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Wi-Gitation: Replica Wi-Fi CSI Dataset for Physical Agitation Activity Recognition

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Abstract: Agitation is a commonly found behavioral condition in persons with advanced dementia. It requires continuous monitoring to gain insights into agitation levels to assist caregivers in delivering adequate care. The available monitoring techniques use cameras and wearables which are distressful and intrusive and are thus often rejected by older adults. To enable continuous monitoring in older adult care, unobtrusive Wi-Fi channel state information (CSI) can be leveraged to monitor physical activities related to agitation. However, to the best of our knowledge, there are no realistic CSI datasets available for facilitating the classification of physical activities demonstrated during agitation scenarios such as disturbed walking, repetitive sitting–getting up, tapping on a surface, hand wringing, rubbing on a surface, flipping objects, and kicking. Therefore, in this paper, we present a public dataset named Wi-Gitation. For Wi-Gitation, the Wi-Fi CSI data were collected with twenty-three healthy participants depicting the aforementioned agitation-related physical activities at two different locations in a one-bedroom apartment with multiple receivers placed at different distances (0.5–8 m) from the participants. The validation results on the Wi-Gitation dataset indicate higher accuracies (F_1-Scores ≥ 0.95) when employing mixed-data analysis, where the training and testing data share the same distribution. Conversely, in scenarios where the training and testing data differ in distribution (i.e., leave-one-out), the accuracies experienced a notable decline (F_1-Scores ≤ 0.21). This dataset can be used for fundamental research on CSI signals and in the evaluation of advanced algorithms developed for tackling domain invariance in CSI-based human activity recognition.

Keywords: human activity recognition; CSI dataset; convolutional neural networks; agitation recognition; fine-grained activity recognition

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1. Introduction

Dementia is a progressive neurodegenerative disorder characterized by deterioration in cognitive functions such as memory, thinking, and judgment, which affects the social and emotional behavior of a person [1]. It is considered one of the prominent causes of institutionalization and disability of the older adult population [2]. At present, 50 million members of the world's population are suffering from dementia which is anticipated to rise by approximately 70% in 2030 as the older adult population is continuously growing [3]. It is found that 90% of persons with dementia (PwD) exhibit agitation as one of the common behavioral conditions [4]. Usually, it is difficult to deal with the person exhibiting agitation specifically in long-term or at-home care settings. PwD demonstrating agitation are more likely to experience a rapid decline in physical health due to unexpected falls or fractures compared to PwD without agitation [5]. They are also susceptible to additional neuropsychiatric symptoms such as sleep impairment, depression, etc. [5]. Therefore, in addition to posing risks to the safety of PwD, it also induces significant distress for caregivers and presents challenges in delivering the necessary assistance and care to PwD [6]. Thus, to optimize care for PwD, it is of extreme importance to monitor and understand agitation symptoms at an early stage so that caregivers can intervene and de-escalate the situation as well as tailor the care provided as per the needs of PwD [7].

Currently, efforts are being made to implement assistive technology leveraging Human Activity Recognition (HAR) techniques to support healthcare [8]. With the help of HAR techniques, PwD can be continuously monitored, providing caregivers with a more profound understanding of their daily routines and behaviors [9]. The available technology for HAR includes video cameras, wearable sensors, and RF-based sensing. However, due to the obtrusive nature of cameras and wearables, they impose various drawbacks for in-house dementia care. For example, PwD can easily forget to wear wearable solutions or they might feel stigmatized/distressed by continuously wearing them [10], whereas video-based solutions can cause privacy and security issues for both PwD and their caregivers. To overcome these drawbacks, unobtrusive sensing systems (USSs) which do not demand the user's attention and can monitor users from a distance while preserving their privacy are required [11]. A recent interview-based study with formal and informal caregivers of PwD also highlighted the value of using USSs for proactive in-home care of PwD [12], thus opening new avenues for context-based development of USSs for in-home dementia care.

Among others, RF-based sensing systems such as Wi-Fi Channel State Information (CSI) are considered unobtrusive and are widely used for HAR [11]. While these systems hold promise for advancing the organization of healthcare, there persists a shortage of CSI-based solutions specifically tailored for in-home dementia care. For the implementation of CSI-enabled Unobtrusive Sensing Systems (USS), a Wi-Fi access point (acting as a transmitter) and a few receiving points, commonly present in devices like laptops and mobile phones, are required. The access point (or transmitter) continuously emits signals that undergo multipath propagation in the monitored environment before reaching the receivers. This multipath propagation induces changes in the transmitted signal properties (such as amplitude and phase) corresponding to different human activities occurring within the monitoring environment (see Figure 1).

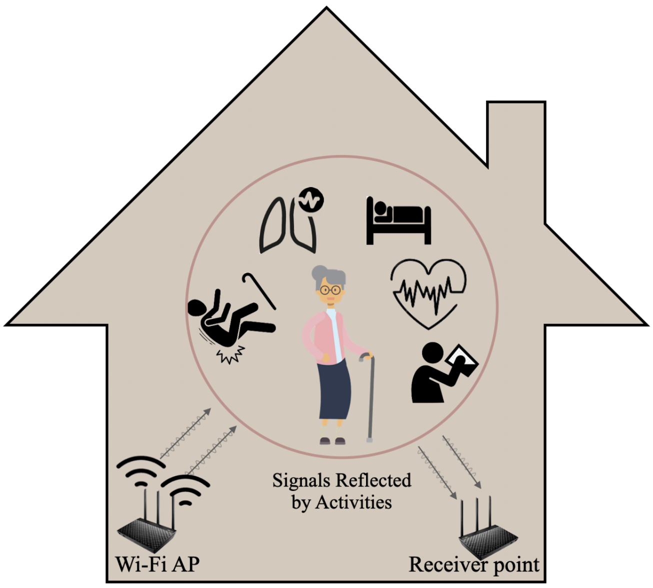

Figure 1. Use of CSI monitoring in home environment.

Inspired by the existing studies utilizing CSI in healthcare, such as sleep monitoring [13], seizure detection [14], fall detection [15], and stress detection [16], the possibility of using CSI in assisting in-home dementia care shall also be investigated. In that regard, this paper presents and evaluates a realistic CSI dataset depicting physical agitation activities, named Wi-Gitation. Note that realistic here means close to real-life, i.e., a real-life home environment was used with healthy participants enacting agitation scenarios.

While the Wi-Gitation dataset can be seen as the first step towards digitalizing agitation detection, it is also advantageous for future research works on HAR with CSI. It will not only save the cost of time and work of researchers but can also speed up the research on CSI-based HAR for fine-grained activities (like kicking, tapping, hand wringing, etc. in realistic scenarios) while accounting for multiple factors impacting the CSI (like environment, location, gender, distance, etc.).

In summary, the main contribution of this paper is twofold:

1. *A realistic Wi-Fi CSI dataset inspired by the standard agitation monitoring scale (SOAPD) for classifying agitation-related physical activities is presented.* To the best of our knowledge, Wi-Gitation is the first publicly available dataset providing CSI of full-body and fine-grained physical activities depicting agitation in a realistic scenario. Moreover, a semi-controlled study setup where participants were given a certain degree of freedom was used. Additionally, the activities were performed at two different locations and observed by four receivers placed at varied distances (details are discussed in Section 2.1).
2. *Baseline evaluation results obtained with the help of mixed-data and leave-one-out analysis using the Wi-Gitation dataset are presented.* For future research, it is important to have a baseline for comparison; thus, mixed-data and leave-one-out analysis utilizing four CNN models, ResNet-50, MobileNet-V2, NASnetmobile, and xception is presented.

2. Related Work

2.1. Agitation Diagnosis

Agitation is broadly defined as occurring in patients with cognitive impairment or dementia syndrome; exhibiting behavior consistent with emotional distress; manifesting excessive motor activity, verbal aggression, or physical aggression; and evidencing behaviors that cause excess disability and are not solely attributable to another disorder (psychiatric, medical, or substance-related) [17]. Traditionally, agitation is diagnosed by using standard scales like the scale for observation of agitation in persons with dementia of Alzheimer's type (SOAPD) [18], Cohen-Mansfield Agitation Inventory (CMAI) [19], clinical dementia rating (CDR) [20], and the modified mini-mental state (3MS) [21]. A clear demarcation in physical and verbal agitation activities is given by SOAPD. SOAPD is considered to be patient-centered while also demonstrating good psychometric adequacy [22,23]. It demarcates seven broad activity categories: total-body movement (disturbed pacing and walking, getting up–sitting down–getting up repeatedly), up/down movements (like getting up–sitting down–getting up repeatedly from a chair or bed), repetitive body motions in place (like rubbing, hand wringing, and tapping), outward motions (like hitting, pinching, and pushing), high-pitched noise (like screaming and shouting), repetitive vocalization (like repetitive requests), and negative words (like swearing and cursing) [18]. SOAPD uses the duration (between 16 s and 5 min) and intensity (mild, moderate, or extreme) of these activities to determine the agitation score which is calculated as the summation of the weights for all observed activities (see Table 1), which is usually calculated by trained professionals, or at times narrated by informal caregivers to medical practitioners. This can make it prone to personal biases and inevitable human errors [24]. Furthermore, this existing method can cause a delay in the diagnosis of agitation level due to the dependency on the professionals, which then delays the course of preventive/precautionary measures [25]. Hence, self-standing methods that can monitor as well as highlight the triggers of agitation in the early stage are required [23,26]. In that direction, the Wi-Gitation dataset is a first step to verify whether CSI can be used to classify the fine-grained hand and leg movements needed to estimate agitation.

Table 1. Physical activities used in Wi-Gitation dataset from SOAPD (Table adopted from [18]).

