Preliminary Study on LLM-Based Lifestyle Monitoring of Older Adults Living Independently Using Smart Water-Meter Event Data B.M. Mathunjwa[1], Y.L. Hsu[1]. *Gerontechnology* 25(s)

Purpose Home monitoring technologies designed to support independently living older adults generally fall into three categories: (1) wearable devices, which may be uncomfortable, intrusive, or require regular user engagement; (2) ambient sensors, which require additional hardware installation and may raise privacy concerns; and (3) household utility meters, such as smart electricity or water meters, which offer an unobtrusive and infrastructure-based alternative for activity monitoring. While electricity-meter data have been applied to long-term lifestyle analysis (Ruano et al., 2019), far fewer studies have explored the use of smart water-meter data for identifying Activities of Daily Living (ADLs) among older adults. Wilhelm et al. (2023) demonstrated the potential of water-flow patterns for recognizing human activity events using a rule-based segmentation algorithm. This preliminary study examines the feasibility of using smart water-meter event data combined with a large language model (LLM) to classify water-related ADLs and characterize daily lifestyle behavior in older adults living independently at home. **Method** A smart water meter was installed in the home of a 62-year-old male participant, recording water consumption at 10-second intervals for 3 days. The participant manually labeled ADLs associated with each water-use instance. Data preprocessing included filling missing values, filtering noise by removing flow readings below 0.2 L per 10 seconds. Water-usage events were identified by locating sequences of nonzero flow preceded and followed by at least 60 seconds of continuous zero flow. Events shorter than 20 seconds were removed, as they were considered unlikely to represent meaningful ADLs. Figure 1 shows typical water consumption data and some water usage events. For each event, key features including event ID, timestamp, duration, and the full sequence of water-volume readings were extracted. Chat GPT-5 was prompted to classify each event into ADL categories and provide an interpretable justification of its prediction. **Results and Discussion** A total of 79 water-usage events were labeled across nine ADL categories, including flushing toilet (22 events), handwashing (5), bathing/showering (11), morning hygiene (8), evening hygiene (9), meal preparation (10), post-meal cleaning (10), laundry (3), and house cleaning (1). The LLM achieved 77% overall classification accuracy, producing two outputs per event: an ADL label and a reasoning explanation (Figure 2). The model performed well for ADLs with distinctive and consistent flow signatures, such as toilet flushing and showering. In contrast, activities with overlapping water-use patterns particularly meal preparation and dishwashing showed lower accuracy due to their similar flow magnitudes and durations. Laundry events were also difficult to capture as a single ADL because the washing-machine cycle includes long zero-flow intervals between phases, which caused the segmentation method to split one cycle into several smaller events. These observations highlight both the potential and the current limitations of using smart water-meter data for daily activity monitoring. Future work will refine the segmentation approach to better capture complete activity cycles, enhance prompting strategies, and compare performance across different LLMs to enhance classification accuracy. Beyond activity classification, a long-term goal is to develop a monitoring system capable of detecting unusual, excessive, or missing ADLs supporting early recognition of potential functional decline in independently living older adults. This study is limited by the inclusion of a single participant, reducing generalizability across genders, ages, and lifestyles. Future work will involve larger and more diverse cohorts. Although LLMs offer interpretability, machine learning and deep learning models tailored for time-series and sensor-event analysis will be explored and comparatively evaluated.

References

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Keywords: Lifestyle monitoring, Smart water meter, Activity of Daily Living (ADL), Older adults, Independent living, Large Language Model (LLM)

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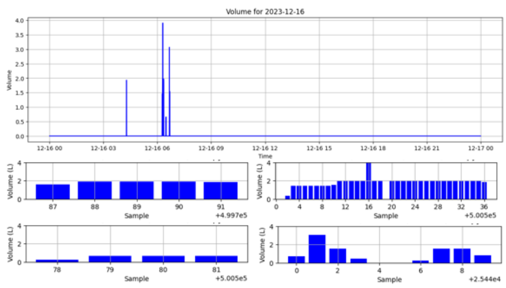

Figure 1 Water consumption data and water usage events

Likely ADL	Reasoning (Shortened for Column Fit)
Toilet Flush	High flow (1.6–1.9 L) for ~50 s, then rapid drop to zero—typical flush pattern.
Showering	Long duration (~350 s) with steady moderate–high flow (mostly 1.9–2.0 L) and brief peak (~3.9 L).
Hand/Face Washing	Short (~50 s), low flow (0.2–0.5 L) with clean shutof —minimal water-use task.
Dishwashing	Fluctuating flow with peaks (~3.0 L) and intermittent usage—suggests rinsing and handling multiple items.

Figure 2 Water usage ADL label and a reason