RouterSense: A Passive, Network-Based Health Monitoring System for In-Home Patients

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Abstract

Remote patient monitoring for older adults is crucial for the early detection of neurological disorders, such as Alzheimer's and Parkinson's, as well as mental health conditions like depression and anxiety. Existing solutions, like wearables and in-home sensors, have limitations in terms of compliance, privacy, and cost. We introduce RouterSense, a plug-and-play, connect-and-forget, always-on, software system that passively analyzes home network traffic to infer health-related behavioral patterns in older adults who live at home. Using machine learning to detect deviations from typical daily behavior patterns, RouterSense can offer insights into disease progression, facilitate early detection, and assess overall well-being. In a preliminary study (N=1), we demonstrate RouterSense's ability to monitor key behaviors such as leaving and returning home, sleep/wake cycles, and screen-time activities. This work lays the groundwork for future developments in passive remote monitoring systems.

Background and Related Work

Need for Long-Term Monitoring: Older adults, particularly those living alone at home, are increasingly vulnerable to chronic health conditions and neurodegenerative diseases (Barnes et al. 2006; Victor et al. 2000; Pugh 2009; Fratiglioni et al. 2000). Research shows that early detection of health changes in this population enables timely intervention and significantly improves outcomes (Popp et al. 2024; Dodge et al. 2012). Alzheimer's disease (AD), for example, has a prolonged preclinical phase, during which subtle cognitive, sensory, and behavioral shifts often emerge years before formal diagnosis (Sperling, Mormino, and Johnson 2014). Early signs—such as changes in cognitive engagement, sleep disruptions, and social withdrawal—are valuable biomarkers for detecting the onset of AD and other conditions (Vitiello et al. 1990; Bliwise 2004). Early identification of these subtle shifts is essential for initiating interventions that may slow disease progression.

Limitations of Current Remote Monitoring Solutions: We compare across existing remote patient monitoring techniques in Table 1. As shown in the table, current solutions—including wearables, in-home sensors, and cameras—are often impractical for long-term use, particularly for older adults with cognitive impairments (Schütz et al. 2022). Traditional neuropsychological assessments, while useful, are episodic and often miss subtle early-stage changes due to limitations in sensitivity and inherent biases (Dorsey et al. 2017). Table 1 emphasizes these challenges, highlighting the need for a tool like RouterSense: a non-invasive, always-on, software-only solution that uses passive network monitoring to deliver continuous behavioral insights.

Digital Biomarkers in Remote Monitoring: RouterSense leverages digital biomarkers—objective, quantifiable data passively collected by digital devices—to monitor cognitive and behavioral health without disrupting daily routines (Vasudevan et al. 2022). Research shows that digital biomarkers can provide early insights into conditions like Alzheimer's and depression (Lussier et al. 2018; Piau et al. 2019; Babrak et al. 2019). For example, reduced computer use correlates with hippocampal atrophy, a marker of early Alzheimer's (Lussier et al. 2018; Piau et al. 2019; Silbert et al. 2016), while time spent outside the home links to cognitive decline and social isolation (Petersen et al. 2013; Buck et al. 2019; Suzuki and Murase 2010). Additionally, disrupted sleep patterns are associated with cognitive and mental health risks, including depression (Cacioppo et al. 2002), and schizophrenia (Birchwood, Spencer, and McGovern 2000; Wang et al. 2016). Monitoring these everyday behaviors enables early detection of health conditions, supporting timely intervention.

Network-Based Machine Learning for Healthcare: Machine learning models for network traffic have been used in various contexts, such as app fingerprinting (Marzani et al. 2023; Bovenzi et al. 2023; Xu et al. 2023; Oh et al. 2023; Buck et al. 2019), device fingerprinting (Babrak et al. 2019; Silbert et al. 2016; Petersen et al. 2013), and user activity inference (Xue et al. 2022; Vasudevan et al. 2022; Babrak et al. 2019; Silbert et al. 2016). However, there are few known systems focused on health monitoring in home environments. To the best of our knowledge, RouterSense is the first tool to detect deviations from established user activity baselines—providing insights that may reveal early markers of disease, track the progression of existing conditions, and support overall patient well-being.

