Real-world ADL Recognition with Deep Learning and Smartwatches: A Pilot Study

Mustafa Ahmed, Pelagia Koufaki
Centre for Health, Activity and Rehabilitation Research
Queen Margaret University, Edinburgh, UK
e-mail: Mahmed@qmu.ac.uk, Pkoufaki@qmu.ac.uk

Hongnian Yu
School of Engineering and the Built Environment
Edinburgh Napier University, Edinburgh, UK
e-mail: H.Yu@napier.ac.uk

Michael Vassallo
Department of Medicine for Older People
Royal Bournemouth Hospital, Bournemouth, UK
e-mail: michael.vassallo@uhd.nhs.uk

***Abstract*— The global aging population poses significant challenges to healthcare systems, especially in promoting independent living and reducing caregiver burdens. Technology-Enabled Care (TEC), which leverages digital tools and Artificial Intelligence (AI), has emerged as a promising solution to support older adults. A crucial component within TEC is the automatic recognition of Activities of Daily Living (ADLs), essential for early detection of health declines and personalized care. Traditional ADL recognition research, often conducted in controlled environments, does not adequately address real-world complexities. This study bridges the gap between laboratory prototypes and practical applications by developing a user-friendly ADL recognition framework using commercial smartwatches. A hybrid model, combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, was trained on accelerometer and gyroscope data to recognize activities like dishwashing and walking. Initially validated in a lab setting with an accuracy of 94%, the model was subsequently tested over a 20-day pilot study involving five participants (mean age = 32 years, SD = 4.5), each wearing an Apple Watch device. Real-world results revealed a significant performance drop, with accuracy declining to 81%. Activities like mopping maintained high recognition accuracy, while subtler tasks, such as walking and washing face posed challenges due to movement variability. These findings underscore the need for model optimization using real-world data to improve recognition accuracy and address variability in movement patterns. Further research is essential to refine these systems for broader applications, develop strategies to enhance user adherence, and ultimately support the independence and well-being of aging individuals.**

Keywords-Activities of Daily Living; Activity Recognition; Deep Learning; Independent living; Smartwatch.

I. INTRODUCTION

The global population is aging rapidly, with a projected 1.5 billion individuals exceeding 65 years old by 2050 [1]. This demographic shift strains healthcare systems as older adults experience higher rates of chronic conditions and functional limitations [2]. Accurate assessment of functional health is crucial for early detection of decline, enabling timely interventions and improved quality of life [3]. In this regard, Technology-Enabled Care (TEC) offers significant advantages over traditional self-reported and clinical observation methods for functional assessment [4]. By providing continuous, objective, and comprehensive monitoring, it facilitates early detection of health issues, timely interventions, and personalized care plans, ultimately enhancing the quality of life and independence of older adults.

Automatic recognition of Activities of Daily Living (ADLs) is a key area within TEC. ADLs, such as brushing teeth, washing dishes, and cleaning the house, are fundamental for independent living and serve as indicators of an individual's functional health [5]. Identifying subtle changes in ADL performance potentially allows for preventative measures and interventions before decline becomes significant [6]. Efficient ADL Recognition (ADL-R) systems can offer users valuable insights into their daily activities, helping them improve routines and adopt healthier behaviors [7]. For caregivers, these systems enhance understanding of the care recipient's needs and patterns, leading to more effective and responsive caregiving and informed decision-making [8]. Additionally, clinicians can remotely monitor patients, thereby reducing the need for frequent in-person visits and facilitating more efficient management of chronic conditions. [9] This allows for timely interventions that can prevent hospitalizations.

Wearable technology and AI have made significant strides in healthcare monitoring, enabling continuous, multimodal assessments that provide a comprehensive view of health. Recent innovations, such as hybrid sensors, track both biochemical and biophysical signals, offering more detailed insights compared to single-parameter devices [10]. Fiber-based strain sensors have also contributed by enhancing flexibility and diagnostic capabilities, while reducing costs, making wearable devices more practical and accessible [11]. These advancements have also expanded the potential of wearable devices in Human Activity Recognition (HAR) and ADL-R. Inertial sensors like accelerometers and gyroscopes are increasingly used as privacy-conscious alternatives to camera-based systems, offering reliable, continuous monitoring that suits personal and home environments [12]. As a result, wearables are becoming a valuable tool for ADL-

R in healthcare, where they can provide insights into routines and health conditions in real time.

