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Sensing the Unseen – Using CO_2 as a Key Indicator for Occupancy Detection in Smart Collaboration Spaces

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Abstract

The Internet of Things (IoT) has received significant attention recently due to its potential to build more innovative solutions to real-world problems. This study examines how IoT sensors can be integrated with Enterprise Information Systems (EIS) to measure the utilization of enclosed workspaces to create Smart Collaboration Spaces (SCS). These spaces are enriched by real-time data on occupancy and air quality measurements to optimize work and study conditions. Using Carbon Dioxide (CO_2) sensors and passive infrared (PIR) sensors makes it possible to detect human presence in the room with an accuracy of over 90%. The generated data is processed and visualized in a workspace occupancy information system, accessible via a web interface. The findings suggest that SCS, through integration into EIS, can significantly improve resource utilization and enhance employee experience in organizations by saving time spent searching for an available workspace. Integrating IoT technologies with EIS holds considerable potential for developing smarter and more efficient work organization solutions in the future.

Keywords: Internet of Things; Smart Collaborations Spaces; Workspace Occupation; CO2; PIR.

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1. Introduction

The Internet of Things (IoT) has transformed into a global technological phenomenon, enabling the automation and networking of intelligent systems and interconnecting several items to attain a shared objective [1,2]. IoT-enabled business models and processes are estimated to open up an annual revenue opportunity of $2.6T to $6.2T [3]. Given the increasing adoption of IoT technologies, their integration with Enterprise Information Systems (EIS) could significantly impact the future of work organization solutions. Chui et al. [4] predict that by 2030, the economic value of all connected IoT devices will encompass between $5,5T and $12,6T.

Many IoT use cases have been formulated and segmented into IoT domains for classifying sensor data in different fields of human endeavor [5–8]. These applications include Smart Buildings, Smart Cities, and Smart Campuses, with the latter two sharing analogous structures and often representing a scaled-down version of Smart Cities [9–13]. Within a Smart Building environment, IoT can help improve processes and workflows for organizations' value creation when integrated into effective applications by monitoring environmental conditions such as temperature, humidity, Carbon Dioxide (CO_2) concentrations, and human presence in workspaces like meeting and study rooms or work desks. This real-time data enables better management of the organizations' resources, improving work and study conditions and reducing transaction costs by providing real-time data.

In this realm of IoT applications, this paper focuses on Smart Collaboration Spaces (SCS) in a university library, which is part of a smart university-of-things [14]. SCS are spaces enhanced with real-time data on attributes like air quality measurements and occupancy data, optimized for work and study conditions. In this context, IoT interconnects several sensors to achieve the objective of improved workplace efficiency. Comparable studies use IoT sensors to measure workstation occupancy, which is helpful for hybrid work models (cf. [15,16]). However, these studies only focus on individual, shared workspaces, not collaboratively used spaces. This study aims to improve resource utilization, optimize workspaces, and enhance the overall collaboration experience for university staff and students by utilizing IoT sensor data in collaborative spaces like creative areas, meeting rooms, and libraries. Therefore, the following research questions are formulated:

RQ1: What types of IoT sensors are most effective for accurately determining workspace occupancy in Smart Collaboration Spaces, considering cost and ease of implementation?

RQ2: How can an IoT-based prototype for determining space occupancy be integrated into a Smart Building environment while considering data privacy and cost-effectiveness?

To address these research questions, a prototype was developed to practically apply human presence detection in a real-world enclosed collaboration space within a university library. This approach aims to streamline resource utilization by saving university staff and students time locating available workspaces. The prototype development follows the Action Design Research Process Model by Mullarkey & Hevner [17], incorporating IoT to detect and visualize occupancy.

The remainder of this paper is structured as follows. Section 2 offers a brief overview of the concepts of IoT and its application within the context of SCS, followed by a presentation of the relevant literature to this study. Section 3 presents this paper's research method, the Action Design Research Model, by Mullarkey & Hevner [17]. Subsequently, Section 4 explains the selection of IoT sensors and describes the experimental setup at the university library. The implementation of workspace occupancy measurement is tested and evaluated in Section 5. Finally, Section 6 concludes the paper and discusses the potential for future work.