Activity Types	**SOAPD Categories**	**Duration (d)**				**Intensity**			
		Not Present	**Short (d $\geq$ 16 s)**	**Medium (16 s $\geq$ d $\leq$ 2.5 m)**	**Long (2.5 m $\geq$ d $\leq$ 5 m)**	**Not Present**	**Mild**	**Moderate**	**Extreme**
Full-body	Total-body movement (Disturbed walking)	0	1	2	3				
Full-body	Up/Down movement (Sitting up and down)	0	1	2	3				
Fine-grained	Repetitive Movements (Rubbing, hand wringing, tapping)	0	1	2	3	0	1	2	3
Fine-grained	Outward Movements (Flipping objects, kicking furniture)	0	1	2	3	0	1	2	3

Human Activity Recognition using Wi-Fi CSI

HAR refers to the process of automatically identifying and interpreting activities performed by individuals based on data collected from various sensors. In general, HAR modeling involves four main steps: the data collection phase (where human activity data are captured via sensors), the pre-processing phase (where pre-processing steps are applied to enhance the quality of data), the learning or training phase (where features are learned from the dataset using techniques like machine learning or deep learning), and the activity recognition phase (where the trained model classifies the activities) [8].

In this research, we use Wi-Fi CSI as a sensor for data collection. The radio waves transmitted using Wi-Fi are sensitive to the environment, i.e., they are affected by the environment (e.g., reflected, absorbed, or scattered), which causes the overall radio signal to arrive at the receiving antenna from multiple paths. This is known as multipath propagation and is the foundation of the aforementioned channel state information. CSI data contain the spatial information of each communication link, including the phase and signal strength. With any change in the environment over time (e.g., a person is cooking, falling, etc.), a change in the received reflected signal over each link is also observed. A pattern observed from these reflected signals results in a spatial–temporal fingerprint of each activity which can be used for human activity monitoring.

Wi-Fi CSI is actively used for the unobtrusive monitoring of coarse- and fine-grained human activities. Past works are evidence of the success of CSI in monitoring both coarse-grained activities (full-body activity, e.g., walking, running, falling, and sitting [27]) and fine-grained activities (e.g., finger gesture recognition) [28]. Along with these, *physiological activities* (e.g., heart rate and breathing rate) were also monitored successfully by leveraging the CSI [29]. These physical and physiological activities were also utilized in monitoring subtle, but important, human behaviors. For example, Liu et al. [29] used heart and breathing rates to determine the sleep events and postures of a person for assessing the quality of sleep. The research by Lin W. et al. used CSI to develop DW-Health for monitoring/distinguishing drinking behavior to promote/remind users to drink water [30]. Similarly, Liu X. et al. [31], Wenyuan et al. [32], Guo X. et al. [33], and Zhu Y. et al. [34] used CSI for monitoring fitness activities.

CSI has also shown its application in healthcare for assisting in the prediction/diagnosis of anomalies. Earlier research demonstrates the successful use of CSI in the detection of eclamptic seizures among pregnant women, possible danger during bathing, post-surgical falls, Huntington's disease, Parkinson's disease, etc. [35]. Considering the COVID-19 pandemic, a recent article proposed CSI for developing a platform for early diagnosis of COVID-19 symptoms [35]. In relation to the domain of dementia research, only one research work was found that used CSI for classifying the wandering patterns of PwD [36]. Thus, to assist caregivers in providing in-home care for PwD, more CSI-based studies are required to identify subtle behavior patterns in PwD which may lead to agitation (as mentioned in SOAPD).

2.2. CSI Datasets

Considering the surge in CSI use, various Wi-Fi CSI-based activity recognition datasets were published to accelerate the research on HAR. WiAR provides data for monitoring upper-body activities like arm waving, hand clapping, and drinking water, lower-body activities like kicking, and whole-body activities like squatting, walking, etc. [37]. Another available dataset provides human-to-human interactions like hugging, handshaking, pushing, kicking, etc. [38]. WiAR enables gesture recognition by providing data on gestures like push and pull, clap, sleep, etc. [39,40]. A dataset by Meneghello et al. [41] provides CSI data of full-body and hand exercises at 80MGz. In another recent dataset by Demrozi et al. [42], data for entering or leaving the office, standing, walking, and sitting activities were collected with six participants in two office setups. As can be noted, most of these available CSI datasets are strictly protocolized/controlled or collected in empty rooms, meeting rooms, or office setups, or when the participant is in the line of sight of the receiver and transmitter, which limits the idea of using them in real-life use cases like in-home monitoring (such as in-home dementia care). This is because CSI signals use multipath propagation and hence can be sensitive to the presence of any complex surroundings.

Therefore, by foreseeing the need for unobtrusive and ubiquitous in-home monitoring, this Wi-Gitation dataset is constructed. Table 2 compares the main characteristics of the Wi-Gitation dataset with some of the recent datasets. It can be observed from the table that available datasets used different monitoring environments individually such as those without furniture (empty rooms) and with some furniture (meeting rooms, office rooms, laboratory, etc.) but measurements were not conducted in a fully furnished home/apartment setting. Moreover, the majority of them conducted experiments when participants were in the line of sight (LOS) or in the nearby vicinity of Tx–RX. In summary, the Wi-Gitation dataset outstands other available datasets on multiple factors: a varied and well-distributed (gender and body mass index) participant pool, data collection in a realistic scenario (one-bedroom apartment having furniture, glass windows, walls, etc.), multiple receivers placed at various distances, multiple monitoring locations in the nearby vicinity and NLOS, and a semi-protocolized experiment paradigm (i.e., duration and type of activities are fixed but slight variations in the manner of performing activities, angle of sitting, etc. were not monitored) containing small-scale hand/leg as well as full-body activities. Overall, the dataset possesses five main characteristics.

- *Realistic setup*: The data were collected in a simulated one-bedroom apartment having all the facilities of a fully furnished real home (e-health house, University of Twente) to see the impact of complex surroundings.
- *Semi-controlled study setup*: The participants were not strictly instructed to sit in the exact same location or orientation; a slight shift (within 0.2 m) was permitted. Moreover, they were given the freedom to choose which leg/hand they wanted to use, with the possibility to switch between them. Similarly, for walking activity, no walking paths were defined and participants were allowed to walk wherever they wanted within the monitoring area. This was done to ensure that the data collected would be close to real-world scenarios.
- *Distributed gender*: The data were obtained from twenty-three healthy participants having a good distribution of gender (11 Female, 12 Male), height (average height 173.52 $\pm$ 8.89 cm), and weight (average weight 67 $\pm$ 11.25 kg).

- *Data from Rx at different distances*: The dataset uses one transmitter and four receivers each placed at different distances from the participants (minimum distance: 0.5 m, maximum distance: 8 m) for further analysis on the ubiquitousness of CSI.
- *Data from non-line of sight (NLOS)*: Among the four receivers, one was placed beyond the wall (approx 5 m distance from the transmitter Tx) for exploring the possibility of using CSI in beyond-the-wall scenarios.
- *Activities at two locations*: To capture the variation in CSI due to the change in location, activities were performed at two different fixed locations (and walking activity at location of participant's choice) within the e-health house.

Table 2. Overview of available datasets (M = Male, F = Female, Tx = Transmitter, Rx = Receiver, R = Room, LOS = line of sight, NLOS = non-line of sight, BHK = bedroom, hall, kitchen, P = protocolized, SP = semi-protocolized).

Dataset	Participants	Environment	Tx–Rx	Location	Activities
2018 [37]	10 (5 M, 5 F)	Empty R (6 m × 8 m), Meeting R (6 m × 10 m), Office R (6 m × 10 m)	1 Tx–Rx; 4 m apart	1 in LOS and nearby vicinity	P: Large upper-, lower-, and whole-body gestures
2017 [43]	6	-	1 Tx–Rx; 3 m apart	1 in LOS	P: Full-body activities
2019 [44]	9	Living R (3.79 m × 3.45 m)	1 Tx–Rx; 2.5 m apart	1 in LOS or nearby vicinity	P: Hand and full-body activities
2020 [38]	40 pairs	Furnished R (5.3 m × 5.3 m)	1 Tx–Rx; 4.3 m apart	1 in LOS	P: Human to human interaction
2020 [45]	30 (28 M, 2 F)	Lab (4.7 m × 4.7 m), Hallway (7.95 m × 3.6 m)	1 Tx–Rx; 3.7 m, 7.6 m, and 5.44 m apart	1 in LOS and NLOS	P: Full-body activities
2021 [46]	-	Lab (4 m × 4.5 m), Furnished R (3.5 m × 4.5 m), Furnished R (4.5 m × 5 m)	1 Tx–Rx; 5 m apart	Multiple in LOS	P: Full-body activities
2021 [39]	16 (12 M, 4 F)	Classroom (4.5 m × 5.5m), Office (2.5 m × 4 m), Hall R (4.5 m × 2.5 m)	1 Tx-3Rx; appx. 1.6 m apart	Multiple in nearby vicinity	P: Hand gestures
2023 [41]	13 (10 M, 3 F)	7 environments—bedroom, living room, kitchen, university laboratory, university office, semi-anechoic chamber	2Tx-2Rx;	Multiple in nearby vicinity	P: Full-body and hand activities
2023 [42]	6	Office room 1 (12 m × 6 m), Office room 2 (6 m × 4 m)	2Tx-1Rx;	Multiple in nearby vicinity	NP: entering or leaving the office, walking, standing, sitting, empty room
Wi-Gitation	**Distributed gender:** 23 (12 M, 11 F)	**Realistic setup:** Simulated 1BHK apartment (8 m × 11 m)	**Varied Rx placement:** 1 Tx-4Rx; 2.7 m, 3.3 m, 6.3 m, 6.5 m apart	**Multiple locations:** Multiple in nearby vicinity and NLOS	**SP:** Fine-grained hand/leg and full-body activities

3. Wi-Gitation Dataset Description

3.1. Participants

The Ethics Committee of Behavioral, Management, and Social Sciences (BMS), University of Twente approved this study. A combination of twenty-three graduate students and employees were recruited through online and offline volunteer registration. Table A1 lists the ranges of age (average ± standard deviation: 25.26 ± 9.49 years), gender (12 male and 11 female), height (average ± standard deviation: 173.52 ± 8.89 cm), weight (average ± standard deviation: 67 ± 11.25 kg), and body mass index (BMI) (average ± standard deviation: 22.25 ± 3.90 kg/m^2) of the twenty-three participants. The information about participant demographics can be important for further research in generalizing CSI-based HAR as CSI is sensitive to participants' physical traits. Considering the privacy-sensitive nature of demographic information, a range-based information presentation method is used (Table A1, in Appendix A). Before beginning the experiment, participants were provided with an oral and written description of the experiment (aim, methods, data collection, data storage, and data usage). Upon agreement, a signed consent form issued by the University of Twente for experimental studies with human participants was obtained from each participant. The participants were free to stop the experiment or quit the experiment at any point in time if they were not comfortable.