However, several challenges hinder the widespread adoption of ADL-R systems outside controlled laboratory environments. Many wearables designed for research are bulky and uncomfortable, making them impractical for daily wear [13]. The complex machine learning models necessary for accurate activity recognition can strain device resources, leading to frequent charging requirements and technical difficulties [14]. Real-life deployments also face logistical hurdles, such as ensuring users can operate the devices independently and maintaining consistency across settings, which often require home visits and substantial user training [15]. These issues highlight a broader limitation of existing solutions: while they may excel in specific contexts, such as tracking upper limb movements for rehabilitation using deep learning models [16], they lack the versatility needed for broader ADL applications. Additionally, stationary sensor setups, like those integrating Wi-Fi and Inertial Measurement Unit (IMU) data [17], though promising for capturing detailed activity characteristics, are often impractical for mobile and daily use.

To address these challenges, recent developments in wearable technology focus on improving user-friendliness and efficiency. For instance, wearable devices that combine photoplethysmography and inertial data offer a more holistic assessment by capturing a broader range of signals [18], though they may introduce added complexity and user burden. Adaptive algorithms, such as “one-size-fits-most” models, generalize across devices and body locations, enhancing accuracy for specific activities like walking [19]. However, these models often struggle to account for the full diversity of daily activities in natural settings.

A user-centric approach that leverages familiar, widely used devices like smartwatches and smartphones offers a promising solution for real-world ADL-R. These devices are accessible, comfortable, and capable of supporting ADL-R systems that optimize for low power consumption, reducing the need for frequent charging and improving practicality for long-term use. Recent studies emphasize that optimizing AI models specifically for these devices not only extends battery life but also ensures that ADL-R is sustainable and adaptable to everyday environments [20].

This pilot study specifically aims to evaluate the feasibility of a smartwatch-based framework in addressing ADL-R challenges under real-life conditions. By using a single, widely adopted smartwatch, we address the common limitations of bulkiness and impracticality that have plagued previous ADL-R systems, enabling a more accessible and minimally intrusive approach to recognize ADLs in natural, home-based environments. This user-centric design reduces the need for specialized equipment and provides a sustainable solution for real-world health monitoring that overcomes these significant barriers. By emphasizing user-friendliness and computational efficiency, this pilot study lays the groundwork for developing robust, accessible TEC solutions for ADL-R. Through this feasibility assessment, we aim to pave the way for broader adoption and improved functional health monitoring, particularly benefiting aging populations who require practical and scalable ADL-R systems.

The remainder of this paper is organized as follows: Section II outlines the methods, including model design, participant recruitment, and data collection procedures. Section III presents the results, covering model performance and participant engagement. Section IV discusses the findings, addressing discrepancies and engagement factors. Section V explores implications for future research and advancements in ADL-R.

II. Methods

A. ADL Recognition Model

The activity recognition model was designed as a hybrid architecture combining lightweight Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to leverage the strengths of both approaches in handling sensor data. The model was trained on accelerometer and gyroscope data collected in a simulated living environment, focusing on target activities, which were: dishwashing, shelving items, brushing teeth, washing face, mopping & hoovering, and walking. Data was sampled at 34Hz and segmented into 442-sample windows, approximately 13 seconds each. The CNN part of the model consisted of multiple convolutional layers, each with varying filter sizes and numbers of filters to extract spatial features from the raw sensor data. Typically, the first convolutional layer used 32 filters with a 3x1 kernel size and Rectified Linear Unit (ReLU) activation, followed by a second convolutional layer with 64 filters of the same kernel size and activation function. Max-pooling layers were used after certain convolutional layers to reduce the dimensionality of the feature maps while retaining important spatial features. The final convolutional layer was followed by a flatten layer, converting the 2D feature maps into a 1D feature vector for the LSTM layers. The LSTM network then processed this feature vector to capture temporal dependencies and sequential patterns in the activity data. Typical configurations included an initial LSTM layer with 128 units and a dropout rate of 0.2, followed by a second LSTM layer with 64 units and the same dropout rate. A grid search was conducted to optimize hyperparameters for both the CNN and LSTM components, including the learning rate, batch size, and dropout rate. The learning rate was tested in the range of 0.001 to 0.01, with 0.001 selected. Batch sizes of 16, 32, and 64 were evaluated, and 32 was chosen. Dropout rates from 0.2 to 0.5 were assessed specifically for the LSTM layer, with 0.2 providing optimal regularization. The output layer was a fully connected dense layer with a SoftMax activation function to predict the activity classes.

