Early Detection of Mild Cognitive Impairment in Elderly through IoT: Preliminary Findings

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***Abstract*—Mild Cognitive Impairment (MCI) results in the gradual decline in a person's cognitive abilities, and subsequently an increased risk of developing dementia. Although there is no cure for dementia, timely medical and clinical interventions can be administered to elderly who have been diagnosed with MCI, to decelerate the process of further cognitive decline and prolong the duration that they enjoy quality of life. In this paper, we present our preliminary findings of early detection of MCI in elderly who are living in the community, through the use of Internet of Things (IoT) devices for continuous, unobtrusive sensing. Multi-modal sensors are placed in the residences of elderly, to monitor their Activities of Daily Living (ADL), as well as to detect signs of forgetfulness, which are considered symptoms of MCI. Early results indicate that IoT is a promising technology that can potentially pick up signs of early cognitive decline in the elderly.**

***Index Terms*—Internet of Things (IoT), elderly monitoring, mild cognitive impairment, early detection, eldercare, dementia**

I. Introduction

In Singapore as well as worldwide, it is estimated that approximately one in ten people aged above 60 years old suffer from dementia [3] [1]. With the increasing ageing population and alarming trend of young-onset dementia [8], the number of people who are diagnosed with dementia is expected to double by the year 2030. This has tremendous impact on healthcare expenditure, on both the individual and national fronts.

Although there is no cure for dementia, elderly who have been diagnosed with Mild Cognitive Impairment (MCI) and subsequently receive timely treatment, can reduce their rate of mental degeneration before eventual dementia. Conventional ways to diagnose dementia include questionnaires such as the Mini-Mental Status Examination (MMSE) [2], which are labor-intensive and thus cannot be administered on a regular basis. This necessitates the need for a continuous and efficient monitoring mechanism that can allow for early detection of MCI in the elderly.

Our research project studies the feasibility of the use of Internet of Things (IoT) technology to differentiate between elderly with MCI and those without. Through the use of multi-modal sensors for continuous and unobtrusive monitoring, we collect data on the daily living activities of the elderly, as well as to detect signs of forgetfulness - which are well-known to be indications of MCI. Our research hypotheses are as follows:

1) Primary: Daily activity patterns that are acquired over a brief period of two months will differ between two groups of community-dwelling elderly who are living alone, i.e., those with MCI and those who are cognitively healthy.

2) Secondary: There are correlations between: (i) sensor-based activity patterns of the elderly who are living alone in the community; and (ii) validated psychometric measures of cognition, mood, sleep and social connectedness.

We aim to validate our hypotheses by deploying IoT sensor monitoring systems in the residences of up to 70 community-dwelling elderly, over a period of 18 months. A total of 7 blocks of deployments are planned; each block of up to 10 elderly will have IoT monitoring systems that are installed in their residences for approximately two months.

We have described the experiences and lessons learned from the systems perspective in [5]. This paper focuses on the preliminary analysis and findings of the sensor data collected from the initial two blocks of deployment of our IoT systems in the residences of 17 elderly from across the two groups - cognitively healthy and cognitively impaired. Our early results indicate that IoT is a promising technology that can distinguish between two distinct groups of elderly, using a small set of features that are derived from the IoT sensor data. This is despite the fact that we currently do not have access to the ground truth about elderly who have MCI; such ground truth information will be provided to us by our clinical partner at a later stage of the research project, for validation purposes.

The rest of this paper is organized as follows: Section II discusses background and related work. Section III details the system components and algorithms for activity feature extraction. We present our preliminary findings based on the data collected from the in-home monitoring system for early MCI detection in Section IV. We conclude the paper with discussions and future work in Section V.

II. Related Work

Conventional ways to detect MCI in elderly include the MMSE [2] and Montreal Cognitive Assessment (MoCA) [4] questionnaires, which are widely used to measure cognitive impairment in clinical settings. However, questionnaires such as these require personnel to administer them to the elderly, and can be labor-intensive. As these questionnaires are typically administered neither frequently nor regularly, they cannot detect or capture minute differences in the elderly's (cognitive) behaviors over time.

