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The Internet-of-Buildings (IoB) – Digital twin convergence of wearable and IoT data with GIS/BIM

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Abstract. Internet-of-Things (IoT) devices in buildings and wearable technologies for occupants are quickly becoming widespread. These technologies provide copious amounts of high-quality temporal data pertaining to indoor and outdoor environmental quality, comfort, and energy consumption. However, a barrier to their use in many applications is the lack of spatial context in the built environment. Adding Building Information Models (BIM) and Geographic Information Systems (GIS) to these temporal sources unleashes potential. We call this data convergence the Internet-of-Buildings or IoB. In this paper, a digital twin case study of data intersection from various systems is outlined. Initial insights are discussed for an experiment with 17 participants that focused on the collection of occupant subjective feedback to characterize indoor comfort. The results illustrate the ability to capture data from wearables in the context of a BIM data environment.

1. Introduction

The Internet-of-Things (IoT) paradigm has driven the deployment of a vast array of sensors and devices that are designed to improve the performance of buildings. There are several key challenges that IoT networks are meant to address. For example, there is a 50:50 chance of an occupant being comfortable in a building according to a survey of 52,980 occupants in 351 office buildings, which found that 50% were dissatisfied with their indoor environment [1]. From the operations and maintenance side, likely, 16% of the energy used in the building could easily be saved using no and low-cost optimization and commissioning [2]. In addition to IoT, professionals in the built environment, such as architects, engineers, and urban planners, have also been digitizing spatial data at a rapid pace through the use of 3D virtual information tools such as building and city information and energy modeling (GIS/BIM/BEM) [3], and a significant amount of effort is going into determining uses in the operations phase [4].

This paper focuses on the creation of a data aggregation platform to test how Internet-of-Things (IoT) and wearable technologies can be better converged with Building Information Models (BIM) and Geographic Information Systems (GIS). Developing and training Artificial Intelligence (AI) models to make predictions based on these data can have an impact on occupancy detection, energy systems optimization, and human comfort and wellness [5, 6, 7]. This process is done through the development of the Internet-of-Buildings (IoB) data convergence

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platform on the campus of the National University of Singapore (NUS). These technologies demonstrate the value of synthesizing data from numerous sources and creating interfaces that enable building operations professionals to make decisions. This work attempts to meet the deficiencies in previous literature [8] through the synthesis of data from dynamic IoT sources such as wearables into GIS and BIM environments.

2. The Internet-of-Buildings (IoB)

The focus of this research is the development and testing of a data convergence platform. Figure 1 illustrates this new paradigm and the potential capabilities within various use case scenarios. First, data connectivity is enhanced with the introduction of 5G capabilities indoors and outdoor, increasing the bandwidth and reducing data exchange latency. Next, the maintainability of buildings is improved due to the use of AI-driven drones that can scan buildings for maintenance issues using the BIM/GIS models as a context. In universities, using the building as a teaching test-bed is enhanced using spatial and temporal data convergence through wearable and mobile augmented and virtual reality devices (AR/VR). Energy systems and digital twin building energy models are calibrated using high-resolution occupancy data, resulting in the optimization of climate control and lighting systems [9]. Indoor and outdoor wellness and thermal comfort is enhanced using data collected from multiple sources and used to inform and even modify energy consumption behavior to achieve conservation targets. Energy behavior is collected by synthesizing occupant information with smart meter data and social and behavioral intervention methods that are tested in a field setting. Wellness, productivity, and space utilization are evaluated at the zone level, and people can be given recommendations about the zones that would result in the most comfortable and productive experience for them. A key feature for tying together the IoT/wearable and spatial domain is the ability to locate where a person or device in the building context beyond the accuracy that GPS can achieve. This situation requires the use of indoor localization technologies such as those powered by Bluetooth. Security is enhanced

