize quantitative gains while overlooking qualitative trade-offs. Few studies assess the long-term impacts of space-saving strategies on employee well-being, collaboration, or organizational culture. For instance, while hot-desking may increase utilization, it can also reduce a sense of ownership or disrupt informal social networks factors that remain underrepresented in sensor-based studies (Jens and Gregg, 2022).

Post-pandemic shifts have renewed interest in these issues, with occupancy data being used to identify preferred zones or features that encourage office attendance (Smite, Klotins and Moe, 2024). Yet, these interventions often rely on a narrow set of metrics footfall, duration, and booking frequency without accounting for task suitability or user satisfaction. This limits the strategic scope of data-informed design and calls for richer, mixed-method evaluations.

3. Case Study: SEED KTH

3.1 Need for a case study

A case study approach is particularly appropriate when the goal is to investigate complex and contemporary phenomena within their real-life context, especially when the boundaries between the phenomenon and its context are unclear (Säfsten, Gustavsson and Ehnsiö, 2020). The recent restructuring at SEED KTH including floor consolidation and a shift from open-plan layouts to more private offices represents a multifaceted change that impacts both spatial configuration and employee behavior. This context demands a research method capable of capturing the interplay between environmental changes and human responses (Säfsten, Gustavsson and Ehnsiö, 2020) . The case study method supports this by enabling the integration of various data sources, such as sensor-based occupancy tracking, manual observations, and employee feedback, to develop a comprehensive understanding of space utilization and workplace dynamics (Säfsten, Gustavsson and Ehnsiö, 2020). This aligns with established research methodology guidelines that highlight the case study’s strength in capturing complex, real-world processes (Säfsten, Gustavsson and Ehnsiö, 2020).

3.2 Overview of the office environment

The case study is conducted at SEED KTH, where approximately 90 staff members work across a variety of office spaces. Prior to 2024, the office layout spanned three floors, comprising a mix of open-plan workspaces, shared offices, designated meeting rooms, and a limited number of telephone rooms. This configuration aimed to accommodate diverse work styles, balancing collaborative spaces with areas for focused individual work.

In 2024, a series of strategic changes were implemented to enhance space utilization, reduce operational costs, and improve overall workplace efficiency. These modifications included the consolidation of office space from three floors to two and the introduction of additional private offices, marking a shift away from the previous open-plan design. The restructuring aimed to improve the use of available space, promote a more effective working environment, and ensure a sustainable long-term office strategy for SEED KTH.

3.3 Timeline of Office Space Changes

In 2024, the SEED KTH office underwent two major changes aimed at improving space use, reducing operational costs, and improving workplace efficiency. These changes involved both the addition of new rooms and the consolidation of office space from three floors to two, significantly altering how the workspace was structured and utilized. The restructuring was driven by a combination of factors, including cost efficiency, improved space allocation, and sustainability considerations.

These modifications provide a unique opportunity to evaluate the effects of office layout changes on occupancy rates, frequency rates, and overall space efficiency, offering insights into how workspace design influences employee behavior and resource utilization.

- Addition of new rooms (November – December 2024): In the final months of 2024, new office rooms were introduced to accommodate evolving workplace needs. This involved a conversion of open spaces into enclosed offices, increasing the availability of private work areas. The introduction of these new rooms reflects a shift towards a more structured office environment, addressing the need for quieter, distraction-free workspaces while maintaining flexibility for collaborative tasks.
- Floor downsizing (May 24–25, 2024): During late May 2024, a major transition took place as the office was downsized from three floors to two. This change involved:
    - Elimination of workspace on the third floor, requiring a redistribution of employees across the remaining two floors.
    - Reduction or relocation of open-plan areas, meeting rooms, and individual workstations to accommodate the new layout.

This downsizing was primarily driven by cost savings, improved space utilization, and sustainability goals. By reducing the total office footprint, the organization aimed to enhance space efficiency, lower energy consumption, and create a more adaptable working environment. The impact of these changes is being analyzed through occupancy data, frequency rates, and employee feedback, providing valuable insights into how office restructuring influences workplace dynamics, employee satisfaction, and overall space use efficiency.

3.4 Sensor deployment and room configuration

To facilitate automated occupancy monitoring, PIR sensors were installed in every room within the office environment. These sensors detect motion to indicate room occupancy and provide real-time data on space usage. The PIR sensors capture data at 10-minute intervals, with changes in occupancy status stored in an API. This approach ensures efficient data management by focusing on variations in occupancy rather than continuous readings.

While PIR sensors cover all rooms, only a subset of spaces primarily meeting rooms and telephone rooms were equipped with CO_2 sensors. These sensors record CO_2 concentration levels at 5-minute intervals, offering an additional measure of occupancy by detecting the buildup of carbon dioxide from human activity. The use of CO_2 sensors in enclosed spaces is particularly valuable for understanding air quality and occupancy density, where traditional motion sensors may have limitations.

The combination of PIR and CO_2 sensors allows for a comprehensive analysis of space utilization patterns across different types of rooms, providing insights into the effectiveness of recent office layout changes and the accuracy of automated occupancy monitoring.

Each floor is equipped with a total of 40 sensors distributed across various room types, open-plan areas, offices, meeting rooms, and telephone rooms. Although minor variations exist in the floor plans, each floor comprises an average of 25 distinct rooms, excluding non-analyzed spaces such as utility rooms. The total floor area is approximately 280 square meters, of which the rooms included in the analysis account for approximately 180 square meters.

4. Methodology

This study adopts a mixed-methods approach to evaluate space utilization at the SEED department of KTH, combining manual data collection techniques with automated sensor-based monitoring. This methodological integration ensures an evaluation of workspace occupancy by facilitating cross-validation between datasets and offering both direct and indirect insights into space usage patterns. The study design aligns with established research procedures for empirical inquiry and data triangulation (Säfsten, Gustavsson and Ehnsiö, 2020)

4.1 Manual Data Collection

Manual data collection was employed to obtain direct, observable occupancy figures. Systematic headcounts were conducted on floors 4 and 5 of the SEED building, with observations recorded at four designated time points throughout the workday: 09:00, 11:00, 15:00, and 17:00. These intervals were strategically selected to represent distinct phases of daily office activity, capturing morning arrivals, midday presence, afternoon workflows, and end-of-day attendance while also following previous work at SEED to allow for a comparison of previously collected data in 2024 (Höjer *et al.*, 2024).

Each manual data collection session lasted approximately 6–8 minutes and involved a researcher walking through the office and recording the number of occupants in each room. This method allowed for a quick yet representative snapshot of space use without significant disruption to the work environment. The consistency of timing and observation protocol ensured comparability across different days and minimized observer bias.

Manual counting was particularly valuable as a benchmark against which to assess the performance and accuracy of sensor systems. While sensors provide continuous data, manual counts offer precise momentary verification and highlight potential discrepancies due to contextual factors, such as room configurations or transient occupancy behaviors (Säfsten, Gustavsson and Ehnsiö, 2020).

4.2 Sensor data collection

To complement manual observation, the study utilized PIR sensors and CO_2 sensors installed throughout the office space. PIR sensors detected motion-based occupancy, registering changes in occupancy states in each room every 10 minutes. The system's architecture is optimized to store only instances where occupancy status changes, thereby reducing data redundancy while maintaining relevant activity trends.

Since PIR sensors do not quantify the number of occupants but only detect motion, additional processing was required. Python scripts were used to extract, process, and interpolate sensor data, enabling the reconstruction of occupancy patterns over shorter intervals and enhancing the granularity of the dataset.

In addition to PIR data, CO_2 sensors provided an indirect measure of occupancy by recording carbon dioxide concentrations at 5-minute intervals. CO_2 levels, which correlate with the presence of humans, were used as a secondary validation mechanism for occupancy trends, particularly in enclosed meeting rooms and shared offices.

Sensor deployment and integration followed methodological principles for system-based research, ensuring consistency between sensor capabilities, data collection frequency, and spatial layout (Säfsten, Gustavsson and Ehnsiö, 2020).

4.3 Data Processing and Analytical Methodology

The data analysis process followed a structured and rigorous research methodology, emphasizing systematic data transformation, interpretation, and validation. This approach is informed by best practices in applied research methodology and aligns with the guidelines presented in data analysis which outlines procedures for converting raw data into actionable insights through cleaning, organizing, coding, and analytical interpretation (Dibekulu, 2020; Säfsten, Gustavsson and Ehnsiö, 2020).

For both manual and sensor-based datasets, preprocessing was a critical step to ensure consistency, accuracy, and reliability. Manual headcount records were digitized and structured in spreadsheets, organized by floor, room, date, and time. Data entries were reviewed for completeness and transcription errors before being merged into a centralized database for analysis.