2. Background and Related Work

2.1. Internet of Things and Smart Collaboration Spaces

IoT can be defined as a system of interconnections between sensing and actuating devices and physical objects that enable traditionally mundane objects to exhibit computing properties and interact with one another with or without human intervention through a unified framework [18,19]. This might be achieved by ubiquitous sensing, data analytics, and data representation with Cloud Computing as the unifying framework.

Smart buildings can be seen as a part or resource of an enterprise or an organization. They integrate intelligence, organization, control, materials, and construction as an entire building system, with adaptability, not reactivity, at its core, in order to meet the drivers for building progression: energy and efficiency, longevity, and comfort and satisfaction [13]. Sensor information from smart buildings, e.g., workspace occupancy measurements, are highly significant to organizations to reduce operations, processes, and transaction costs and tightly integrate this information into an organization's information system.

IoT sensors can provide data for detecting workspace occupancy, giving rise to the concept of SCS in organizations. Organizations may include companies, NGOs, or educational institutions such as universities. From our point of view, the definition of SCS can be derived from the related concept of Smart Working Spaces (SWS), where SCS leverage the digitization of physical objects and create new models that can potentially increase the efficiency of the organizations' affiliates (cf. [20]). This term also encompasses the collaborative nature of various workplace environments, including meeting rooms.

2.2. Related Work

Various approaches have been proposed for detecting workspace occupancy using IoT sensors. For example, Arz von Straussenburg et al. [16] propose an IoT sensor setup that includes a PIR sensor, an accelerometer, and a gyroscope. This setup leverages the Long Range Wide Area Network (LoRaWAN) protocol, complemented by an open-source network server, The Things Stack (TTS). By computing a reference value using cloud functions, the authors achieved an accuracy of 95.32%. Consequently, the proposed prototype application can be effectively and cost-efficiently installed on workplace desks within a desk-sharing environment, even using low-end sensors.

Contrastingly, Sheik Khan et al. [15] sought to measure occupant presence, achieving an accuracy of 87.5% in comparison to manual observations. Their work primarily concentrates on developing, demonstrating, and evaluating a solution to enhance accuracy through lower-cost PIR sensors.

In addition to these studies, other related work zeroes in on network protocols, such as WiFi and Bluetooth, employing a variety of sensors, including CO_2 [21–24]. However, some of these studies exhibit a common shortcoming. At the same time, they discuss the sensors utilized to a certain extent but neglect to provide comprehensive details about whether entry-level or industrial-grade sensors were implemented. Furthermore, these studies give inadequate attention to the description of the methodologies employed to achieve IoT data quality.

3. Research Method

To answer the research questions outlined in Section 1, a technical solution to the problems identified is imperative. Consequently, the Design Science Research (DSR) method is employed to formulate such a solution [25]. While applying DSR to create hardware-based artifacts is possible and explicitly mentioned in multiple seminal method papers [25–28], traditional Design Science Research Process (DSRP) models, exemplified by [26], are frequently utilized in research to craft digital artifacts [27] primarily. Despite this, the research subject of this paper extends to include the creation of a hardware artifact as well. During the construction of hardware artifacts, pursuing various approaches to prototypes is often a necessity [28]; these are usually dismissed early in the process, well before the emergence of a Minimal Viable Prototype [29] that could signify the conclusion of a DSR cycle [30] Therefore, the stringent alignment to comprehensive and multi-step DSR iterations of traditional process models might inadvertently hinder the speed of prototyping required for this work.

The artifact's development adheres to the Action Design Research (ADR) process model [17], encompassing four cycles of problem Diagnosis, Design, Implementation, and Evolution, which are displayed in Fig. 1. In this model, each ADR cycle involves the activities of Problem Formulation (P), Artifact Creation (A), Evaluation (E), Reflection (R), and Learning (L). This process model was chosen because of its balance of flexibility and disciplined approach to artifact development. Its iterative nature, applied to individual ADR cycles such as design, facilitates swift prototyping of hardware artifacts without necessitating repeated completion of entire DSR cycles inherent in traditional process models.

