Multiarmed Bandits for Sleep Recognition of Elderly Living in Single-Resident Smart Homes

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***Abstract*—Sleep is an essential activity that affects an individual's health and ability to perform activities of daily living (ADL). Inadequate sleep reduces cognitive capacity and leads to health-related issues, such as cardiovascular diseases. Sleep disorders are more prevalent in older adults. Therefore, it is essential to recognize sleep patterns and support older adults and their caregivers. In our study, we collect data in real-world unconstrained and nonintrusive environments. This article presents a novel sleep activity recognition method using motion sensors for recognizing nighttime and daytime sleep, which can further enable the development of insightful healthcare applications. The research objectives are to evaluate the application of using multiarmed bandit (MAB) methods to 1) learn normal sleep patterns; 2) evaluate sleep quality; and 3) detect anomalies in sleep activity for 11 elderly participants living in single-resident smart homes. We evaluate the performance of Thompson sampling (TS), random selection, and upper confidence bound MAB methods. TS outperformed the other two methods. Our findings show most elderly participants slept between 6 and 8 h with 85% sleep efficiency and up to three awakenings per night.**

***Index Terms*—Anomaly detection, elderly healthcare, Internet of Things (IoT), multiarmed bandits (MABs), reinforcement learning, sleep patterns, smart homes.**

I. Introduction

Internet of Things (IoT) for real-world applications in different domains has witnessed significant growth in recent years. IoT applications have seen rapid developments in different domains, such as medical diagnosis and energy management applications based on IoT systems for e-health and scheduling home appliances, to save energy [1], [2]. Developing diagnosis models in health applications is important, especially during pandemic times. Shankar et al. [3] proposed a classifier of the COVID-19 model to control the disease. For classification, they used fuzzy bilateral filtering (FBF) to preprocess Chest X-Ray Images and deep convolutional neural networks (DCNNs). The proposed model showed promising results compared to other evaluated models, with an average accuracy of over 96%.

In 2020, there were about 1.37 billion connected devices, with about 0.36 billion within the healthcare sector, mainly for monitoring patients [4]. Sensors alone contributed $15 trillion to the IoT market in 2020, and by 2030 this number will reach $100 trillion [5]. By 2025, the market for IoT services in the healthcare sector will likely reach $1.6 trillion in annual income, rising from $0.2 trillion in 2015. Smart home devices embedded in the physical environment or attached to human bodies are increasingly used to support health monitoring systems [6]. Specifically, IoT services have the potential to facilitate nonintrusive sleep monitoring for older adults living independently [7]. In real-life environments, motion sensors in smart homes can recognize activities of daily living (ADLs), such as leaving home and sleeping [8], and track sleep behavior [7]. In general, these motion sensors are better accepted by older adults than other devices (smart watches) [9] due to their practicality, nonintrusiveness, and robustness to changes in the surrounding environment [10]. IoT platforms integrate these motion sensors and collect and process the data to run different healthcare applications. Advanced IoT devices and off-the-shelf sensors enable lowering the cost of data collection [8]. Detecting abnormal behaviors by ADL applications in healthcare systems could help healthcare providers conduct their work more effectively, particularly in elderly care.

Sleep is an essential activity that affects an individual's health and ability to perform ADL. Inadequate sleep can impact daily behavior [11], reduce cognitive throughput [12], and increase the risk of cardiovascular diseases [13], [14]. Adequate sleep, a combination of the right amount of sleep duration and quality, is associated with aspects of healthy living, such as a healthy diet and regular meal patterns [15]. However, older adults are more affected by insomnia and other sleep disorders than younger people because they are more likely to have medical conditions [16], [17].

The Swedish National Study on Aging and Care investigated 1400 older adults and showed that about 60%–76% of people aged 66 years or older had sleep problems, which tended to increase with age [16]. Another study of 876 participants aged 65–79 reported that about 24% of women and 13% of men had sleep problems, and 44% of participants had complaints about continuing sleep [18]. In another study, over half of the 9000

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by Regional Ethical Board under Application No. 2018-189/31.

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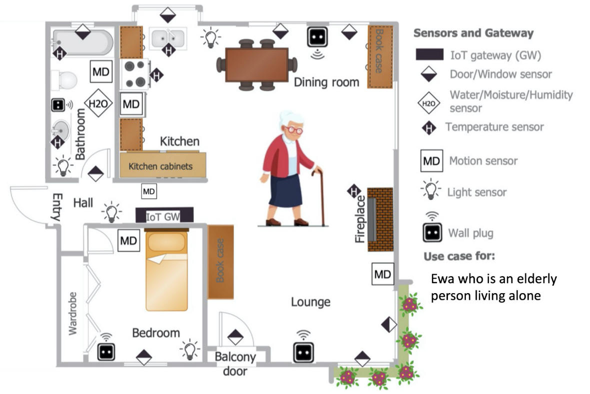

Fig. 1. Real-life apartment layout with smart home sensors (for example, motion sensors in each room) connected to an IoT gateway.

participants had sleep complaints, with 23%–34% complaining of insomnia [19]. The findings of large-scale studies of the elderly suggest that adherence to daily routines is associated with better sleep quality and reduced insomnia [14].

The current study also investigated daytime sleep behavior, as there is a paucity of such information in [7]. Also, 20% of people over 65 years old have longer sleep duration during the daytime than nighttime, which might indicate sleep Apnea and Alzheimer's [20]. About 32% of older men and 23% of older women complained of daytime sleepiness [18], which agrees with another study in northern Sweden [21].

In our study, we targeted older adults who live independently in their homes because they have particular challenges with recent technological advances that can provision healthcare to them [22]. There are over 266 000 men and 497 000 women between 65 and 95 years old living in single-resident households in Sweden—about 28% and 51% of men and women, respectively, and about 38% of the total population of +65 years old are living independently [23].

In this article, we use off-the-shelf IoT devices installed in single-resident elderly homes to identify sleep patterns and any health-related anomalies to support these older adults to live independently for longer, as illustrated in Fig. 1. Perez-Pozuelo et al. [7] can allow for early diagnosis of sleep disorders by clinicians and assist individuals in changing their habits [24].

Data collection through nonintrusive sensors present in the individual's smart homes has the potential to track changes in sleep patterns [24] and help epidemiological studies [7]. Several studies have used wearable devices to capture data for low-level activities, such as walking, falling, and gestures [8], [25], as well as smartphones to recognize human behaviors [26].

However, these devices can be impractical—the elderly user may forget to use the device or dislike wearing it, design constraints may inhibit 24/7 use, or the users may already wear other emergency buttons on their wrists necessary for their well-being. Furthermore, vision-based techniques raise privacy concerns and may not be the best option for monitoring ADLs [10], [27]. Various studies have explored sleep patterns by collecting data from PSG/EEG, wearable devices, actigraphy, and accelerometry sensors [7]. However, challenges, such as usability, privacy, and human annotation of the sleep EEG remain [27]. Nonintrusive IoT devices were found to be more accepted by users than these other devices [9].

In addition to the challenges of using wearable devices, collecting historical data to recognize higher activity abstractions, such as behaviors or ADLs, to build an anomaly detection system is emphasized in different human activity recognition (HAR) systems [27], [28]. However, the collection of long-term activity data from real-world smart homes is a challenge, especially in the case of older residents. Most existing approaches require large amounts of training data sets to learn the user's behavior [27], however finding the right number of data sets—enough to learn the behavior without taking too long, but not too few to learn the behavior correctly—is an open issue that needs to be explored. Multiarmed bandit (MAB) methods are applied in different application domains where it successfully learns the different variations in patterns through periods of exploration and exploitation at the same time. It treats the sleep recognition problem as a classical reinforcement learning problem. The MAB identifies different sleep behaviors of a person as a bandit and rewards them based on the highest probability, which then is recognized as normal behavior, and the arms with lower probability represent the less likely behavior, which can also sometimes be identified as an anomaly.

MAB methods learn human behavior faster with less training data than ML and statistical approaches. MAB, a reinforcement learning method, is more adaptable to changes in human behavior. In our use case, we had multiple elderly pilots for which we had a requirement to learn sleep patterns with less training data and identify abnormal patterns in sleep. In our previous work [29], we applied a statistical method to learn behavior which worked well. However, we needed to collect data for more extended periods.

The research objectives are 1) to investigate if nonintrusive off-the-shelf IoT motion sensor devices can identify sleep patterns and 2) to evaluate the use of MAB algorithms in discovering sleep patterns and identifying anomalies.

In this article, in our proposed system, we used three methods of reinforcement learning known as MABs were evaluated on data sets of between 62 and 324 days: 1) Thompson sampling (TS); 2) upper confidence bound (UCB1); and 3) random selection (RS). The correctly classified percentage (PCC) was used to assess the overall accuracy and compare the performance of the methods [30]. The highest PCC in our tests represented the best of the three proposed methods.

The contribution to our research is as follows.