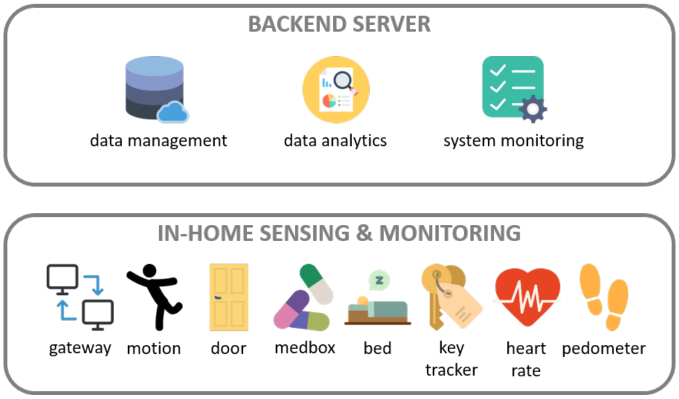


Fig. 1. Simplified overview of system components.

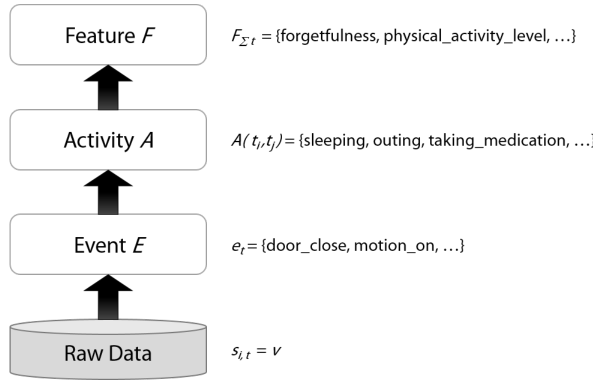


Fig. 2. Feature extraction framework.

Several elderly-centric technologies to improve the wellbeing of elderly have emerged in recent literature. For instance, studies such as SHINESeniors [9] utilize unobtrusive in-home monitoring systems to enable community caregivers to provide timely care for elderly who are living alone. Remote monitoring of elderly with chronic conditions through the use of multi-modal sensors, as a means of improving care efficiency and improving patient outcomes, have also been widely studied [7]. However, these applications are not specifically targeted at the early detection of MCI in elderly who are living in the community.

An in-home video monitoring system to assess the activities of daily living and detect MCI in the elderly is proposed in [6]. However, such video-based methodologies are subject to privacy concerns, and may not be scalable or replicable across different elderly demographics. Zygouris et al [10] proposes the use of a virtual reality cognitive training application for remote detection of MCI. This requires active participation by the elderly on a daily basis, and may lead to participation fatigue, which can affect the early detection of MCI.

Our work focuses on the use of unobtrusive and passive IoT devices for the continuous monitoring of the elderly, for early detection of MCI. These in-home monitoring systems have secondary uses, such as to enhance physical safety of elderly who are living alone at home.

III. IoT Monitoring System for Early Detection of MCI

A. System Components

Figure 1 illustrates the simplified overview of the components of the IoT monitoring system used for early detection of MCI in community-dwelling elderly. The system comprises two key components: (i) IoT device frontend that is deployed in each elderly residence for in-home sensing and monitoring; and (ii) backend server that houses the data management, data analytics and system monitoring engines.

The IoT device frontend comprises the following:

1) Infrastructured Sensors: Passive Infra-Red (PIR) motion sensors are placed in each part of the elderly's residence - such as the living room, kitchen and washroom. A door contact sensor is placed on the main door of the residence, to detect if the door has been opened/closed; together with the sensor data from the motion sensors, we can derive if the elderly has left the residence. The medication box sensor provides information on inferred medication adherence (based on usage of the medication box). A bed sensor based on fibre optics technology is placed under the mattress of the elderly, to detect if he/she is sleeping on the bed. These infrastructured sensors are equipped with either ZWave or WiFi radios for communications to the gateway(s).

2) Non-Infrastructured Sensors: A commercially available wearable is used to acquire heartrate and daily pedometer readings, and provide indications on the physical activity level of the elderly. Bluetooth Low Energy (BLE) enabled proximity beacons are also tagged to essential items such as keychains and wallets; these are used as proxies for indications of forgetfulness - for instance, if the elderly leave their residences without carrying these items with them.

3) Gateway: Gateway devices are used to aggregate and transmit data from the multi-modal in-home sensors to the backend system, for further processing and analysis.

