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Towards an Interactive Longitudinal Visualization of Daily Living Activities for Aging in Place

Vers une visualisation interactive et longitudinale des activités de la vie quotidienne pour le maintien à domicile

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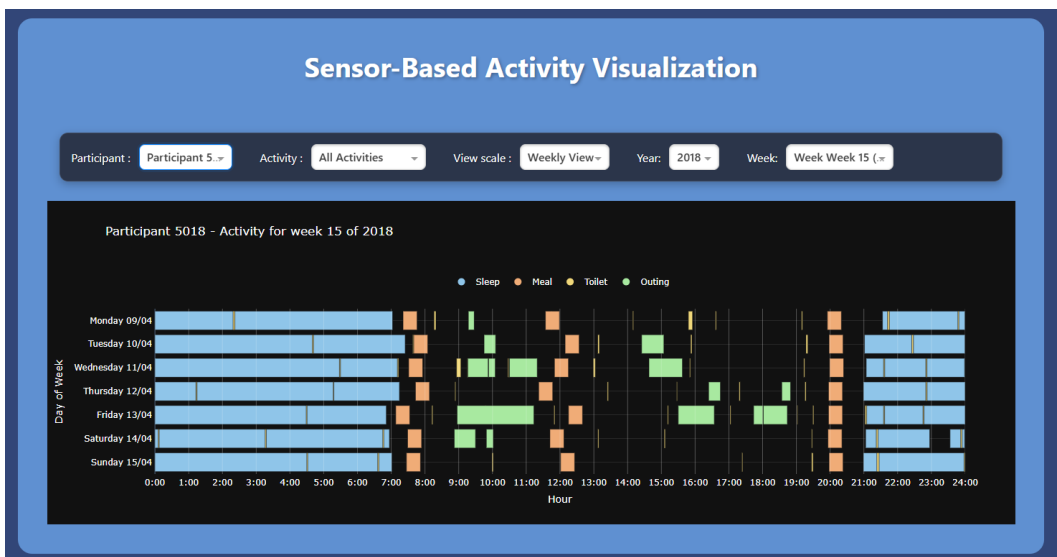


Fig. 1. Example multi-scale visualization from our prototype, using smart home sensor data from the HomeAssist project [14]. This weekly timeline shows detected activities of daily living (Sleep, Meal, Toilet, Outing) for a participant of the study, derived through concise, interpretable Allen Temporal Logic rules. Toilet events were included here to illustrate the tool's capacity to represent multiple activity types. The stacked hourly bars help reveal the participant's stable daily routines across the week while also making potential deviations easily identifiable. For Meal, a 25-minute default duration is applied to approximate eating periods given appliance usage sensors. This visualization demonstrates our approach's ability to transform raw, timestamped sensor logs into interpretable, clinically relevant overviews of daily living routines.

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Monitoring daily activities in the home using unobtrusive sensors can provide valuable insights to support aging in place. However, raw logs of detected activities over months remain dense and difficult to interpret. We present an interactive visualization prototype that transforms these dense, rule-based annotations into multi-scale timelines designed to support sensemaking about routines, changes, and data quality. Our approach relies on interpretable formal rules (Allen Temporal Logic) applied to smart home sensor data from the HomeAssist project, and was iteratively designed and tested with data from five older adult participants. This work-in-progress focuses on four activities of daily living (sleep, meals, toilet use, outings) and aims to make such annotations more exploitable. Our approach supports refining detection rules and the identification of changes in daily routines. We discuss future directions, including broader participatory design and the use of larger datasets (131 participants) to extend activities covered and validate the approach.