3.2. Activities

In this work, both full-body and fine-grained physical activities as described in 'a scale for observation of agitation in persons with Dementia of Alzheimer's type (SOAPD)' is used [18] (see Table 1). In addition to these activities, the CSI data of normal walking and normal sitting were also collected as activities of daily living and can be used in comparison to agitation activities. For example, normal walking can be compared with disturbed walking and normal sitting with other fine-grained hand and leg activities. Briefly, these activities are:

1. Agitation-related full-body activities: to-and-from disturbed walking and getting up–sitting down–getting up repeatedly from the chair;
2. Agitation-related fine-grained activities: rubbing hands on table, hand wringing, tapping on table, kicking slowly on furniture, flipping objects;
3. Baseline normal–daily life activities: normal walking and normal sitting.

Note that, for agitation detection, the activities need to be carried out with different intensities (slow, medium, and high) and varied duration (detailed in Section 3.7).

3.3. Device Used

In the experiment, five mini-PCs equipped with the Intel Ultimate Wi-Fi Link 5300 NIC were used to collect the channel state information, for which the hardware specification can be found in Table 3. One mini-PC acted as a packet injector (transmitter), while the others were placed in monitor mode (receivers, conforming to the 802.11n specifications). Channel 64 was chosen as it is the most commonly selected one in the literature, with a center frequency of 5.32 GHz, as it allows for fine-grained activity monitoring due to the shorter wavelength (6 cm and 12.5 cm for 5 GHz and 2.4 GHz, respectively). Ideally, 2.4 GHz is good for wall penetration (due to the longer wavelengths), although 5 GHz can also provide adequate results for through-the-wall activity monitoring [37]. The transmitter injected packets at a frequency of 100 Hz for which the monitoring nodes recorded the CSI. Each mini-PC consisted of three antennas, resulting in a CSI matrix of $3 \times 3 \times 30$ (as the software only allows recording at most 30 subcarriers, with a channel spacing of 312.5 kHz). Furthermore, packets were transmitted using 48 Mbps and 64 Quadrature amplitude modulation (QAM). By using the Linux CSI Tool [47], the received traces consist of a received signal strength indicator (RSSI) and CSI can be obtained. RSSI is the sum of signal energy from multiple paths (both LOS and NLOS) between the transmitter and the receiver calculated per chip. CSI provides fine-grained information by describing signal propagation through the effect of time delay, energy attenuation, and phase shift in the wireless channel. Thus, CSI is effective at monitoring fine-grained activities using Wi-Fi signals, like those involved in agitation detection. To summarize, in the present study for agitation monitoring, CSI data were collected by using 5 transceivers: one as a transmitter node (3 antennas) and four receivers (3 antennas each) working at 5.32 GHz.

Lastly, to annotate the CSI data, four video cameras mounted on the ceiling of the eHealth house were used. The camera angles were adjusted in such a way that fine-grained movements such as rubbing, tapping, and kicking could be easily captured.

Table 3. Specifications for Gigabyte Brix IoT.

Component	Specification
Hardware	
Processor	Intel Apollo Lake N34500
RAM	1x HyperX 8GB DRR3L-SO DIMM 1866 MHz
Hard drive	Transcend MTS800 SSD 128 GB (M.2 2280)
Wireless adapter	Intel N Ultimate Wi-Fi Link 5300
Size	165 × 105 × 27 mm
Operating System	Ubuntu 14.04.4
Parameters	
Channel	64
Center frequency	5.32 GHz
Packet transmission rate	100 Hz
Number of antennas	3
Subcarriers	30

3.4. Experiment Location: eHealth House

It is important to evaluate a CSI system in complex surroundings (like a fully furnished house) specifically while considering scenarios such as in-home care for early-stage PwD living alone in their houses. To replicate these scenarios, the eHealth house, which is a simulated one-bedroom apartment designed specifically for scientific research in the Tech Med Centre at the University of Twente, The Netherlands, is used. This fully furnished apartment consists of one bedroom (20.52 m^2), one bathroom (6.76 m^2), and a kitchen plus living room (44.16 m^2) to provide a real-life scenario for experimentation whereas the control room (11.87 m^2) and meeting room (22.37 m^2) are designed to enable monitoring of the experiments. Two walls of this apartment are made up of glass (shown in blue in Figure 2) whereas the others are made up of concrete. Test runs were conducted to see the effect of people walking outside the eHealth house. It was observed that the signals were not able to transverse through the outer glass and concrete walls. Lastly, the experiments were performed in the living area at location L1 and location L2. In Figure 2, the layout of the eHealth house is shown. For more information, a virtual tour of the eHealth house can be found on the official website [48].

Moreover, a visualization of the most/least frequently walked paths for both normal and disturbed walking was plotted by tracing the individual walking patterns of all the participants from the recorded videos. In Figure 2, five commonly walked paths (L3.1 to L3.5) were plotted with 1 being the most commonly walked and 5 being the least commonly walked path. This graphical representation can potentially explain the difference in walking performances of CSI data from different receivers, such that, if good performance is observed by Rx3 (in the bedroom) or Rx4 (in the kitchen), this can be because participants walked paths close to these locations more frequently. Moreover, these walking paths can also help in making sense of the varied performances of the individual participants, such that a participant spending more time in the same area likely affects the signal in a similar fashion, whereas a participant moving throughout the entire space generates a larger variance. It should be noted that these paths are participant-independent, meaning that not all the paths were walked by each participant as they were free to walk anywhere they wanted in the living and kitchen area.

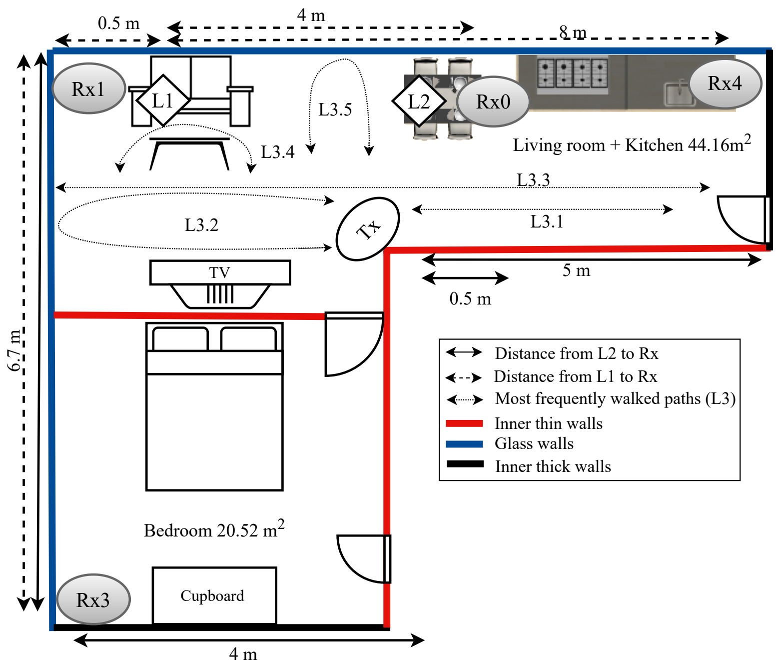

Figure 2. Layout of eHealth house and visualization of the most commonly walked paths, with L3.1 being the most commonly walked and L3.5 being the least commonly walked. Note that individual participants may have slightly deviated from the shown paths.

3.5. Experimental Setup

The nodes were placed in different locations of the eHealth house. A rough estimate of optimal locations for the placement of receivers is obtained by considering commonly used spaces in the house and utilizing Fresnel Zone theory [49]. As per the theory, the signal strength decay is proportional to the distance and longer (multi)paths; therefore, the activity should not occur too far from the line of sight. Considering this, an estimation of optimal locations for the four receivers was identified by taking a rough estimate of the space around each antenna pair and ensuring more condensed Fresnel Zones but with sufficient signal strength. Figure 3 provides an idea of plotted Fresnel Zones. It should be noted that while the Fresnel Zones give a suggestion on node placement, radio waves are highly sensitive to obstacles in the environment. Thus, for this research, it was merely used as an indication rather than a precise measurement to explore the effect of Fresnel Zone theory.

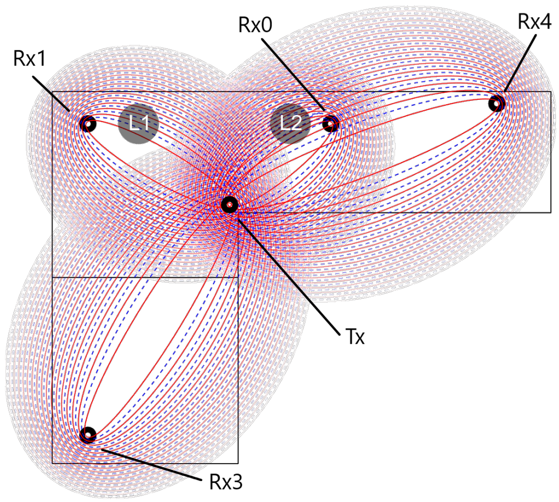

Figure 3. Visualization of Fresnel Zones in the experimental setup (plotting for 5.32 GHz (30th subcarrier), showing only every third zone.