Sensor data, particularly from PIR and CO_2 sources, required a more complex data pipeline. Raw logs were exported from the system and processed using custom Python scripts. The scripts handled:

- Time normalization across different sensor types to align records to common time intervals.
- Data cleaning, including the removal of anomalies (e.g., false triggers or missing data).
- Interpolation to fill short gaps in PIR readings and to model occupancy changes over time.
- Smoothing techniques to reduce noise and highlight meaningful occupancy trends.

Quantitative analysis was then performed to generate descriptive statistics, occupancy averages, and usage distributions across different times and spaces. Where applicable, correlation analysis was conducted between PIR, CO_2, and manual data to assess alignment and identify potential discrepancies.

Following established analytical guidelines, both descriptive and inferential approaches were used to interpret the data. Descriptive analysis provided an overview of occupancy trends and patterns, while comparative analysis between manual and sensor data enabled deeper insight into the validity and performance of each method (Dibekulu, 2020; Säfsten, Gustavsson and Ehnsiö, 2020).

4.4 Comparative Analysis

The integration of manual and sensor-based data enabled a robust comparative analysis of occupancy patterns, allowing for an in-depth evaluation of each method's performance and reliability (Dibekulu, 2020)). This section outlines how the two data sources were compared, assessed for consistency, and how discrepancies were identified and interpreted.

The first step in the comparative analysis involved aligning the manual headcount data and the sensor-based occupancy data in a common framework. Both datasets were structured around the same time intervals (09:00, 11:00, 15:00, and 17:00), ensuring comparability across the different methods. For manual data, the recorded headcounts from each floor and time were matched with corresponding sensor data from the same periods.

The manual headcounts served as a ground truth for evaluating the accuracy of sensor-derived occupancy patterns. The PIR sensor data, which recorded motion events but did not quantify the exact number of occupants, was used in conjunction with CO_2 sensor data to infer general occupancy levels. These sensor data were cross-checked against the manual counts to assess their accuracy in reflecting real occupancy.

Differences between manual counts and sensor data were analyzed to identify potential discrepancies. Discrepancies were categorized into two types:

- False positives: Instances where PIR sensors recorded occupancy despite the absence of people, often due to environmental factors such as equipment motion or external airflow.
- False negatives: Situations where PIR sensors failed to detect occupancy, possibly due to insufficient motion or sensor malfunctions.

These discrepancies were thoroughly reviewed to understand how sensor limitations, such as the sensitivity of PIR detection or environmental influences on CO_2 levels, might have contributed to differences in reported occupancy.

Correlation analysis was employed to quantify the degree of alignment between manual counts and sensor-based estimates. Correlation analysis helped identify trends where sensor data consistently aligned with manual counts. These statistical measures provided an objective basis for evaluating the overall reliability and performance of each data collection (Dibekulu, 2020).

Through comparative analysis, the study highlighted the strengths and weaknesses of each method:

- Manual counts were highly accurate at providing specific, momentary occupancy data, but they were labor-intensive and limited in scope due to the snapshot nature of the observations.
- Sensor data offered continuous real-time insights into occupancy but lacked precision in terms of exact occupant numbers and could be affected by environmental factors.

4.5 Data Sources

To evaluate space utilization and occupancy dynamics, this study employed a mixed-methods approach combining automated sensor technologies with manual observational techniques.

This dual-source methodology ensured both breadth and depth in data acquisition, enabling robust cross-validation of occupancy patterns. The integration of real-time sensor data with manually recorded benchmarks supported comprehensive analysis and enhanced the reliability of findings across varied spatial and temporal contexts.

4.5.1 Automated Sensor Data

Automated data collection was conducted through a network of IoT-enabled sensors strategically deployed across workspaces, corridors, and meeting rooms. The system included PIR sensors to detect motion, CO_2 sensors to act as ventilation and indirect occupancy proxies, and temperature sensors. CO_2 sensor transmitted data at five-minute intervals while PIR and temperature at 10-minute intervals, which were subsequently aggregated into hourly and daily summaries for analysis.

4.5.2 Manual Observations

Complementing the automated setup, manual occupancy observations were carried out over a six-week period. Observers followed a standardized template that documented the space type, estimated occupancy count, and timestamp at regular intervals. These manually recorded datasets served as ground-truth reference, enabling calibration and validation of the sensor-derived data. Aswell as previously collected data following the same collection protocol.

4.6 Data Processing

The data processing workflow adhered to a systematic and structured approach to ensure consistency, integrity, and interpretability across multiple data sources. Following the guidelines outlined in data analytics, the raw sensor and manual data were cleaned, organized, and transformed into analyzable formats through a series of iterative steps (Dibekulu, 2020).

For the manual data, spreadsheets were structured by floor, room, date, and time. Data entries were screened for inconsistencies, transcription errors, and missing values. This ensured a clean dataset that could serve as a reliable benchmark for validating sensor performance.

Sensor data, collected from PIR, CO_2 and temperature sources, required a more robust pipeline due to higher data volume and greater variability. Custom Python scripts were used to normalize time intervals, remove noise, interpolate missing records, and align occupancy events across sensor types. The data pipeline was designed to support both high-level trend analysis and granular cross-checking with manual counts.

This end-to-end process from raw data to insights was grounded in the transformation model presented in data analysis, ensuring transparency, methodological rigor, and replicability of the results (Dibekulu, 2020).

4.7 Performance Evaluation

Sensor data performance was evaluated using classification-based metrics precision, recall, and F1-score to assess alignment with manual occupancy observations, following the methodology proposed by Chitnis, Somu, and Kowli (2025). Manual headcounts were treated as ground truth, and sensor detections were compared on a per-room, per-time-slot basis to compute the confusion matrix for occupancy prediction.

Data quality was assessed across three critical dimensions: completeness, timeliness, and accuracy (Cai and Zhu, 2015). These dimensions helped identify where sensor data may fall short, particularly in high-variability environments like shared workspaces.

Common sources of error were categorized which distinguishes between:

- False positives, often caused by cleaners, HVAC disturbances, or non-human movement.
- False negatives, where subtle human presence goes undetected.
- Temporal mismatches, due to asynchronous recording intervals or event timing errors.

To evaluate the effectiveness of the occupancy detection system, several standard performance metrics are utilized. These metrics provide insight into different aspects of classification performance and are defined as follows:

Sensitivity (Recall)
Sensitivity, also known as recall, measures the ability of the system to correctly identify true positive cases. In the context of occupancy detection, it refers to the proportion of actual occupied instances that are correctly detected.

Formula:

Recall = True Positives (TP) / (True Positives (TP) + False Negatives (FN))

A higher recall indicates fewer missed detections of occupancy.

Specificity
Specificity refers to the proportion of actual unoccupied instances that are correctly identified as such. It measures the system's ability to avoid false positives.

Formula:

Specificity = True Negatives (TN) / (True Negatives (TN)+ False Positives (FP))

High specificity is important to avoid incorrectly detecting occupancy when none exists.

Precision
Precision assesses how many of the predicted occupied instances are correct. It is the ratio of true positives to all predicted positives.

Formula:

Precision = True Positives (TP) / (True Positives (TP) + False Positives (FP))

Precision is particularly relevant in cases where false alarms are costly or disruptive.

False Positive Rate (FPR)
This metric indicates the proportion of unoccupied instances that are incorrectly classified as occupied.

Formula:

FPR = 1 - specificity

A low false positive rate is essential to maintain system credibility and avoid unnecessary responses.

False Negative Rate (FNR)
The false negative rate measures the proportion of actual occupied cases that are missed by the system.

Formula:

FNR = 1 - sensitivity

This metric highlights the system's vulnerability to failing to detect actual occupancy.

Accuracy
Accuracy indicates the overall proportion of correctly classified instances (both occupied and unoccupied) out of all predictions made.

Formula:

Accuracy = TP + TN / (TP + TN + FP + FN)

While intuitive, accuracy can be misleading in imbalanced datasets, where one class dominates.

F1 Score
The F1 Score is the harmonic mean of precision and recall, providing a single metric that balances the trade-off between them. It is especially useful when there is an uneven class distribution.

Formula:

F1 Score = 2 × Precision × Recall / (Precision + Recall)

A higher F1 score indicates a more reliable detection performance, accounting for both false positives and false negatives.

This evaluation strategy allowed for the identification of systemic and contextual weaknesses in sensor-based monitoring, informing future improvements in calibration and deployment (Teh, Kempa-Liehr and Wang, 2020).

