

# Measurements of User and Sensor Data from the Internet of Things (IoT) Devices

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## 1. Contributions to the Special Issue

The evolution of modern cyber-physical systems and the tremendous growth in the number of interconnected Internet of Things (IoT) devices are already paving new ways for the development of improved data collection and processing methods.

Modern devices, including smartphones, wearables, sensors, and actuators, generate tremendous amounts of data related to both human factors (biometrics, behavior, contact-tracing, etc.) as well as general environmental monitoring information (humidity, temperature, tracking, etc.) being collected and analyzed by the data scientists all over the world. However, most of the collected measurements are only available for a small range of people deeply involved in its actual collection or processing.

This Special Issue on “Measurements of User and Sensor Data from the Internet of Things (IoT) Devices” in MDPI’s *Data* is devoted, but not limited to, data sets, including any raw data collected by different IoT devices, supplemented by methods, algorithms, sensor fusion models, and related aspects of such kinds of data for wireless communications, tracking, personal data processing, positioning, eHealth monitoring, and sports analysis, among others.

### 1.1. Systematic Reviews and Surveys

The authors in [1] targeted a review that covered privacy issues and cyberattacks on the network of the Industrial Internet of Things (IIoT). Their main aim was to identify challenges and ideas for future research to enhance IoT security, and therefore, they focused on different areas in the detection of IoT attacks. In addition, it also aimed to describe in detail the development of the cybersecurity datasets used to train the algorithms used for building intrusion detection systems and analyze and summarize different and famous IoT attacks. According to the authors, machine learning and big data analytics are often used in these systems to assure security; however, when it comes to real-world application, these algorithms can fall short.

### 1.2. Data Descriptors

The authors in [2] presented *TRIPOD*—Treadmill, IMU, Pedobarographic and Photoelectric Dataset—which is hosted on Zenodo and available upon request, as the participants’ consent only allows using the data for legitimate scientific interest. It consists of treadmill walking data collected from 15 young, healthy adults. More specifically, the dataset contains IMU data recorded from the lower body and reference data from a pressure distribution measurement system and a photoelectric gait analysis system. A baseline use case was also provided, where the performance of a foot trajectory estimation algorithm from the literature was implemented and assessed. The code for loading the dataset and example implementations of the used algorithms are also available.



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The authors in [3] introduced “IntelliRehabDS” (IRDS), a dataset of diverse physical rehabilitation movements. The dataset was captured with a Kinect motion sensor to provide automatic feedback on the execution of rehabilitation exercises, even in the absence of a physiotherapist. The dataset contains repetitions of 9 gestures performed by 29 subjects, out of which 15 were patients and 14 were healthy controls. The data are presented in an easily accessible format, provided as 3D coordinates of 25 body joints, and the corresponding depth map for each frame. Each movement was annotated with the gesture type, the position of the person performing the gesture, and a correctness label. In the context of the limited availability of gesture-related datasets that contain real patient movements, the authors envisioned this dataset to be used either on its own or in combination with other datasets, especially with the rapid expansion of transfer learning.

The authors in [4] introduced the “Urban LPWA Measurement Public” database, whose primary goal was to provide the researchers lacking LoRaWAN devices with an opportunity to compare and analyze the information obtained from 303 different outdoor test locations transmitting to up to 20 gateways operating in the 868 MHz band in a varying metropolitan landscape. To collect the data, the authors developed a prototype equipped with a Microchip RN2483 Low-Power Wide-Area Network (LPWAN) LoRaWAN technology transceiver module for the field measurements. As an example of data utilization, the authors showed the Signal-to-noise Ratio (SNR) and Received Signal Strength Indicator (RSSI) concerning the closest gateway distance.

The authors in [5] introduced the dataset “Fitness-gym and Living-room Occupancy Estimation Data,” which contributed to the goal of having a reference dataset for occupancy estimation and energy efficiency. The described dataset comprised indoor environmental information (pressure, altitude, humidity, and temperature) and the corresponding occupancy level for two different rooms: (1) a fitness gym and (2) a living room. The fitness gym data were collected for 6 days (10,125 samples with a 1-second resolution), whereas the living room data were collected for 11 days (295,823 objects with a 1-second resolution). Samples in both sets comprised low, medium, and high occupancy levels. This dataset can train and compare different machine learning, deep learning, and physical models for estimating occupancy in enclosed spaces.

The authors in [6] introduced the “Large-scale dataset for the analysis of outdoor-to-indoor propagation for 5G mid-band operational networks”, a dataset of measurements performed over commercial 5G networks. In particular, the dataset included measurements of channel power delay profiles from two 5G networks in Band n78, i.e., 3.3–3.8 GHz. Such measurements were collected at multiple locations in a large office building in Rome, Italy, using the Rohde and Schwarz (R&S) TSMA6 network scanner for several weeks in 2020 and 2021. A primary goal was to provide an opportunity for researchers to investigate a large set of 5G channel measurements, aiming at analyzing the corresponding propagation characteristics toward the definition and refinement of empirical channel propagation models.

To sum up, this Special Issue has introduced a relevant review regarding privacy issues and cyberattacks and introduced five pertinent novel datasets. The described datasets enable new challenging applications using wearable devices and smartphones as sensory devices and shed some light on the use and validation of wearables in different contexts/scenarios. Some authors have identified the application of state-of-the-art machine learning, such as transfer learning, as possible future use of their datasets. However, a common evaluation setup involving wearable data is still a pending task of the research community. Having common evaluation metrics and data sets for the same topic may pave the way for a comprehensive assessment that enables the generalizability of results.

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## References

1. Alshaibi, A.; Al-Ani, M.; Al-Azzawi, A.; Konev, A.; Shelupanov, A. The Comparison of Cybersecurity Datasets. *Data* **2022**, *7*, 22. [[CrossRef](#)]
2. Trautmann, J.; Zhou, L.; Brahms, C.M.; Tunca, C.; Ersoy, C.; Granacher, U.; Arnrich, B. TRIPOD—A Treadmill Walking Dataset with IMU, Pressure-Distribution and Photoelectric Data for Gait Analysis. *Data* **2021**, *6*, 95. [[CrossRef](#)]
3. Miron, A.; Sadawi, N.; Ismail, W.; Hussain, H.; Grosan, C. IntelliRehabDS (IRDS)—A Dataset of Physical Rehabilitation Movements. *Data* **2021**, *6*, 46. [[CrossRef](#)]
4. Masek, P.; Stusek, M.; Svertoka, E.; Pospisil, J.; Burget, R.; Lohan, E.S.; Marghescu, I.; Hosek, J.; Ometov, A. Measurements of LoRaWAN Technology in Urban Scenarios: A Data Descriptor. *Data* **2021**, *6*, 22. [[CrossRef](#)]
5. Vela, A.; Alvarado-Uribe, J.; Ceballos, H.G. Indoor Environment Dataset to Estimate Room Occupancy. *Data* **2021**, *6*, 133. [[CrossRef](#)]
6. Ali, U.; Caso, G.; De Nardis, L.; Kousias, K.; Rajiullah, M.; Alay, O.; Neri, M.; Brunstrom, A.; Di Benedetto, M.G. Large-Scale Dataset for the Analysis of Outdoor-to-Indoor Propagation for 5G Mid-Band Operational Networks. *Data* **2022**, *7*, 34. [[CrossRef](#)]

## Short Biography of Authors



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