Finally, the antennas were positioned as follows: the middle antenna was placed vertically; the left and right antennas were placed at approximately 30 degrees from the middle antenna for all the receivers and transmitters to complement the wavelengths. Ultimately, Figure 2 depicts the placements of Rx nodes at the following locations: near the sofa (Rx1), near the dining table (Rx0), in the bedroom (Rx3), and in the kitchen (Rx4), and it shows the positioning of the antennas. Table 4 (and Figure 2) provide the details of distances between Tx–Rx pairs and locations L1 and L2, as well as the distances of all the nodes from the floor.

Table 4. Distances between Transmitter (Tx) and Receiver (Rx) with respect to location L1, L2, and floor.

Node	Tx (in m)	L1 (in m)	L2 (in m)	Floor (in m)
Rx0	2.7	4.1	1	1.1
Rx1	3.3	1	4.1	0.45
Rx3	6.5	7.7	7.7	0.45
Rx4	6.3	7	4.5	0.85
Tx	-	2.85	0.5	0.85

3.6. Experiment Paradigm

The total time required for this experiment session (including instructions) was approximately 60 min, which included 40 min for the experimentation and 20 min for the other parts (providing instruction, briefing about the experiment, and signing the consent forms). The experiment was designed as a time-controlled experiment, i.e., for each activity, a specific time was given. Figure 4 illustrates the series of activities conducted during the experiment. As described in Section 3.1, activities monitored, the experiment paradigms adopted seven physical activities representing agitation and two additional normal activities (see Section 3.1). These include getting up and sitting down repeatedly, rubbing on a surface, hand wringing, tapping on a surface, kicking, flipping objects, and to-and-fro disturbed walking, normal walking, and normal sitting. Each activity took place for two minutes followed by a gap of 10 s and 20 s of instructions for the next activity. Activities like walking normally and disturbed walking were performed in the kitchen + living room area, whereas other activities were conducted in two locations, L1 (on the sofa) and L2 (on the dining chair). These locations are shown in Figure 2. Note that participants were free to move anywhere they wanted in the given area for normal and disturbed walking activities, whereas for other activities they were asked to sit at L1 and L2 but slight changes in distance, angle of sitting, movement of hands, etc. were not monitored. Though CSI is highly affected by these small changes in real life, these things cannot be avoided. Hence, in order to make the dataset as realistic as possible, participants were given these choices.

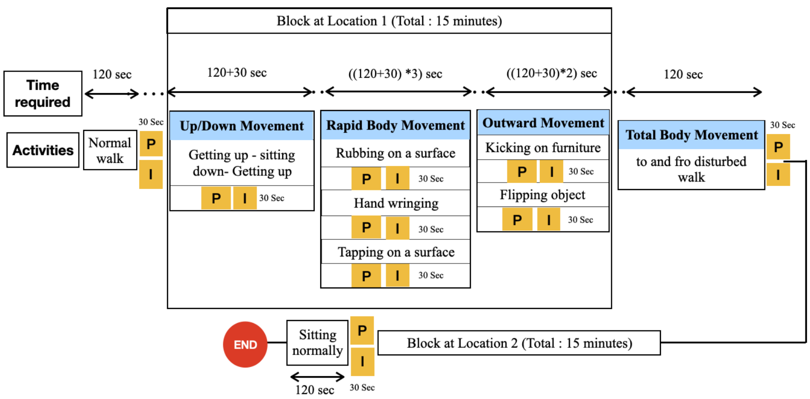

Figure 4. Experiment Paradigm (P: pause of 10 s, I: instructions for next activity for 20 s).

3.7. Instructions for the Participants

English was used as the language of instruction. Before starting the experiment, a video demonstrating a possible way to perform the above activities in relation to the agitation scenario was shown to the participants on the television screen installed in the living room of the eHealth house (see Figure 5). This screen was visible from both locations L1 and L2. The video was also shown to participants before starting each activity (during experimentation) in order to guide them through the experiment. The information on the video included the name, location, duration, and an example video (at the start) of each activity. During the activities, a two-minute countdown timer was shown on the screen to show the remaining time for the ongoing activity. This was done to avoid confusion among participants regarding the start and stop times. Along with these, some other important instructions were given to participants as follows:

- Participants were asked to act as if they were agitated.
- They could be inspired by the video demonstration of activities but they were also free to modify it a bit. For example, for rubbing the table they could use any or both hands (right or left) and they could also vary the intensity (slow, medium, or high) of the activity.
- For disturbed walking, they could walk anywhere in the living room and kitchen area. They were also allowed to use a cane (like older adults use for walking support) or simply walk nervously with regular steps in one direction and then back again.
- The location for performing the activities was fixed, i.e., on the sofa and dining chair but slight shifts (within 0.2 m) in distance, angle of sitting, hand placements, etc. were not protocolized.
- While sitting on the sofa (L1), for the rubbing activity, they were asked to rub on the table (as a surface) placed in front of the sofa. For the activity flipping object, a book (size: 21.5 cm $\times$ 14 cm), and woodcraft (size: 26 cm(height) $\times$ 5 cm(diameter)) were given and they were allowed to choose any one or switch in between. For the kicking activity, they were asked to hit (gently but repetitively) on the leg/legs of the table placed in front of the sofa. Here also, they could choose the intensity, with any or both legs (right or left).
- While sitting on the dining chair (L2), for the rubbing activity, they were asked to rub on the dining table (as a surface). For the activity flipping objects, the same book and woodcraft were used and participants were allowed to choose any one or switch in between. Similarly, for the kicking activity, they were asked to hit (gently but repetitively) on the leg/legs of the dining table with their own choice of leg and intensity of the kicking.

(**a**) (**b**)

Figure 5. Data collection in e-health house at (**a**) Location 1 and (**b**) Location 2. The transmitter (Tx) and the receivers (Rx) placed in the living room are highlighted with red circles. Note that these images were captured from the video data obtained through cameras mounted on the ceiling of the e-health house.

4. Data Extraction

4.1. Extracting and Annotating the Data

The data from receiver nodes were collected and extracted using the open-source Linux 802.11 n CSI Tool [47]. The annotation process was conducted manually by the authors through a visual examination of the video data. For each participant, start time, end time, activity name, and location of each activity were noted from the video data. Then, for each activity, the noted duration data were selected and segregated in the CSI for further processing. Also, note that the experiment was time-controlled; thus, it was already known where, when, and for how long each activity would take place.

4.2. Separating the Data

MATLAB 2021a was used for data pre-processing [50]. The obtained raw CSI dataset was first checked for any possible missing data due to technical reasons. It was found that the node placed in the kitchen (Rx4) failed to obtain the data for all activities of one participant (P 23) whereas the node placed in the bedroom (Rx3) was not able to collect data from six participants (P3, P4, P18, P19, P20, P21) for all the activities. Similarly, data for the "Normal sitting" activity were also not captured by all receivers for two participants (P1 and P14). Thus, empty data files for these participants for these specific receivers and activities were removed. Ideally, Tx is expected to send 100 data packets per second (in this case) but in practice collected CSI data might suffer from non-uniform sampling in the time domain due to possible packet loss and transmission delay. Therefore, in the next step, packet loss (by subtracting received packets from expected packets) for each participant and activity was checked. A few packets were lost from the data but overall no significant packet loss was found. Table A2 in Appendix B presents the removed data corresponding to each node. With the dataset detailed information about packet loss corresponding to each participant, each node, and each activity can be found. From here on, data were separated for each node, each participant, and each activity. Lastly, all the participants used a cane for the disturbed walking activity except P19 and P21 who performed disturbed walking without a cane.

4.3. Obtained CSI Signals

The obtained CSI signal is represented in a three-dimensional channel state matrix, $H = Ntx \times Nrx \times Nsc$, where Ntx is the number of Tx antennas (3), Nrx is the number of Rx antennas (3), and Nsc is the number of subcarriers (30). This gives $3 \times 3 \times 30$ or 270 data streams or 270 channels for each instant. The multiple antennas were used to increase the heterogeneity of the data. In total, two minutes of data for each activity was collected, which is expected to be 12,000 samples (120 s $\times$ 100 Hz) without packet loss. Overall, for each activity, a matrix having 12,000 samples and 270 data streams was obtained. To observe the temporal pattern in the CSI waveform pertaining to agitation activities conducted during the experiment, Figure 6 was plotted by using five raw samples of different activities performed at location 2 (random participants) and one channel of receiver 1 with a window size of 200. By visual inspection, no specific pattern in signals pertaining to different activities and participants was observed in this window size of data.

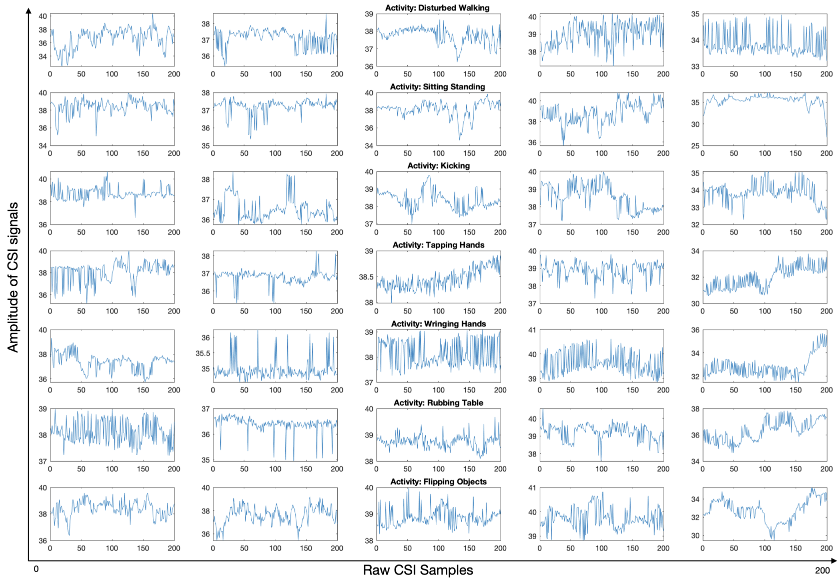

Figure 6. Raw signals pertaining to different agitation activities at location 2 from random participants and one channel.