Contribution:

1) We proposed, developed, and evaluated a framework to learn sleep patterns (nighttime and daytime) with MAB algorithms TS, UCB1, and RS for 11 elderly participants with a median age of 89 years living in single-resident apartments for approximately two years. Each method's performance was evaluated using 88-463 days of night sleep, training, and a testing ratio is 30:70.
2) We classified the outcomes of the MAB algorithms with a high and low probability of returning expected rewards as corresponding to normal and abnormal days,

respectively. We further investigated the arms with the highest probability by classifying them into good or poor sleep quality based on sleep efficiency (SE) scores and the number of awakenings per night recommended by sleep literature in [31]. Similarly, we classified the predicted arms with the lowest probability as abnormal sleep days.

This study was part of a project, "The IoT within health and care" (iVO) [32], which was started in 2018 and focuses on older people living independently in smart home environments.[1] Participant apartments were in three Swedish municipalities: 1) Skellefteå; 2) Kiruna; and 3) Uppsala. We collected data for analysis during the project for approximately two years to model sleep behavior for each household. We considered the ethical principles raised and applied to the project in collaboration with the Department of Homecare at Skellefteå municipality. The participants consented to the use of their data and the installation of in-home sensors. The project complied with the EU GDPR guidelines [33]. The Regional Ethical Board approved the study method and data collection and processing included in this study in Umeå, Sweden (diary no. 2018-189/31).

II. Multiarmed Bandits for HAR and Anomaly Detection

MAB is a simple formulation of reinforcement learning. It is concerned with decision-making problems where the algorithm tries to maximize its rewards by selecting the possible correct arm/action or choice [34], which is a "learning-by-doing" method. The motivation and advantages for using MAB in our work as compared to other ML methods are presented as follows.

1) Most machine learning solutions learn from the underlying distribution of data. However, human behavior changes over time under different circumstances, and we do not know the probability distribution of each participant's sleep data. We need to think of a system adaptable to these changes that applies in uncertain conditions, i.e., where we have many variations in data.
2) Most existing HAR techniques that follow a supervised learning approach requires annotation before implementation. They also require extensive training data sets [27]. MAB addresses the challenges of collecting large data sets since its learning is based on repetitive tasks [35]. For early participation in the deployments, participants with insufficient training data could benefit from the MAB method as it learns and adapts quickly, even though it might not initially be the correct guess.
3) With MAB, there is no need to test all data to show statistical significance—the optimization of the outcomes of the arms is either rewards or losses. When the rewards are high, TS and UCB1 will converge quickly—within only a few data samples. Hence, a few data samples are sufficient to learn unsupervised fashion.

[1]iVO: https://skelleftea.se/digitalisering/digitalisering-i-skelleftea-kommun/arkiv/iot/2020-12-31-ett-forsta-steg-mot-stor-samhallsnytta

TABLE I
Applications of Different MAB Methods in Marketing, Recommendation, Medical Applications, and Anomaly Detection in IoT Devices

Ref.	Year	Application	Data
[46]	2015	Online website marketing optimization	Synthetic data
[47]	2018	Psychology and Neuroscience for human learning	107 students played 200 games each for 15 trials
[48]	2012	Personalized recommendation of news articles	Yahoo! Front Page Today Module dataset, 33 million events
[49]	2015	Online monitoring of high-dimensional streaming data	Solar flare data (satellite images)
[45]	2020	Anomaly detection	One synthetic data set and two real datasets (Twitter, Yahoo! Today Module)
[44]	2017	Anomaly detection	Synthetic and real data (Twitter)
[50]	2020	Database activity monitoring and for anomaly detection	Simulated data of 10 datasets, for 200 users for 3,000 timeframes
[43]	2019	Anomaly detection on attributed networks	Three real datasets attributed networks (BlogCatalog, Flickr, ACM)
[51]	2020	Monitoring IoT devices for Network accessing	Simulated data of 1500 IoT devices

Thus, using MAB, it is possible to build an activity recognition learning-based model that works well on a small training data set to find a balance between learning from historical data. In the next section, we present MAB and HAR-related work to identify the gaps that intersect HAR and MAB research-related topics.

A. Related Work

Most health conditions impact a human's sleep activity and vice versa; thus, analysis of sleep patterns is essential for both daytime and nighttime. This analysis of sleep patterns using motion sensor data is valuable in our research, as we consider both temporal and spatial data of daily activity behaviors [36], [37]. Spatial aspects are considered by looking at motion behavior across different rooms in the apartment/home. Various IoT-based systems using motion sensors for HAR exist to detect the presence and track the movement of residents indoors [27]. This tracking mainly involves current activities ignoring the important (habits) of the residents [28]. The use of sufficient historical data helps to analyze individual behavior patterns better since these discovered patterns provide insights into the habits of the residents. This could enable us to identify ADLs and anomalies that can be helpful for elderly care, and healthcare [28].

Anomaly detection reduces human resource costs by informing caregivers about these anomalies. Also, long-term behavioral changes in users with underlying health issues [38] require offline evaluation of long-term activities. This evaluation can help detect and diagnose diseases, such as Alzheimer's and analyze disturbed sleep patterns, indicating other health issues [39]. These observations could be part of health condition analysis systems for older adults.

Table I summarizes MAB-based applications in literature focusing mainly on anomaly detection. MAB was studied in 1933 by William Thompson to address the exploration-exploitation dilemma [40] and is used in applications, such as clinical trials [41] and Microsoft's AdPredictor [42], where TS is used to predict ad click-through rates on the Bing

TABLE II
HAR SYSTEMS IN SMART HOME ENVIRONMENTS USING MOTION SENSORS AND WEARABLE DEVICES

Ref.	Year	Sensors	Data	Subject Info	Setting	Method	Performance
[52]	2020	PIR, door sensors, pressure sensors	Start time, duration, the transition between the rooms	A single resident	RH, 65 days	Probabilistic model	96%-100% accuracy
[53]	2020	8 PIR sensors in each household	Time duration	30 Households of single residents, multi occupants	RH, 355 days	Long Short-Term Memory-VAE	0.52-0.88 AUC
[37]	2017	Motion, door, and temperature sensors	Time duration	20 Single residents	RH, NA	LR, SVM, decision trees, RF	86% accuracy
[54]	2020	Fitbit Charge HR™ device.	Time duration	39 Volunteer students	106 days	LSTM-RNN	60% accuracy
[60]	2016	ActiGraph GT3X+1 accelerometer	Time duration	92 Adults	One week	CNN and TB-LSTM	92% and 89% accuracy
[61]	2020	Bed sensor	Entry/exit of bed, movement, and posture changes	RH (5 days) and in-lab experiments (18 minutes), and senior care center (2 days)	35 Adults and two older adults	Shannon entropy	92.08% - 99.73% accuracy
[56]	2022	accelerometer and gyroscope	UCI dataset	Smartphones	trained 18-48 years old and validated on 14 participants 66-86 years old	LSTM	89.07% accuracy
[57]	2022	PIR	Two elderly residents' datasets	Multi-resident smart homes	One week of motion sensors data	Decision Tree (DT) classifier	achieved 96%
[58]	2023	gyroscope, accelerometer, and magnetometer	Opportunity dataset from 12 persons	wearable devices	25 hours of data	CNN	88.57%
[59]	2023	gyroscope and accelerometer	8 participants labeled observations	smart watches	21-28 years old activities	LSTM	94% accuracy

search engine. Anomaly detection using MABs in attributed networks [43] and website data have been studied [44] using a statistical threshold known as the K-sigma rule. This works well with a normal distribution, but there are drawbacks to using this rule with skewed distributions [45]. We implemented the MAB algorithms epsilon-greedy, TS, and UCB1 to detect anomalies in attributed networks in real-world data sets, such as BlogCatalog and ACM [43]. Similarly, Ban and He [45] proposed an MAB algorithm that evaluated synthetic and real-world data sets (Twitter and Yahoo Webscope), and the model achieved 98% accuracy.

Table II summarizes previous studies in the pervasive computing area for sleep activity recognition and anomaly detection using IoT-based devices in smart homes. Passive infra-red (PIR), switch sensors [52], thermostat sensors [53], and ambient sensors [37] were used to identify sleep patterns and detect anomalies in sleep from physical activity during waking time using different deep learning methods and probabilistic approaches. Furthermore, in the pervasive and wearable computing research area, wearable sensors capture daily physical data to analyze sleep patterns and measure sleep quality [54], [55].

Hayat et al. [56] proposed LSTM with twofold and tenfold cross-validation methods to classify activities like walking and sitting in a sample of the University of California Irvine (UCI) data set within the 18–48 age group. The model classification accuracy reached 89.07%.

Naccarelli et al. [57] proposed a method for monitoring and measuring two older adults' activities in multiresident smart homes using motion sensors; the goal is to detect walking, moving the arms, and standing events among different persons. The decision tree (DT) classifier achieved 96% in identifying the identity of residents in a supervised test compared to other ML methods. The results vary depending on the distance between the sensor and the person, with a better capacity for detecting movements like walking and moving arms.

Javeed and Jalal [58] proposed a monitoring system using motion-based wearable sensors to analyze motion patterns which may lead to identifying health issues. When evaluated on the Opportunity HAR data set, the CNN model outperformed other state-of-the-art methods, with an accuracy of 88.57% in classifying actions, such as standing, walking, and sitting.