Methods	Strengths	Weaknesses
Self-Reports (e.g., Diaries, Interviews)	Provides detailed, subjective insights into perceived behaviors, moods, and cognitive changes.	Prone to recall bias; inconsistent or inaccurate due to memory issues in cognitively impaired patients; episodic data may lack continuity.
In-Home Sensors and Cameras	Captures comprehensive data on in-home activities, such as movement and environmental interactions.	Privacy-invasive, high setup and maintenance costs, may feel intrusive, requires regular calibration.
App-Based Monitoring	Always-on, continuous monitoring of app usage	Drains battery; limited to phone activity, no multi-device tracking.
Wearable Sensors (e.g., Apple Watch, EEG Monitors)	High-resolution data collection, including metrics like heart rate and movement patterns.	Expensive, adherence issues, requires wearing device; challenging for long-term use in those with cognitive impairments.
Router-Based Passive Monitoring (This work)	Always-on, "connect-and-forget" setup; privacy-preserving and highly scalable, providing continuous insights into daily activity patterns across multiple connected devices and applications within the home.	Coarse-grained, indirect measurement based on network activity; captures broad behavioral patterns only.

Table 1: Comparison of Remote Monitoring Methods

System Overview

System Design

Patients, caretakers, and/or healthcare providers can install RouterSense software on the patient's existing commodity computers. Supported operating systems include Windows 10/11 and macOS. If a patient does not have a spare computer, we can also ship a pre-configured Raspberry Pi, and they only need to connect the Raspberry Pi to the home router's Ethernet port, requiring no additional setup or technical expertise—an essential feature for the elderly. This connect-and-forget design enables RouterSense to continuously capture and analyze encrypted network traffic of mobile devices (including apps), computers, and various IoT devices on the elderly participant's home network. RouterSense runs in the background; there is no need for the patient to interact with RouterSense after the installation.

How RouterSense Collects Data

RouterSense leverages the existing IoT Inspector's codebase (Huang et al. 2020), which uses ARP spoofing, to enable hardware-free, software-based network traffic collection from all connected devices on the home network. This allows RouterSense to monitor device usage patterns continuously without requiring any direct user engagement.

Key Components of RouterSense

Baseline Profiling: RouterSense establishes behavioral baselines using unsupervised clustering algorithms, capturing typical daily patterns such as sleep and wake times, time spent at home versus outside, and app and device usage trends. These baselines serve as reference frameworks, providing a benchmark that reflects normal activity levels and routines for the elderly individual.

Anomaly Detection: Building on these established baselines, RouterSense monitors for deviations in patient behavior in real-time. Anomalies—such as unusual late-night screen usage, unexpected inactivity, or an increase in specific types of application use—are flagged as potential indicators of behavioral shifts. These flagged events may signal emerging health concerns, including disrupted sleep, social isolation, or cognitive decline, thereby supporting proactive monitoring and facilitating early intervention.

Preserving Patient Privacy

Federated Learning for Local Processing: RouterSense employs federated learning to process raw data locally, ensuring that personal information remains within the home network and preventing external transmission. Initially, a baseline model is built centrally to capture general behavioral patterns. As participants use the system, RouterSense learns additional individual behaviors by collecting model weights from their devices without accessing their actual data. This approach enhances privacy while allowing the model to adapt to unique user interactions, resulting in more accurate and personalized health monitoring.

Hostname-Based Whitelisting: RouterSense uses hostname-based whitelisting to ensure that monitoring is limited to only the devices and applications specified by the user. By focusing on specific hostnames associated with authorized apps and devices, this method decreases the risk of collecting network traffic from sources the user has not explicitly approved. This approach helps protect user privacy by excluding traffic from non-monitored apps and devices, ensuring that data collection aligns strictly with user preferences and minimizes unnecessary data collection.

Methodology and Preliminary Study (N=1)

Study Design

A pilot study was conducted in a single household over a 48-hour period, featuring one of the co-authors as the participant—a healthy male aged 30 to 40 years. RouterSense was deployed on a MacBook Air, and was passively capturing continuous network activity as the participant went about their normal daily routine. To validate specific behaviors, the participant provided recall-based labels for activities such as social media usage and video streaming. This preliminary study aimed to explore RouterSense's effectiveness in identifying behavioral patterns through passive network monitoring. The following analysis highlights insights derived from the captured traffic patterns, focusing on screen time, sleep activity, and time spent in and out of the house.