5. Wi-Gitation: Baseline Performance

The aim of the presented analysis is not to develop advanced algorithms for improving accuracy but is only to present baseline results that can be used for comparison with different or future algorithms developed for CSI data. Thus, in this section, the performance of the Wi-Gitation dataset (seven activities representing agitation were used: disturbed walking, sitting–standing, tapping on the table, hand wringing, rubbing hands on the table, flipping objects, kicking on furniture) is demonstrated by using mixed-data analysis and leave-one-out analysis. Mixed-data analysis means that different samples from the same participant will appear in the train, test, and validation sets [28,51]. For mixed-data analysis, data were randomized for all participants and the abovementioned agitation activities before splitting for training (60%), validation (20%), and testing (20%). This analysis approach favors the real-life situation in older adult care. Usually, older adults/PwD live alone in their apartments which means that the system can be calibrated on the resident and then utilized for continuous monitoring.

In leave-one-out analysis, the model will be trained with CSI data from all the available participants (N-2) except two which were used for validation and testing (one each). Therefore, a total of 22 models for Rx0 and Rx1, 16 models for Rx3, and 21 models for Rx4 were trained and tested, respectively. This analysis can help in understanding the behavior of CSI when unseen data are presented to the trained model. An illustration of the process can be found in Figure 7. Note that the classification was done for both the locations (L1 and L2) and all four receiver nodes (Rx0, Rx1, Rx3, and Rx4) separately.

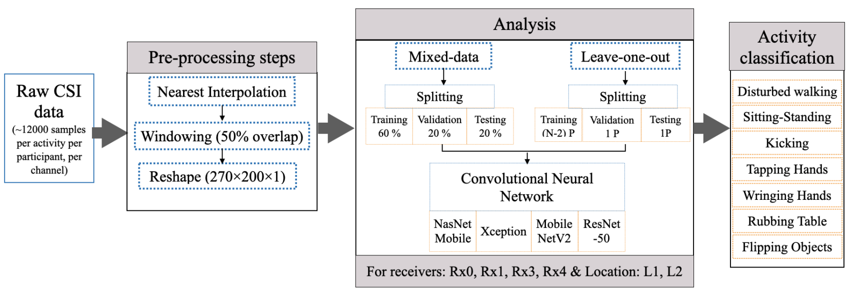

Figure 7. Schematic flow of agitation-based activity classification.

Considering the aim of presenting the baseline results of the dataset, simple pre-processing steps which include the nearest interpolation and sliding window with 50% overlap were applied before feeding data into the CNN. Though the packet loss (presented along with the dataset) was not very significant, to make the number of samples consistent across all the participants and activities, nearest neighbor interpolation was used. In nearest neighbor interpolation, the value at the nearest sample grid point is taken as a new value at the query points [52]. Furthermore, 50% overlapping was performed to overcome the loss of information while segmenting for further processing [53].

Furthermore, both the analyses were performed by using four commonly used convolutional neural network (CNN) architectures: ResNet-50 [54], MobileNet-V2 [55], NASnet-mobile [56], and xception [57]. These networks are widely used for image and non-image data classification with proven performance in achieving optimization and state-of-the-art performance. These specific CNN models were chosen by looking at the number of layers, top-1 accuracy, and size (MB) (Table 5) for comparing their effect on classifications of physical agitation activities. ResNet-50 uses only 50 layers whereas NASNetmobile uses 914 layers; MobileNet-V2 is of only 16MB whereas ResNet-50 occupies 98 MB; and Xception has better top-1 accuracy then others [58]. Untrained network architectures of ResNet-50, MobileNet-V2, Xception, and NASnetmobile were obtained from MATLAB and fine-tuned as per the input ($270 \times 200 \times 1$)—output (seven classes) requirements of the dataset. Other model training hyperparameters include a minibatch size of 8, a learning rate of 0.001, and stochastic gradient descent with momentum (sgdm) optimizer. Additionally, an early stop if validation accuracy was not improving from the last five iterations was used to deal with the problem of over-fitting.

Table 5. Overview of CNN architectures used.

CNN Architecture	Top-1 Accuracy	Size (MB)	Number of Layers
ResNet-50 [54]	0.749	98	50
MobileNet-V2 [55]	0.713	16	53
NASnetmobile [56]	0.744	23	914
xception [57]	0.790	88	174

6. Baseline Results

For both mixed-data analysis and leave-one-out analysis, seven agitation-based physical activities (disturbed walking, sitting–standing, kicking, tapping hands, wringing hands, rubbing table, and flipping objects) were classified using four different CNN models, ResNet-50, MobileNetV2, Xception, and NASnetmobile, at both locations (L1 and L2).

The F_1-score was used to evaluate these models [59]. It is the harmonic mean of precision and sensitivity. Mathematically, precision is the ratio of true positives to the sum of true positives and false positives. In the present context, it can be interpreted as the measure of how many instances predicted as a specific activity by the classifier were actually that activity in general. On the other hand, sensitivity (or recall) is the ratio of true positives to the sum of true positives and false negatives. A high sensitivity indicates that the model is good at classifying or recognizing instances of a particular activity, emphasizing the importance of minimizing instances where the activity is present but not identified (False Negatives). Overall, F_1-score provides a balance between precision and sensitivity and thus can be considered a better evaluation matrix (than accuracy) for trained models (see Equation (1)). The F_1-score ranges from 0 to 1, with a higher score indicating better model performance in terms of both precision and recall. Therefore, the F_1-score corresponding to both the analysis methods was used for comparison.

$$F_1\text{-}Score = 2 \times \frac{Precision + Sensitivity}{Precision \times Sensitivity} \tag{1}$$

Overall, these baseline results cover two aspects: (a) mixed-data analysis of the Rx dataset (Rx0, Rx1, Rx3, and Rx4) with respect to *activity locations L1 and L2*, and *individual activities* by using different CNN models; (b) a leave-one-out analysis of the Rx dataset (Rx0, Rx1, Rx3, and Rx4) with respect to *activity locations L1 and L2* and *individual activities* by using different CNN models. Note that disturbed walking activity is independent of locations and the same data were used while training models for both locations.

6.1. Mixed-Data Analysis with Different CNN Models

Performance with respect to activity locations: In Table 6, four CNN models were compared for both the activity locations (L1 and L2) when using data from all four receivers (Rx0, Rx1, Rx3, and Rx4) trained and tested individually. The average along Rx suggests that ResNet-50 performs slightly better than others (for L1: ResNet-50 > MobileNet-V2 > Xception > NASnetmobile; for L2: ResNet-50 > Xception > MobileNet-V2 & NASnetmobile) for both the locations with L2 being the better-observed place than L1 in this house and with given Tx–Rx placement. Furthermore, these four CNN models gave comparable results with not much difference between obtained F_1-scores. Moreover, it was noteworthy to observe that despite the difference in the distance of receiver and activity location (appx 5–8 m), an overall good average F_1-score (for all activities) between 0.977 and 0.937 was obtained. Figure 8 was plotted to visualize the impact of receivers and activity location. From this, it can be observed that the receivers close to the activity locations, i.e., Rx1 for L1 and Rx0 for L2, compared to the distant receivers, have higher F_1-scores.

Table 6. Mixed-data analysis: Average F_1-score from ResNet-50 (RN-50), MobileNet-V2 (MN-V2), Xception (Xcep), and NASnetmobile (NAS) for both activity locations and all receivers. (* represents the nearest receiver to the monitoring location.)

Activity Location	Rx Data Used	RN-50	MN-V2	Xcep	NAS	Average Models
Location 1: on sofa	Rx0 (near dining table)	0.965	0.962	0.941	0.945	0.953
	Rx1 (near sofa) *	**0.977**	0.963	0.970	0.961	0.968
	Rx3 (in bedroom)	0.962	0.947	0.956	**0.937**	0.950
	Rx4 (in kitchen)	0.965	0.953	0.945	0.929	0.948
	Average: Rx0, Rx1, Rx3, Rx4	0.967	0.956	0.953	0.943	0.955
Location 2: on dining chair	Rx0 (near dining table) *	**0.977**	0.974	0.984	0.975	0.978
	Rx1 (near sofa)	0.970	0.937	0.971	0.965	0.961
	Rx3 (in bedroom)	0.969	0.968	0.954	0.946	0.959
	Rx4 (in kitchen)	0.975	0.975	0.969	0.964	0.971
	Average: Rx0, Rx1, Rx3, Rx4	0.973	0.963	0.970	0.963	0.967

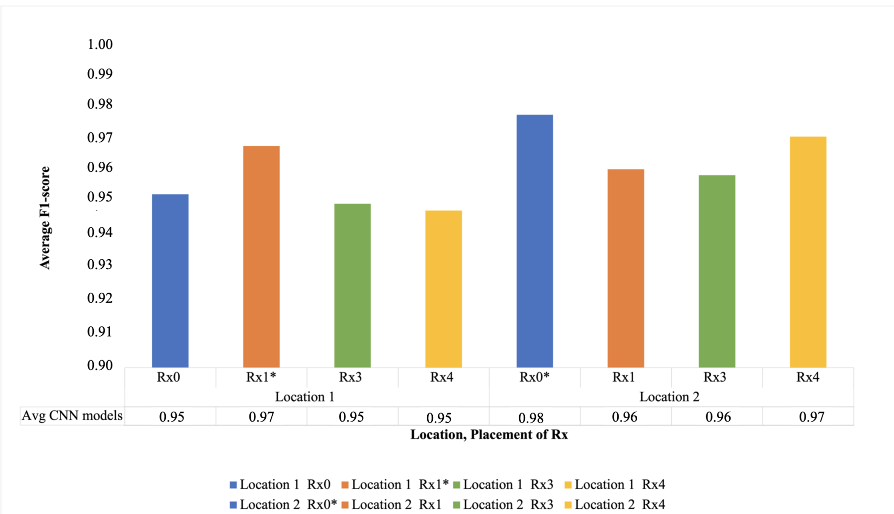

Figure 8. Mixed-data analysis: Average F_1-score with respect to activity location and placement of Rx (* represents the nearest receiver to the monitoring location).