Kandpal et al. [59] proposed LSTM to recognize the actions of an individual wearing a smartwatch using gyroscope and accelerometer data. They collected and labeled data from 8 participants between 21 and 28 years old. The proposed model achieved an overall accuracy of 94%.

In Table I, we show that recent works in MAB applications have not investigated HAR task and anomaly detection research topics within a smart homes context. This observation motivated us to explore the use of MAB algorithms to achieve the goals mentioned in section (II). MAB is rarely implemented within IoT-based systems and is mainly evaluated on attributed networks' real-world and synthetic data sets. Therefore, we foresee the potential of exploring the opportunities of applying the MAB methodology for learning sleep activity and anomaly detection of older adults living in single-resident smart homes. Furthermore, In Table II, we highlight the recent work for the HAR system for recognizing sleep patterns, mainly focused on wearable devices [56], [58], [59]. Wearable devices are considered uncomfortable and impractical for the elderly, as users forget to wear them before sleep [27].

Similar to our study, several studies have also attempted to evaluate sleep quality based on SE [54], [55], [60]. However, the methodology is based on DL methods requiring large training data sets to achieve a relatively acceptable model's performance. For example, for real-time analysis, Clemente et al. [61] proposed a nonintrusive system for sleep monitoring of older adults using a bed sensor that detects movement, posture changes, and other functionalities. They showed high-prediction accuracy in detecting bed usage, entries and exits, movements, posture, and falls from bed. This may be useful with specialized sensors installed in beds; however, our approach focuses only on the off-the-shelf motion sensors installed in smart homes, similarly to [37], [52], [53], and [57]. In contrast to our study, which focuses on sleep patterns, as mentioned above, these studies [54], [56], [58], [59], [60] targeted recognizing other activities, such as standing, sitting, and typing. In our study, we analyzed data for nighttime and daytime sleep to identify sleep patterns and measure the quality of nighttime sleep patterns.

III. PROPOSED SYSTEM

This section describes our research method, including the experimental setup, iVO architecture for sleep activity recognition, and anomaly detection service, identifying participant sleep routines and reported needs from interviews, data sets, installed sensors, and proposed MAB methods.

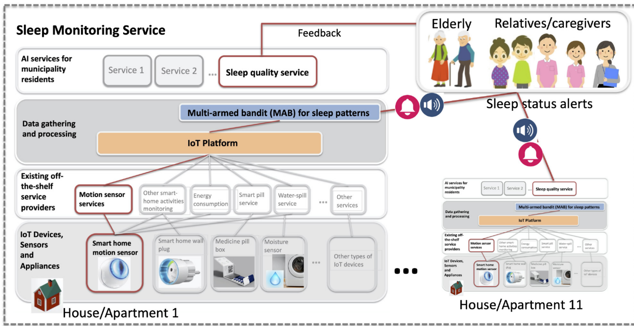

Fig. 2. Sleep monitoring service using off-the-shelf smart home motion sensors running atop our IoT platform for 11 apartments.

A. Sleep-iVO Architecture

This article continues the research work from our previous prestudy on the experiences and challenges of providing IoT-based care for the elderly in a real-life smart home environment [29], [62]. Fig. 1 shows a real-life single-resident older adult (Ewa) in her smart home equipped with IoT devices and a gateway to collect, transmit, and process data for nonintrusive ADL monitoring, including sleep monitoring. We collected data from single-resident smart homes that were equipped with different IoT devices (Fig. 1), offering individuals different types of services when integrated with an IoT platform, as shown in Fig. 2.

Our IoT architecture runs a sleep quality service with a horizontal integration of diverse off-the-shelf sensors and IoT devices for multiple smart homes. It is built using FIAWRE [63], connecting off-the-shelf sensors and IoT devices via an IoT platform, Societal development through Secure IoT and Open Data (SSiO) [64]. The SSiO platform was designed and implemented for IoT applications and services within a smart city. A detailed description of the iVO architecture is described in [62]. The installed sensors are connected via gateways to a service provider to push the sensor data into the SSiO platform, as shown in Fig. 2. For this study, we collected data from motion sensors in each room of the participants' apartments, such as the lounge, kitchen, bedroom, hall, and bathroom, to extract the necessary features.

B. Collected Data Sets

Data collected from interviews helped us validate our data-driven analysis and contributed to data analytics and the minimization of false alarms [29]. Adherence to regular daily routines by the elderly contributes to improved sleep quality [14]. We obtained the routine data for sleep time as shown in Table III from interviews where the participants were asked, "What is your usual sleep time (possible to give approx. time range)?" and to list activity(ies) they do before going to sleep at night. Most participants reported that they woke between 05:00 and 07:00 and went to sleep between 21:00 and 22:00. We collected data from the motion sensors of each participant between 2019 and 2021. The number of days varied between 88 and 463. The size of each collected motion sensor data set was 0.4 to 3.5 megabytes (MB), as shown in Table III. There was variation in the data set size, even though they were collected within the same period as, for example, the case with ID1 and ID2. This can be due to differences in each participant's ADLs triggering the motion sensors differently.

TABLE III
PARTICIPANTS' REPORTED SLEEP TIME BASED ON INTERVIEWS. THE TOTAL NUMBER OF DAYS OF PROCESSED DATA WAS BETWEEN 88 TO 463 DAYS AND OCCURRED BETWEEN APRIL 2019 AND FEBRUARY 2021. THE TOTAL NUMBER OF DAYS USED FOR TRAINING WAS 70% OF THE TOTAL NUMBER, AND THE SIZE OF PREPROCESSED MOTION SENSOR DATA RANGED FROM 0.37 TO 3.4 MB

Household	Wake-Sleep time	Historical datasets date spans From-To	No. of total days	No. of training days	Size MB
ID1	05:00_22:00	2019-04-05 to 2020-10-01	463	324	1.9
ID2	07:00_22:00	2020-04-23 to 2020-10-28	189	132	3.4
ID3	07:00_22:00	2020-06-15 to 2021-02-20	238	166	1.5
ID4	05:00_22:00	2020-04-23 to 2020-11-03	161	112	0.75
ID5	07:00_22:00	2020-04-23 to 2021-02-20	284	199	0.59
ID6	07:00_21:00	2020-04-23 to 2021-02-20	297	271	0.37
ID7	05:00_22:00	2020-04-23 to 2021-02-20	245	172	1.7
ID8	05:00_21:00	2020-04-23 to 2021-02-20	290	203	0.4
ID9	06:00_23:00	2020-04-23 to 2020-10-28	88	62	0.66
ID10	05:00_21:00	2020-04-23 to 2020-10-01	168	118	0.4
ID11	07:00_22:00	2019-04-01 to 2020-01-11	200	140	0.9

TABLE IV
IN-HOME PIR MOTION SENSORS FOR RESIDENTS

Trigger for sensor firing	Place of installation	Function	Sensor data upload	Data type
Detects movement using a PIR sensor. Range set up to 7m	Wall (near the ceiling) in all rooms	Motion, Illuminance, Thermometer, Battery, Battery alarm	Sends signals every 30 seconds if no change in state detected	Binary

C. Sensors and Data Preprocessing

In this study, we looked only at the motion sensors for each apartment. Table IV shows the functionality of the motion sensors, and we used only the function detecting movement in the room [65]. We collected data from single-resident smart homes where the individuals have no pets or relatives. The sensors are installed in locations that cover the whole room without overlapping with other motion sensors in other rooms and thus be able to detect only the older adult—e.g., was not facing a window, so it did not detect someone else outside or other moving objects, in addition, most of the apartments has a similar floor plan.

An example of the sensor installation and floor plan of an elderly home is shown in Fig. 1. Data cleaning was essential to the first phase of the study implementation. It is unavoidable that sensors fail, readings are lost, and duplicated, leading to vagueness and imprecision, and false alarms [66]. This has great importance in elderly care health monitoring systems. Data cleaning applies in particular to motion sensors, redundant data being removed, and missing reading values being identified. An example of a motion sensor reading value is

TABLE V
MOTION SENSOR DATA

Timestamp	Trigger
2019-01-31 14:39	non-active
2019-01-31 14:40	2019-01-31 14:40:02_lounge
2019-01-31 16:45	non-active
2019-01-31 16:46	active
2019-01-31 16:46	non-active
2019-01-31 16:47	2019-01-31 16:46:59_kitchen
2019-01-31 19:21	non-active

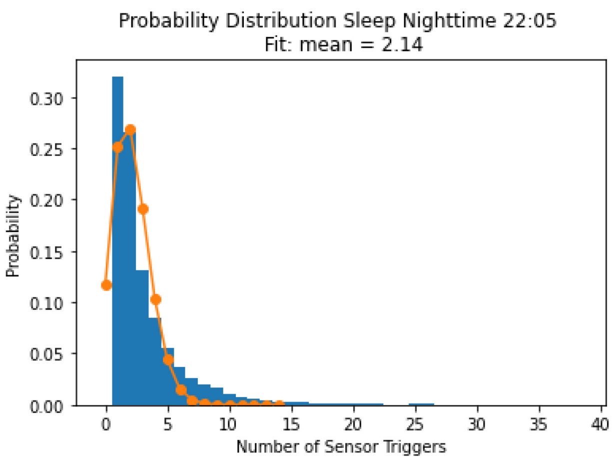

Fig. 3. Poisson probability distribution of raw data from motion sensors, with the mean number of motion triggers (λ) = 2.14 within 22:00 and 05:00 o'clock at night for all participants.

depicted in Table V. The motion sensor is triggered when a motion is detected in the covered area. The time duration elapses in between a sensed movement to an inactive state in the room represents the activeness/movement duration and vice versa. The sensor sends an update every 30 s and when there is a change in the state.