Findings from Network Traffic Patterns

Leaving and Returning Home: At approximately 4:00 PM, as shown in Figure 1, a marked decrease in upload network traffic from the participant's phone suggests they have likely left the house. Leveraging baseline profiles that capture each device's typical background traffic—both during active and idle states—RouterSense identifies this deviation as a drop below expected activity levels. This absence of usual background traffic, combined with periodic ARP scans showing the phone is no longer responding, supports the inference of the participant's absence. The pattern reverses around 8:00 PM, when the phone reconnects, resuming its baseline activity and responding to ARP requests, signaling the participant's return. Although not depicted here, RouterSense also detects an overall reduction in network activity across all household devices during the participant's absence, further supporting this inference. These observations were validated by the participant, who confirmed the times of departure and return.

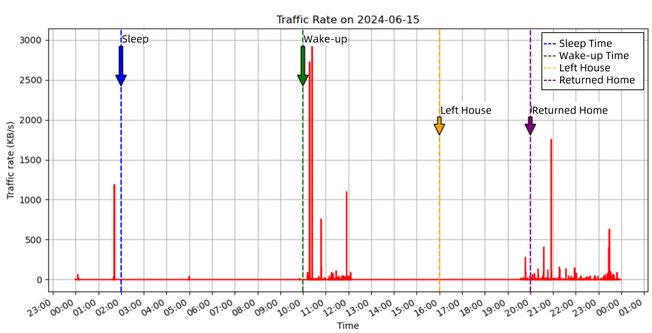

Figure 1: Real-world uplink traffic rate (KB/s) of an author's phone on June 15, 2024, illustrating the correlation between network activity and daily events. Key moments include going to sleep at approximately 2:00 AM, waking up at 10:00 AM, leaving the house at 4:00 PM, and returning home at 8:00 PM, as indicated by corresponding fluctuations in the phone's traffic. We will apply the same method to monitor traffic patterns of phones and other devices in an elderly person's household.

Sleep and Wake Patterns & Screen Time Usage: At approximately 6:00 AM, during the "interrupted sleep" period (see Figure 2), RouterSense detected an unusual spike in network traffic from the participant's phone. This spike fell outside the established baseline sleep patterns for this device, indicating unexpected activity. A detailed analysis of features such as incoming and outgoing packet sizes, as well as the specific hostnames accessed, revealed that the participant was watching a series of videos on Instagram. This inference was later validated through participant recall, as they confirmed using Instagram to watch videos at that time.

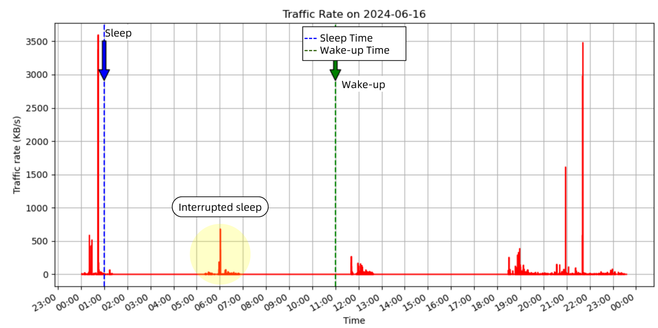

Figure 2: Real-world uplink traffic rate (KB/s) recorded on June 16, 2024, illustrating network activity patterns during the participant's sleep period. Key moments include going to sleep at approximately 1:00 AM, an "interrupted sleep" spike at around 6:00 AM (highlighted in yellow), and waking up at 11:00 AM.

Clinical Significance

Leaving and Returning Home: Tracking the frequency and duration of time spent outside the home serves as a valuable digital biomarker for neuropsychiatric health and early detection of cognitive decline. Research shows a strong association between reduced out-of-home activities and cognitive deterioration; individuals with cognitive impairment or early neurodegenerative conditions often exhibit fewer outings—a pattern linked to declining cognitive and social function (Suzuki et al. 2007; Harada et al. 2019; Suzuki and Murase 2010).

RouterSense provides clinicians with real-time insights into a patient's social and physical engagement by analyzing outing patterns. For instance, Figure 2 highlights a single day's outing data, demonstrating how even brief, daily insights can help identify early indicators of cognitive decline and elevated dementia risk (Petersen et al. 2001; Petersen 2003; Fratiglioni et al. 2000; Rovio et al. 2005; Verghese et al. 2003; Seidler et al. 2003; Churchill et al. 2002; Richards, Hardy, and Wadsworth 2003).

Sleep: Nighttime phone use is a common behavior that disrupts sleep quality, with night-time awakenings and sleep fragmentation recognized as early indicators of cognitive decline, particularly in Alzheimer's disease (AD) (Vitiello et al. 1990; Bliwise 2004; Yulug, Hanoglu, and Kilic 2017). Tracking these disruptions serves as an important biomarker for cognitive health, helping distinguish healthy aging patterns from those indicative of neurodegenerative decline (Bernstein et al. 2021).