Due to considerations of available space and a precise focus definition in this paper, not all activities within each cycle are explicitly presented. Instead, the subsequent description of the approach will be confined to the most meaningful activities within each cycle. The initial chapters, comprising the Introduction (Section 1) and the scientific background, convey the results of the first ADR cycle - the Diagnosis. Following this, the chapters addressing the technological setup (Section 4) and sensor data evaluation (Section 5) correspond to the ADR design and implementation cycles, respectively. Finally, the discussion in Section 6 delves into the fourth cycle - evolution, within the ADR process model.

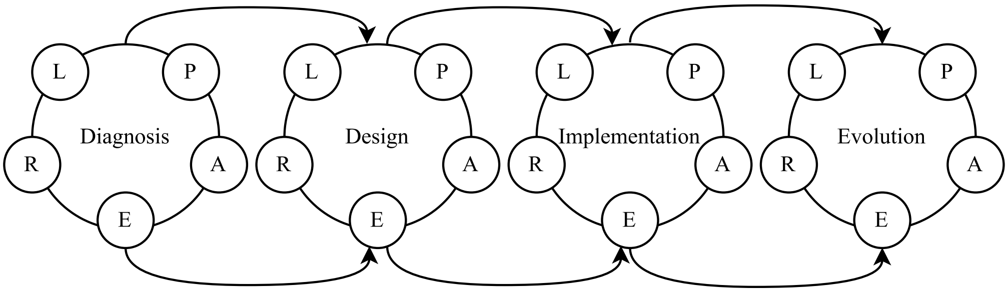

Fig. 1. All four ADR cycles, according to [15].

4. Technological Setup

The library building provides 16 enclosed workspaces, 12 of which are individual workspaces and four group workspaces for 4-6 students. Due to little fresh air supply, the rooms have a relatively high CO_2 concentration when occupied and a baseline CO_2 concentration of about 854 parts per million (ppm). We used Pycom brand hardware, consisting of a *LoPy4*[1] microcontroller, an Expansion Board 3.0 from the same manufacturer, and an add-on module to the *LoPy4* microcontroller. This hardware was chosen because of its wide accessibility and low cost. Furthermore, *Sensirion SCD30*[2] CO_2 sensors are used, which are soldered to the *Expansion Board 3.0*. The CO_2 sensors were fixed in each individual and group workroom to set up the test environment.

The CO_2 sensor now collects environmental data, which is transmitted by the *LoPy4* microcontroller via the LoRaWAN protocol to LoRa gateways installed on the university campus. The LoRa gateways, in turn, send the data to The Things Network (TTN), an IoT platform that provides an open source-based LoRaWAN network server. The MQTT protocol sends sensor data to the university's private, on-premises cloud, where data is stored in an adequate database [31]. It is processed~~,~~ and visualized in a prototypical web dashboard for room occupancy built on *ReactJS*, *NodeJS,* and *TailwindCSS*.

On the one hand, using CO_2 sensors in the library's enclosed workspaces makes it possible to measure room occupancy by detecting increasing CO_2 concentrations. Using CO_2 sensors in shared working environments ensures that as little personally identifiable data as possible is collected, as opposed to, e.g., camera-based systems. At the same time, air quality can be measured and assessed, contributing to monitoring occupational health data. A high CO_2 concentration is considered harmful to humans, causing headaches, light-headedness, and fatigue [32]. Thus, the CO_2 reading from the sensor could be used to take precautionary measures next to informing available workspaces.