The data management module in the backend server is responsible for the storage of the data in an enterprise-level database, and retrieval of the data via Application Programming Interfaces (APIs). The data analytics engine implements the algorithms required for feature extraction of the daily activities of the elderly, based on the raw sensor data that is collected by the IoT devices in the home. A system monitoring tool is in place, to ensure that the IoT sensor data collected by the system is sufficiently reliable.

B. IoT Data Streams

Each of the IoT sensors may send periodic or event-driven data, depending on its modality. Each sensor data point is in the form of the tuple {`sensor id`, `timestamp`, `value`}. We denote the raw sensor data from a sensor i at timestamp t as $s_{i,t}$.

1) Event-Based Sensors: The PIR motion sensor is an event-based sensor that is triggered whenever motion is detected to be on or off. Similarly, the door contact and medi-

Algorithm 1: Computation of `outing` activities between time t_0 and t_n

Input : Continuous data streams of door contact sensor d and all the motion sensors $m \in S_m$, in the form $s_{i,t} = v$, where $t_0 \leq t \leq t_n$, and $v = \{0, 1\}$.

Output: T containing set of tuples in the form of $\{t_{start}, t_{end}\}$, where t_{start} and t_{end} are the start and end timings of each `outing` activity.

$t_{curr} = t_0$; $t_{start} = \emptyset$;
while $t_{curr} \leq t_n$ **do**
    if $s_{d,t_{curr}} = 0$ **then**
        $t_{start} = t_{curr}$
    else
        if $t_{start} \neq \emptyset$ **then**
            if $s_{m,t} = 0 \; \forall m \in S_m, t_{start} < t < t_{curr}$ **then**
                $T = T \bigcup \{t_{start}, t_{curr}\}$
            else
            end
        else
        end
        $t_{start} = \emptyset$
    end
    $t_{curr} = t_{curr} + 1$
end
return T

Algorithm 2: Computation of *forgetfulness* feature between time t_0 and t_n

Input : Continuous data streams of all proximity beacons $b \in S_b$ in the form $s_{i,t} = 1$, where $t_0 \leq t \leq t_n$; and T containing set of tuples of all `outing` activities between time t_0 and t_n as computed by Algorithm 1.

Output: F containing set of forgetfulness incidents for each `outing` activity.

for $T_{curr} \in T$ **do**
    $t_{start} = T_{curr}[t_{start}]$; $t_{end} = T_{curr}[t_{end}]$;
    for $b \in S_b$ **do**
        if $s_{b,t} = 1 \; \forall \; t_{start} < t < t_{end}$ **then**
            $F = F \bigcup \{t_{start}, t_{end}, b\}$
        else
        end
    end
end
return F

cation box sensors are event-based sensors that are triggered when the door or medication box is opened or closed.

2) Periodic Sensors: Periodic sensors in the system include the proximity beacons, which broadcast Eddystone packets at configurable periodic intervals to indicate their presence. The wearables provide periodic updates on the heartrate and daily stepcount (pedometer readings) of the elderly. The bed sensor from a third-party vendor provides periodic status updates on whether the elderly is asleep in bed, or whether the elderly is out of the bed.

C. Feature Extraction

Figure 2 illustrates the feature extraction framework used in our IoT system for elderly monitoring and early detection of MCI. Each raw sensor data $s_{i,t}$ from sensor i at time t is first converted to an event of interest e_t. Some of the events that are of relevance and interest include, but are not limited to: door open/close events, motion on/off events in each part of the residence, medication box open/close events, proximity sensor present/absent events, and so on. A sequence of one or more events are then used to compute the activity of interest $A_{t_i,t_j} = \{e_{t_i}, e_{t_{i+1}}, ..., e_{t_{j-1}}, e_{t_j}\}$ between two time intervals t_i and t_j, where $t_i \leq t_j$. Finally, the feature of interest over a period of time $F_{\sum t}$ is computed based on the activity levels A of the elderly. Some of the features that are of interest in our work include the level of forgetfulness, physical activity levels, and sleep quality.

We demonstrate the feature extraction framework through the computation of one key feature in our study, i.e., *forgetfulness*, which can be measured by the incidence of the elderly forgetting to bring his/her key and/or wallet when he/she leaves the residence.