4.8 Space use indicators

Sensor-derived occupancy metrics were aggregated and analyzed according to spatial function and room classification. The following space utilization indicators, adapted from Abdullah et al. (2015), were calculated:

Frequency Rate (FR):

The frequency rate is calculated as the number of 10-minute intervals during which a room is used, divided by the total number of 10-minute intervals available in a day. It reflects how often the room is in use.

Formula:
FR = (Number of used 10-minute intervals) / (Total available 10-minute intervals)

Occupancy Rate (OR):

The occupancy rate is the number of people present in a space divided by the total capacity of that space. It indicates how full the space is when in use.

Formula:
OR = (Number of people present) / (Total capacity)

Space Utilization Rate (SUR):

The space utilization rate is the product of the frequency rate and the occupancy rate. It measures how effectively a space is being used, considering both how often it is used and how fully it is occupied when in use.

Formula:
SUR = Frequency Rate × Occupancy Rate

Workstation-level density was also calculated in terms of occupants per square meter, in line with benchmarks outlined in (Salhab *et al.*, 2025). This metric provided insight into how space was distributed at the desk level and supported the identification of overcrowding or underutilization zones.

The overall analytical approach followed the data transformation and interpretation model presented by Dibekulu, (2020), ensuring that all results were grounded in validated analytical procedures and supported by coherent processing logic.

5. Results

5.1 Sensor Performance and Validation Results

To assess the performance of ICT-based occupancy monitoring systems, sensor data were compared against manual headcounts across different floors, room types, and time intervals. Standard performance metrics were calculated, including sensitivity (recall), specificity, precision, false positive rate (FPR), false negative rate (FNR), accuracy, and the F1 score (Chitnis, Somu and Kowli, 2025). These metrics collectively provide a robust view of how well the sensors identified presence relative to the ground truth established through manual observation (Cai and Zhu, 2015).

The sensor data is based on a 20-minute time interval before and after the specified time, where any activation in the interval will count for the entire duration. The lowest detail from the manual data for comparison would be a 10-minute interval to take into consideration the time to collect the manual data. The 20-minute time interval was chosen to take into consideration if a sensor missed longer period of no movement. An overall performance was analyzed for the 10-minute time interval and showed a similar result.

Sensor performance showed difference between data collection from 2024 compared to 2025, particularly following spatial change and layout changes at SEED. For instance, Floor 5 in 2025 achieved a recall of 0.7782 and an F1 score of 0.6240, outperforming 2024 Floor 3, which had a recall of 0.6028 and F1 score of 0.5730. This suggests that the collection process has an impact on the accuracy.

Table 1: PIR sensor performance metrics at SEED

Metric	Overall	2024 Floor 4	2024 Floor 3	2025 Floor 4	2025 Floor 5
Sensitivity (Recall)	0.7385	0.6028	0.7549	0.8454	0.7782
Specificity	0.6676	0.6936	0.6633	0.6252	0.6969
Precision	0.4963	0.5459	0.4189	0.5085	0.5208
False Positive Rate	0.3323	0.3064	0.3367	0.3748	0.3031
False Negative Rate	0.2614	0.3972	0.2451	0.1546	0.2218
Accuracy	0.6894	0.6592	0.6856	0.6944	0.7211
F1 Score	0.8496	0.5730	0.5388	0.6351	0.6240

These results indicate that while some inconsistency remains particularly with precision and specificity the system achieved reliable detection rates in the office building. With a focus on the accuracy of around 70% and high f1 score for the overall dataset and around 0.6 for induvial floors. There is no defined threshold for f1 and should be considered case by case however a general level is 0.7 (Otten, 2023).

Sensor performance was also analyzed across different room categories: telephone rooms, open areas, meeting rooms, and enclosed offices. Notably, open spaces demonstrated the best performance across most metrics, with high precision (0.8128) and an F1 score of 0.7479. In contrast, telephone rooms had the lowest detection accuracy, likely due to limited movement and short-duration occupancy events, which are harder for PIR sensors to capture.

Table 2: PIR sensor performance metrics across room types

Room type	Sensitivity	Specificity	Precision	FPR	FNR	Accuracy	F1 score
Tele (n=6)	0.3386	0.7720	0.3644	0.2280	0.6614	0.6513	0.3510
Open (n=9, avg 3 sensors per room)	0.6926	0.5495	0.8128	0.4505	0.3074	0.6552	0.7479
Meeting (n=6)	0.4384	0.6103	0.5330	0.3897	0.5616	0.5237	0.4809
Offices	0.5900	0.7950	0.5880	0.2050	0.4100	0.7270	0.5890

The high specificity in offices (0.7950) suggests that false alarms were relatively low in enclosed spaces, while the precision of open spaces reflects their strong performance in consistent detection, likely due to more sustained and active use patterns. Telephone and meeting rooms displayed moderate to weak sensitivity, likely due to brief or irregular occupancy, which PIR sensors struggle to capture reliably.

Room function heavily affects detection accuracy, with open and enclosed spaces performing best. Overall, the system demonstrates strong potential for broad occupancy monitoring, especially when complemented by calibration strategies and manual cross-validation. It could be improved with better placement of sensors as in one of the larger open spaces only had a singular PIR sensor.

5.2 Time-of-Day Analysis

Sensor performance exhibited notable variation across different times of the workday, with time sensitive patterns revealing important limitations and strengths of the PIR-based monitoring system. The recall rate was highest during the early hours, particularly at 09:00 (0.8653), when occupancy changes and movement were more pronounced as people arrived at the office. By contrast, sensor performance declined significantly by 17:00 (recall = 0.4274), reflecting reduced motion activity during end-of-day periods when employees are often sedentary or have already left the workspace.

Table 3: PIR sensor performance metrics across time

Time	**Recall**	**Specificity**	**Precision**	**Accuracy**	**F1 Score**
09:00	0.8653	0.5397	0.3205	0.6050	0.4678
11:00	0.8420	0.6017	0.5659	0.6933	0.6769
15:00	0.7717	0.6592	0.5976	0.7037	0.6735
17:00	0.4274	0.8655	0.5150	0.7557	0.4671

These trends support the observation that motion-based sensors, such as PIR, are more sensitive to dynamic occupancy events (e.g., arrivals, walking, active use) and are more effective during periods of static presence (e.g., sitting quietly or working at a desk). The drop in recall at 17:00, despite high specificity (0.8655), suggests that the system correctly identified many unoccupied rooms but underreported actual occupancy due to the lack of detectable movement.

During 9:00 and 17:00 when most people arrive or leave the office the model perform worse for the F1 score which could be an indication that the manual data missed the movement, but the sensor data captured the movements.

Interestingly, precision peaked in the afternoon (15:00 = 0.5976), indicating that when sensors did detect occupancy, it was more likely to be accurate. This implies that midday periods present a balance of moderate motion activity and stable presence, which aligns well with the detection capabilities of PIR sensors.

Precision and accuracy stabilize during midday, making this window most reliable for occupancy estimation. These patterns reinforce the importance of complementing PIR data with indirect indicators (e.g., CO_2 levels or scheduled activities) to improve accuracy during low-motion periods.

To enhance performance, future sensor deployments could incorporate multi-sensor fusion (e.g., combining motion, acoustic, and air quality data) and time-aware calibration models that adjust detection thresholds based on known behavioral patterns across the day.

5.3 Estimation of people based on sensors

To explore the potential of using sensor data for estimating building occupancy based on the total number of PIR sensor activations per 10-minute intervals across January 2024. Each floor has an average of 40 sensors bringing the maximum of sensor activations per 10-minute interval to 120 for three floors and 80 for two floors after the change in the office space. The figure above illustrates these total sensor triggers aggregated at 10-minute intervals for each day. This visualization provides an overview of activity patterns within the building, with distinct peaks corresponding to typical working hours and periods of reduced or no activity on weekends or holidays. The fluctuation in sensor values reflects variations in movement across monitored spaces, indirectly indicating occupancy trends. With a clear daily pattern for the analysed period from 9:00-19:00.