The CO_2 concentration in an enclosed room takes a few minutes to increase and is thus not suitable for informing real-time data for live users. For this reason, a motion sensor using an *HC-SR501*[3] PIR sensor is also incorporated into the platform. These sensors are frequently used in security systems or smart homes and detect human presence using infrared radiation. For the development of the prototype, the PIR sensor validates the readings from the CO_2 sensors

[1] https://docs.pycom.io/datasheets/development/lopy4/ (accessed on 3rd July 2023)

[2] https://www.sensirion.com/products/catalog/SCD30/ (accessed on 3rd July 2023)

[3] https://www.mpja.com/download/31227sc.pdf (accessed on 3rd July 2023)

on human presence. As the presence of people in the room impacts the CO_2 concentrations, the PIR sensors' information is then utilized to assess if the CO_2 sensor readings are correct.

5. Evaluation of the Sensor Data

Initially, tests were conducted using only CO_2 sensors to detect human presence in enclosed shared rooms. While the results were accurate, they also contained significant noise and delay. The delay is because the amount of time it takes for the CO_2 concentration to rise significantly enough for the sensors to differentiate between vacant and occupied rooms is relatively high, and vice versa. As per the findings, the time it took for the CO_2 concentration in a room to increase by 150 ppm was around 35 minutes when occupied by a single person and about 13 minutes for two persons, as depicted in Fig. 2.

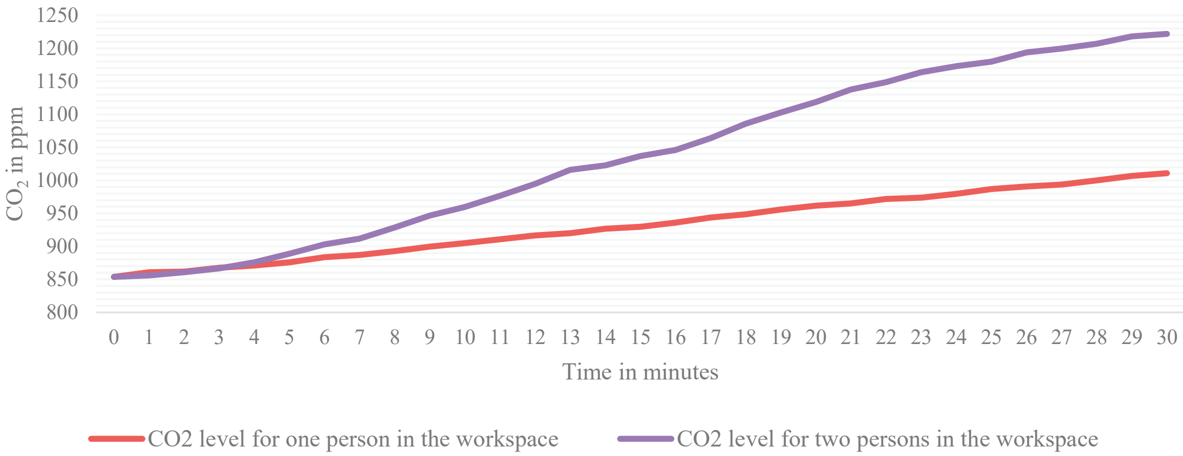

Fig. 2. CO_2 concentration increase in the workspace.

Moreover, it can be observed that people sometimes leave the door open while occupying the rooms. The additional airflow causes the CO_2 concentration inside the room to stay lower, leading to inaccurate results. Therefore, in the next iteration of our ADR design cycle, a PIR sensor was introduced in conjunction with the CO_2 sensor to obtain more reliable results. When implementing the PIR sensors, two modes were tested separately to determine the effectiveness of each way in detecting human occupancy, retriggering, and non-retriggering. With the retriggering mode, the sensor sends a continuously *HIGH* signal for as long as motion is detected. In non-retriggering mode, the sensor sends a *HIGH* signal only for a specific duration and goes temporarily inactive after detecting motion.