In Fig. 3, we show the distribution of the motion sensor data of the 11 participants: How many times the sensors were triggered between 22:00 and 05:00?

D. Features Engineering

We considered both temporal and spatial data during our analysis of motion patterns, as shown in Table VI. These features were calculated using the algorithm in Fig. 4. These parameters were used to define the sleep variables and to classify sleep quality as good or poor using the principles and desired benchmarks of sleep quality that the National Sleep Foundation defined. We used a time window specified as the start and end times of wake-sleep times, as shown in Table III. The algorithm calculated duration based on the person's presence in the bedroom, either moving or still. During the stillness instance, if a movement is detected in another room, it is identified as a transition. In Fig. 4, we identify room transition and activity/inactivity in rooms.

When the state changed from inactive to active, we looked for movement in other rooms, and then that sensed movement

TABLE VI
EXTRACTED FEATURES FROM MOTION SENSOR DATA

Nighttime sleep	Daytime sleep
Duration of the participant's presence in the bedroom	Duration of the participant's presence in the bedroom
Duration of the participant's activeness or motions	
Number of transitions; leaving the bedroom to another room	

instance in the other room became the transition time. An example of processed data after implementing the algorithm is shown in Table VIII. The feature of the duration of stay in the bedroom combining both movements and stillness is meaningful information that can indicate a change in health, e.g., an increased time spent in the bedroom during the day shows an increased need for the body to rest. Another feature is the duration the sensor is activated (activeness) compared with the stillness duration, providing a better understanding of health conditions. For example, in the Restless Leg Syndrome scenario [36], the bedroom's duration of stillness (quietness) is very short during sleep time. The bedroom motion sensor is triggered all night, indicating the body is continuously moving, causing the sensor to activate.

In sleep science studies [67], [68], good sleep quality for older adults ($\geq$ 65 years) is defined by different variables.

1) *Sleep Latency (SL):* The time spent trying to fall asleep being not more than 30 min.
2) *Sleep Awakening (AW):* The number of sleep awakenings that last more than 5 min during the night and up to two awakenings per night.
3) *Wakefulness Time (WT):* The time being awake after sleep onset being not more than 20 min.
4) *SE:* The actual time spent sleeping in a bed, which is required to be 85% of total sleep time (TST) (S_{time}).

The National Sleep Foundation recommends that normal sleep for older adults lies between 7 and 8 h daily, although between 5 and 6 h can also be considered appropriate [31]. Sleep quality variables are shown in Table VII.

In our study, we calculated sleep variables based on extracted features: the WT as the time being active in the bedroom during the participant's predefined sleep night; SL is the active time during the participant's first hour of reported sleep; AW is the number of times the person transited from the bedroom to another room and returned; and we assumed that the transition would take 5 min or more. In addition, we considered the total time spent in the bedroom during the daytime as the time between waking up in the morning until bedtime sleep. We use these features to train MAB algorithms for sleep behavior analysis of elderly participants during nighttime and daytime.

E. Real-World Data Sets

We assume the underlying distribution of the hourly sleep time duration at night and daytime is binomial for the 11 participants, as depicted in Fig. 5(a) and (b). Each line represents the frequency of sleeping duration in hours for each

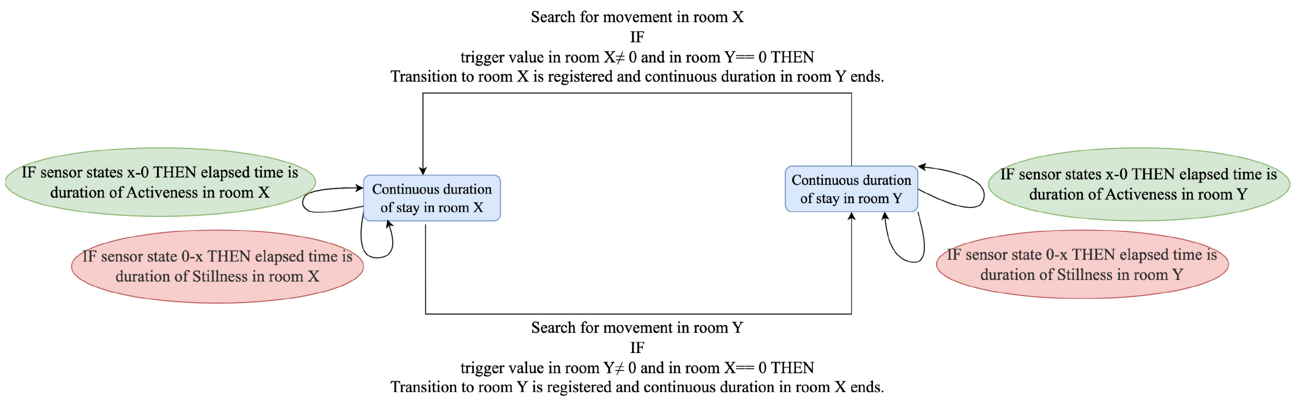

Fig. 4. Algorithm for extracting features from motion sensors data, one sensor located in each room.

TABLE VII
NOTATIONS AND VARIABLES

Term	Abbreviation
Total Sleep Time	S_{time}
Sleep Latency	SL
Sleep-Awakening	AW
Wakefulness Time	WT
Sleep Efficiency	SE
Actual Time Sleeping	ATS
Internet of Things	IoT
Activities of Daily Living	ADL
Human Activity Recognition	HAR
Multi-Armed Bandits	MAB
Thompson Sampling	TS
Upper Confidence Bound	UCB1
Random Selection	RS
Correctly-classified percentage	PCC
Passive Infra-Red	PIR
Megabytes	MB
Independent Identically Distributed	IID
Swedish Association of Local Authorities and Regions	SKL
General Data Protection Regulation	GDPR
Variational autoencoder	VAE
Support vector machine	SVM
Random forest	RF
Logistic regression	LR

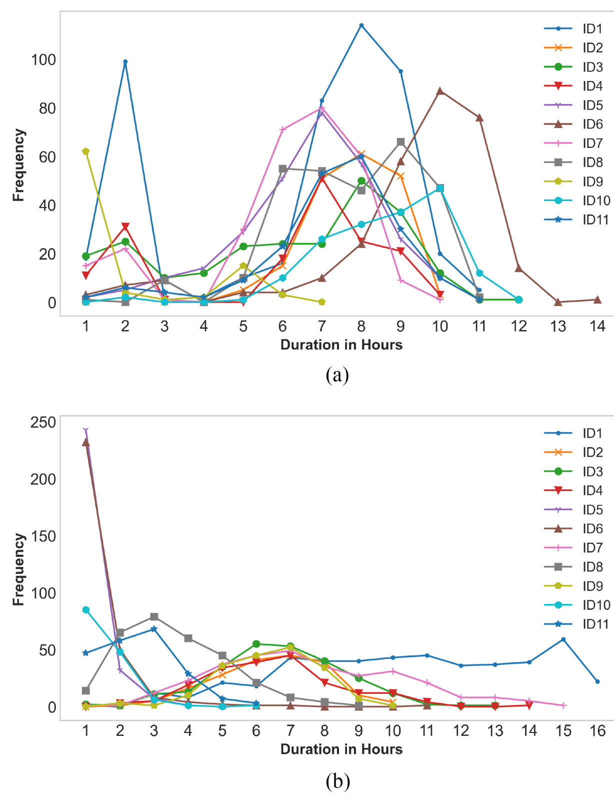

Fig. 5. Frequency distribution of 11 participants' sleep time (a) at night and (b) during the day. Each line represents the frequency of sleep duration of each participant in the bedroom; the number of days is between 88 and 463 from April 2019 until February 2021.

participant. Several abrupt spikes can be spotted in each participant's sleep duration, such as participant ID1, due to changing sleep routines or health-related issues, as shown in Fig. 5(a). Daily routines in a population could have common features, especially if they have the same health conditions, are of the same age group, and live in the same geographical area. This could manifest as having similar sleep distribution, i.e., independent identically distributed (IID) sleep routines. The data drawn from one individual may deviate from normal. Such deviations demonstrate that each participant has a unique sleep routine due to age and health issues—a non-IID data set.

F. MAB Terminology

The terms of MAB are explained in Table IX and are used throughout this article within the sleep recognition context.