The model was trained using the Adam optimizer with categorical cross-entropy as the loss function and then evaluated using a 5-fold cross-validation approach to ensure an unbiased assessment of its performance. Accuracy and F1-score were used to evaluate the model's effectiveness in recognizing the target activities. After the model was developed and initially tested, a pilot study was designed to validate its feasibility and effectiveness in real-life settings.

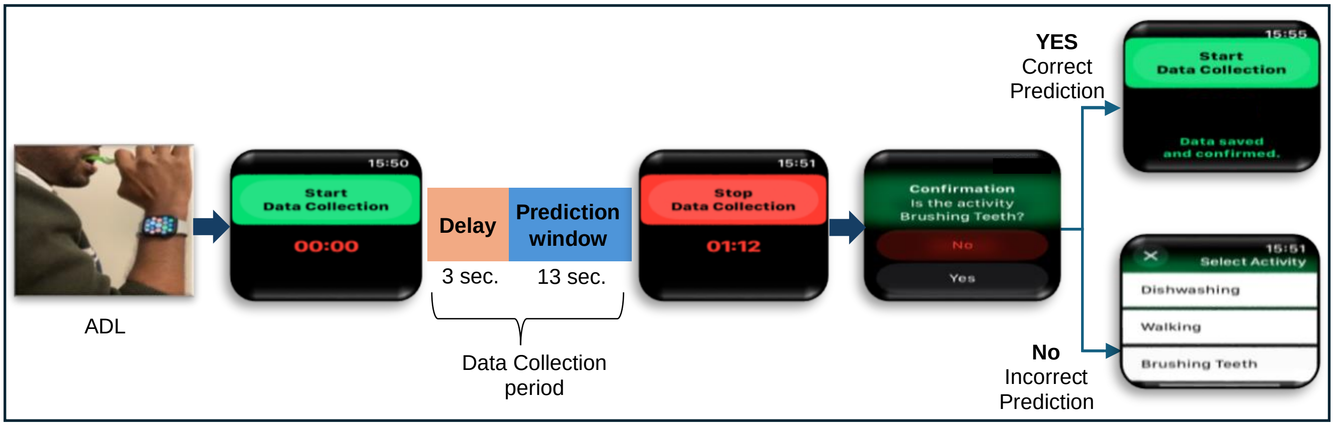


Figure 1. Workflow of the smartwatch app's data collection and activity prediction process.

This study aimed to assess the practical application of the ADL-R system, focusing on user interaction, data collection, and system performance in everyday environments. Over the course of 20 consecutive days, participants wore Apple watch devices (series 8) that collected motion data through a custom-developed application and used these data to recognize the activity performed.

B. *Participants*

Participants were recruited through convenience sampling, primarily targeting individuals within the University community for convenience and accessibility. Five participants (mean age = 32 years, SD = 4.5), including two females and three males, were enrolled. The only inclusion criterion was to have access to an iPhone. All participants were generally familiar with technology and provided written informed consent before commencement of data collection. The study was reviewed and received a favorable ethical opinion by the Queen Margaret University Ethics Committee, (REP 0278).

C. *Real-life ADL Recognition procedures*

The custom-developed iOS application, QMU ADL Tracker, was created using Xcode and deployed via Apple TestFlight for easy installation and updates. The application consists of a smartphone app with a companion smartwatch app, designed to facilitate seamless data collection and user interaction. Data collection is conducted through the CoreMotion framework, ensuring consistent and precise capture of sensor data. The CNN-LSTM model was deployed in the app through CreateML.