The door contact sensor d generates a raw data point $s_{d,t} = v$ at time t. This raw data is translated into a `door close` ($v = 0$) or `door open` ($v = 1$) event $e_t = \{d_{close}, d_{open}\}$ at time t. Similarly, each motion sensor m generates the raw data $s_{m,t} = v$ at time t, which can be translated to a `motion off` ($v = 0$) or `motion on` ($v = 1$) event $e_t = \{m_{off}, m_{on}\}$ at time t. The sensor data from each proximity beacon b is in the form $s_{b,t}$; the presence of the beacon data indicates the event that the item (such as keychain or wallet) that the beacon b is tagged to is present within the residence at time t.

We define the `outing` activity as the period of time that the elderly spends out of his/her residence. In our IoT system, this is derived based on a combination of the door and motion events, which are in turn computed based on the raw door and motion sensor data. Specifically, an `outing` is defined semantically by the time period between a pair of `door close` and `door open` events, during which there are no `motion on` events. Algorithm 1 summarizes the computation of the `outing` activity based on the sensor data from the door sensor d and all the motion sensors $m \in S_{motion}$ in the residence.

We can then compute one of the *forgetfulness* features, based on the `outing` activities computed in Algorithm 1. Semantically, this is determined by whether the proximity beacon device that is tagged to each elderly is still detected (by the gateway in the elderly's residence) during each of the `outing` activity. The computation of the *forgetfulness* feature

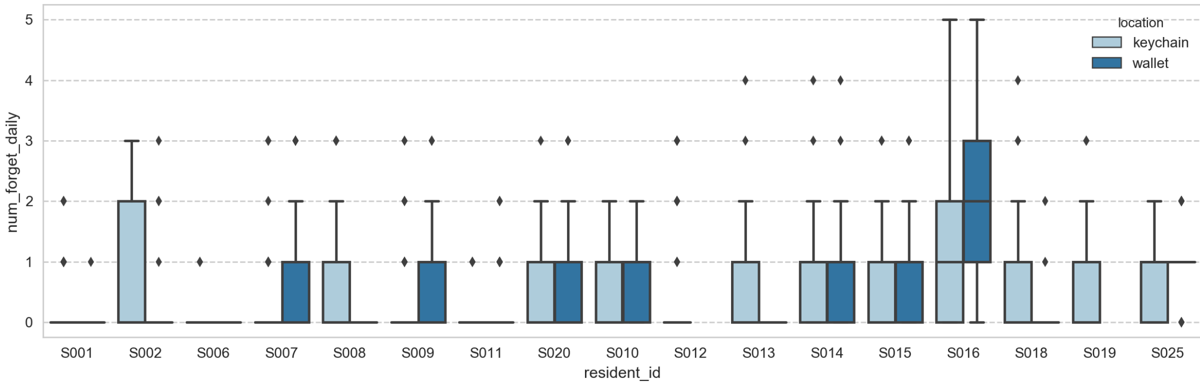


Fig. 3. Daily *forgetfulness* incidents in the 17 elderly, involving the keychain and/or wallet. Each boxplot represents the distribution of number of daily forgetfulness incidents, for either the keychain (light blue) or wallet (dark blue). Two elderly S012 and S019 have not consented to the use of beacons that are tagged to their wallets.