La surveillance des activités de la vie quotidienne à domicile à l'aide de capteurs non intrusifs peut fournir des informations précieuses pour soutenir le maintien à domicile des personnes âgées. Cependant, les journaux bruts d'activités détectées sur plusieurs mois restent denses et difficiles à interpréter. Nous présentons ici un prototype de visualisation interactive qui transforme ces annotations denses et basées sur des règles formelles (Allen Temporal Logic) en chronologies multi-échelles conçues pour faciliter l'interprétation des routines, de leurs évolutions et de la qualité des données. Notre approche repose sur des règles interprétables appliquées aux données de capteurs du projet DomAssist, et a été conçue et testée de manière itérative avec les données de cinq participants âgés. Ce travail en cours se concentre sur quatre activités de la vie quotidienne (sommeil, repas, passages aux toilettes, sorties) et vise à rendre ces annotations plus exploitables. Notre approche soutient l'affinement des règles de détection et l'identification des changements dans les routines quotidiennes. Nous discutons également des perspectives futures, incluant une conception participative élargie et l'utilisation de jeux de données plus importants (131 participants) pour étendre les activités couvertes et valider l'approche.

CCS Concepts: • **Human-centered computing** → **Visualization design and evaluation methods**; *User interface design*; • **Applied computing** → **Health informatics**.

Additional Key Words and Phrases: Ambient Assisted Living, Smart Home, Aging in Place, Activities of Daily Living, Interactive Visualization, Human-Centered Design, Sensor Data, Longitudinal Monitoring, Interpretability

Mots Clés et Phrases Supplémentaires: informatique ambiante, Maison Intelligente, Maintien à domicile, Activités de la vie quotidienne, Visualisation interactive, Conception centrée utilisateur, Données de capteurs, Suivi longitudinal, Interprétabilité

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1 Introduction

Enabling older adults to age in place safely and independently is a major societal priority, motivated by demographic shifts and the desire to maintain quality of life while containing healthcare costs [8, 12]. Ambient Assisted Living (AAL) technologies, including smart home systems equipped with unobtrusive sensors, have emerged to support this goal by continuously monitoring Activities of Daily Living (ADL) in the home environment [13]. These activities, such as sleep, meals, toileting, and outings, are important indicators of functional health, helping to detect emerging support needs or early signs of decline.

Despite advances in sensing infrastructure and detection algorithms, transforming raw smart home sensor data into clinically meaningful insights remains a persistent challenge. Current systems often rely on rule-based approaches or machine learning classifiers to infer activities from

low-level sensor events, producing dense, timestamped logs of detected activities. While detection performance itself has improved, these logs are often fragmented and lack contextual cues, making them difficult to interpret over long periods. This significantly limits their utility for informing clinical decisions, monitoring evolving routines, or supporting personalized adaptation of assisted living services and care plans [6, 16].

Moreover, many existing interfaces focus on short-term views such as daily or weekly timelines, which are insufficient for capturing gradual changes in behavior that can emerge over months. Clinicians and caregivers need tools that help them track routines over time, assess stability in independent living, and distinguish between true behavioral changes and apparent absences caused by sensor faults. Without these capabilities, integrating smart home data into clinical workflows remains challenging.

Our work addresses these limitations by proposing an exploratory prototype that combines interpretable, rule-based detection of daily activities using the Allen Temporal Logic DSL [15], with an interactive, multi-scale visualization tailored to long-term monitoring. This approach was iteratively designed and tested on data from five older adults living independently, illustrating varied cognitive and functional profiles. Our goal is to support sensemaking across months of smart home data, highlight sensor reliability issues, and facilitate the review and refinement of detection rules and detected routines. By making these behavioral records more exploitable and understandable, we aim to help clinicians, caregivers, and researchers better support aging in place.

2 Related Work

Monitoring activities of daily living in smart homes has been a major research focus in ambient assisted living for two decades, with significant advances in automatic detection. Numerous systems use rule-based or machine learning approaches to transform raw sensor events into high-level ADL annotations [13]. This detection problem has seen strong progress, with models able to recognize meals, sleep, toileting, and outings from ambient sensor data.

However, making these detections clinically actionable remains challenging. Early interfaces often presented raw sensor events or short-term summaries. For example, Le et al. [10] proposed a dashboard for older adults combining a 60-day stream graph and daily radial plots to help users spot patterns and drill down into single-day events. Chung et al. [6] applied the EventFlow timeline visualization to two weeks of activity logs, showing that sequence visualization can reveal typical routines and variations, supporting tailored interventions. While these approaches demonstrated the potential of temporal event displays, they primarily addressed short durations (days to weeks) and often targeted older adult users or researchers rather than clinicians.