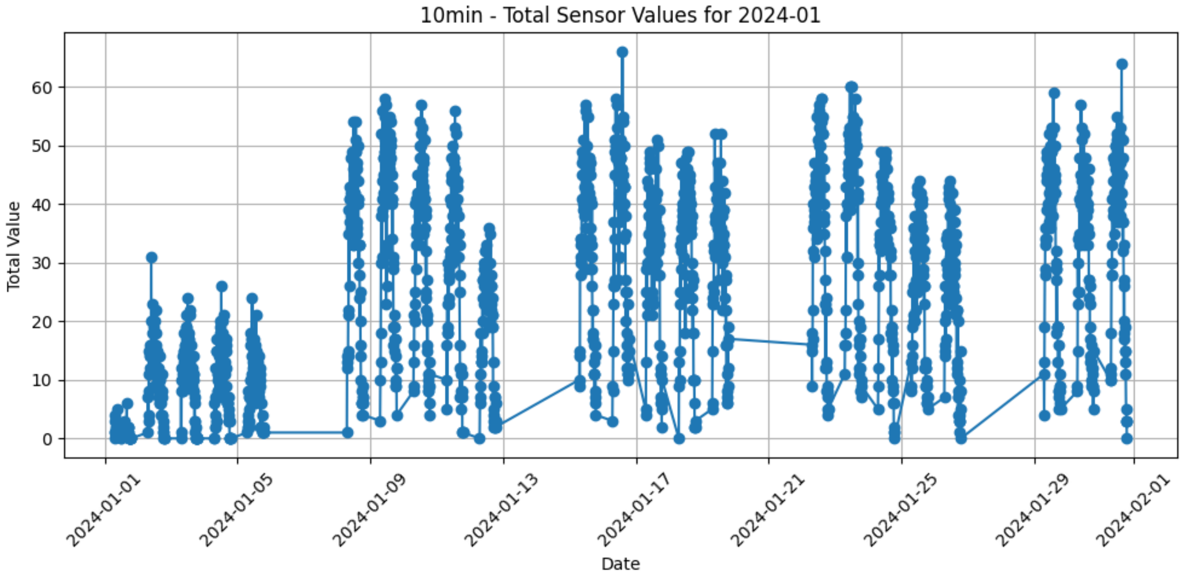

Figure 1: Total PIR at SEED during 2024-01 in 10-minute intervals

To enhance interpretability and align with manual headcount data, these sensor values were further aggregated into hourly intervals corresponding to the manual observation times (09:00, 11:00, 15:00, and 17:00). These aggregated sensor values served as the independent variable in a series of linear regression analyses, aiming to model and predict the number of people in the building based on sensor data.

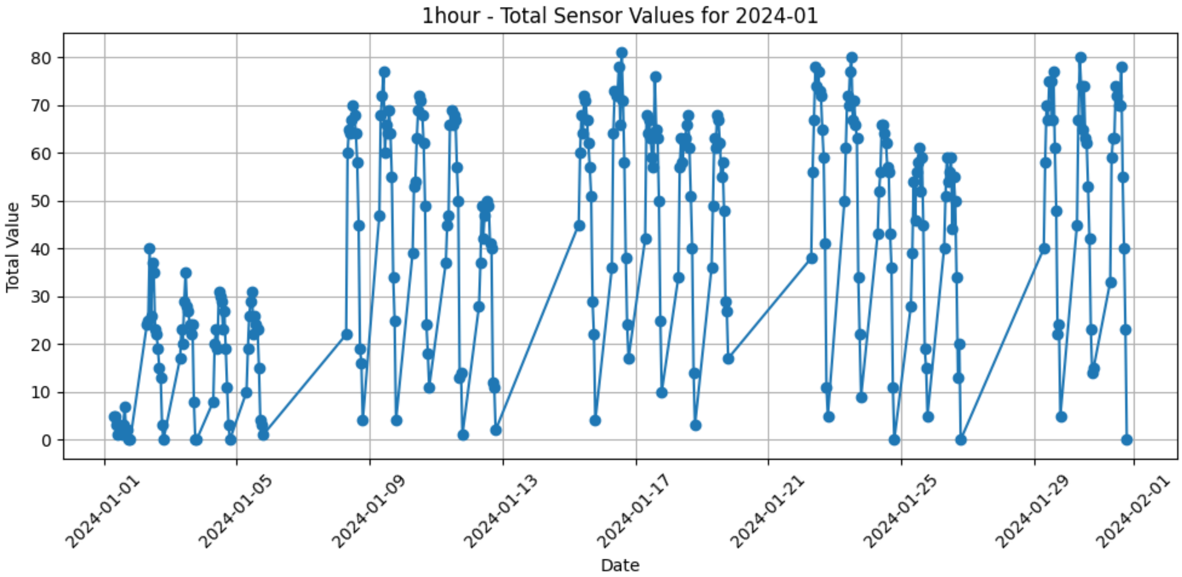

Figure 2: Total PIR at SEED during 2024-01 in 1-hour intervals

The data indicates that sensor activation levels increase as more individuals enter the office and decrease as they exit, reflecting general occupancy trends. To explore the relationship between total sensor activations and the number of people in the building, four specific time points 09:00, 11:00, 15:00, and 17:00 were examined.

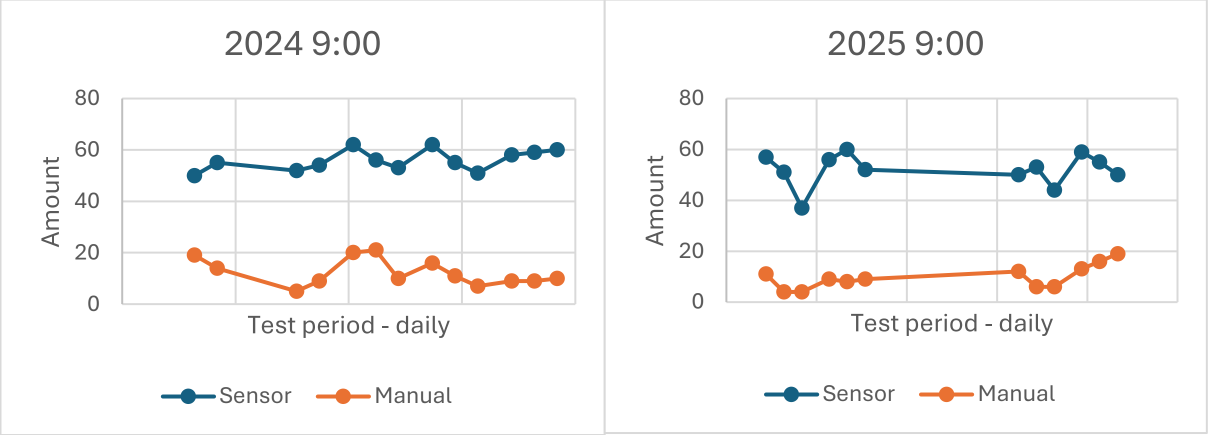

Figure 3: Total PIR activations at SEED compared to manual headcount at SEED 9:00

At 09:00, the Pearson correlation between the number of people in the office and the number of sensor activations was 0.386, with a Spearman correlation of 0.344. Neither of these correlations was statistically significant at the 0.05 level, indicating a weak and non-significant relationship at this time.

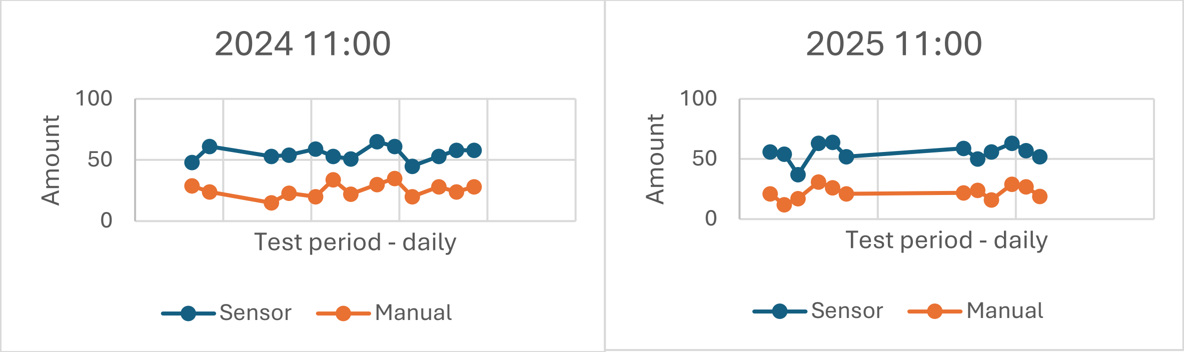

Figure 4: Total PIR activations at SEED compared to manual headcount at SEED 11:00

At 11:00, the Pearson correlation increased to 0.434 and the Spearman correlation to 0.442, both of which were statistically significant at the 0.05 level. This suggests a moderate and meaningful association between sensor activity and occupancy during mid-morning hours.