The smartwatch app features a user-friendly interface (Fig. 1), including a Start/Stop toggle button that simplifies the process of beginning and ending data collection. To ensure accurate activity recognition, users are instructed to start data collection prior to performing an activity and to stop it afterward. Once data collection is stopped, the sensor data is processed by the CNN-LSTM model, which provides a real-time prediction of the activity. Users are then prompted to confirm the prediction's accuracy by selecting "Yes" or "No" (Fig. 1). If the prediction is correct, users press "Yes." If incorrect, they press "No," prompting a list of remaining target ADLs for selection. In cases where the user's activity is not a target ADL, an "Other" button allows access to a list of additional activities, such as tidying up, cleaning windows, driving, shopping, sitting, lying down, eating, drinking, and preparing meals. Once the user confirms the activity, both the motion data and the user's selection are sent to the smartphone app for storage. The smartphone app primarily functions as a data repository, allowing users to view collected information and providing instructional support.

Data collection parameters, including sampling frequency and window size, were aligned with those used in the simulated environment for consistency with the CNN-LSTM model. As shown in Fig. 1, the application was configured to include a 3-second buffer period to stabilize sensor readings before data collection begins. Consequently, the minimum total time required for a prediction was 16 seconds (3 seconds delay plus a 13-second prediction window). Participants were instructed to perform each activity for at least 16 seconds to ensure accurate predictions.

III. Results

A. *Model Performance: Simulated Data Training and Testing*

As shown in Table I, the validation of the CNN-LSTM model assessed accuracy and F1 score for each activity, with the F1 score reflecting the balance between precision and recall, indicating the model's accuracy in classifying true positives from false positives and negatives. The model achieved an overall accuracy of 94% and an F1-score of 93% in recognizing ADLs within the simulated environment. A more granular analysis reveals that shelving items exhibited the highest accuracy (99%) and respectable F1-score (94%), suggesting robust recognition of this activity. Conversely, while washing face achieved a high accuracy of 96%, its F1-score of 89% indicated potential challenges in correctly identifying this activity. The model's confusion matrix, as shown in Fig. 2, provides a detailed visualization of the model's predictions compared to the true activities. To further

TABLE I. CNN- LSTM MODEL PERFROMANCE ON REAL-LIFE DATASET

Activity	Accuracy	F1 Score
Walking	95%	91%
Brushing Teeth	95.8%	85.6%
Washing Face	96%	79%
Mopping/Hoovering	97%	94.7%
Dishwashing	92.5%	80.9%
Shelving Items	99%	94.5%
Overall	**94%**	**93%**

Figure 2. Confusion Matrix for Model's predictions using simulated data.

TABLE II. CNN- LSTM MODEL PERFROMANCE ON REAL-LIFE DATASET

Activity	Accuracy	F1 Score
Walking	68%	68%
Brushing Teeth	85.5%	85.5%
Washing Face	65.8%	45.8%
Mopping/Hoovering	95%	95%
Dishwashing	79%	72.5%
Shelving Items	92.6%	92.6%
Overall	**81%**	**76.5%**

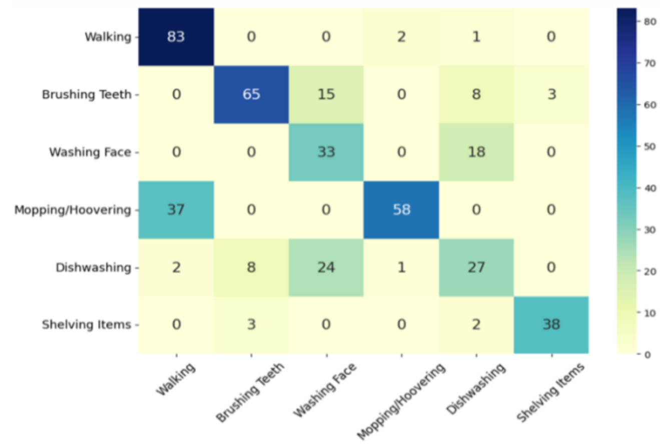


Figure 3. Confusion Matrix for Model's predictions using simulated data.

investigate the model's generalization capabilities, we carried out the validation in real-life through this pilot study.

B. *Model Performanece in real-life*

Feedback from participants on the predicted activities provided valuable insights into the model's performance. Based on this feedback, we constructed a confusion matrix (Fig. 3) to quantitatively assess the accuracy of activity recognition. The matrix revealed an overall accuracy of 81% in identifying daily activities in real-world settings, indicating a moderate level of success in ADL-R. However, this also highlights the challenges of applying the model to real-life scenarios.