Moreover, most prior visualizations offered limited support for real-world data quality issues. Demiris and Hensel [8] highlighted the importance of addressing sensor reliability and accuracy, yet many systems still fail to indicate gaps or faults in the data, risking misinterpretation. This gap is particularly problematic when moving from lab prototypes to long-term monitoring in real homes with diverse layouts and behaviors.

Recent work has recognized the need for more clinically meaningful visualizations. Belloum et al. [2, 3] proposed tools combining formal, knowledge-based detection of ADLs with longitudinal visual summaries to help explore routine stability over months. Their approach showed that supporting clinicians requires moving beyond daily timelines to identify subtle trends. Similarly, Wuestney et al. [16] reported an early participatory design process with nurses to define clinically relevant behavior markers from smart home data and outlined plans for visualizations highlighting behavioral anomalies over time and across scales. However, to the best of our knowledge, no published prototype or interactive system has yet been described, leaving open questions about design and clinical integration.

In summary, while detection algorithms for ADLs have matured, turning raw annotations into reliable, interpretable tools for clinicians remains an open challenge. Bridging this gap requires not only accurate sensing but also interactive visualizations that support sensemaking over months of real-world data, account for sensor failures, and make detection rules transparent. Our work aims to address these needs by offering a rule-based detection pipeline coupled with an interactive, multi-scale visualization, designed to help clinicians and caregivers interpret activity patterns in the wild and develop trustworthy, personalized assistance strategies.

3 Methodology

3.1 Dataset and Detection Pipeline

Our data comes from the HomeAssist project [7, 14], a long-term smart home deployment supporting aging in place through unobtrusive, in-home sensing. Motion detectors, contact switches, and appliance monitors were installed in the homes of frail or pre-frail older adults living alone, collecting continuous streams of low-level events over many months in real-world conditions.

To transform these raw events into high-level ADLs, we employed the Allen Temporal Logic DSL [15], which enables defining human-readable rules that capture temporal relationships between sensor events. For instance, to detect sleep, we specify periods of prolonged inactivity in the bedroom while excluding other motion elsewhere in the home. A simplified Allen-style rule might be expressed as:

```
sleep = ex(night, holds(~any_motion_elsewhere, ("MotionD_B" >= 30min) <= 10hr))
```

This approach ensures that detection logic remains transparent and adaptable. Clinicians and researchers can review or customize these rules to reflect individual routines or household layouts, supporting personalization and trust.

Below is an excerpt from our annotated dataset, showing the structured but still dense and often opaque activity intervals produced by the pipeline. These intervals include both recognized activities and periods flagged as sensor faults:

```
2017-08-01 08:09-08:50: Outdoor; 2017-08-22 21:24-07:50: Sleep; 2017-10-20 04:56-05:00: Toilet; 2018-08-01
15:05-08:42: Bed failure; 2018-02-07 14:18-02:59: Platform failure.
```

While more structured than raw sensor logs, these annotations remain difficult to interpret over longer periods without dedicated visualization and analytical support.

3.2 Participants

The iterative design of our prototype used sensor data from five older female participants in the HomeAssist project, selected by convenience sampling to cover a range of living environments and cognitive profiles. Table 1 summarizes their characteristics at baseline.

Table 1. Participant Profiles

ID	5018	6004	6024	10019	13012
Age	78	85	72	83	79
Gender	F	F	F	F	F
Education (years)	8	8	8	9	10
Living Space	Rural	Semi-urban	Semi-urban	Rural	Urban
MMSE [0-30]	30	26	23	23	30
Lawton IADL [8-40]	8	15	11	9	9
Routinization [0-40]	21	4	14	11	3

Based on these characteristics, our participants ranged from old to older-old, all women, with three having middle-school education and two some high-school education. Living environments varied from rural to urban. Regarding cognitive status (MMSE [9]), two participants showed no impairment while three had mild to moderate decline. Functional status (Lawton IADL [11]) indicated overall relative autonomy, though participant 6004 was less independent. Routinization scores [5] varied, with participants 5018 and 6024 showing more routinized behaviors.