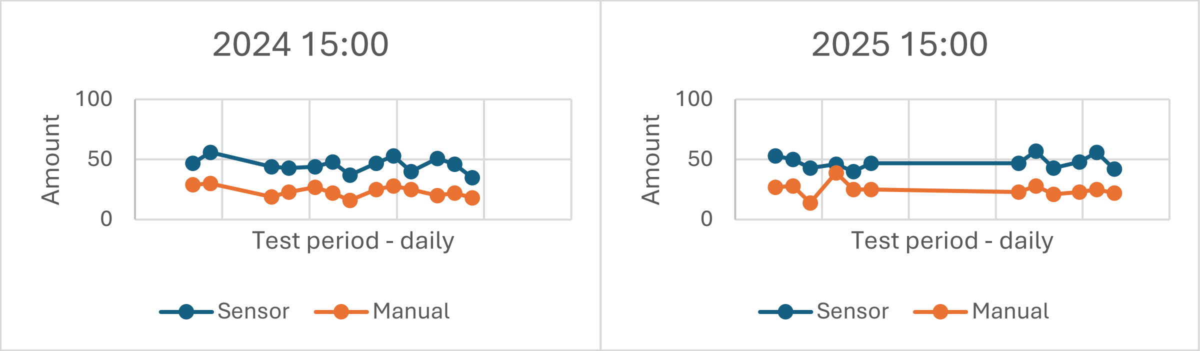

Figure 5: Total PIR activations at SEED compared to manual headcount at SEED 15:00

At 15:00, the correlation was strongest, with a Pearson coefficient of 0.481 (significant at the 0.05 level) and a Spearman coefficient of 0.541 (significant at the 0.01 level). This time window showed the clearest and most statistically robust relationship between sensor activations and the number of people in the office, indicating that mid-afternoon represents a peak in both occupancy and activity levels.

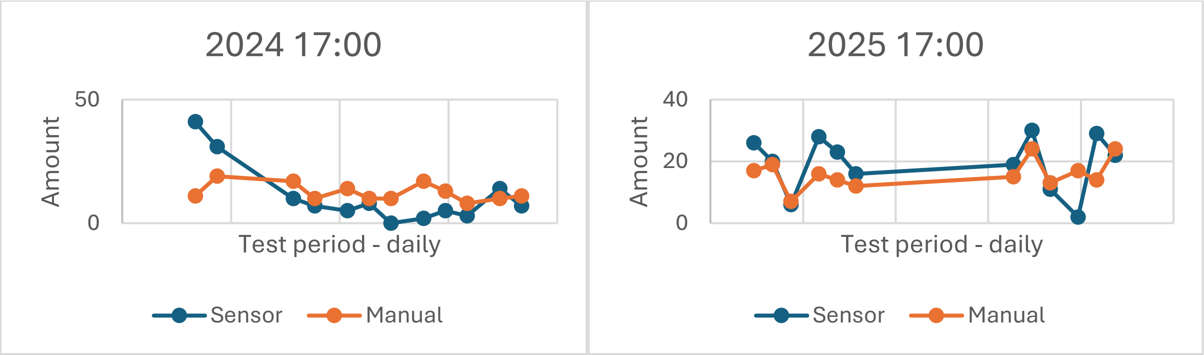

Figure 6: Total PIR activations at SEED compared to manual headcount at SEED 17:00

At 17:00, the Pearson correlation was 0.462 and the Spearman correlation was 0.453, both statistically significant at the 0.05 level. This indicates a moderately strong association between occupancy and sensor activity as individuals begin to leave the office for the day.

Overall, sensor activity tends to correlate positively with the number of individuals in the office, with the relationship being most pronounced and statistically significant around mid-afternoon (15:00). Earlier and later time points show weaker or less consistent correlations.

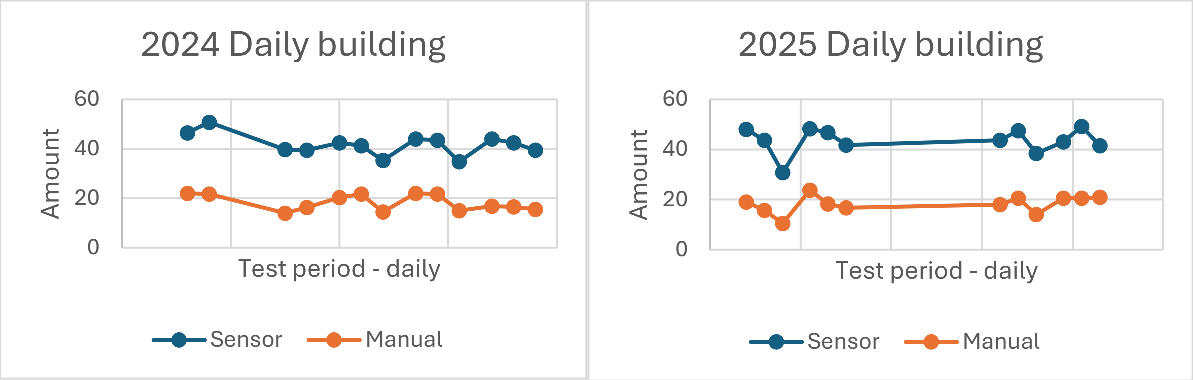

Figure 7: Average total PIR activations at SEED compared to average manual headcount at SEED

When comparing the total number of people across different floors to the average sensor activations at the four observed time points, the analysis yielded a Pearson correlation of 0.764 and a Spearman correlation of 0.699, both statistically significant at the 0.01 level. This indicates a strong overall relationship between sensor activity and building-wide occupancy levels.

While daily aggregates provide a reliable estimate of overall building occupancy, they lack the temporal granularity needed to understand occupancy dynamics during specific hours. To capture occupancy during peak hours, a more focused analysis is necessary. The time window between 11:00 and 15:00 represents the period of highest activity and is therefore the most informative for estimating real-time occupancy.

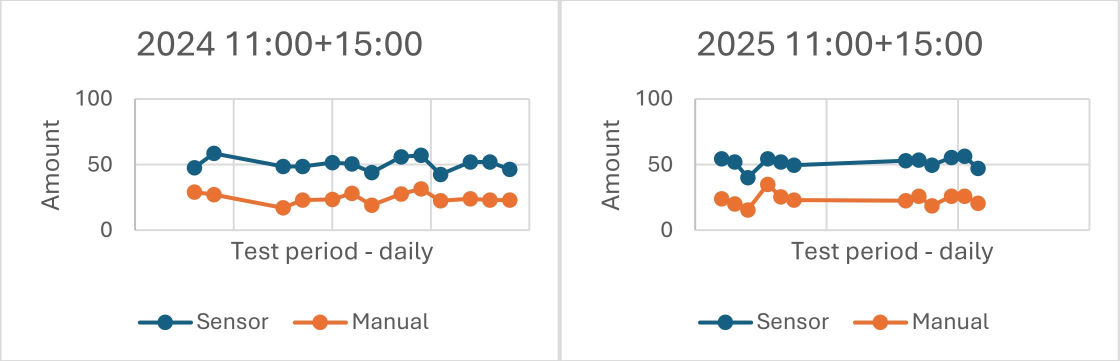

Figure 7: Average total PIR activations at SEED compared to average manual headcount at SEED midday

When averaging the number of people in the office based on data from 11:00 and 15:00 combined, the Pearson correlation with sensor activations was 0.636, and the Spearman correlation was 0.659, both statistically significant at the 0.01 level. These results confirm that mid-day sensor data offers a reliable proxy for estimating peak occupancy levels within the building.

5.4 Estimation model

A series of linear regression analyses were conducted to evaluate the relationship between sensor readings and manually recorded measurements at various times throughout the day. The primary objective was to assess the strength, direction, and statistical significance of the relationship at specific time intervals, as well as to explore the potential of combined and full-day models for improving predictive accuracy. Linear regression analyses were conducted at four distinct time points 09:00, 11:00, 15:00, and 17:00 to assess the predictive relationship between sensor readings and building occupancy. Each analysis was based on a one-hour interval, during which six sensor activation periods were recorded instead of the 5 used in the validation.

In addition to individual time-point analyses, two aggregate models were developed: a midday model combining data from 11:00 and 15:00, and a full-day model incorporating data from all four time points. These combined analyses aimed to evaluate whether temporal aggregation could enhance model robustness and improve the accuracy of occupancy prediction.