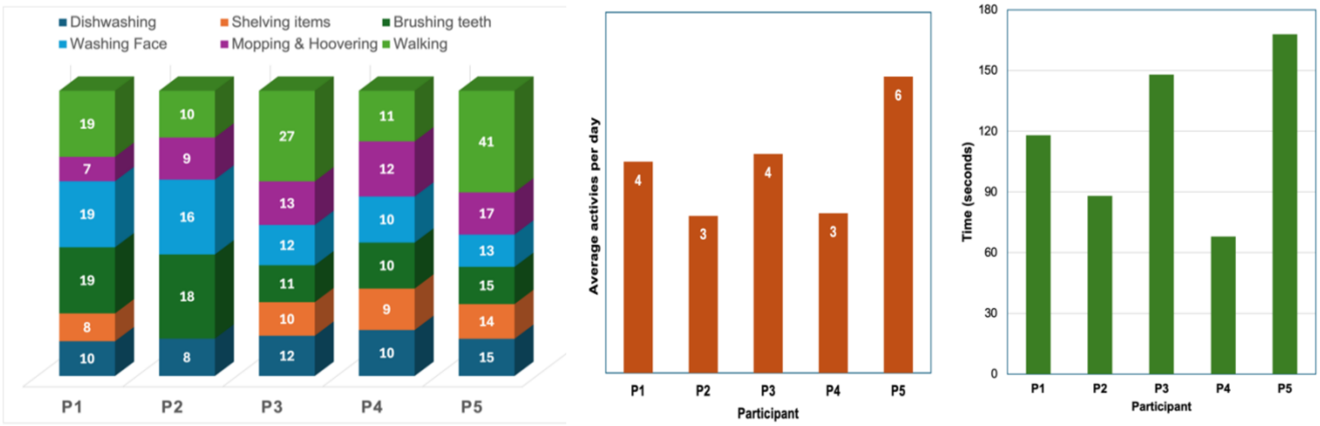
As detailed in Table II, the activities of mopping/hoovering achieved the highest accuracy at 95.08%, which suggests that the model is particularly adept at recognizing the distinct motion patterns associated with this activity. Despite its high accuracy, mopping/hoovering was sometimes misclassified as dishwashing. Another activity, shelving items, showed a similarly commendable accuracy of 92.68%. While it was generally well recognized, there were instances of confusion with the activity of brushing teeth, likely due to the similar repetitive hand movements involved. The high accuracy rates for these specific activities demonstrate the model's effectiveness in distinguishing certain types of ADLs.

On the other hand, washing face had the lowest accuracy at 65.83%, with frequent misclassifications as brushing teeth and dishwashing. This high confusion rate highlights the challenge in recognizing the movements involved in washing the face, pointing to a need for better feature differentiation and potentially additional sensor data. Unexpectedly, walking also exhibited a low accuracy of 68.21%, with the primary confusion occurring with mopping/hoovering. The substantial misclassification rate indicates that the model struggles to distinguish between these activities, possibly due to similar sensor data patterns. Brushing teeth exhibited a moderate accuracy of 85.53%. Misclassifications primarily occurred with dishwashing and shelving items, suggesting challenges in distinguishing repetitive hand movements across these tasks. Similarly, dishwashing had a moderate accuracy of 79.03%, often confused with brushing teeth and washing face. This overlap in recognition points to the difficulty in differentiating between activities involving similar hand and arm movements, indicating a need for refined feature extraction to improve accuracy.

C. *Participants' Engagement*

Various indicators related to participant engagement with the ADL tracker app are shown in Fig. 4, which reveals variations in how participants used the app. In Fig. 4A, the number of each activity participants performed using the application during the study data collection period is illustrated. On average, participants logged approximately 81 activities over the 20-day period, with noticeable individual differences in activity logging. Participant P5 exhibited the highest level of engagement, recording 115 activities, while Participant P2 logged the fewest with 61.

The frequency of app usage, as measured by average sessions per day (Fig. 4B), was consistent across participant with a mean of four sessions. This suggests a limited engagement with the study's requirements. Nevertheless, the



(A) (B) (C)

Figure 4. Indicators of participants engagement showing: (A): Number of each ADL logged by participants during the 20-day data collection period, (B): Frequency of app usage (sessions per day), and (C): Average duration of data collection in each session.

duration of these sessions, as shown in Fig. 4C, varied considerably. Participant P3 demonstrated the longest average session duration at 148 seconds, while Participant P4 recorded the shortest at 68 seconds. These findings imply differences in how participants utilized the app, with some spending longer periods per session, potentially logging multiple activities or engaging in more detailed data exploration.