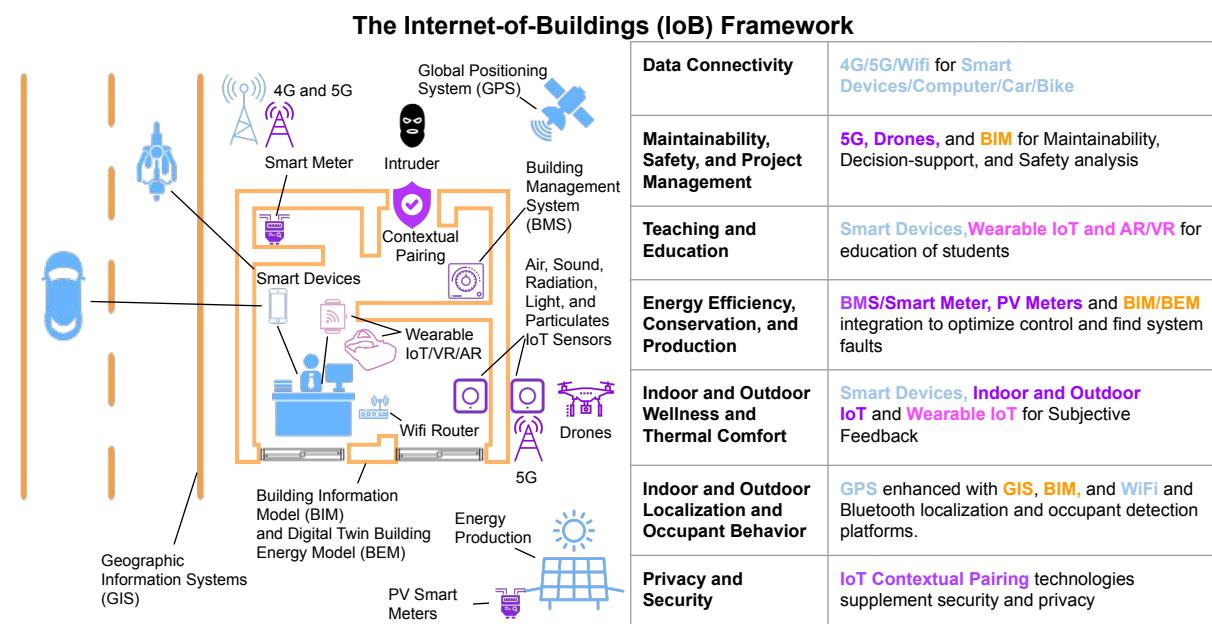


Figure 1: The deployment of IoT in the built environment combined with spatial and human data sources creates the IoB Framework.

through contextual pairing with other sensors that add more layers to the authentication process for digital access control systems. Finally, privacy is improved as the access to personal information for IoB is not controlled in a centralized way; smartphones and wearable IoT owners are able to choose what information is shared through the application interface.

3. Case study deployment

The case study implementation in this paper focuses on the aggregation and synthesis of data from sensors located at various parts of the NUS campus, including the *SDE4* building, a 5G-enabled, net-zero energy building. Figure 2 illustrates the various data sources that have been converged or are in progress of being connected. The first pillar focuses on the collection of data from humans through wearable devices, an example of which is when smartwatches were deployed to collect physiological and subjective feedback data from building occupants [10]. The following two pillars fall within the category of 5G-connected devices such as smartphones, robots, and drones [11]. The next pillar focuses on collecting spatial information from occupants and objects using an indoor localization system based on Bluetooth beacons deployed across the test case buildings. This spatial information is then converged with a digital twin of the building extracted from the BIM. The last two pillars focus on the data convergence of fixed smart sensors from indoor (building-scale) and outdoor (urban-scale) environments. These are sensors, for example, that measure environmental air quality and thermal conditions across campus. The merging of these data sets is possible through a series of technologies from third parties such