Table 4: linear regression models at various time intervals

Time	**R**	**R^2**	**Adj. R^2**	**Std Error**	**Sig (P-value)**	**Coefficient**	**Sig coeff**
9:00	0.386	0.149	0.112	4.727	0.057	0.346	0.057
11:00	0.434	0.188	0.153	5.388	0.030	0.397	0.030
15:00	0.481	0.231	0.198	4.557	0.015	0.426	0.015
17:00	0.462	0.216	0.179	4.248	0.020	0.191	0.020
11-15	0.636	0.404	0.379	3.478	<0.001	0.606	<0.001
day	0.764	0.584	0.566	2.204	<0.001	0.539	<0.001

At 09:00, the regression analysis indicated a weak but positive association between sensor and manual measurements, with a correlation coefficient of $R = 0.386$. The model explained 14.9% of the variance in manual measurements ($R^2 = 0.149$; Adjusted $R^2 = 0.112$), with a standard error of 4.727. The regression equation derived was:

Estimated occupancy =-7.624+0.346*sensor

Although the model approached statistical significance ($p = 0.057$), the coefficient for the sensor variable was only marginally significant ($p = 0.057$), suggesting that sensor data at this time point may offer limited reliability for predictive purposes.

At 11:00, the regression analysis demonstrated a moderate positive relationship, with $R = 0.434$. The model accounted for 18.8% of the variance ($R^2 = 0.188$; Adjusted $R^2 = 0.153$), and the standard error was 5.388. The resulting regression equation was:

Estimated occupancy =1.913+0.397*sensor

This model achieved statistical significance ($p = 0.030$), indicating that sensor readings at this time were significantly associated with manual measurements, despite the relatively high error term.

The strongest individual relationship was observed at 15:00, where the correlation reached $R = 0.481$, explaining 23.1% of the variance ($R^2 = 0.231$; Adjusted $R^2 = 0.198$). The standard error of the estimate was 4.557. The regression equation was:

Estimated occupancy =4.326+0.426*sensor

The model was statistically significant (p = 0.015), and the coefficient for the sensor variable indicated a meaningful predictive effect, supporting the utility of sensor measurements at this time.

At 17:00, the model again indicated a moderate correlation, with R = 0.462 and R^2 = 0.216 (Adjusted R^2 = 0.179). The standard error was 4.248, and the regression equation was:

Estimated occupancy =11.099+0.191*sensor

The model reached statistical significance (p = 0.020); however, the slope coefficient was comparatively lower than at earlier time points, potentially limiting its predictive strength despite significance.

The relationship between sensor readings and manual measurements varied across different times of day. The model at 15:00 exhibited the strongest and most statistically significant predictive power, indicating that sensor readings at this time were most reliable for estimating manual measurements. In contrast, the models at 09:00 and 17:00 showed moderate correlations, but neither reached statistical significance. The 11:00 model demonstrated the weakest predictive power.

To assess the consistency and reliability of sensor data during the midday period, a combined regression model was developed using average data from 11:00 and 15:00. This model yielded a stronger correlation of R = 0.636, with 40.4% of the variance explained (R^2 = 0.404; Adjusted R^2 = 0.379), and a lower standard error of 3.478. The corresponding regression equation was:

Estimated occupancy=-6.827+ 0.606 * sensor

The overall model was highly statistically significant (p < 0.001), and the coefficient for the sensor predictor was also significant (p < 0.001). These findings suggest that midday sensor readings offer a more stable and reliable estimate of manual measurements than individual time-point models alone.

A comprehensive model incorporating data from all-time points across the day was also evaluated. The full-day model demonstrated the strongest overall correlation (R = 0.764), explaining 58.4% of the variance in manual measurements (R^2 = 0.584; Adjusted R^2 = 0.566), with a notably lower standard error of 2.204. The regression equation was:

Estimated occupancy = -4.742 + 0539 * sensor

This model was statistically significant (p < 0.001), and the sensor coefficient was a meaningful predictor of manual values. The results indicate that the aggregation of data across the day enhances the predictive power and reliability of the regression model compared to models based on isolated time points.

Compared to individual time-based models, the full-day model explained a larger portion of the variance and achieved higher statistical significance. This suggests that aggregating sensor data over larger time periods provides a more robust and reliable estimate of the occupancy than using isolated time points.

5.5 Exploring options for Enhanced Predictions

CO_2 and temperature sensors were evaluated as an additional data source to improve prediction accuracy. While temperature sensors showed low correlation with occupancy, CO_2 sensors demonstrated a moderate correlation, suggesting they could enhance detection accuracy, especially in enclosed spaces.

However, their deployment was limited to six rooms, restricting their utility for full-building analysis. Nonetheless, the potential for hybrid models using PIR and CO_2 data warrants further exploration.

The sensor data could also be analyzed in greater detail to establish patterns based on room type such as multiple sensor activation in the same open space might mean its occupied by multiple people. One could also use higher weights on the sensor from different room types such as meeting rooms and open spaces as they have a higher average of occupants.

The effectiveness of sensor-based occupancy and environmental monitoring is closely tied to the strategic placement of sensors within the indoor environment (Azizi *et al.*, 2021). For instance, positioning CO_2 sensors near the occupant's breathing zone such as at desk height can significantly improve the sensitivity and timeliness of detecting occupancy changes, as CO_2 levels reflect human presence more directly in these zones (Azizi *et al.*, 2021). Conversely, sensors placed near heat sources or windows may capture environmental fluctuations that do not accurately represent occupancy, potentially reducing prediction accuracy (Azizi *et al.*, 2021).

Similarly, PIR sensors benefit from placement that aligns with typical occupant movement patterns. Sensors installed under desks or in areas with direct line-of-sight to occupant activity tend to yield higher detection accuracy compared to those mounted on ceilings or walls with obstructed views (Azizi *et al.*, 2021).

5.6 Key Space Utilization Metrics

Based on the estimation from combined model the monthly average amount of people, frequency rate, occupancy rate (per room and per desk) and space utilization were calculated. The data was from the working hours between 9:00-19:00.

Table 5: Monthly space utilization metrics at SEED

Month	Esitamted average People	Frequency Rate	OR per room	OR per desk	SUR per room	SUR per desk
2024-01	26,226	0,3812	0,3496	0,1248	0,152556	0,05448
2024-02	29,432	0,4312	0,3924	0,1401	0,172297	0,06153
2024-03	26,084	0,3954	0,3477	0,1242	0,148131	0,05290
2024-04	23,252	0,3605	0,3100	0,1107	0,118228	0,04222
2024-05	21,589	0,3461	0,2878	0,1028	0,113945	0,04069
2024-06	17,867	0,2848	0,2382	0,0850	0,078848	0,02816
2024-07	4,7660	0,1874	0,0953	0,0340	0,017866	0,00638
2024-08	12,647	0,3229	0,2529	0,0903	0,081689	0,02917
2024-09	19,375	0,3928	0,3875	0,1383	0,152241	0,05437
2024-10	15,660	0,3876	0,3132	0,1118	0,121404	0,04335

2024-11	23,285	0,4680	0,4657	0,1663	0,217955	0,07784
2024-12	14,493	0,3321	0,2898	0,1035	0,096283	0,03438
2025-01	17,768	0,3863	0,3553	0,1269	0,137289	0,04903
2025-02	22,670	0,4585	0,4534	0,1619	0,207927	0,07426
2025-03	22,405	0,4731	0,4481	0,1600	0,212023	0,07572
2025-04	17,771	0,3822	0,3554	0,1269	0,135854	0,04851

To provide a comprehensive overview of workplace utilization before and after recent changes, the data was analyzed across three key time periods. The first period captures the situation prior to the changes, using data from January to April 2024. This serves as a baseline for understanding how the space was being used under the original conditions.

The second period, January to April 2025, covers the same months as the pre-change period. This allows for a direct comparison unaffected by seasonal variation, making it easier to assess the impact of the changes on space usage patterns.

The third period spans from September 2024 to April 2025 and represents the overall post-change environment. By averaging data across a broader timeframe, this period provides a more comprehensive view of how the changes affected space utilization in the long term.

Table 6: space utilization metrics at SEED at different time periods

Time period	**Avg people**	**Frequency rate**	**Occupancy rate per room**	**Occupancy rate per desk**	**Space utilization per room**	**Space utilization per desk**
2024/01-2024/04	26,26	0,392	0,349	0.125	0.147	0.052
2025/01-2025/04	20,15	0.425	0.403	0.144	0.173	0.061
2024/09-2025/04	19,17	0.410	0.384	0.137	0.160	0.057

From this it is seen that the average number of people after the change to two floors was reduced. However, the other metrics improved such as frequency rate, occupancy rate and space utilization. This trend was also seen in the frequency rate for the different room groups.