3.3 Design Goals

The development of our visualization tool was primarily motivated by the need to iteratively refine rule-based detection of activities of daily living (ADLs) in sensor data and make the resulting annotations interpretable and usable. We focused on four ADLs (sleep, meals, toilet use, outings) for this work in progress. These rules, based on Allen Temporal Logic, were iteratively tuned based on their plausibility when applied to raw sensor data from our five participants. Visualization played a central role in this process: by comparing rule outputs with raw sensor traces and cross-checking plausibility across multiple participants, we refined the rules to produce coherent annotations that could reasonably reflect actual behavior.

Our goal also was to support the identification of both strong and weak signals in behavioral routines. Strong signals may include abrupt changes (e.g., sudden increase in nighttime toilet visits), while weak signals involve more subtle patterns (e.g., gradual decrease in outings or sleep duration). Our aim was not to provide diagnostic conclusions, but to assist experts in identifying deviations or trends that may warrant further investigation.

Finally, we designed the visualization to highlight anomalies related to sensor functioning or data coverage. By visualizing missing data, partial detections, or overlaps, the tool encourages critical review of data quality and supports discussions around system reliability and limitations.

As shown in Section 4, the prototype supports routine visualization and rule inspection.

3.4 Prototype Implementation

We developed an interactive web-based prototype using Dash (Plotly in Python). The interface allows users to select participants and focus on specific activities of interest, while navigating the data across multiple temporal scales, from yearly overviews down to daily detail. Detected activity intervals are displayed alongside explicit markers of sensor faults, helping users distinguish between true behavioral absences and periods of data loss. This design approach moves beyond the raw annotations to provide a meaningful, clinically usable overview of residents' routines over time, aiming to support more informed care planning.

4 Illustrative Views of the Prototype

Figure 1 (shown at the top of the paper) introduces our main dashboard view: a weekly multi-scale timeline showing four detected activities of daily living (sleep, meals, toileting, outings). This view supports quick comparison across days, helping clinicians or caregivers notice stable routines or potential deviations at a glance.

To further illustrate how our prototype supports sensemaking from months of dense sensor annotations, we present complementary views below. These show annual, monthly, and daily aggregations designed to reveal broader trends and potential issues with the underlying data.

Figure 2 shows an annual view of mean sleep duration for participant 5018, overlaid with failure rates. Most months indicate stable sleep of 9–10 hours per night. However, September shows a marked drop to around 4 hours, despite no sensor or platform failure. This pattern could warrant discussion with the participant or clinician to interpret potential contextual causes.

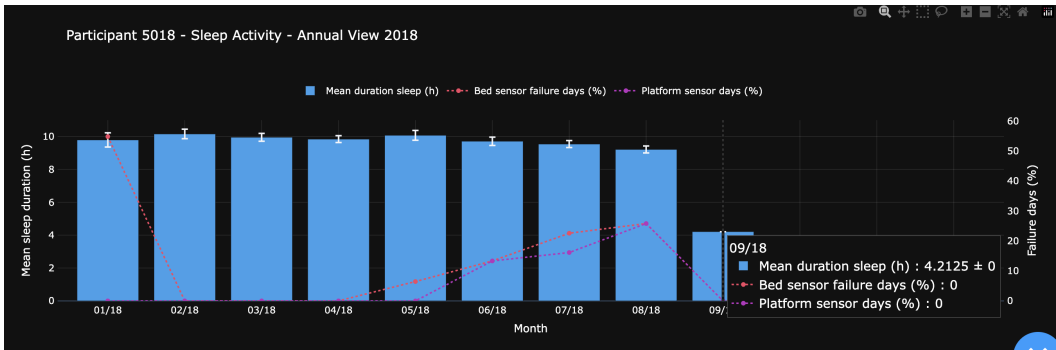


Fig. 2. Annual sleep duration view for participant 5018. Stable high sleep duration for most of the year contrasts with a marked drop in September despite no sensor/platform failure, prompting reflection on behavioral change.