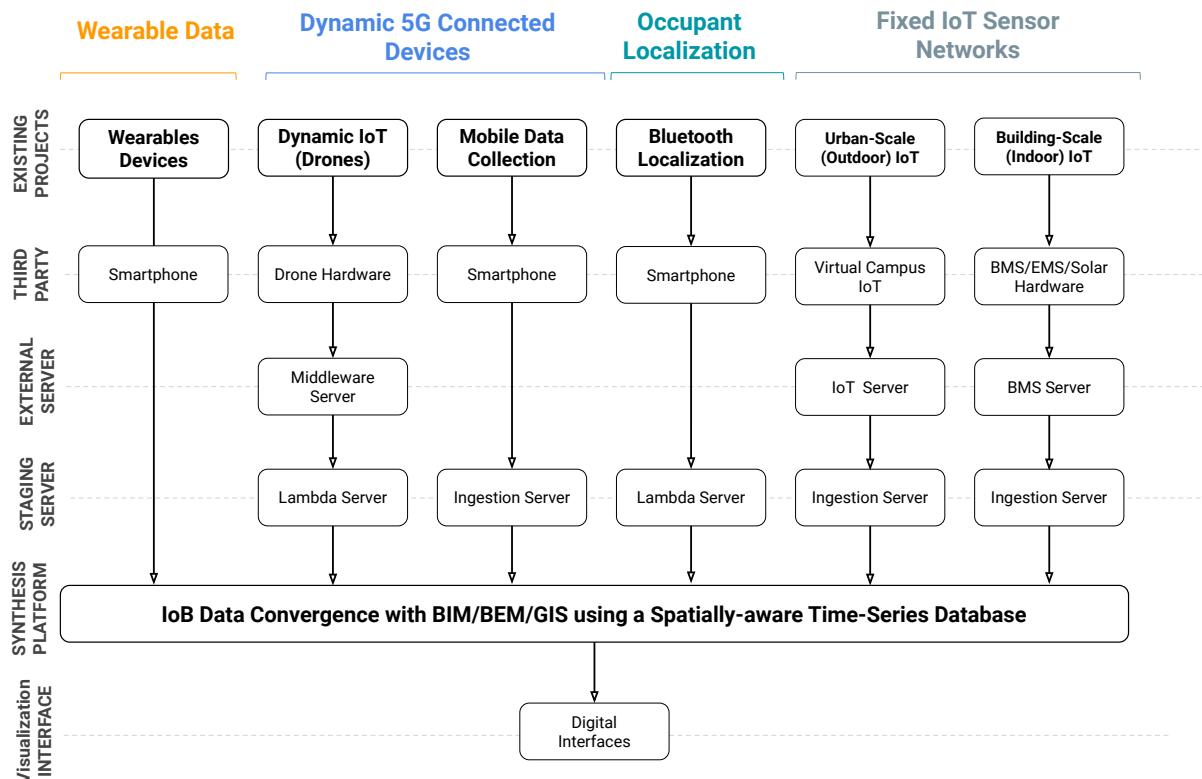


Figure 2: The development of the IoB platform focuses on the data convergence of data from various projects and systems in terms of data sources (columns) and stages of data processing and convergence (rows).

as hardware devices, middleware servers, and event-driven lambda function services. Finally, the data convergence occurs in a time-series database that indexes the various sources using the spatial context.

3.1. Dynamic wearable data convergence with BIM

Figure 3 shows this methodology from an experiment that used the IoB to collect and converge data related to comfort preferences [12]. It shows the path of a human across the floor plan of the SDE4 building at NUS (left). As the occupant traverses the space, IoB collects physiological information such as heart rate and step count while using indoor localization to calculate the proximity to various objects in the building. These dynamic relationships are calculated using BIM convergence with the IoT and human-generated data. The illustration shows a fish-eye view of the occupant (bottom center) and the indoor localization app being used to track the path. Finally, the visualization shows a vector-based proximity diagram (right) that illustrates the relationship of the human and the various spatial objects in a vector model [13].

3.2. Thermal comfort preference experiment

For six weeks in early 2021, an experiment was deployed in the SDE1, SDE2, and SDE4 buildings with the use of the Cozie Fitbit smartwatch platform (<https://github.com/cozie-app>) to collect subjective thermal preference feedback. This method builds upon previous work [12, 14], but with adaptations to increase the number of ecological momentary assessment questions and the diversity of spaces in the case study buildings. The test participants were asked about their thermal preference, clothing level, and activity level on the Cozie watch-face several times per day while they were in the case study buildings. Their responses were attached to the BIM through a Bluetooth localization app that was also installed on their phone.