After extensive testing and continuous revisions, the sensors were set to a non-retriggering mode, with a sleep time introduced after each detection cycle. This configuration allows the sensors to send data every 60 seconds, reducing the overall data volume and avoiding redundancy. We calibrated the activation threshold and the waiting time to monitor room occupancy with the PIR sensor to optimize the data relay to TTN. The most accurate out of various tested intervals for data collection and transmission was a 10-second sleep per cycle, allowing for six detection cycles before sending the data, thus avoiding redundant data. A binary value of *0* is registered in a list when radiation is detected for 10 seconds. The created list is then examined, focusing on the last six entries to check for instances of a *0* value. If any *0* values are found, a data packet with the key *isAvailable* set to *0* is sent to TTN, signaling that the room is occupied. Conversely, if no *0* values are found, the *isAvailable* key is set to *1*, implying a vacant room.

Table 1 assesses the sensors' efficacy in detecting human presence in the enclosed rooms tested. The data displayed is an average from multiple experiments conducted over three months in different scenarios. The duration of the experiments ranged from 40 to 60 minutes each. This detection is based on the room's PIR motion readings and the CO_2 concentration measurements. Since scenarios 3 and 4 occurred infrequently during the test period, the trials were only conducted 30 times instead of 70.

Table 1. Accuracy measurements of CO_2 and PIR sensors for detecting workspace occupancy.

Test scenario	Number of Experiments	Ø CO_2 concentration after 30 minutes	Ø change in CO_2 per minute	Accuracy
1. One person stays in the room	70	945.31 ppm	+ 5.24 ppm	98.88 %
2. Two persons stay in the room	70	1068.87 ppm	+ 12.27 ppm	98.98 %
3. A person enters & exits the room after 3 seconds	30	-	< ± 1 ppm	71.88 %
4. Occupied room with open door	30	823.63 ppm	− 1.6 ppm	99.00 %

The third column (*Average CO_2 concentration after 30 minutes*) presents the average CO_2 concentration measured by the sensors throughout each experiment. This parameter is measured in ppm, a standard unit for measuring atmospheric gas concentrations. Because this data was collected over an extended period, it was necessary to take the average readings for each scenario to understand the average CO_2 concentration better. By doing so, getting a more reliable estimate of the CO2 concentration for each scenario is possible, allowing for a more meaningful data analysis. Moreover, increasing or decreasing the number of experiments in each category can affect the success rate. The fourth column (*Average change of CO_2 per minute*) displays the average change in CO_2 concentration per minute during each experiment, as displayed in Fig. 2. The accuracy shows the rate at which the CO_2 concentration changes in response to different scenarios or experiments. The fourth column (*Accuracy*) includes the accuracy of human detection and the experiments compared to manual measurements. This column indicates how successful the tests were at detecting human presence and identifying the proper test results. A high success rate would imply that the sensors accurately detect human presence, whereas a low success rate would imply that the sensors were less successful. However, the accuracy of test results reflects how frequently the test results were correct.

The average baseline CO_2 concentration in an empty room was 854 ppm, with a standard deviation of 3 ppm per sitting. For the tests in group study rooms, the sensors were placed in the corner of the room, pointing diagonally toward the work desks. Based on the analysis of 89 data points in the group study room, the average CO_2 concentration was 1068.87 ppm, with a standard deviation of 12.27 ppm when two people were present. The success rate for detecting human presence in this scenario was approximately 99%. The lowest average CO_2 concentration was observed when the room contained people, and the door was left open, with an average value of 823.63 ppm and a standard deviation of 1.6 ppm.

Overall, the success rate for detecting humans was nearing 100% in all cases, demonstrating that the sensors were highly effective at detecting the presence of humans in a room. Nevertheless, the success rate varied depending on the scenario. For the first two scenarios, with people staying in the room, we achieved the highest success rates of about 99%. In scenario 3, where a person entered and exited the room 30 times in two hours, the success rate was only around 75%. For data collected in an empty room, measurements were taken continuously for 30 to 50 minutes at four different intervals, resulting in a success rate of 92.8%. The distortion in an empty room was probably a direct result of ventilation and flow of air in the room. For having a controlled scenario, we have installed the sensor in a separate room with controlled access, keeping the door closed. The sensor was placed next to a window in that room, and the window was left half-open overnight. As a result, around 95% of false measurements were observed, confirming that the airflow from the window directly affected the CO_2 concentration in the room. When a difference of 30 ppm between a maximum and minimum reading in one minute is listed, it leads to the wrong test results. Based on this discovery, using a CO_2 sensor alone to detect human presence in rooms with access to open air may produce inaccurate results. However, once again, the positioning of the sensor can exceptionally decrease the chances of erroneous data.