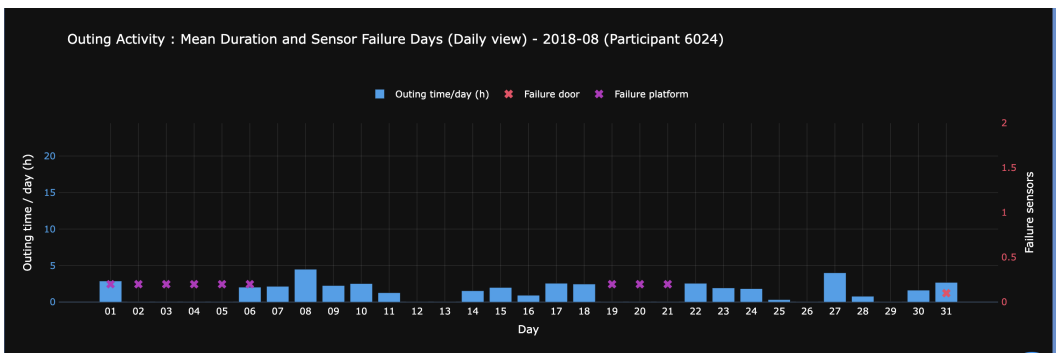


Fig. 3. Daily outings duration for participant 6024 in August 2018. Despite sensor faults on certain days, periods with no failure also show absent outings, supporting nuanced discussion of behavioral variability.

Figure 3 presents daily outing durations for participant 6024. While some days have door or platform failures, other days without sensor faults show no recorded outings. The visualization enables distinguishing sensor issues from actual behavioral variability, supporting clinicians in nuanced interpretation rather than simple binary conclusions.

Figure 4 shows total and mean daily toilet passages for participant 10019 over 2018. While some months are consistent, August reveals a higher number of passages. This prompts questions about health changes or routines that clinicians could explore further, without making automatic diagnostic claims.

Finally, Figure 5 illustrates a daily Gantt-style view for toilet activity, offering fine-grained review of visit timing and duration. Such detailed views support validation of detected episodes and help refine detection rules collaboratively.

Overall, these examples demonstrate how our prototype transforms dense sensor logs into multi-scale, interpretable visualizations. By making patterns in routines and sensor reliability explicit, it aims to support collaborative sensemaking among researchers, clinicians, and caregivers. While not delivering diagnostic conclusions, the tool is designed to help surface meaningful questions for further investigation. Future extensions as mentioned in the following section will refine rule sets and integrate larger datasets to validate generalizability and clinical utility.

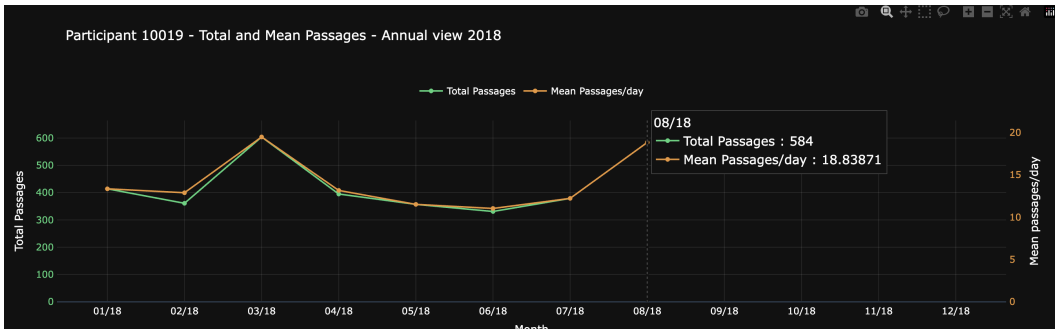


Fig. 4. Annual view of toilet activity for participant 10019. Elevated numbers of passages, especially in August, may prompt review of health context, recognizing the clinician’s role in interpretation.