G. Problem Formulation

In our study, we consider the problem of sleep pattern recognition and anomaly detection using MAB as a tuple of a set of a known number of bins and unknown probability distributions over the values of the binned data, i.e., sleep

TABLE VIII
PROCESSED MOTION SENSOR DATA

Timestamp	Trigger/Transition	Duration	Place
2019-01-31 14:39	non-active	0.283	bedroom
2019-01-31 14:40	transition	0.0	lounge
2019-01-31 16:45	non-active	0.5	bedroom
2019-01-31 16:46	active	0.7	bedroom
2019-01-31 16:46	non-active	0.12	bedroom
2019-01-31 16:47	transition	0.0	kitchen
2019-01-31 19:21	non-active	0.4	bedroom
2019-01-31 19:22	transition	0.0	lounge
2019-01-31 19:36	non-active	0.52	bedroom
2019-01-31 19:37	active	0.5	bedroom

TABLE IX
MAB TERMINOLOGY WITHIN THE SLEEP RECOGNITION CONTEXT

MAB terms	Our study's problem terms
Arm	Bin of duration or transition
Episode	A day or a night sleep
Bandit is a collection of arms	An extracted feature is a collection of bins
Reward	Value of time duration or number of transitions
Expected reward	Average duration or transition
Exploration	A learning function of participants' sleep duration preferences uses the posterior distribution of rewards to get more information about the estimated mean duration of the other bins.
Exploitation	Optimize decisions based on current knowledge/ observed data so far to select a bin that is selected most of the time
Winner	Bins with the highest probability; normal behaviour
Non-Winner	Bins with the lowest probability; outliers

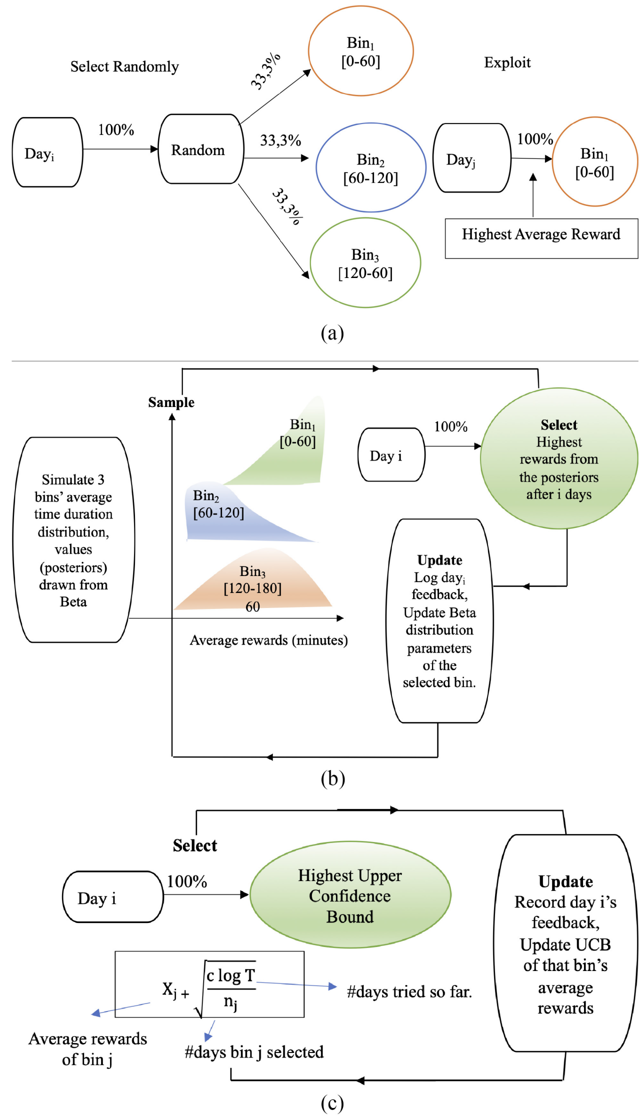

Fig. 6. MAB framework for exploration and exploitation policy of a feature/bandit for three arms/bins: (a) RS, (b) TS, and (c) UCB1.

duration and transitions. The MAB method is good at adapting and learning from the data normal sleep patterns as well as anomalous behavior. Each day, the method selects a bin in the bandit to maximize the total accumulated rewards, assuming they have a uniform distribution. Deciding the length of sleep duration is challenging, as is deciding which duration and number of awakenings are required to classify sleep as poor. Hence, the identification of anomalous sleep behavior is difficult. The solution involves selecting a few binned data (duration/transitions) among many alternatives that have unknown distribution. This decision dilemma can be viewed as a testing problem as we have multiple cases comprising participants' different duration and transition values. We formulate the MAB for this problem by considering each test case as binned duration/transition values instead of the arm. The MAB allows us to continuously update our estimates of the probability distribution of the duration and transitions of each bin. For instance, if the highest expected reward falls within 5–6 h of sleep time at night, it is considered appropriate, and the participant has good sleep habits. However, if interruptions during sleep time occur more than two to three times, it is classified as poor sleep [31] but is considered a normal sleep behavior because it has accumulated the highest rewards.

H. Input Features for MAB

The extracted features of duration in state and transition between rooms are different continuous variables of various participants. Preprocessing these continuous variables by binning them allows for a better representation of the knowledge than continuous values. Since the number of continuous values can be infinite, binned values are fewer. The proposed MAB algorithms require discrete values for duration and transition variables [69]. The bin intervals include the minimum and maximum time shown in Table X. We binned each feature S_{time}, WT, and SLs as 0–60, 0–15, and 0–5 min, respectively. We exploited this frequency for each hour duration and room transition to estimate the expected reward and map each bin into an MAB arm. At each episode, we selected an arm (i.e., a predicted bin duration/transition) as shown in Fig. 6. For instance, in the case of the S_{time} feature, we kept

TABLE X
EXAMPLE OF BINS/ARMS OF S_{TIME} CASE WITH 60-MIN INTERVALS

Bins	0-60	60-120	120-180	180-240	240-300	300-360	360-420
Hours	1	2	3	4	5	6	7

a fixed 1-h frequency value to simulate a sample every day. Initially, we did not have any information on the estimated rewards value of each bin. Each bin was explored, and as time passed, this estimate eventually converged toward the true reward value. We initialized each bin's value to zero. The algorithm selected all bins with equal probability, with about 10–11 bins. Depending on each participant's total sleep duration, each was chosen with an 11.11% probability.

1) Random Selection or Greedy Policy: The RS algorithm selects a bin randomly at each trial. The algorithm performs a uniform exploration over the bins, i.e., at the same rate, by initializing the value of each bin to zero. When a bin is selected, a reward is obtained. However, there is no consideration of what has been observed previously to choose from the best available options for the exploitation phase. The algorithm selects the bin's value with the maximum estimated reward without considering previous observations. This approach only exploits the bin with the maximum reward and no exploration policy to try other alternatives. As shown in Fig. 6(a), the algorithm locks to the bin with the highest estimated reward as time progresses. Each day, the bins tried to maximize the accumulative rewards. The other options with higher long-term returning rewards were missed, and their reward estimates cannot converge to the true value

$$q(b) = \mathbb{E}[r_t | b_t = b]. \tag{1}$$

The action-value function in (1) where q is the value for selecting the bin $b \in B$ at time t is equal to expected reward r at that time. At each trial, each selected bin will have a different reward value

$$b_t = \underset{b}{\operatorname{argmax}}\ (q_t(b)). \tag{2}$$

The policy selects a bin with the highest expected reward, known as the greedy policy. This policy is shown in (2), where the choice of the bin is based on maximizing the current value.

2) Thompson Sampling Bayesian Bandits: Thompson Sampling (TS) addresses the explore-exploit dilemma in the MAB problem with a long-term policy that generates a model of reward probabilities. This method extends the estimated reward to a probability model to sample from to select the optimal bin, which provides confidence in the rewards that increase as we progress. The learning function in TS has only two possible outcomes, a value of 1 or 0, which has a behavior described by the prior Bernoulli distribution. The goal is to find the bin with the highest probability of returning a reward rather than the bin that gives the maximum reward. In (3) and [34], each bin is assigned a Beta distribution with the hyperparameters (α), which counts for successes as S and (β), which counts for failures as F, and initialized to one to generate the uniform distribution. Observing the successes $S_i(t)$ at time t with reward is equal to the value of the selected bin and $F_i(t)$ as the failures with reward as 0 in $b_i(t)$ selecting a bin i

$$\theta_i(t) = \text{Beta}(S_i + 1, F_i + 1). \tag{3}$$

We built a probability model as shown in Fig. 6(b), where values are drawn from a Beta distribution, using (α) and (β) as its parameters. This new probability is known as Posteriors. The algorithm then selects a bin with the probability of its mean being the largest, as depicted in

$$\text{bin}_i(t) = \underset{i}{\operatorname{argmax}}\ (\theta_i(t)). \tag{4}$$

Then, the algorithm updates the counts of the number of times a bin is selected with a reward by increment (α). Otherwise, it updates (β) as shown in (5)

$$\begin{cases} S_i = S_i + 1, & \text{if reward} > 0 \\ F_i = F_i + 1, & \text{otherwise.} \end{cases} \tag{5}$$

As time progresses, the confidence in each bin's estimated reward increases since the distribution concentration is around the mean. The mean of Beta is

$$\bar{x} = \frac{\alpha}{\alpha + \beta}.$$

This is shown when the probability distribution narrows, and the sampled value is closer to the true mean, as shown in Fig. 6(b) first bin's distribution. Hence, it increases the frequency of selecting the bins with the highest probability of the estimated rewards, and those with a low estimate will quickly be dropped from the process. Consequently, exploration will decrease, and exploitation will increase. Different studies explored TS in online settings like Netflix and Twitter, where many alternatives must be selected. As time passes, the strategy is readjusting (i.e., the distribution of the other options) to give more weight to the best bins [34].