Performance with respect to individual activities: Average F_1-score along the Rx and locations for seven activities (disturbed walking, sitting–standing, kicking, tapping hands, wringing hands, rubbing table, and flipping objects) for ResNet-50, MobileNet V2, Xception, and NASnetMobile can be observed in Table 7. The overall average F_1-score for all the activities and the CNN models was between 0.92 and 0.98 (approx) with not much difference in performance with respect to different CNN models. Further, Figure 9 was plotted by taking an average along the CNN models. Here, a trend was observed in the F_1-score of the models. The models were able to classify activities as follows in descending order: disturbed walking, flipping objects, kicking, sitting– standing, tapping, wringing hands, and rubbing tables.

Table 7. Mixed-data analysis: F_1-score from ResNet-50 (RN-50), MobileNet-V2 (MN-V2), Xception (Xcep), and NASnetmobile (NAS) for all the activities.

Activities	RN-50	MN-V2	Xcep	NAS	Average Models
Disturbed walking	**0.989**	0.983	0.986	0.975	0.983
Flipping objects	0.982	0.969	0.972	0.965	0.972
Kicking	0.973	0.961	0.966	0.960	0.965
Sitting–standing	0.968	0.958	0.962	0.954	0.961
Tapping	0.962	0.955	0.949	0.945	0.953
Wringing hands	0.959	0.952	0.947	0.941	0.950
Rubbing tables	0.952	0.941	0.944	**0.928**	0.941
Average activities	0.969	0.960	0.961	0.953	0.961

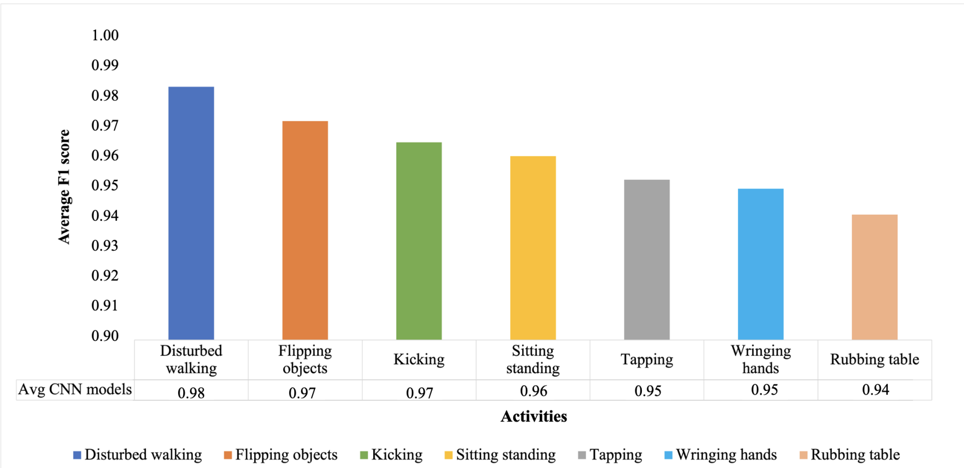

Figure 9. Mixed-data analysis: Average F_1-Score for different activities.

6.2. Leave-One-Out Analysis with Different CNN Models

Performance with respect to activity locations: In leave-one-out analysis, the models were not able to train very well (i.e., training accuracies at times were below 50%). But to obtain a basic understanding, the F1-score from the trained CNN models corresponding to both locations and all receivers' data (Rx0, Rx1, Rx3, and Rx4) was calculated. Compared to mixed-data analysis, significantly lower F_1-scores were observed here (between 0.24 and 0.11). These F_1-scores can be observed in Table 8, which compares the performance of four CNN models at both the activity locations (L1 and L2) when using data from all four Rx (Rx0, Rx1, Rx3, and Rx4) individually. The average along Rx suggests that MobileNet-v2 performs slightly better than the others. For both L1 and L2, the performance of the models is as follows (descending order): MobileNet-V2 > NASnetmobile > ResNet-50 > Xception. Similar to mixed-data analysis, here also L2 is a better-observed place (based on average across Rx, F_1-score for L1 is 0.171 whereas for L2 it is 0.191). Furthermore, Figure 10 was plotted to observe the impact of receivers and activity location.

Table 8. Leave-one-out analysis: F_1-score from ResNet-50 (RN-50), MobileNet-V2 (MN-V2), Xception (Xcep), and NASnetmobile (NAS) for both activity locations and all receivers. (* represents the nearest receiver to the monitoring location.)

Activity Location	Rx Data Used	RN-50	MN-V2	Xcep	NAS	Average Models
Location 1: on sofa	Rx0 (near dining table)	0.212	0.235	0.168	0.243	**0.215**
	Rx1 (near sofa)*	0.183	**0.241**	0.167	0.212	0.201
	Rx3 (in bedroom)	0.116	0.158	0.112	0.165	0.137
	Rx4 (in kitchen)	0.187	0.234	0.187	0.235	0.211
	Average: Rx0,Rx1,Rx3,Rx4	0.175	0.217	0.158	0.214	0.171
Location 2: on dining chair	Rx0 (near dining table) *	0.187	0.224	0.156	0.226	0.189
	Rx1 (near sofa)	0.144	0.207	0.149	0.161	0.165
	Rx3 (in bedroom)	0.151	0.178	**0.110**	0.154	0.148
	Rx4 (in kitchen)	0.167	0.207	0.138	0.207	0.180
	Average: Rx0,Rx1,Rx3,Rx4	0.162	0.204	0.138	0.187	0.191

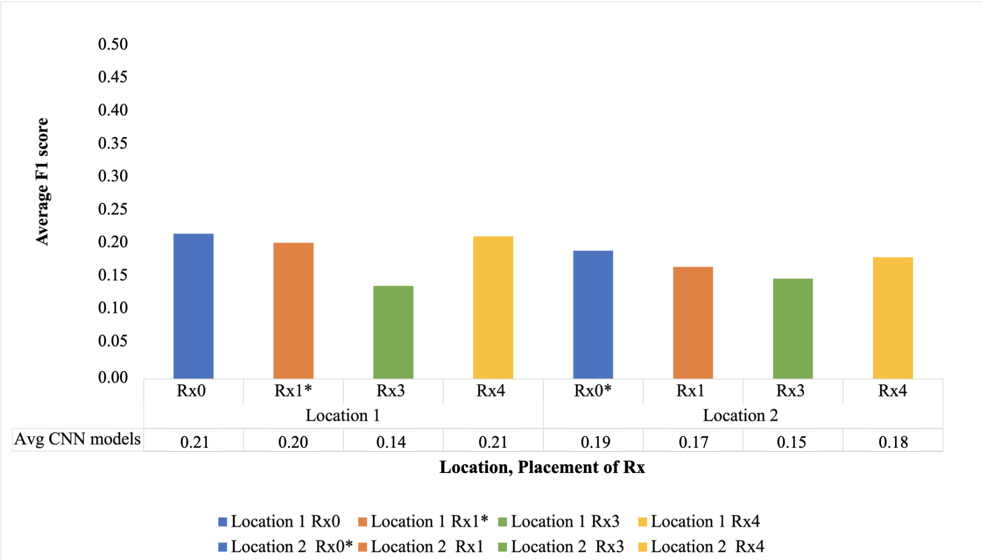

Figure 10. Leave-one-out analysis: Average F_1-score with respect to activity location and placement of Rx (* represents the nearest receiver to the monitoring location).

Performance with respect to individual activities: Similar to the mixed-data analysis, the average F_1-score along the Rx and locations were calculated for seven activities (disturbed walking, sitting–standing, kicking, tapping hands, wringing hands, rubbing table, and flipping objects) for ResNet-50, MobileNet V2, Xception, and NASnetMobile (Table 9). For most of the activities, MobileNet-V2 outperformed other CNN networks (except kicking). Overall, all the models were able to classify disturbed walking and sitting–standing comparatively better while other fine-grained activities like kicking, flipping objects, tapping, wringing hands, and rubbing tables had comparable F_1-scores (between 0.49 and 0.06).

Table 9. Leave-one-out analysis: F_1-score from ResNet-50 (RN-50), MobileNet-V2 (MN-V2), Xception (Xcep), and NASnetmobile (NAS) for all the activities.

Activities	RN-50	MN-V2	Xcep	NAS	Average Models
Disturbed walking	0.362	**0.493**	0.387	0.414	0.414
Sitting–standing	0.287	0.399	0.206	0.297	0.297
Tapping	0.112	0.149	0.109	0.123	0.123
Kicking	0.133	0.118	0.110	0.12	0.120
Flipping objects	0.108	0.117	0.103	0.113	0.110
Rubbing tables	0.092	0.102	0.061	0.097	0.088
Wringing hands	0.084	0.094	**0.060**	0.092	0.083
Average activities	0.168	0.210	0.148	0.179	0.177

7. Results Analysis and Discussion

The aim of this paper is to provide the Wi-Gitation dataset encompassing fine-grained hand, leg, and full-body activities followed by presenting baseline results using four different state-of-the-art convolutional neural networks for facilitating future research on using CSI for HAR specifically for in-home PwD care. In that direction, first, we summarize the novel characteristics of this dataset followed by providing its implications in real-life settings. Thereafter, we extend the discussion on future usage of CSI-based monitoring systems by comparing, contrasting, and interpreting the results of mixed-data and leave-one-out analysis.