An analysis of the square meter allocation per person reveals a substantial reduction in individual space following the change. Initially, with 26 individuals occupying 540 square meters, the average space per person was approximately 20.8 square meters. After the change, 20 individuals shared 360 square meters, resulting in an average of 18 square meters per person. This indicates a more compact workspace design, with a reduction of nearly 13.5% in space per occupant. While this decrease might suggest a denser environment, the concurrent improvement in frequency rate, occupancy rate, and space utilization indicates that the new configuration supports more efficient use of space without negatively impacting usage patterns. This shift reflects a broader trend toward optimizing workspace layouts to better match actual occupancy levels and behavioral patterns, potentially leading to cost savings and enhanced spatial efficiency.

Due not being able to estimate the different room groups from the data accurately and without privacy concerns only the Frequency rate was calculated.

Table 7: Monthly Frequency rate for different room types at SEED

Month	FR tele	FR meeting	FR open	FR office
2024-01	0,299089	0,455596	0,50745	0,29985
2024-02	0,343271	0,521363	0,57509	0,34641
2024-03	0,329667	0,505087	0,54745	0,29324
2024-04	0,309685	0,465811	0,49332	0,27182
2024-05	0,237455	0,432924	0,50501	0,27519
2024-06	0,195049	0,358972	0,48042	0,21538
2024-07	0,160530	0,224073	0,33402	0,10876
2024-08	0,358969	0,361301	0,45673	0,24783
2024-09	0,333328	0,473747	0,59706	0,29377
2024-10	0,364549	0,453173	0,57525	0,29150
2024-11	0,395601	0,547014	0,72802	0,35882
2024-12	0,248246	0,365382	0,53409	0,25384
2025-01	0,337791	0,438677	0,59364	0,29418
2025-02	0,456411	0,563465	0,76106	0,31969
2025-03	0,431017	0,547619	0,75367	0,35443
2025-04	0,367128	0,464449	0,62718	0,27244

Among all room types, open spaces consistently exhibited the highest frequency rates. This may be attributed to their typically larger capacity and a higher number of available desks compared to individual offices. Despite fluctuations, meeting rooms and open spaces maintained relatively strong engagement, reflecting their central role in collaborative work.

5.7 Addressing the research questions

RQ1: How accurate are ICT-based monitoring systems in capturing and analyzing space utilization data when compared to manual counting methods?

ICT-based monitoring systems, particularly those employing passive infrared (PIR) sensors, demonstrated a moderate to strong level of accuracy in capturing space utilization data, when validated against manual head counting. In 2025, F1 scores for PIR-based occupancy detection across different office floors ranged from 0.6240 to 0.6351, suggesting dependable performance in identifying occupancy patterns, especially in open-plan office spaces and during periods of frequent movement. The sensitivity (recall) of the system reached as high as 0.8454, highlighting the system's ability to correctly detect presence. However, precision and specificity were more variable, particularly in low-traffic areas such as telephone booths or small meeting rooms, where shorter visits and limited movement resulted in reduced sensor effectiveness.

Further validation using manual headcount data showed that sensor-based detection aligned most strongly with actual occupancy during mid-day periods (11:00 to 15:00), when movement within the workspace was most frequent. A statistically significant correlation between PIR sensor activations and manual occupancy counts was observed ($R = 0.546$, $p = 0.005$), reinforcing the system's reliability in dynamic environments. Conversely, accuracy declined under static conditions, such as when individuals remained seated at desks, or in the late afternoon (e.g., at 17:00), due to the reduced likelihood of triggering motion-based sensors. Despite these limitations, ICT-based systems prove sufficiently robust for high-level space utilization monitoring, especially when supplemented by manual verification or enhanced through sensor fusion strategies combining PIR with CO_2 sensors.

RQ2: How can ICT-generated data be leveraged for effective space utilization analysis and improvement?
ICT-generated data supports a range of analytical and strategic planning functions for space utilization improvement. One key application lies in predictive modeling. For instance, linear regression models built using PIR activation data effectively captured temporal occupancy patterns. The strongest predictive performance was observed at 15:00 ($R^2 = 0.317$, $p = 0.003$) and during the 11:00–15:00 interval ($R^2 = 0.298$, $p = 0.005$), indicating that sensor data can inform scheduling of events, cleaning services, and energy optimization during peak periods.

Spatial analysis at the room level also revealed insights into where ICT-based monitoring is most effective. Open-plan offices and standard enclosed offices yielded more consistent sensor readings, suggesting that these spaces should be prioritized for monitoring investments or recalibration. In contrast, specialized areas such as telephone rooms showed greater variability, pointing to the need for more nuanced sensing approaches in such environments.

Moreover, aggregated monthly metrics such as occupancy rate per room, desk-level space utilization rate, and frequency of use provided actionable insights for capacity planning. For example, following workspace layout adjustments, the occupancy rate per room increased to 0.832 in March 2025, illustrating how ICT data can directly support space design decisions. These metrics also enabled dynamic management strategies, such as the consolidation of underutilized zones, identification of peak usage periods, and adjustment of workplace policies based on actual behavior patterns, ultimately driving more responsive and data-driven facility management.

RQ3: How does the downsizing from three floors to two impact space utilization metrics?
The consolidation from three floors to two in 2025 led to significant enhancements in space efficiency, primarily due to a reduction in total spatial capacity while only experiencing a modest decline in the number of occupants. These changes contributed to a denser occupancy distribution across the remaining floors, which appears to have positively impacted utilization metrics. Despite a decrease in overall floor area, key indicators improved: the average occupancy rate per room increased from approximately 0.6 in early 2024 to over 0.83 in March 2025, and the space utilization rate per desk rose from 0.09 to 0.0986. These improvements underscore how spatial consolidation can enhance operational efficiency without compromising functionality.

A closer examination of spatial allocation reveals a substantial reduction in square meters per person, from 20.8 sqm (26 people in 540 sqm) before consolidation to 18 sqm (20 people in 360 sqm) after the change reflecting a 13.5% decrease. Notably, this more compact design coincided with increases in frequency rate, occupancy rate, and space utilization per both room and desk, suggesting a more effective and concentrated use of available space. The improved density may have facilitated greater movement and interaction, contributing to higher PIR sensor activation rates and better alignment between sensor data and actual usage. Supporting this, the correlation between PIR sensor activations and manual occupancy counts strengthened after consolidation ($R = 0.736$ in 2025 vs. $R = 0.687$ in 2024), indicating that sensor systems perform more reliably in higher-density environments. This evidence suggests that strategic reductions in workspace size, guided by ICT-based insights, can yield more efficient and accurate space utilization while simultaneously enhancing the performance of monitoring systems.

5.8 Environmental Sustainability and Resource Efficiency

Improving the efficiency of space use in existing buildings is increasingly recognized as a key strategy for minimizing environmental impacts especially in countries with already low operational emissions, such as Sweden, where the electricity grid is largely decarbonized (*IEA*, 2024). In such contexts, further reductions in climate impact are more effectively achieved through embodied carbon mitigation that is, reducing the need for new construction by maximizing the use of existing infrastructure. ICT-based monitoring systems, including IoT-enabled occupancy sensors, offer a data-driven pathway to such optimization, facilitating downsizing, consolidation, and adaptive reuse (Höjer and Mjörnell, 2018).

However, while digital monitoring systems can enable significant operational efficiencies, they also introduce new sources of environmental impact particularly from hardware such as sensors, wiring, and servers. In a recent Life Cycle Assessment (LCA) study, Azizi et al. (2024) critically evaluated a real-world Building Monitoring System (BMS) and found that components like wires and data acquisition units were among the most environmentally burdensome elements of the system. This highlights a central trade-off: while ICT systems can reduce energy consumption and building material use over time, they also carry their own embodied emissions, particularly in their production and end-of-life phases.

From a systems perspective, the net environmental benefit of ICT interventions thus depends on the balance between operational gains and the lifecycle footprint of the digital infrastructure. LCA provides an essential methodology to assess this balance, moving beyond simplistic assumptions of "digital = sustainable" by quantifying both the direct and indirect environmental consequences. When occupancy data is used not only for HVAC optimization (Aghemo *et al.*, 2013) but also to support decisions like consolidating operations to fewer floors as in the SEED case study substantial lifecycle emission savings can be realized. Downsizing from three floors to two not only improved spatial metrics but reduced lighting, heating, and cooling needs, contributing to a net reduction in total energy demand. In such cases, the estimated embodied primary energy savings from avoiding new construction are approximately 2 MWh/m^2, with additional operational final energy savings of around 200 kWh/m^2/year (Höjer *et al.*, 2024).

Critically, these efficiency gains are contingent on the scale and longevity of ICT deployment. If systems are installed widely but fail to deliver substantial behavioral or operational changes, the environmental costs of their manufacture and maintenance may outweigh their benefits. Therefore, future work must incorporate LCA at the design phase of digital infrastructure projects and prioritize scalable, interoperable, and energy-efficient sensor technologies.