3) Upper Confidence Bound: The UCB1 algorithm follows an optimistic policy [70]. The algorithm selects the bin with the highest probability of returning the expected reward within a confidence interval. The bin with the highest upper bound is determined based on each day's updated confidence interval, as shown in Fig. 6(c). In (6), the first term computes the average reward $\bar{X}$ of that bin j, representing the exploitation policy which lies within a confidence interval. The second term is the confidence level of exploration for each bin j at time step T, n_j is the number of times that bin j was selected, and T is the overall total number of times bins were chosen so far. c is a hyperparameter that measures the uncertainty of the bin's expected reward. This confidence bound shrinks by trying that specific bin more often and increases with the total number of bins we have tried. As time passes, the smaller the confidence bounds become, the smaller the uncertainty; hence the exploration chance decreases. Then, the selection of the bins will be mainly based on exploitation

$$b(j, T) = \bar{X}_j + \frac{\sqrt{c \lg\ T}}{n_j}. \tag{6}$$

The outputs from MAB algorithms are S_{time}, SL, WT, and AW bins with high and low probability. In the next section, we will exploit the outcomes of high-probability bins to estimate the SE of each participant and classify sleep quality as poor or good based on 85% SE of TST and two to three awakenings per night.

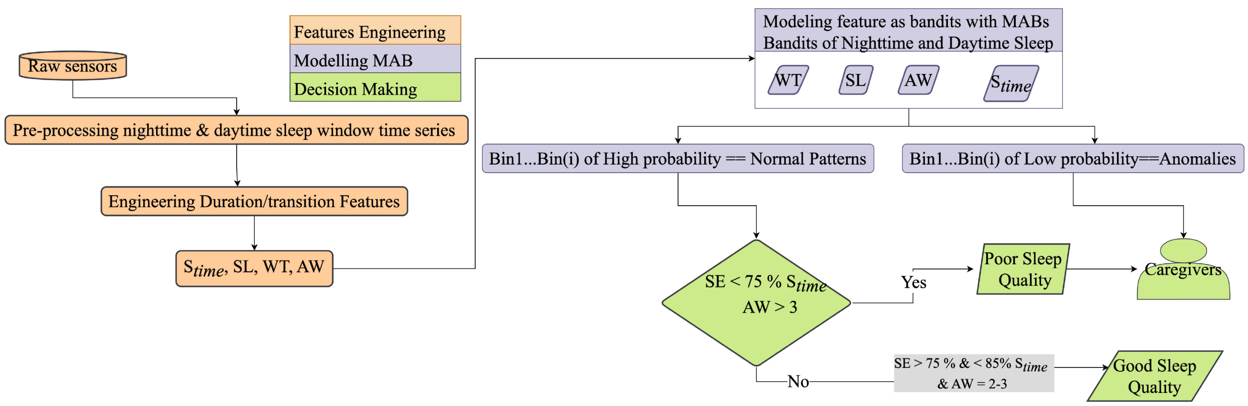

Fig. 7. Framework to identify normal sleep quality and detect anomalies using MAB.

I. Framework for Sleep Quality

Different variables define sleep quality [67], [68]. We used the identified sleep time duration with the estimated high-probability rewards of S_{time}, SL, and WT predicted by MAB algorithms at nighttime to further evaluate sleep patterns as good or poor sleep quality based on the SE [54], [55], [60] and a number of awakenings of each participant. SE in (9) is the ratio between actual time sleeping (ATS) and S_{time}. We designed a framework based on data from the off-the-shelf sensors and IoT devices installed in homes to learn sleep patterns, evaluate sleep quality, and detect anomalies, as depicted in Fig. 7.

There are three stages in this study framework's design for preprocessing the data and features engineering. We used a fixed window based on sleep time reported from the interviews to model the data, Table III. Motion sensor data (Table V) are preprocessed to avoid errors that lead to false outliers. The Poisson distribution of sensor activation of 11 participants, shown in Fig. 3, is further processed to build features based on our algorithm as shown in Fig. 4.

In the third phase, we used the distribution of the sleep duration at nighttime and daytime [Fig. 5(a) and (b)] and exploited the frequency of each bin's bandits to estimate each day's expected sleep variables (S_{time}, SL, WT, and AW in the night). We then used them as bandits for MAB algorithms RS, TS, and UCB1 to learn the patterns and detect anomalies. We analyzed the outcomes of each bandit for each of the 11 participants to evaluate sleep quality using the National Sleep Foundation scores [31] and to identify abnormal sleep behavior based on the resulting bins with high and low probability. Identifying inadequate sleep and anomalies could be used as alerts to caregivers in decision making to identify other health-related issues.

IV. Evaluation and Results

In this section, we present the results of testing the MAB models. Our sleep activity recognition method is primarily based on feature extraction algorithms for nighttime and daytime sleep by quantifying the daily duration of staying in the bedroom, counting the number of transitions, and then learning the behavior by employing MAB models. We trained the proposed models on the S_{time}, WT, SL, and AW features for nighttime and daytime sleep twice for each environment to evaluate the effectiveness of the proposed models. We trained the MAB models on 70% of each participant's original data set. With the assumption that MAB requires few training data [35], the training samples ranged between 62 and 324 days for different participants in this study.

A. Performance Evaluation of MAB

Fig. 8 shows experiments for 9 participants regarding the nighttime sleep behavior during the May–July months and shows the performance of each MAB algorithm in terms of the collected rewards versus the time needed to converge, as well as how each algorithm is adaptable to the changes present in sleep behavior in each day. RS achieves this by taking the bin that currently gives the maximum reward without exploring and randomly trying other bins. On the other hand, UCB1 and TS present more complex solutions than RS. UCB1 selects the bins with the highest reward to ensure most bins are tested. TS locks onto the best bin to exploit, resulting in a high reward. It builds and updates a probabilistic model of the rewards for each bin, sampling from this distribution to select the bins. TS identifies and locks onto the optimal bin and converges early to choose the best bin by updating the hyperparameters without any tuning, providing confidence in the returned rewards as time progresses. Within the first 30–40 trials/days, TS determined the best bin compared to the other algorithms.

Initially, all bins are equally distributed with the same priors, with a rate of choosing the best bin set at 11.11%, i.e., a random chance to select the best out of 10 bins. The results show that TS progression is smoother and more gradual than UCB1 and random algorithms. By the end of 80 days, it averages about 8000 cumulative rewards among all participants, outperforming Random and UCB1. The deterioration of these two is also due to the slight difference between the returned rewards from the bins. TS outperforms RS and UCB1, and it converges quicker than both of them. The TS algorithm identifies the best bin early on and accumulates rewards quicker than the UCB1 and RS policies. Therefore, we selected the TS model to evaluate and classify the learned sleep patterns as good or poor quality, trained on 70% of the data sets. Our objective is a long-term behavioral analysis of sleep patterns [39], [54].

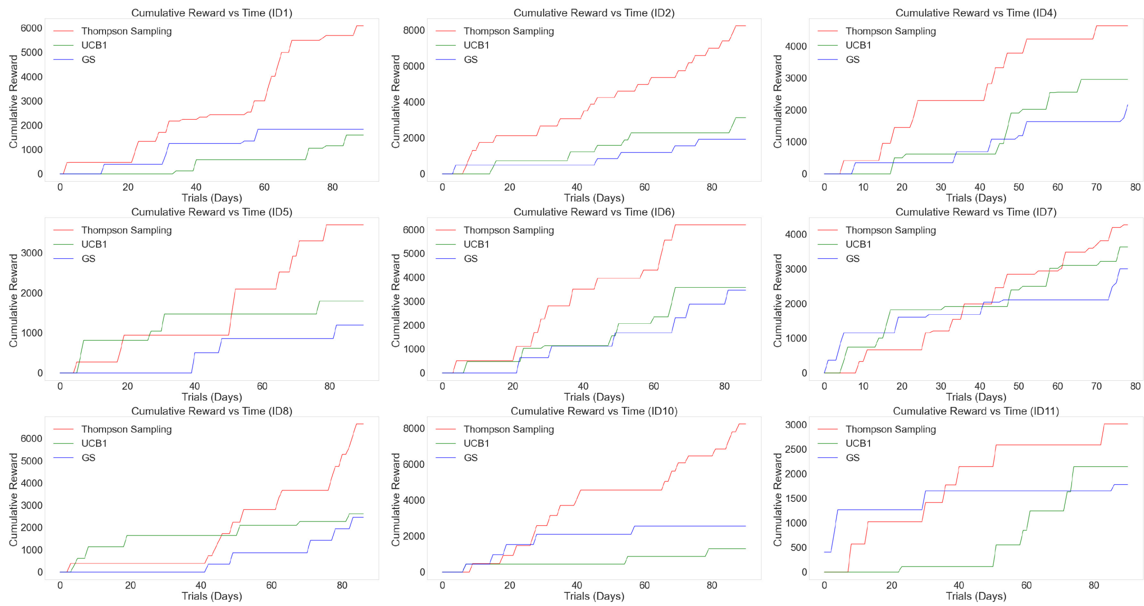

Fig. 8. Performance of MAB algorithms converging over 90 days of sleep nights in the bedroom from May to July for nine households.