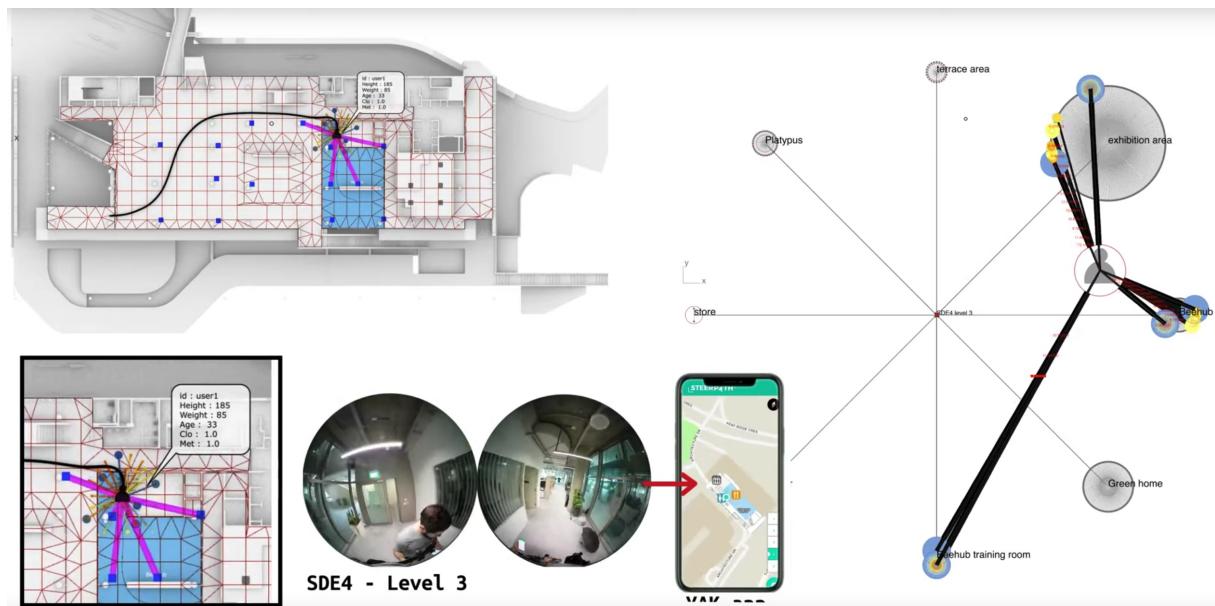


Figure 3: An example of the data convergence from BIM, IoT, BEM, and human-generated data in the Internet-of-Buildings platform. A full animated demo is found at this link: <https://youtu.be/7KHRDFbT74Y>

4. Results and discussion

Figure 4 shows the results of the experimental implementation. The top row of the figure illustrates the data collected in the spatial context in three levels of the case study building. The IoB platform facilitated the capture of physiological and subjective feedback data from a smartwatch and connected it to the spatial context of the BIM environment. The charts in the next two rows show an overview of the preliminary analysis of this data set towards the characterization of thermal preference in these buildings.

The use of the IoB platform to merge the subjective feedback data with the spatial context resulted in several key insights. Many of the zones were outdoor spaces, and the results show a higher than usual number of *prefer cooler* feedback, especially from the male participants. The point clouds developed in the various regions of the floor plan illustrate the potential *hot spots* in which there could be causes of discomfort not captured by the temperature and humidity sensors installed. These initial results set the foundation for further analysis in contextualizing the feedback according to each point's relationship with the objects around it. There was an expected imbalance in the feedback, which can be investigated using techniques to enhance the data set before prediction [15]. There is further work planned that falls outside the scope of this