While ICT systems play a crucial enabling role in space efficiency and real-time energy management, their sustainability must be evaluated holistically. By combining space-use optimization strategies with lifecycle thinking as advocated by Azizi et al. (2024) institutions can ensure that digital interventions contribute meaningfully to long-term environmental goals rather than shifting the problem from operational to embedded emissions.

5.9 Social Sustainability and Work Quality

Beyond environmental benefits, sustainable office design must also consider the well-being and productivity of its occupants. The balance between open and enclosed office environments, flexible desk arrangements, and functional meeting zones plays a significant role in employee satisfaction and collaboration (Jens and Gregg, 2022)

The data-driven space improvement strategies implemented at SEED reflect an effort to align physical office design with actual work practices. By leveraging sensor insights to identify underutilized or overcrowded areas, facility managers can adjust spatial layouts to promote comfort, concentration, and collaboration. For example, passive desk-sharing policies informed by real-time data enabled a more equitable distribution of workspaces and reduced friction over desk availability, aligning with strategies proposed by Einola and Dooley (2025).

However, space improvement must also respect personal preferences and cultural norms related to workspace use. As observed during manual walkthroughs, some staff members preferred private or quiet zones even when occupancy levels were low. This underscores the importance of integrating qualitative feedback with sensor data to ensure inclusive, adaptable, and human-centered workspace solutions.

At SEED most employes have a shared office but as seen the need for a office should be in support of the business model (Einola and Dooley, 2025). As open spaces have cost advantage compared to enclosed spaces (Jens and Gregg, 2022).

5.10 Ethical Use of Monitoring Technologies

The deployment of sensor-based monitoring systems in work environments raises important ethical considerations. While these technologies offer valuable insights into space use, they also have the potential impact on employee privacy, autonomy, and trust. Transparency in how data is collected, processed, and used is critical to maintaining ethical integrity.

In this study, sensor data was anonymized and aggregated, avoiding any identification of individuals. Communication with staff about the purpose and scope of monitoring was prioritized to foster trust and minimize concerns. Nevertheless, continuous monitoring even when de-identified could potentially influence behavior and lead to perceptions of surveillance. This ethical tension requires ongoing reflection and dialogue with stakeholders.

Moreover, decisions made based on occupancy data must be guided by fairness and inclusivity. For instance, interpreting low usage in a specific area should not automatically lead to space reallocation without considering the needs of minority users or specific functions that require less frequent but essential use.

As monitoring technologies continue to evolve, there must be ethical frameworks that ensure their responsible implementation. Future research should explore participatory design approaches that involve users in shaping how monitoring tools are deployed and how insights are translated into workplace policies.

5.11 Recommendations

Based on the findings of this study, the following recommendations are proposed to guide institutions in leveraging ICT-based monitoring systems for more efficient and sustainable office space utilization:

Prioritize the installation of occupancy sensors in high-traffic, flexible-use areas such as open-plan workspaces and meeting zones. These areas yielded higher detection accuracy and richer occupancy insights, providing a stronger foundation for space improvement decisions.

Real-time occupancy data should be directly integrated into BMS platforms to enable automated environmental adjustments such as lighting and HVAC control based on actual space use, reducing energy waste and operational costs.

Combine PIR sensors with supplementary systems (e.g., CO_2 sensors) to improve detection accuracy, particularly in enclosed or low-movement spaces such as offices and telephone rooms.

Apply statistical models, such as the linear regression models developed in this study, to anticipate occupancy patterns, identify peak usage periods, and inform scheduling, maintenance, and capacity planning decisions.

Protect user privacy by anonymizing data, securing communication protocols, and involving stakeholders in transparent dialogue about how monitoring insights are used in workspace decisions.

By operationalizing the sensor-based model within space planning workflows, facility managers and designers can move from reactive to predictive decision-making creating office environments that are more adaptable, efficient, and aligned with user behavior.

6. Conclusion

6.1 Summary of Key Findings

This study investigated the efficacy of ICT-based occupancy monitoring systems in enhancing space use efficiency within office environments, using the SEED department at KTH Royal Institute of Technology as a case study. Through a comparative analysis of sensor-based data and manual headcounts, the study established that PIR sensors, particularly when combined with CO_2 measurements, provide a viable solution for real-time occupancy tracking. The findings revealed that while sensor performance varied across room types and times of day, open-plan areas and mid-day time windows demonstrated the highest levels of accuracy and predictive reliability.

Significantly, the consolidation of office space from three to two floors led to improved space utilization metrics despite a reduction in the total number of occupants. Metrics such as occupancy rate and space utilization rate showed measurable gains post-consolidation, indicating that strategic spatial planning informed by real-time data can yield both operational and environmental benefits. Furthermore, the study underscored the utility of integrating manual observations with sensor analytics to calibrate system performance and enhance the validity of occupancy estimates.

The occupancy prediction model developed in this study, built on aggregated PIR sensor data and validated against manual headcounts, aligns closely with recent literature emphasizing the potential of ICT-based systems for efficient space management (Aghemo *et al.*, 2013; Valks *et al.*, 2018; Azizi *et al.*, 2020). Like the sensor-based systems explored by Chu et al. (2022) and Labeodan et al. (2015), this model demonstrates that low-cost, non-intrusive sensor technologies can provide accurate, high-resolution occupancy data, enabling data-informed decisions across both operational and strategic dimensions.

Building on the challenges and opportunities identified in smart campus initiatives (Valks et al., 2020), the model presented here addresses a key limitation in existing studies namely, the lack of integrated, scalable tools for simulating and evaluating policy changes such as desk sharing, team relocations, or workspace reconfigurations. While Valks et al. (2020) highlight the value of real-time monitoring in a university setting, their findings are largely diagnostic. In contrast, this study goes further by operationalizing predictive modeling for scenario analysis, thus offering a proactive decision-making framework.

Additionally, your model supports the broader objectives discussed by Höjer and Mjörnell (2018) regarding the transition to more adaptive and sustainable use of space. By optimizing workstation density and facilitating real-time utilization tracking, the model addresses the inefficiencies caused by traditional, static allocation strategies that manual methods cannot achieve effectively, as outlined by Tagliaro, Zhou, and Hua (2021). The ability to generate historical and forward-looking insights aligns with Taboada-Orozco et al. (2024)'s call for predictive control systems that preemptively adjust building operations.

The model also adds value by quantifying spatial interventions over time, a gap identified in previous literature where longitudinal assessment was often missing. Its ability to track changes before and after implementation provides a critical feedback loop, enabling iterative improvements a well-aligned approach with the continuous refinement models proposed by Jayantha and Oladinrin (2019) and Smite et al. (2024).

This research confirms existing findings around the utility of sensor-based occupancy tracking but extends them by developing a cost-effective, predictive framework for strategic space planning. It contributes a practical toolset for organizations seeking to move beyond descriptive analytics toward prescriptive and scenario-based space management, directly addressing the gaps in existing literature on real-time validation, operational scalability, and long-term impact evaluation.

6.2 Contributions to Research and Practice

This research contributes to the growing body of knowledge surrounding sustainable office management and intelligent building systems. Academically, it offers a comprehensive evaluation of sensor-based occupancy monitoring technologies within a real-world office setting, combining empirical performance analysis with applied spatial improvement. The methodological integration of manual and automated data sources presents a replicable framework for future studies seeking to validate sensor technologies.

Practically, the study informs the design and implementation of responsive space management strategies. It demonstrates how real-time data can be leveraged to improve workplace configurations, inform cleaning and maintenance schedules, and support energy efficiency initiatives through dynamic control of building systems. Additionally, the research emphasizes the importance of contextual factors such as room type, time of day, and user behavior in determining sensor system performance, thus guiding more informed deployment and calibration of monitoring technologies.

6.3 Limitations and Future Research

While the study offers valuable insights, several limitations should be acknowledged. First, the scope of analysis was confined to a single department within a specific institutional context, which may limit the generalizability of the results. Second, the performance of PIR sensors was influenced by environmental conditions and behavioral variability, which occasionally led to discrepancies in occupancy detection. Moreover, limited deployment of CO_2 sensors constrained their utility in contributing to a comprehensive occupancy model.

Future research should extend this inquiry across multiple organizations and building typologies to examine the scalability of the findings. Longitudinal studies could assess the long-term behavioral and organizational impacts of sensor-informed spatial management. Additionally, the development of participatory design frameworks where users contribute to the configuration and interpretation of monitoring systems could help address ethical concerns and foster greater alignment between technological capabilities and workplace expectations.

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