The analysis of the activities performed by participants reveals several important trends and patterns. Notably, walking was the most frequently performed activity, with participants engaging in it between 10 and 41 times over the testing period. Additionally, personal hygiene activities such as brushing teeth and washing face were consistently performed by all participants, indicating regular adherence to daily hygiene routines. Less frequent activities, such as mopping & hoovering and shelving items, were performed less often compared to other activities. This lower frequency could be attributed to the nature of these activities, which may not occur on a daily basis, resulting in fewer recorded instances.

Examining participant-specific trends, Participant P5 demonstrated the highest overall engagement, particularly in walking (41 instances) and dishwashing (15 instances). Conversely, Participant P2 did not record any instances of shelving items, which may indicate a lack of engagement in this specific activity or a potential oversight in the recording. The data also reflects a diverse range of activities performed by the participants, with each individual engaging in multiple types of activities. Participant P4, for example, exhibited a balanced engagement across all activities, performing at least nine instances of each, which is beneficial for comprehensive training of the recognition model.

IV. DISCUSSION

A. *Model Performance and the Gap Between Simulation and Reality*

The proposed hybrid CNN-LSTM model demonstrated good performance in the simulated environment, achieving a notable accuracy of 94% in ADL-R. This highlights the potential of such architectures in handling sensor data for activity recognition tasks. However, the stark contrast between simulated and real-world performance, with an overall accuracy of 81% in the latter, underscores the challenges inherent in bridging the gap between controlled environments and complex, dynamic real-world settings.

Several factors may contribute to this performance discrepancy. The simulated environment likely presents a more idealized representation of ADLs, with controlled conditions and limited variability in sensor data. In contrast, real-world activities are subject to a multitude of factors, including environmental noise, variations in how objects are utilized, and the inherent variability of wearable sensor performance. These complexities introduce significant challenges for the model, hindering its ability to generalize effectively.

Moreover, the way participants performed ADLs in the real world may have differed substantially from the simulated patterns. The model, trained on simulated data, might not have been adequately prepared to handle the diverse and nuanced variations observed in real-life behavior. This discrepancy highlights the need for more representative training data that captures the full spectrum of human activity.

The differential performance of the model across different ADLs provides valuable insights into the factors influencing recognition accuracy. Activities like mopping/hoovering and shelving items, characterized by distinct and repetitive movement patterns, were recognized with high accuracy. This suggests that the model can effectively capture and classify well-defined activities. In contrast, washing face and walking presented significant challenges. The low accuracy for washing face might be attributed to the subtle and often occluded movements involved in this activity, making it difficult to differentiate from similar actions. For walking, the confusion with mopping/hoovering suggests potential overlap in sensor patterns, especially when considering variations in walking speed and style.

These results highlight the complexities involved in automatic feature extraction. While the model's ability to learn discriminative features directly from raw sensor data is advantageous, it also presents certain limitations. A hybrid approach, combining automatically learned features with carefully crafted domain-specific features, could offer a promising avenue for enhancing the model's overall performance. By leveraging the strengths of both approaches, it may be possible to address the challenges posed by complex and varied ADLs.

B. *Participant Engagement and Data Quality*

Participant engagement in the ADL tracker app varied significantly, influencing the quantity and quality of data collected, which, in turn, impacted the model’s performance. This variability highlights a critical challenge: while some participants frequently interacted with the app, others engaged less consistently. Such differences in engagement can affect the representativeness of the dataset, as well as the accuracy and generalizability of the model in real-world settings.

Several factors may contribute to these engagement disparities. One primary challenge is that certain ADLs, like mopping/hoovering or shelving items, are not performed frequently, which naturally leads to less frequent app usage. Additionally, the perceived inconvenience of wearing a device throughout the day and a lack of immediate, visible benefits from using the app may also contribute to lower engagement levels. These factors underscore the difficulty of integrating wearable technology seamlessly into everyday life when it doesn’t directly align with the user's regular routine. To address these challenges, accurately measuring engagement could provide valuable insights into adherence patterns. Developing metrics that capture not just the frequency of app usage but also the context of interactions would offer a clearer understanding of participant behavior. By gaining a more detailed view of how participants engage with the app, researchers can better align ADL-R models with real-world usage patterns, ultimately enhancing model accuracy and generalizability.