We separated a portion of the real-world data set to run the accuracy evaluation—a 30% test set. The number of test days correctly guessed within the winner bins has the highest probability, and the nonwinner bins have the lowest probability of returning the expected rewards. We selected the cutoff score to classify days as normal days using the first three bins with the highest probability for the S_{time} feature, and we selected the first bin for the AW, WT, and SL features as the winner bin. We considered the rest of the bins with the lower probabilities as nonwinners or as an indication of anomalous behavior.

We evaluated the performance of each MAB method using PCC as a metric to assess the overall accuracy of each method, as shown in (7). We used 30% of the data for evaluation. Each day's sleep time values and sleep AW fall within the list of winner bins considered correct predictions. PCC is the ratio of correct predictions, i.e., the number of days (p) within the winner bins list divided by the total number of test days (m). The TS models showed higher PCC rates than RS and UCB1 of the S_{time} and AW features for nighttime sleep (Table XIII). Also, most participants reported waking between 05:00 and 07:00 and sleeping between 21:00 and 22:00; the PCC rates of predicted regular daytime patterns by the TS model had a higher classification rate than other models (Table XIII)

$$PCC = \frac{p}{m}. \quad (7)$$

B. Nighttime and Daytime Sleep Behavior

The best bins by TS model of S_{time} duration in hours and AW patterns of each participant are shown in Table XI. The most probable sleep time S_{time} in hours identified by TS of most households was between 6 and 9 h. For example, the predicted sleep time of participant ID6 is 9 h, the next most probable sleep time is 11 h, and the third most probable sleep time is 10 h, in addition to one-time awakening (AW). There is a pattern among most households in terms of the total time asleep during the night. The awakening frequency during the night, predicted by the TS model, shows that most households woke at least two to three times each night. The awakenings occurred when the participant transited from the bedroom to another room.

TABLE XI
HIGHEST PROBABILITIES OF NIGHTTIME SLEEP IN HOURS S_{TIME} AND FREQUENCY OF AWAKENINGS (AW)-LEARNED PATTERNS IDENTIFIED BY TS MODEL

Households	1st highest Prob.TST	2nd highest Prob.TST	3rd highest Prob.TST	1st highest Prob.AW
ID1	2	7	9	2-3
ID2	7	9	8	2-3
ID3	8	9	3	2-3
ID4	2	7	8	0-1
ID5	7	8	6	4-5
ID6	9	11	10	0-1
ID7	6	7	8	0-1
ID8	9	7	8	0-1
ID9	1	5	3	0-1
ID10	9	8	10	0-1
ID11	8	7	6	2-3

Also, the TS model identified the hours spent in the bedroom as sleeping/resting during the daytime. For example, the most probable amount of time spent in the bedroom between 07:00 and 21:00 for participant ID6 is one hour, the second is 2 h, and the least probable amount of time is 6 h. Also, we observed that the most probable amount of daytime sleeping/resting for most participants is between 1 and 3 h, as shown in Table XII.

C. Sleep Efficiency Scores Evaluation

We evaluated the sleep quality of the identified sleep patterns based on sleep scoring data of ATS and SE calculated in (8) and (9). The S_{time} predicted by the TS model for most

TABLE XII
HIGHEST PROBABILITIES OF DAYTIME SLEEP/RESTING IN HOURS S_{TIME}-LEARNED PATTERNS IDENTIFIED BY TS MODEL

Households	1st highest Prob.	2nd highest Prob.	3rd highest Prob.
ID1	8	7	9
ID2	7	5	6
ID3	5	7	8
ID4	6	7	8
ID5	1	2	3
ID6	1	2	6
ID7	7	5	6
ID8	2	4	6
ID9	7	8	2
ID10	1	2	5
ID11	3	2	1

TABLE XIII
PCC OBSERVATIONS OF THE WINNERS AND NONWINNERS BINNED DATA OF NIGHTTIME SLEEP FEATURES ACHIEVED BY TS, RS, AND UCB1 FROM 70% OF THE TRAINED DATA OF EACH HOUSEHOLD

PCC%	ID1	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11
S_{time} TS	0.6	0.92	0.52	0.57	0.6	0.65	0.84	0.65	0.96	0.74	0.6
S_{time} RS	0.2	0.5	0.31	0.48	0.27	0.09	0.4	0.2	0	0.28	0.04
S_{time} UCB1	0.01	0.01	0.16	0.57	0.47	0.048	0.13	0.65	0.1	0.08	0.53
AW TS	0.81	1.0	0.55	0.73	0.84	0.85	0.84	0.74	0.52	0.97	0.82
AW RS	0.3	0.6	0.25	0	0.46	0.40	0.47	0.74	0.22	0.97	0.82
AW UCB1	0.74	0.14	0.62	0	0.05	0.51	0.45	0.24	0.04	0.022	0.71
S_{time} Daytime TS	0.6	0.6	0.6	0.56	0.73	0.76	0.63	0.45	0.61	0.7	0.77
S_{time} Daytime RS	0.3	0.3	0.04	0.2	0.07	0	0.17	0.14	0.71	0	0.3
S_{time} Daytime UCB1	0.16	0.1	0.57	0.3	0.07	0.76	0.05	0.4	0.01	0.05	0.51

households was 6 to 9 h. The ATS, shown in Fig. 9(a), was between 6.5 and 8.5 h for most households. Most households' SE was above 85% [Fig. 9(b)] of all actual time sleep ranks identified by TS. According to sleep-related studies, SE of 75% is considered uncertain and 85% as appropriate efficiency [68]. One of the participants had a SE score of 66%, which related to lack of S_{time} in the bedroom and identified as a regular pattern for this participant. The TS model predicted the duration patterns of WT and SL as 0–15 min and 0–5 min for each participant, respectively. Most participants had WT and SL less than 20 or 30 min [68]. Also, the ranked probabilities of all participants identified similar sleep behavior as shown in Fig. 9(a)

$$\text{ATS} = S_{\text{time}} - SL - WT. \tag{8}$$

ATS in (8) is the difference between S_{time} and SL plus WT

$$\text{Sleep Efficiency} = \frac{\text{ATS}}{S_{\text{time}}} \times 100. \tag{9}$$

D. Anomaly Detection in MAB

In this article, we studied the problem of anomaly detection in MAB settings, considering the bins with the lowest probability of returning low rewards that significantly deviate from others. Such bins can be insightful in healthcare applications [44]. In Table XIV, we show an example of the normal behavior of the detected bins with high-expected rewards, (the first three bins) for S_{time} and (first two arms) for AW features. The rest of the remaining bins are identified as abnormal

TABLE XIV
EXAMPLE OF IDENTIFIED NORMAL (N) AND ANOMALOUS (A) DAYS OF BOTH S_{TIME} AND AW BY TS MODEL TRAINED ON 70% OF EACH HOUSEHOLD

Sleep night	ID1		ID2		ID3		ID4		ID5		ID6		ID7		ID8		ID9		ID10		ID11	
S_{time} N—A	81	58	53	4	37	35	36	32	53	35	68	37	69	28	47	25	1	26	46	16	42	29
AW N—A	136	3	58	0	41	33	17	6	73	14	74	13	75	14	64	22	14	13	43	1	50	11

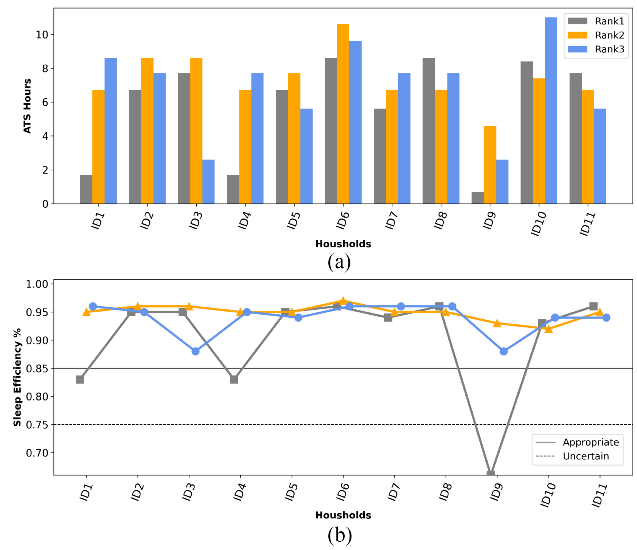

Fig. 9. Three identified bins by the TS Algorithm with the highest probability of actual time sleep and SE: (a) ATS and (b) SE scores based on ATS values and S_{time} prediction outcomes by the TS algorithm

behavior. This enables us to analyze the observations of each participant in terms of any sleep feature.