Figure 2 illustrates RouterSense's capability to approximate sleep quality through network traffic analysis, identifying nighttime awakenings and assessing sleep continuity. By detecting patterns of nighttime phone usage—a behavior associated with poor sleep and early markers of Alzheimer's disease (AD)—RouterSense can flag sleep disruptions that may signal cognitive decline (Lim et al. 2013). This passive monitoring potentially enables clinicians to detect early cognitive deterioration, supporting timely interventions that may slow disease progression and improve quality of life.

Screen Time: Smartphone usage patterns have been linked to mental health, with addiction correlating with social anxiety, loneliness, and depressive symptoms (Chow et al. 2017; Cornet and Holden 2018; Dogan et al. 2017; Seppälä et al. 2019). Specific behaviors, such as the frequency of text messaging and engagement in non-social activities, emphasize the need to monitor digital behaviors as indicators of mental health and early signs of cognitive decline (Lyketsos et al. 1997; Holtzman et al. 2004). Recent studies suggest that baseline social activity levels can predict dementia progression (Gauthier et al. 2010), while current social engagement is closely tied to cognitive decline (Krueger et al. 2009). In Alzheimer's disease (AD), neuropsychiatric symptoms often lead to reduced social participation, increasing social withdrawal, which in turn shrink patients' social networks (Landes et al. 2001; Mega et al. 1996). This withdrawal frequently manifests as passive behaviors, such as scrolling (Thorisdottir et al. 2019) or decreased use of apps for social purposes (Jin and Park 2010).

Late-night scrolling on platforms like Instagram (Figure 2) may signal reliance on digital interaction to counter loneliness, anxiety, or restlessness—markers of mental health issues and cognitive decline. Monitoring these patterns offers clinicians early insights into behavioral disruptions, supporting timely interventions for sleep, mental health, and cognitive well-being.

Discussion

The preliminary study highlights RouterSense's potential as a passive monitoring tool for assessing mental and cognitive health in home environments, particularly for individuals with chronic illnesses. By tracking changes in sleep patterns, screen time, and out-of-home activities, RouterSense can identify early behavioral signs of neuropsychiatric decline.

Future research will aim to expand the range of measurable digital biomarkers and conduct larger, longitudinal studies involving diverse older adult populations, including those with neurological and mental health conditions. Subsequent iterations will also explore real-time alerts and caregiver interfaces, allowing clinicians and family members to respond quickly to observed behavioral changes.

However, this preliminary study has limitations, including its focus on a single, healthy adult, which restricts the finding's generalizability to broader populations or those with specific health conditions. Additionally, RouterSense relies on home network devices, particularly smartphones, for data collection. Its coarse-grained insights may overlook clinical biological metrics, such as heart rate, which higher-resolution tools like wearable sensors can provide. RouterSense may complement existing clinical studies that use wearables by providing additional data points, especially when there could be gaps in the wearables' data (e.g., due to lack of adherence and compliance). RouterSense aims to deliver a sustainable and accessible solution for real-time, continuous health monitoring. This approach effectively addresses critical gaps in early detection and preventive care for at-risk older adult populations.

Broader Impact Statement

This work is in the initial usability testing phase, demonstrated through a preliminary study (N=1) with a healthy adult co-author. Future efforts will deploy RouterSense in longitudinal studies focused on older adults with neurological conditions.

This work addresses the need for long-term, passive health monitoring solutions for aging populations, particularly those managing chronic conditions like Alzheimer's, Parkinson's, etc. Current methods including wearables and in-home sensors face scalability challenges (see Table 1). RouterSense offers a plug-and-play, connect-and-forget, always-on, software tool to identify early markers of disease, monitor chronic condition progression, and assess the overall well-being of older adults. This approach addresses a critical gap in the early detection of cognitive and mental health issues, enabling timely interventions and potentially improving health outcomes for the elderly. This work is not an experience report but provides a feasibility study that assesses the accuracy and effectiveness of RouterSense.

RouterSense (1) analyzes longitudinal network data to monitor in-home behavior patterns, providing continuous support for older adults; (2) supports independence of older adults through remote monitoring, allowing caregivers to oversee well-being without physical presence; and (3) facilities care interactions by flagging potential health concerns and notifying clinicians or family members.

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