To improve engagement, several strategies could be implemented. Personalized feedback that provides insights into activity patterns can make the data collection process more relevant and motivating for users. Gamification elements, such as rewards for consistent engagement, could foster a sense of accomplishment and incentivize regular app usage. Additionally, in-app reminders may help prompt users to engage without being intrusive. Streamlining the user interface and ensuring that the app operates smoothly in the background could reduce perceived burdens, encouraging participants to incorporate the technology into their routines more naturally. Collectively, these strategies aim to create a more engaging and user-friendly experience, enhancing adherence and supporting the broader application of wearable ADL-R systems.

V. IMPLICATION FOR FUTURE RESEARCH

This pilot study provides first critical insights into the challenges and opportunities for improving ADL-R in real-world settings. It successfully demonstrates the feasibility of conducting ADL-R research using a user-centric approach, highlighting practical applications and potential enhancements. The seamless recruitment of participants with minimal interaction, facilitated by online platforms like TestFlight, and the user-friendly design of the app, enhanced the efficiency of the study. Moreover, the dataset collected in this study serves as a valuable resource for refining ADL-R models. By retraining the model on an expanded sample, we can enhance its accuracy and robustness, enabling it to learn from a wider range of activity patterns and variations. To further improve performance, combining automatically learned features with carefully crafted domain-specific features is essential, leveraging the strengths of both data-driven and knowledge-based approaches. Enhancing feature engineering to capture temporal dynamics, contextual information, and activity transitions can further enrich the model's representational power. In addition to that, exploring advanced model architectures, such as attention mechanisms, transformers, or graph-based approaches can unlock the potential for capturing complex dependencies within the data.

To maximize the potential of ADL-R systems, a paramount focus on user engagement and data quality is essential. Implementing strategies to increase user participation and motivation is crucial for the success of such systems. Understanding the most frequently performed ADLs allows for a more targeted approach to app customization. By focusing on core activities, the app can provide relevant features and notifications, enhancing the user experience and encouraging sustained engagement. This interplay between user engagement, data quality, and app personalization is fundamental to the development of robust ADL-R systems.

Moreover, these insights can inform future developments in wearable technology for ADL-R by emphasizing the importance of user-centric design. As wearables evolve, integrating advanced sensing capabilities that capture a broader range of ADLs could enhance the comprehensiveness of ADL-R systems. Furthermore, the development of adaptive algorithms capable of personalizing recognition based on individual usage patterns can make ADL-R systems more responsive to user needs. Such advancements could expand the scope of wearable technology, making it more versatile for different user demographics and environments, ultimately broadening the impact of ADL-R systems beyond specific study settings. By leveraging data on user engagement and preferences, future wearable devices could incorporate enhanced features, such as context-aware prompts and dynamic feedback, which adjust in real-time to optimize user adherence and data quality.

While this pilot study provides valuable insights, the small sample size may limit the generalizability of the findings.

Future research should aim to recruit a larger and more diverse participant pool, potentially by partnering with community organizations or leveraging online recruitment platforms. This approach would enhance the representativeness of the data and further validate the model's effectiveness in broader real-world settings.

ACKNOWLEDGMENT

Apple Inc. provided the Apple Watch devices for the research. Apple was not involved in the design of the research, nor was it involved in the collection, analysis, or interpretation of the research data, or the content of this or any related publication.

REFERENCES

[1] World Health Organization, "Progress report on the United Nations decade of healthy ageing, 2021-2023," World Health Organization, 2023. retrieved: June, 2024, from https://www.who.int/publications/i/item/9789240079694

[2] J. Parajuli, D. Berish, and Y. L. Jao, "Chronic conditions and depressive symptoms in older adults: The mediating role of functional limitations," Aging & Mental Health, vol. 25, no. 2, pp. 243-249, 2021.