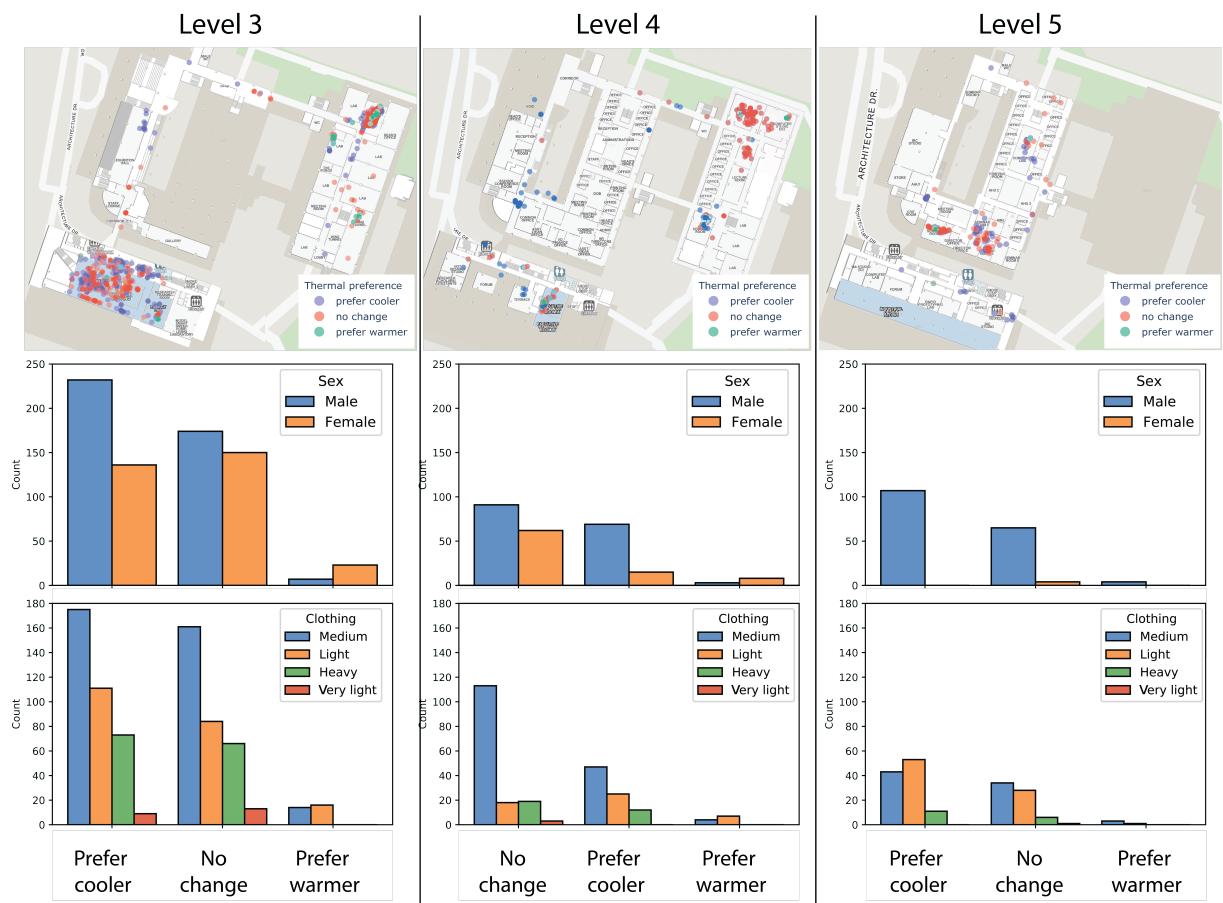


Figure 4: Data collected during experiments related to characterize different parts of the spatial context for thermal preference for three levels in the case study buildings (SDE1-4). The floor plans of each level illustrate the locations of subjective data collection (top) while the histograms (middle and bottom) show a breakdown of occupant feedback according to gender and clothing levels. This figure is best viewed in color.

paper to use these data for modeling techniques that can predict which zones would best fit the preferences of individual occupants.

5. Conclusion

This paper outlines the creation and testing of a data convergence platform for IoT/wearable and BIM/GIS data. This methodology converges data for this case study from indoor and outdoor sensor networks and occupants using smartwatch and smartphone interfaces. These data are combined with the BIM of the case study using a mapping process between the spatial and temporal contexts. Data collected from a deployment with 17 experimental participants focused on the collection of thermal comfort preference subjective feedback. The data from this experiment were converged on the IoB platform in the BIM context and showed insight into thermal comfort preference in different spatial zones. The next phase is to train machine learning models for occupant preference prediction in the spatial context provided by the BIM.

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