7.1. Implications of Wi-Gitation Dataset

Most of the available CSI datasets collect data in controlled environments, i.e., strictly defined activity locations, closely or in-line-of-sight-placed Tx–Rx pairs, and fewer participants. In contrast, the presented realistic Wi-Gitation dataset contains CSI data of seven agitation-based activities performed at two different locations in simulated home settings (one-bedroom apartment) by twenty-three participants. Furthermore, the dataset also provides normal walking and normal sitting activities which can be used to differentiate between activities of daily life and agitation activity. Furthermore, the data were captured by four different receiver nodes placed at different distances (0.5–8 m with one of the Rx beyond the wall) from the participant. Though for fine-grained activities locations were defined (sofa and dining chair), slight shifts in the distance, angle of sitting, etc. were not monitored, whereas for walking activities participants were free to roam anywhere they wanted in the kitchen and living room area. Additionally, while performing fine-grained hand and leg activities, participants were free to improvise the activities (such as by modifying the intensity and choice of hand/leg). This was done to make the dataset resemble real-life agitation scenarios. Therefore, this dataset can be utilized to draw an early understanding of the performance of newly developed algorithms in this domain during the development and testing phases. In the later or pre-implementation stage (in real-life settings), actors or PwD can be invited for determinative performance analysis of the system.

Additionally, this dataset opens new avenues for gaining insights into the ubiquitousness and domain-transfer applications of CSI-based sensing as it contains parameters like different activity locations, participant characteristics, and placement of Tx–Rx [60]. Insights into ubiquitousness can help in making informed decisions on using these advanced sensing systems. For example, if one Tx–Rx pair is sufficient for an apartment (of a certain size), then opportunities for possible use might increase as this would be more cost-effective compared to when multiple Tx–Rx pairs are required. Moreover, while considering unobtrusiveness and ubiquitousness, it is also important to highlight the privacy and security issues. The topic of privacy and security concerning CSI is still debatable in the literature. It is difficult to extract CSI data and knowledge of advanced signal processing is required to make sense of this data. But in the case of a hack, the unobtrusive property of CSI can also be useful in the information leakage without anyone noticing it [61]. Thus, along with developing advanced signal processing algorithms for CSI, serious consideration of making them more privacy-aware is required. On a higher level, an effort to establish new protocols, policies, and architectures is demanded before implementing CSI-based HAR systems in real life.

7.2. Interpretation of Obtained Baseline Results

The majority of available CSI-based works present intriguing and complex algorithms for processing CSI data. These algorithms help achieve better accuracy but to understand the behavior of CSI data it is also important to present and discuss the results with minimal data pre-processing before applying advanced signal processing. To gain an understanding of the behavior of the raw CSI data, we used available raw CSI data (270 data streams) for training, validation, and testing.

To start with, mixed-data analysis was used where training and testing were performed on the same participant group but with different samples. This analysis showed promising classification results for agitation activities at both locations and given Tx–Rx distances for the used CNN models. From the obtained mixed-method results, it can be interpreted that the classification performance is dependent on the location of the participant (or monitoring location) with respect to Tx–Rx placement and the type of activity monitored. First, the observation from the closest Rx was comparatively better (Figure 8). Second, the performance decreases with distance but not sharply, i.e., overall good observation of activities up to a distance of 8m (maximum tested in this experiment) can be made with a few/or one Tx–Rx pair(s) (Figure 8). Here, it is worth highlighting that both the closest receivers to the monitoring locations L2 (Rx0) and L1 (Rx1) were placed at the same distance from the monitoring location but the distance between Tx and Rx was different (Tx–Rx0:2.7m, Tx–Rx1:3.3m), which seems to impact the location-wise classification performance slightly (as L2 appeared to be a better monitoring location compared to L1). Third, the presence of a wall (NLOS scenarios) also degraded the classification performance but not significantly (Figure 8). Fourth, activity-wise results suggest that classification performance degrades with a decrease in the size of the activity, i.e., full-body activities like walking had better scores compared to fine-grained activities like rubbing the table (Figure 9). Fifth, not much difference in performance was found after training and testing with different CNN models though ResNet-50 performed preeminently compared to others (Table 7).

Moreover, despite using fully furnished home settings for data collection, the obtained mixed-data results (F_1-Scores ≥ 0.95) are comparable to the state-of-the-art works. In the existing CSI-based HAR research, dangerous poses while bathing were estimated with an accuracy of 96.23% [62]; paraparesis (paralysis of the lower body) with an accuracy of 99.4% [63]; Parkinson's disease with an accuracy of 99.8% [64]; post-surgical falls with an accuracy of 90% [65]; and wandering behavior among dementia patients with an accuracy of 90% [36]. This demonstrates the possibility of implementing CSI-based agitation monitoring systems in real-life settings for the specific case where training is carried out on the to-be-monitored person.

In the next step, a leave-one-out analysis was performed to examine the behavior of CSI when testing was done on a new person different from the one it was trained on. The results are suggestive of the negative impact of new participant data on the activity-wise, location-wise, and Tx–Rx distance-wise classification performance (F_1-Scores ≤ 0.21). Though the performance was significantly lower compared to mixed-data analysis, some commonalities are striking. Here also, Rx close to the monitoring location had slightly better results and the NLOS scenario had slightly poorer results (in the majority of cases) (Figure 10). The impact of the placement of Tx–Rx with respect to participants is also consistent with the mixed-data analysis results (Figure 10). Furthermore, in accordance with the mixed-data analysis, the classification performance degrades with the size of the activity but not significantly. F_1-Scores declined by 0.04 in mixed-data analysis across activities (Figure 9) whereas they declined by 0.33 in leave-one-out analysis (Figure 11). Lastly, MobileNet-V2 performed slightly better but as such not much difference in performance was found with different CNN models (Table 8).

To further understand the contrasting results of these two methods, Figure 12 was plotted, showing raw CSI signal waveforms for two random participants for all the receivers and different activities. This figure assists in understanding the achieved mixed-data analysis performance of the Wi-Gitation dataset. A visual inspection of the waveform of the raw signal reveals the difference in signals (amplitude change) concerning different activities which means that the algorithm is trained impeccably well (or able to differentiate) on the given activities and participants' data; hence, it gives good testing results. In Figure 12, it is also important to note the difference in the same activity's signals within data from different Rx (Rx0, Rx1, Rx3, and Rx4) and participants. In this direction, the observed decline in F_1-score in the leave-one-out analysis makes activity-wise, location-wise, and distance-wise sensitivity apparent. More specifically, not only physical attributes like gender, age, height, weight,and BMI of the participants but also any kind of environmental freedom like different orientations, angle of sitting, and manner of performing the activity largely influence the overall classification performance, indicating challenges in the generic analysis. The same was also highlighted by the research work [49]; CSI waveforms are sensitive to location/person and can be different for similar activities if performed in different environments by different persons. Finally, Figure 13 was plotted to compare the difference in F_1-score corresponding to different activities for mixed-data and leave-one-out analysis at both locations (L1 and L2) by using the results of MobileNet-V2. From this figure, it is evident that models perform poorly when presented with a new participant's data, i.e., 'over-fitting' may occur even though early stopping was used.

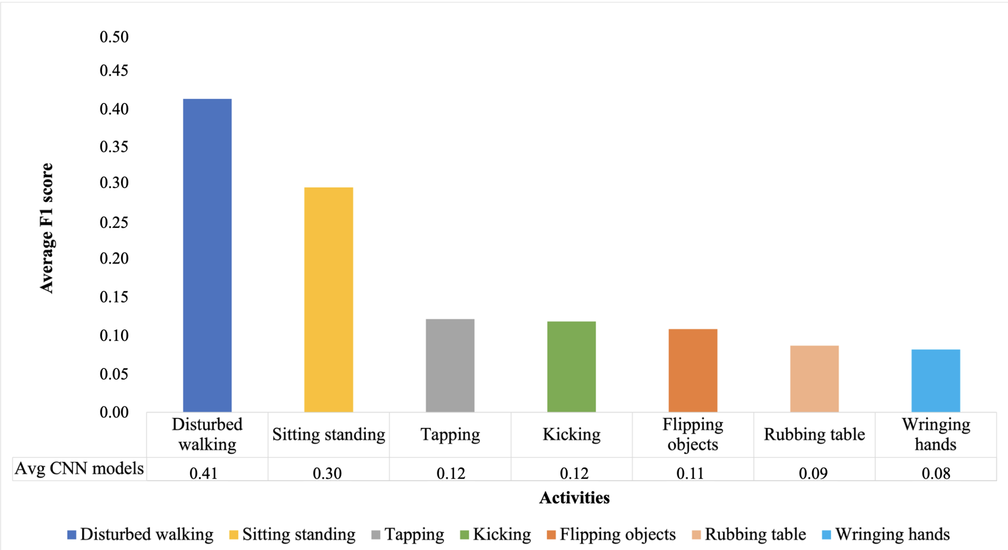

Figure 11. Leave-one-out analysis: Average F_1-Score for different activities.

Lastly, it can be summarized that Wi-Fi CSI can be potentially used for recognizing different activities demonstrated in agitation scenarios. Through different types of analysis (representing different real-life scenarios), it became apparent that factors such as new persons, monitoring locations, devices, and size of activities might impact the performance of CSI-based USSs. For instance, if a receiver is placed nearby or in LOS to observe large body movements of the seen person (during training), then chances of better observation are high but the challenge comes when the receiver is in NLOS and fine-grained movements need to be observed on an unseen person's data. This makes the performance contingent on the specific scenario. On the positive side, it is also worth underlining that, although distance plays a key role in CSI monitoring, the performance does not decline sharply (at least up to 8 m) with distance. This can be translated as follows. If we can improve performance at nearby locations with unseen data, then the chances of improving performance at distant locations with unseen data are also high. Thus, this indicates the ubiquitousness of the CSI.