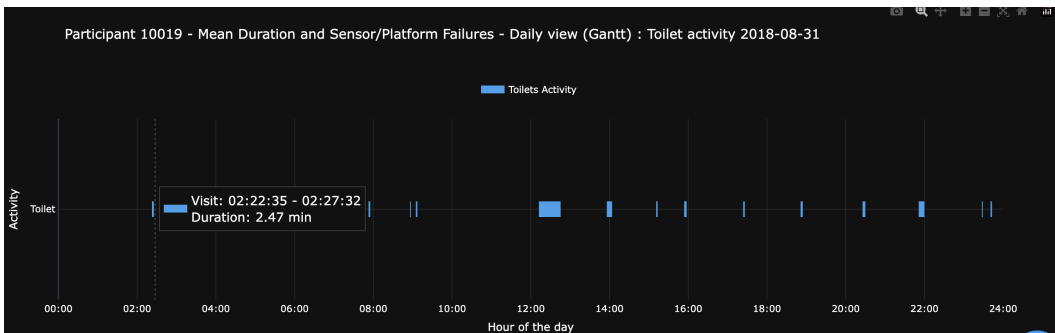


Fig. 5. Daily Gantt view of toilet visits, showing time-of-day distribution and number of episodes. Helps review daily patterns in detail.

5 Discussion and Perspectives

This work represents an ongoing effort to bridge the gap between raw, sensor-based ADL detection and clinically meaningful insights that can support aging in place. While our prototype demonstrates core functionality, important challenges and opportunities remain to deliver a clinician-friendly, explainable, and reliable decision-support tool that integrates into real-world workflows, reduces cognitive load, and enhances proactive care for older adults wishing to remain at home..

Co-Design and Evaluation. We plan to conduct co-design workshops with clinicians, caregivers, and aging researchers to refine the interface, interaction flows, and ensure alignment with real clinical tasks and needs. While early design iterations included feedback from cognitive scientists researchers within our team, further evaluation in clinical contexts is needed. Expanding the data from the current 5 participants to the broader HomeAssist cohort of 131 will also expose the prototype to greater diversity in routines, living environments, and sensor configurations, allowing us to test how the interface and Allen rules can be adapted to individual contexts.

Integrating Additional Data and Activities. Future work will focus on broadening the range of detected activities (e.g., dressing, showering) and integrating clinical assessment data (such as cognitive scores or functional evaluations) alongside sensor-based routines. This will enable clinicians to contextualize observed patterns over time with other health indicators, supporting more informed and personalized care planning. By linking sensor data with known clinical trajectories,

the tool can help experts retrospectively explore how daily routines evolve in different situations. We also plan to develop visual analytics features such as trend highlighting over time and natural-language explanations of the detection rules, aiming to improve transparency and assist clinician sensemaking without replacing expert judgment.

Personalization and Explainability. An additional avenue involves supporting direct editing of Allen DSL rules within the interface, enabling domain experts to tailor detection logic to specific contexts without programming expertise. This aligns with end-user development paradigms previously explored in AAL research [1, 4], and would enhance personalization and transparency. We are also exploring the development of an interactive explanation module capable of generating participant-specific, contextualized descriptions of how an activity, anomaly, or sensor fault was detected. By leveraging large language models (LLMs), such a feature could deliver human-readable justifications directly in the interface, making complex temporal rules and detection outputs more accessible to non-technical users.

Spatial and Contextual Visualization. Finally, we plan to design an immersive 3D visualization of the apartment layout showing sensor activations during detected activities. This spatially grounded view is hypothesized to enhance clinicians' and caregivers' ability to interpret behavior patterns, contextualize anomalies, and assess environmental factors contributing to routines or risks. By making the spatial dimension of activity data salient, this approach could support richer sensemaking and strengthen interdisciplinary communication between technical developers and clinical stakeholders.

6 Conclusion

This work-in-progress presents an interactive, multi-scale visualization prototype designed to support sensemaking around long-term ADL detection logs in smart home settings. By combining a formal, interpretable rule-based detection pipeline with clear visual representations of routines and sensor faults, the tool seeks to make dense sensor data more clinically actionable. This initial study uses data from five participants as a case study to demonstrate feasibility and guide iterative design. Future work will extend to the full HomeAssist dataset (131 participants) to test generalizability, support more activities, and better evaluate the tool's utility in clinical workflows.