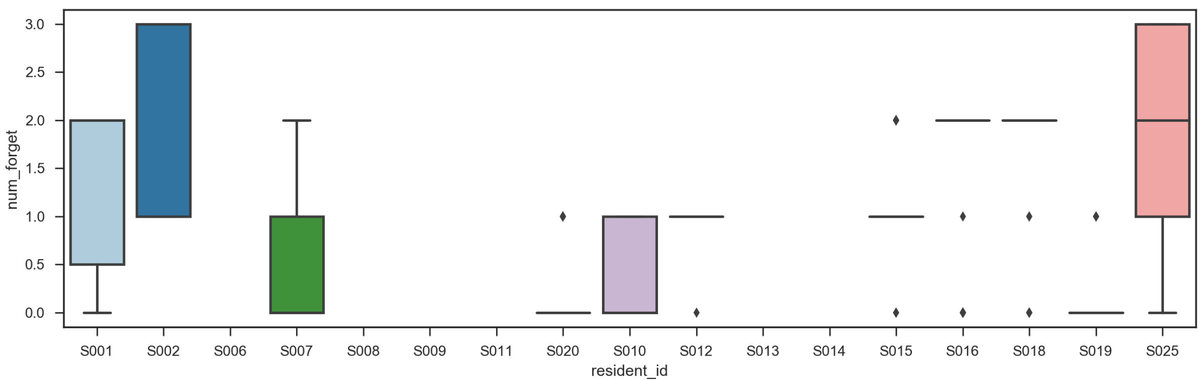


Fig. 4. Daily medication intake forgetfulness frequency of the elderly. Each boxplot represents the distribution of number of times that the elderly has missed his/her medication on a daily basis, as inferred from usage of the sensor-enabled medication box that is issued to them. S006, S008, S009, S011, S013 and S014 are not issued with sensor-enabled medication boxes, as they do not have medications that they consume on a regular basis. S012 is reported to have lost the medication box; S001 and S007 are reported to have technical issues with their medication boxes.

is outlined in Algorithm 2.

In addition to the *forgetfulness* feature, we compute features such as outdoor activity levels and sleep quality (as determined by the periods of `outdoor` and `sleep` activities). These are indicative of the physical and mental wellbeing of the elderly as they go about their daily activities.

Due to the complexity of the IoT sensor system, there may be periods of time during the deployment that the system is deemed to be *offline*, i.e., there is no data that is received from the sensors between a period of time. We take into account the *offline* periods of the system, and omit readings of days with partial system data.

IV. Evaluation

In this section, we discuss some of the preliminary findings obtained from our IoT deployments in the initial two blocks of the study, involving a total of 17 elderly participants. In particular, we seek to answer the primary hypothesis of the research project, to determine if there are differences in the daily activity patterns of the two groups of community dwelling elderly, over a period of two months.

A. Forgetfulness Incidents based on Personal Items

Figure 3 illustrates the number of forgetfulness incidents (based on the frequency that the elderly forgets to bring his/her keychain and/or wallet during outing activities), on a daily basis. Elderly S002 and S016 exhibit particularly high levels of forgetfulness in forgetting to bring their items when they leave their residence, and likely to be suffering from MCI. Elderly S001, S006, S011 and S012 have very few forgetfulness incidents based on their items, and are likely to be cognitively healthy.

B. Forgetfulness Incidents based on Medication Intake

The daily medication intake forgetfulness frequency, as inferred from the usage of the sensorized medication box sensor, is shown in Figure 4. Elderly S002, S016, S018 and S025 exhibit consistently high frequencies of forgetting to consume their medication intake, and are likely to be suffering from MCI. S002 and S016 have previously been highlighted to have high incident levels of forgetfulness, based on their keychains and wallets. S001 and S007 are reported to have technical issues with their sensorized medication box; hence, their readings can be ignored. Elderly S012 is reported to have lost the medication box that was issued.