Based on the statistics gathered from the study rooms in the library, utilizing CO_2 and PIR sensors to detect human presence in workspaces can yield satisfactory outcomes and serve as an initial step toward creating SCS.

6. Discussion and Conclusion

Implementing SCS using IoT sensors provides a practical, cost-effective, and privacy-respecting approach to enhancing the efficiency and efficacy of learning environments within university libraries. To address our first research question (RQ1), combining CO2 and PIR sensors provides an effective and efficient solution for detecting human presence in enclosed collaboration spaces. The data from these sensors are transmitted via MQTT protocol over TTN and displayed on a web application. The combination resulted in an average human detection accuracy of approximately 90% when both sensors were used in tandem.

Initially, only the CO_2 sensors were used to monitor changes in CO_2 concentration to indicate human presence. Using CO_2 sensors proved particularly practical because of the ubiquitous deployment of CO_2 sensors during the COVID-19 pandemic in many organizations that indicate air quality levels. Moreover, these sensors are readily available, affordable, and easy to deploy anywhere in a room. Given that human respiration elevates CO_2 concentration in enclosed spaces, this approach was, to some extent, a helpful proxy for room occupancy. However, a time delay in the increase of CO_2 concentration following the entrance of individuals (and vice versa) results in a delay in obtaining accurate information. Considering the primary objective of minimizing the time spent locating available workspaces, a solution with such a delay is deemed unsuitable. Therefore, the CO_2 sensors are supplemented with PIR sensors, which detect motion in the room and provide more immediate and precise results.

We found that room size, shape, and ventilation significantly influence the sensor data during the study. Consequently, the settings of each sensor pair must be tailored to a room's specific characteristics. All the learning spaces were identical in the experiments, so no substantial adjustments are necessary.

Addressing the second research question (RQ2), the developed IoT-based prototype was successfully integrated into a Smart Building Environment, considering data privacy and cost-effectiveness. The collected data is displayed in real-time on an application, enabling users to monitor room occupancy and plan their work accordingly. This innovation presents a promising direction for the evolution of collaborative learning and working environments, particularly when considering its ease of deployment, scalability, and the possibility of accommodating multiple people in a room. Despite the success of our implementation underscoring the potential of IoT sensors in creating SCS, it is crucial to acknowledge the inherent limitations.

Both sensor types are susceptible to various conditions that may produce erroneous results. On the one hand, CO_2 sensors can be sensitive to their position within the room, and room size and shape variations can impact their reading. Additionally, the delayed response of CO_2 sensors and the impact of room ventilation can lead to inaccuracies. On the other hand, PIR sensors can be influenced by heat sources such as sunlight or heating systems within the room, potentially leading to false positives or negatives.

Integrating the sensor data with EIS augments the benefits presented in this study. For instance, room occupancy data can enrich a booking system's utility by providing real-time occupancy data. Furthermore, occupational health can be monitored more effectively by considering CO_2 concentration, which has health implications. As many CO_2 sensors are deployed in organizations already, enabling both occupational health and workspace management solutions combined presents a promising opportunity.

Despite the inherent limitations, an IoT-based web application's potential to provide real-time room occupancy data is considerable. The study shows the viability and potential of IoT sensors in creating SCS, represents an advancement in SCS technology, and can potentially transform collaborative spaces. In addition to providing immediate occupancy information, the prototype developed in this study can be scaled up to provide occupancy statistics for collaborative spaces across buildings. A scaled solution could offer a comprehensive view of space availability. Further research may continue exploring the potential of further integrating various IoT sensors for enabling SCS and scaling the solutions to enable thorough integration into enterprise environments.

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