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References

- [1] Rafik Belloum and Charles Consel. 2020. End-user development of activity-supporting services for smart homes. In *2020 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*. IEEE, 1–2.
- [2] Rafik Belloum, Charles Consel, and Nic Volanschi. 2020. A tool-based methodology for long-term activity monitoring. In *Proceedings of the 13th ACM international conference on pervasive technologies related to assistive environments*. 1–10.
- [3] Rafik Belloum, Antoine Riche, Nic Volanschi, and Charles Consel. 2021. A tool-based method for developing knowledge-based activity recognizers. In *2021 IEEE SmartWorld, ubiquitous intelligence & computing, advanced & trusted computing, scalable computing & communications, internet of people and smart city innovation (SmartWorld/SCALCOM/UIC/ATC/IOP/SCI)*. IEEE, 17–24.
- [4] Rafik Belloum, Amel Yaddaden, Maxime Lussier, Nathalie Bier, and Charles Consel. 2021. Caregiver development of activity-supporting services for smart homes. *Journal of Ambient Intelligence and Smart Environments* 13, 6 (2021), 453–471.
- [5] Jean Bouisson. 2002. Routinization preferences, anxiety, and depression in an elderly French sample. *Journal of Aging Studies* 16, 3 (2002), 295–302.

- [6] Jane Chung, Mustafa Ozkaynak, and George Demiris. 2017. Examining daily activity routines of older adults using workflow. *Journal of biomedical informatics* 71 (2017), 82–90.
- [7] Charles Consel, Lucile Dupuy, and H el ene Sauz eon. 2018. HomeAssist: An assisted living platform for aging in place based on an interdisciplinary approach. In *Advances in Human Factors and Ergonomics in Healthcare and Medical Devices: Proceedings of the AHFE 2017 International Conferences on Human Factors and Ergonomics in Healthcare and Medical Devices, July 17–21, 2017, The Westin Bonaventure Hotel, Los Angeles, California, USA 8*. Springer, 129–140.
- [8] George Demiris and Brian K Hensel. 2008. Technologies for an aging society: a systematic review of “smart home” applications. *Yearbook of medical informatics* 17, 01 (2008), 33–40.
- [9] Marshal F Folstein, Susan E Folstein, and Paul R McHugh. 1975. “Mini-mental state”: a practical method for grading the cognitive state of patients for the clinician. *Journal of psychiatric research* 12, 3 (1975), 189–198.
- [10] Thai Le, Blaine Reeder, Jane Chung, Hilaire Thompson, and George Demiris. 2014. Design of smart home sensor visualizations for older adults. *Technology and Health Care* 22, 4 (2014), 657–666.
- [11] LAWTON MP. 1982. A research and service oriented multiple assessment. *J Gerontol* 37 (1982), 91–99.
- [12] World Health Organization. 2015. *World report on ageing and health*. World Health Organization.
- [13] Parisa Rashidi and Alex Mihailidis. 2012. A survey on ambient-assisted living tools for older adults. *IEEE journal of biomedical and health informatics* 17, 3 (2012), 579–590.
- [14] H el ene Sauz eon, Arlette Edjolo, H el ene Amieva, Charles Consel, Karine P er es, et al. 2022. Effectiveness of an ambient assisted living (HomeAssist) platform for supporting aging in place of older adults with frailty: protocol for a quasi-experimental study. *JMIR Research Protocols* 11, 10 (2022), e33351.
- [15] Nic Volanschi, Bernard Serpette, Adrien Carteron, and Charles Consel. 2018. A language for online state processing of binary sensors, applied to ambient assisted living. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 4 (2018), 1–26.
- [16] Katherine Wuestney, Javier Ramirez, Diane Cook, and Roschelle Fritz. 2022. SMART HOME DATA VISUALIZATION FOR PROACTIVE HEALTH MONITORING OF COMMUNITY DWELLING OLDER ADULTS. *Innovation in Aging* 6, Suppl 1 (2022), 597.