C. *Daily Living Patterns based on Medication Intake Timings*

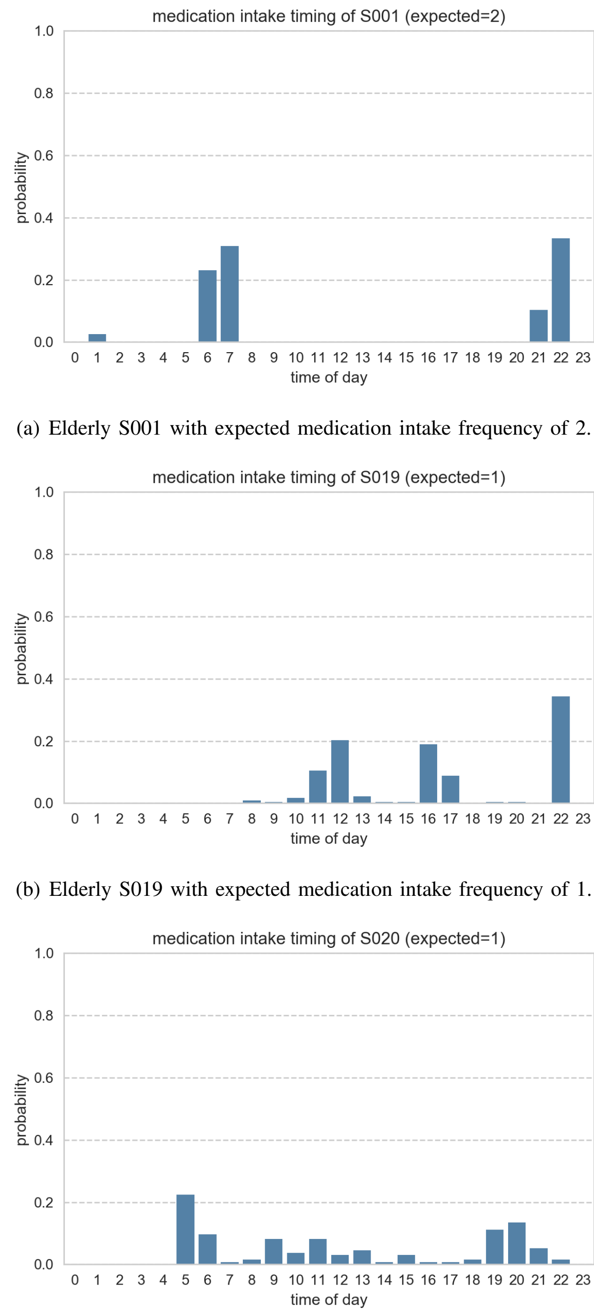
Medication intake timings based on usage of the sensorized medication box, can also shed some light into the cognition levels of the elderyly. Figure 5 illustrates the inferred medication timings of three elderly - S001, S019 and S020 - with differing medication intake timings. Elderly S001, who is believed to be cognitively healthy (based on the forgetfulness incidents), has an expected daily medication intake of 2. Figure 5(a) shows that the elderly adheres to very regular medication intake timings twice a day, viz. between 6 AM to 7 AM, and between 9 PM to 10 PM.

Although Elderly 019 does not appear to have forgotten to consume medication (based on Figure 4), the elderly has an average daily medication consumption intake frequency of 2 to 3 times, as shown in Figure 5(b). The medication intake timings are distributed over 3 distinct timings, viz. between 11 AM to 12 noon, between 4 PM to 5 PM, and at 10 PM. Further studies on other aspects of the daily living patterns are required to better understand if the elderly is overdosing on medication (due to forgetfulness), or if the elderly is taking more medication due to other chronic conditions.

Figure 5(c) shows the medication intake timings of Elderly S020, who is likely to be suffering from MCI (based on the forgetfulness incidents). Although the elderly is expected to consume medication only once a day, the medication consumption timings are very widely distributed across all the waking hours. This is an indication that the elderly does not have regular patterns of daily living, and can potentially be a cause of concern - especially if the there are other indices to suggest that the elderly is suffering from MCI.

D. *Other Daily Living Patterns*

We have also studied other daily living patterns (features) that can be derived from the IoT sensors that are deployed in the elderly's residences. These include the frequencies and durations that the elderly spends out of the residence, heartrate, steps taken daily, and sleeping patterns. Further research and analysis on the data is required to support the use of these features to differentiate between elderly who are cognitively healthy, from those who suffer from MCI.



(a) Elderly S001 with expected medication intake frequency of 2.

(b) Elderly S019 with expected medication intake frequency of 1.

(c) Elderly S020 with expected medication intake frequency of 1.

Fig. 5. Medication intake timings of the elderly.

V. Discussion and Future Work

With early detection of Mild Cognitive Impairment (MCI), elderly who are at risk of suffering from dementia can receive timely medical interventions, which can slow down the process of cognitive decline.

We have presented our preliminary findings on the use of Internet of Things (IoT) technology to differentiate between elderly who are cognitively healthy, from those who suffer from MCI. This is achieved through the use of passive and unobtrusive sensor devices that are placed in the elderly's residence, to monitor their daily living patterns.

Early results indicate that the use of IoT for early detection of MCI is promising. Out of an initial sample size of 17 elderly from across two blocks of deployment, and using only three features (forgetfulness incidents of personal items, forgetfulness incidents of medication intake, and medication intake timings), we are already able to identify elderly who are likely to be suffering from MCI (S002, S016), as well as elderly who are likely to be cognitively healthy (S001, S006, S011, S012). Further research is required to analyze other data features and provide more accurate classifications on the two groups of elderly, as well as to enhance system reliability for data acquisition from the IoT system. We will also validate our results with ground truth information (about whether the elderly has MCI) from our clinical partner, at a later stage of the research project.

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