For example, participants ID1, ID4, and ID9 had less than 85% SE, as shown in Fig. 9(b). ID9 returned the highest accumulated rewards of the selected duration of 2-h sleep as seen in Fig. 9(a). This is a normal pattern of night sleep for participant ID9, which is considered an alarming normal sleep behavior given the ATS and SE scores. Meanwhile, identifying the bins with lower expected rewards as anomalous days helped us identify anomalies from a data-driven analysis perspective. The identified anomalous bins could belong to either good or poor sleep quality.

We used score indicators related to sleep science studies [67], [68] to classify sleep as having a good or poor quality for older adults ($\geq$ 65 years), defined by different variables. For example, good sleep is defined by a number of AWs ≤ 2 per night; and SE of at least 85% of TST (S_{time}). The National Sleep Foundation recommends normal sleep for older adults between 7 to 8 h daily, although between 5 and 6 h can be considered appropriate [31]. Most participants slept less than 5 h, which is not recommended [31]. In our study, as shown in Table XV, we classified AW and SE as appropriate, uncertain, or inappropriate. AW and SE indicator scores are based on scores from [68]. As our participants in the study were elderly adults, an AW of 0–2 was considered appropriate, 2–3 as uncertain, and >3 as inappropriate. For SE, we considered $\geq$ 85% as appropriate, 75%–84% as uncertain, and $\leq$74% as inappropriate. In our study, we use these indicators to assess sleep quality.

TABLE XV
PARTICIPANTS' SLEEP QUALITY BASED ON THE TS MODEL. APPROPRIATE (AP), UNCERTAIN (U), AND INAPPROPRIATE (I) SLEEP FOR OLDER ADULTS [68]

Household	AW	SE	Sleep quality Good/Poor
ID1	2-3 (U)	82% (U)	Poor
ID2	2-3 (U)	96% (AP)	Good
ID3	2-3 (U)	96% (AP)	Good
ID4	0-1 (AP)	82% (U)	Good
ID5	4-5 (I)	95% (AP)	Poor
ID6	0-1 (AP)	94% (AP)	Good
ID7	0-1 (AP)	93% (AP)	Good
ID8	0-1 (AP)	95% (AP)	Good
ID9	0-1 (AP)	65% (I)	Poor
ID10	0-1 (AP)	92% (AP)	Good
ID11	2-3 (U)	96% (AP)	Good

1) If both indicators belong to an uncertain category, they are classified as poor sleep quality.
2) If one indicator is appropriate and the other is uncertain, it is classified as good sleep quality.
3) If an indicator is inappropriate, it is classified as poor sleep quality.

Given the fact that the elderly participants' median age was 86 years old in this study, the use of wearable devices was considered to be inconvenient in this study. Instead, we used a fixed window based on sleep and wake-up time from the interviews of each participant, Table III and the hourly distribution of the sleep duration at night and day, shown in Fig. 5(a) and (b) to validate the outcomes. In this way, we could evaluate the outcomes of the MAB algorithm versus the distribution of hourly sleep. For example, the TS algorithm predicted the most probable amount of nighttime sleep for ID6 participants 9 h, as shown in Table XI using 70% of the data set, also TS was quick to identify the sleep duration (9 h) using only 30% of the data set. That number of hours is close to the participant's hourly sleep distribution of 10 h, as shown in Fig. 5(a).

V. DISCUSSION

Healthcare for disease diagnosis [3] showed promising results for improving the health of individuals and making healthcare more efficient. Sweden is the second-largest country in the OECD that dedicates resources to elderly care. The Swedish Association of Local Authorities and Regions (SKL) considers human resources a challenge for health organizations in the coming years. There is a need to improve efficiency by providing more services (scaling up) using the same resources, thus lowering costs. Therefore there is an opportunity for cost savings without affecting the quality of elderly care [22].

Various health and sleep analysis applications rely on wearable devices to track sleep [7] and depend on the unknown implementation of data processing and modeling methods. Hence, further research on the methods used is necessary to maximize the potential for sleep studies in healthcare. The advantage of our approach is that we assessed sleep quality in smart homes, where motion sensors are embedded in the elderly participants' environment. Wearable devices, such as smartwatches or trackers, might not be convenient for older adults since they are placed on the body. Users might forget to wear them or charge them. Also, considering their socioeconomic background, smartphones can be challenging to use [71].

Therefore, nonintrusive technologies that are invisible to the users can be easily embedded into the environments, such as walls, beds, etc., to monitor sleep patterns. Sleep trackers might overestimate TST and SE [71]. For example, bed-based sensors have shown promising results and can be convenient sleep monitoring devices since they are nonintrusive. They mainly use the body's movements and respiration with a pressure mattress underneath the bed that provides in-bed and out-of-bed states [72]. However, these sensors only collect data when the person lies on the bed and cannot provide continuous monitoring [71].

In this study, we implemented MAB algorithms TS, UCB1, and RS in real-world environments of 11 elderly participants using data sets between 2019 and 2021. We conducted experiments to compare the proposed MAB algorithms' performance after training on 70% data sets. In our study, we sought to determine which algorithm performs better in predicting sleep patterns. We decided that an anomaly occurred when the model predicted a set of bins (3) with the lowest probability of returning a reward, nonwinner bins. The percentages of correctly classified results shown in Table XIII indicate that the TS method performed best. The overall accuracy in terms of PCC showed that the TS model could predict most observations within the winner bins for most of the 11 participants.

TS models can, therefore, easily detect people with abnormal sleep behavior. Also, TS converged more quickly over the same period than UCB1 and RS, as shown in Fig. 8. In summary, TS predicted ATS between 6.5 and 8.5 h for most participants, which is the recommended sleep duration for adults over 65 and indicates healthy eating habits [15], [31].

Our study focused on predicting sleep quality based on sleep metrics used in sleep studies. For most of the evaluated sleep variables (SL, AW, WT, and SE), the committee in [67] and [68] agreed that these measures are appropriate indicators of sleep quality in different age groups [11], [13], [15]. We identified sleep patterns and quantified the overall SE to differentiate between poor and good sleep quality, which is crucial for health. Three participants, ID1, ID4, and ID9, slept less than 5 h, which is not recommended [31]. They may be at risk of cognitive decline and irregular meal patterns [15]. Short sleepers who sleep 5 to 6 h tend to have a poor diet and irregular meal patterns [15]. In a follow-up interview, a relative of participant ID9 showed concerns that their parent might not be taking lunch and dinner regularly. For ID4, the participant had irregular sleep patterns and visited the bathroom more often than normal. Such conditions need attention from healthcare providers, and in this case, after she received a diagnosis and treatment, her condition improved, returning to normal sleep. The TS model identified five participants sleeping/resting 5 to 7 h during the daytime, as shown in Table XII. This is an indication of sleep apnea or excessive daytime sleepiness [20]. Our findings in Table XV show that most participants transited up to three times per night from the bedroom to another room, which is an indicator of inappropriate sleep [68]. However, most participants had high-SE scores and good sleep quality.

Our approach allows for understandable features from raw motion sensor data as shown in the designed framework in Fig. 7. This approach is not limited to sleep activity assessment—it can be used for other human activities, such as eating time and the level of activeness of the person, in terms of how many times they transit from one room to another or movements while staying in a room. From a medical expertise perspective, it is essential that the development of algorithms is transparent to all stakeholders [7] to help them understand the relationships between different sleep and awake features to use them to support their decision making. Our models work well when evaluating small data sets, ranging between 62 and 324 days (Table III), as shown in Fig. 8 and Table XIII. Given the current interest in ML algorithms, which require large data set samples, our study shows that MAB can achieve good predictions with less training data. Our study attempted to classify sleep quality solely by relying on motion sensor data.

VI. Conclusion and Future Work

Our study showed the feasibility of MAB in predicting sleep quality using motion sensor data from sleep and awake periods and a few data sets to learn the behavior. We showed we could identify and learn sleep patterns from simple off-the-shelf motion sensors installed in 11 single-resident elderly apartments. This approach alleviated the privacy concerns raised by the participants regarding vision-based techniques [9]. The TS method outperformed RS and UCB1 in terms of overall accuracy. Our results show that 70% training, i.e., about 62 to 324 days for different participants, was sufficient to learn sleep patterns.

Our study discovered that most elderly participants slept between 6 and 8 h with 85% SE per night. Considering the 11 apartments and the AW in relation to SE, we identified three participants who suffered from poor sleep quality and eight who had good sleep quality, as shown in Table XV. For most of the participants in the 11 apartments, the anomalies belonged to poor sleep quality. In our approach, we built one model per participant since there is a need to personalize sleep analysis from a healthcare perspective.

Sleep quality analysis is important to observe how health evolves and how participants react to, for example, certain medications. This may help diagnose various health conditions linked to irregular/abnormal sleep patterns, thus contributing to preventive healthcare. We foresee many single-resident older adults using such a system for self-awareness of their sleep routines, as it has the advantage of having a nonintrusive setup. In the future, combining motion and bed sensors could enable a more accurate long-term sleep evaluation. Also, we see the need for a global model to identify overall health and sleep trends at the population level, which could be a direction for future research.

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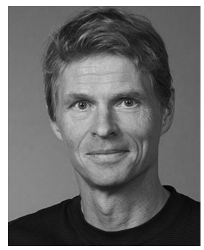

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