[3] A. M. Jahan, "Insight into Functional Decline Assessment in Older Adults: A Physiotherapist's Perspective," Archives of Gerontology and Geriatrics Plus, vol. 100048, 2024.

[4] M. Schmitter-Edgecombe, C. Luna, and D. J. Cook, "Technologies for health assessment, promotion, and intervention: Focus on aging and functional health," in Positive Neuropsychology: Evidence-based perspectives on promoting brain and cognitive health, Cham: Springer International Publishing, pp. 111-138, 2022.

[5] S. Tomsone, V. Horstmann, F. Oswald, and S. Iwarsson, "Aspects of housing and perceived health among ADL independent and ADL dependent groups of older people in three national samples," Aging Clinical and Experimental Research, vol. 25, pp. 317-328, 2013.

[6] Y. Angerova et al., "Utilization of ADL performance tests to predict expected functional status in patients after stroke," KONTAKT-Journal of Nursing & Social Sciences related to Health & Illness, vol. 23, no. 3, pp. 320-326, 2021.

[7] M. J. van Het Bolscher-Niehuis, M. E. den Ouden, H. M. de Vocht, and A. L. Francke, "Effects of self-management support programmes on activities of daily living of older adults: A systematic review," International Journal of Nursing Studies, vol. 61, pp. 230-247, 2016.

[8] S. Hvalič-Touzery and V. Dolničar, "Attitudes towards smart technologies among older people and their informal carers in Slovenia," Health of the Elderly, 2021. Retrieved October, 2024, from https://doi.org/10.26493/978-961-293-129-2.71-80

[9] D. G. Leo et al., "Interactive remote patient monitoring devices for managing chronic health conditions: systematic review and meta-analysis," Journal of Medical Internet Research, vol. 24, no. 11, pp. e35508, 2022.

[10] K. Mahato et al., "Hybrid multimodal wearable sensors for comprehensive health monitoring," Nature Electronics, vol. 1, pp. 1-16, 2024.

[11] J. Zhang et al., "Revolutionizing digital healthcare networks with wearable strain sensors using sustainable fibers," SusMat, vol. e207, 2024.

[12] S. Muhammad, K. Hamza, H. A. Imran, and S. Wazir, "Enhanced Human Activity Recognition Using Inertial Sensor Data from Smart Wearables: A Neural Network Approach with Residual Connections," in 2024 International Conference on Engineering & Computing Technologies (ICECT), IEEE, pp. 1-6, May 2024.

[13] U. Martinez-Hernandez et al., "Wearable assistive robotics: A perspective on current challenges and future trends," Sensors, vol. 21, no. 20, pp. 6751, 2021.

[14] O. El-Gayar and A. Elnoshokaty, "Factors and design features influencing the continued use of wearable devices," Journal of Healthcare Informatics Research, vol. 7, no. 3, pp. 359-385, 2023.

[15] Y. Wang, S. Cang, and H. Yu, "A survey on wearable sensor modality centred human activity recognition in health care," Expert Systems with Applications, vol. 137, pp. 167-190, 2019.

[16] A. S. Nunes, İ. Yildiz Potter, R. K. Mishra, P. Bonato, and A. Vaziri, "A deep learning wearable-based solution for continuous at-home monitoring of upper limb goal-directed movements," Frontiers in Neurology, vol. 14, pp. 1295132, 2024.

[17] W. Guo, S. Yamagishi, and L. Jing, "Human Activity Recognition via Wi-Fi and Inertial Sensors with Machine Learning," IEEE Access, 2024.

[18] N. Hnoohom, S. Mekruksavanich, and A. Jitpattanakul, "Physical activity recognition based on deep learning using photoplethysmography and wearable inertial sensors," Electronics, vol. 12, no. 3, pp. 693, 2023.

[19] M. Straczkiewicz, E. J. Huang, and J. P. Onnela, "A 'one-size-fits-most' walking recognition method for smartphones, smartwatches, and wearable accelerometers," NPJ Digital Medicine, vol. 6, no. 1, pp. 29, 2023.

[20] J. M. Peake, G. Kerr, and J. P. Sullivan, "A critical review of consumer wearables, mobile applications, and equipment for providing biofeedback, monitoring stress, and sleep in physically active populations," Frontiers in Physiology, vol. 9, pp. 743, 2018.

 ISBN: 978-1-68558-204-3