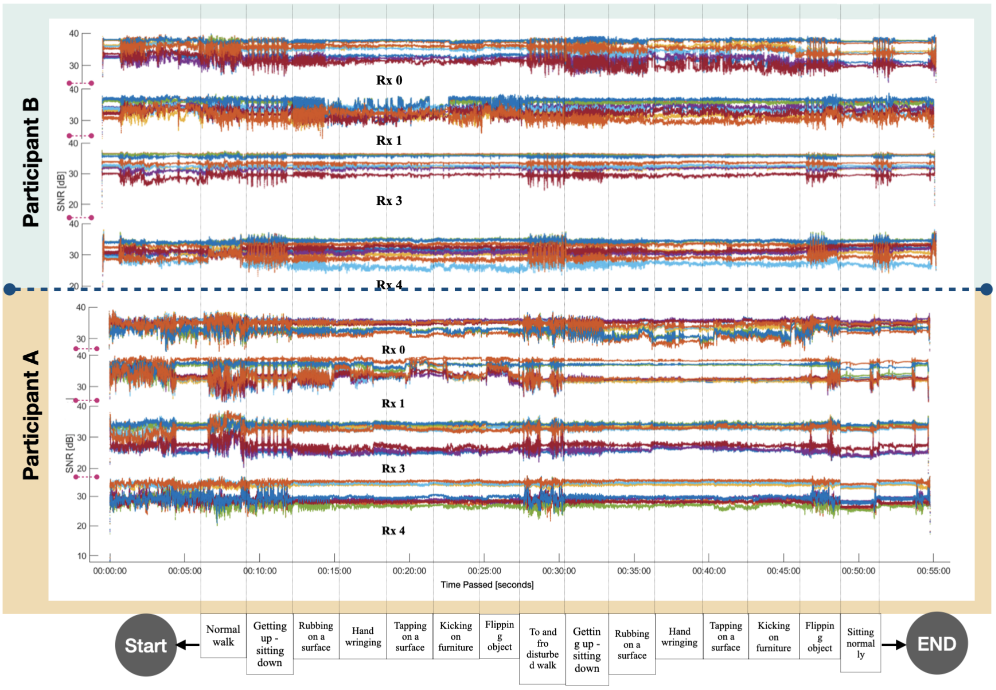

Figure 12. Raw CSI signal waveform from Rx0, Rx1, Rx3, Rx4. (Note that different colors correspond to different channels in the receivers).

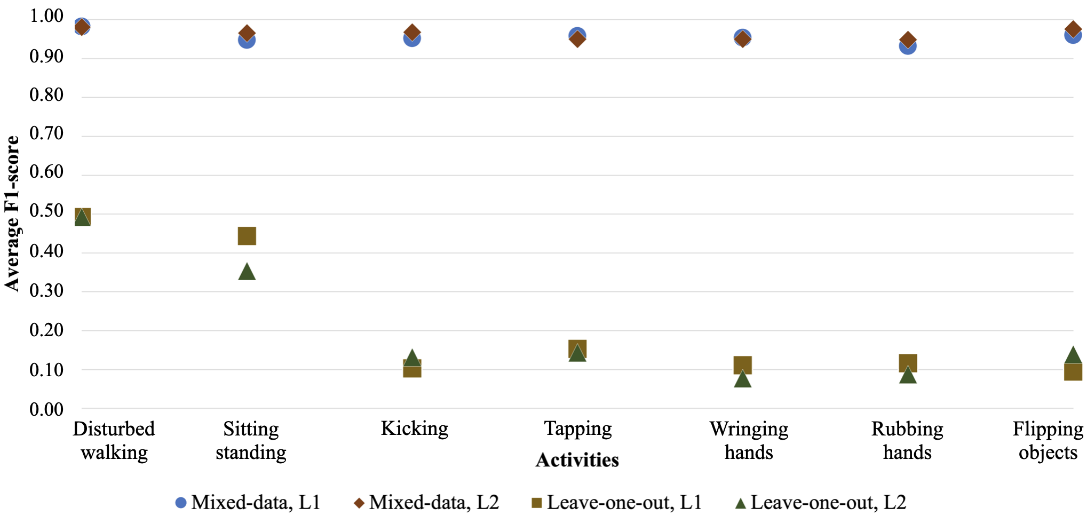

Figure 13. Comparing activity-wise F_1-scores from leave-one-out and mixed-data analysis.

8. Future Challenges

Considering the demand for unobtrusive sensing solutions for in-home monitoring of PwD/older adults (and other user groups), Wi-Fi-based sensing solutions are recommended [11,12]. In this direction, the Wi-Gitation dataset can facilitate research on using Wi-Fi-based sensing for real-life use cases such as agitation among older adults/PwD living alone. To detect agitation, the first challenge is to classify/recognize the agitation-related activities, which are usually of fine-grained, varied intensity/time-duration as described in SOAPD [18]. Then, on top of activity classification, algorithms that can compute agitation scores based on classification results can be developed to automatize the agitation process followed by rigorous testing with older adults.

With agitation detection, this dataset can be utilized to encourage research in both fundamental and application domains. From the bottom-up perspective, many attempts to advance CSI have been observed in the literature but a deeper understanding of the behavior of raw CSI signals in more realistic scenarios is desirable (for example, how and which factors impact CSI) to be able to make justifiable progress as well as to foresee the limitations of CSI in HAR detection [66]. Moreover, the dataset presents data from nine Tx–Rx antenna pairs (i.e., 270 data streams). Fundamentally, it would be worth looking at which Tx–Rx antenna pair contributes better in which activity so that only those pairs can be further used for data analysis. This might reduce noise in the data as well as processing time. The same can be done for subcarriers. In a recent work, an adaptive antenna elimination algorithm that adaptively eliminates antennas based on their sensitivity to different activities was proposed [67]. Such algorithms can be further evaluated by using the Wi-Gitation dataset. Application-wise, as indicated by the leave-one-out analysis, the problem of 'over-fitting' in CSI when testing on unseen data appears as the biggest challenge for 'generalizing the CSI data'. In this regard, the Wi-Gitation dataset provides data from twenty-three participants who have different body mass indexes and fairly distributed gender which can help in assessing the person-wise generalizability of new possible algorithms. Additionally, the dataset advances the existing CSI-based HAR research by adding the CSI data for fine-grained activities such as tapping, wringing, rubbing, kicking, etc. These activities can also be seen as cues of complex behavior like anxiety, nervousness, stress, etc. Thus, by recognizing these activities, a step ahead in behavior recognition using CSI can be taken.

9. Conclusions

The Wi-Gitation dataset aims to advance research in unobtrusive and ubiquitous monitoring, particularly for detecting agitation in PwD. While the evaluation results suggest the potential of Wi-Fi CSI in monitoring agitation-related activities, it is crucial to recognize that the performance of CSI-based USS is contingent on the specific end-use case. For instance, optimal performance is achieved when trained on data from older adults/PwD living alone (mixed-data analysis approach) but deploying the system after training on others' data (leave-one-out analysis approach) may result in poor performance, which can potentially be addressed through advanced data processing methods.

The obtained results reveal the sensitivity of CSI data to factors like location, participants, and Tx–Rx placement. Nevertheless, the potential of CSI in ubiquitous monitoring is undeniable. The results indicate that only a few Tx–Rx pairs were optimal for monitoring distances up to 8 m (the maximum tested in this study). However, in larger spaces or when monitoring subtle activities like heart or breathing rate, the number of Tx–Rx pairs may need to increase. Additionally, the dataset opens avenues for future research, particularly in making CSI generalizable to fine-grained hand or leg activities. Lastly, comprehensive investigations into user perspectives and implementation challenges are necessary before implementing such advanced technologies.

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Institutional Review Board Statement: The Ethics Committee of Behavioral, Management and Social Sciences (BMS), University of Twente, has approved this study (request number: 200033).

Informed Consent Statement: Written informed consent was obtained from all participants involved in the study.

Data Availability Statement: The pre-processed Wi-Gitation dataset can be found on https://drive.google.com/drive/folders/1xeGeoozZzomMi04KOk9L7j0HahqNg37t?usp=share_link (accessed on 19 December 2023). Along with the dataset, codes used for baseline validation (both mixed-data and leave-one-out) in this work are also available. Additionally, a presentation demonstrating the activities with instructions given to participants and a document containing information about packet loss corresponding to each participant, each node, and each activity is also made available for possible future usage. Note that this dataset can be used only for research purposes (CC-BY-NC).

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Appendix A. Participants' Demographics

Table A1 presents the following demographics of the participants: Height (cms), Weight (kgs), Gender (M/F), Age (years), and BMI (kg/m^2).

Table A1. Participants' demographic information.

Demographics	Data Range	Participant Number
Height Range (in cms) (173.52 ± 8.89)	157–160	P17, P4
	161–165	P10, P8, P23
	166–170	P13, P21, P14
	171–175	P2, P6, P7, P15, P3
	176–180	P22, P16, P9
	181–185	P20, P18, P19, P1
	186–190	P5, P11
Weight Range (in kgs) (67 ± 11.25)	46–50	P6
	51–55	P4, P12, P17
	56–60	P15, P8
	61–65	P13, P21, P16, P10
	66–70	P3, P7, P2, P23
	71–75	P5, P9, P18, P19
	76–80	P11, P14,
	81–85	P22
	91–95	P20
	115–120	P1
Gender	Male	P1, P2, P5, P9, P11, P13, P16, P18, P19, P20, P22, P23
	Female	P3, P4, P6, P7, P8, P10, P12, P14, P15, P17, P21
Age (in years) (25.26 ± 9.49)	18-20	P3, P6, P7, P8, P10, P14, P15
	21–25	P2, P4, P5, P9
	26–30	P1, P12, P13, P16, P18, P19, P20, P21, P22, P23
	31–35	P17
	60–64	P11
BMI (kg/m^2) (22.25 ± 3.90)	16–18.4	P6, P15
	18.5–20.9	P12, P16, P4, P5
	21–24.9	P13, P21, P8, P17, P3, P11, P9, P18, P19, P7, P2
	25–30.9	P10, P23, P22, P14, P20
	31–35.9	P1

Appendix B. Data Removed from Each Node

Table A2 presents the data that were removed from receiver (Rx) nodes, participants, locations, and activities.

Table A2. Table showing the removed data per node, participant, location, and activity.

Node	Participant	Location	Activities
Rx0	1, 14	L1, L2	Normal sitting
Rx1	1, 14	L1, L2	Normal sitting
Rx3	3, 4, 18–21 1, 14	L1, L2 L1, L2	All Normal sitting
Rx4	23 1, 14	L1, L2 L1, L2	All Normal sitting

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