Mobile Application for Improving the Quality of Life and Elderly Health Care

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Abstract

Imagine a smartphone application that acts as your health companion, understanding your unique needs and offering guidance throughout your golden years. This mHealth app aims to improve an elderly person's health management by analyzing simple physical tasks to assess key health indicators such as ADL, mood, cognitive function, mobility, and potential fall risks. It monitors daily activities to gain insights into overall well-being, identify potential health risks, and proactively suggest preventive measures or connect with appropriate healthcare services. Healthcare services are being offered on the LINE platform through a feature called "Long-term Care". This feature provides personalized health advice and recommendations that are tailored to Thai cultural health beliefs and practices. It also includes interactive communication to ensure better understanding. To analyze this feature, a healthcare dataset consisting of 913 samples has been collected from both Ubon Ratcha Thani and Sisaket provinces. This dataset will be used with machine learning algorithms. It analyzes and presents the principal component analysis (PCA) approach of activities of daily living (ADL), highlighting important features for AI models. It also allows users to share their health data and progress with family members or caregivers, enabling informed decision-making and collaborative care. This can help develop intervention services for the community. Finally, the team has successfully developed a mobile health (mHealth) application using Principal Component Analysis (PCA) to gain data-driven insights. In the future, they plan to use the identified features to create personalized intervention protocols for caregivers, which will improve support for elderly individuals in their Activities of Daily Living (ADLs). The app integrates with the LINE platform to encourage community engagement and empower both caregivers and healthcare providers to provide comprehensive care.

Keywords: DL, Long-Term Care, mHealth, Rajabhat Dataset, Stress

1. Introduction

Long-term care (LTC) refers to a broad spectrum of services and support provided to individuals who require assistance with daily living activities due to chronic illness, disability, or age-related limitations. These services can be provided in various settings, such as in-home assistance with daily tasks like bathing, dressing, meal preparation, and medication management. Assisted living facilities offer housing and on-site support services for individuals who need help with daily living but want to maintain their independence. Additionally, nursing homes provide skilled nursing care and comprehensive medical services for individuals with complex medical needs.

Technology applications can play a crucial role in supporting family caregivers by facilitating access to relevant information, community resources, and formal and informal services. Monitoring technologies are particularly useful for caregivers who need to keep an eye on their loved ones' status or activities while they are away at work or a remote location. Additionally, telemedicine applications can help care providers monitor patients' health and deliver healthcare services effectively [1]. Since LINE has a massive user base in Thailand, it is easily accessible to both residents and caregivers. The platform provides Thai language support and eliminates language barriers for users.

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Features such as photos, videos, and voice messages can enhance communication and provide richer data for ADL monitoring. One crucial benefit is the "Group chats" feature that facilitates communication between caregivers, family members, and healthcare professionals involved in a resident's care. Additionally, LINE's user-friendly interface makes it easy for both residents and caregivers to navigate, promoting adoption and reducing training needs. Caregivers can use LINE groups to record and share daily observations about residents' activities of daily living (ADLs) through text, photos, or videos. These observations could include tasks like bathing, dressing, eating, toileting, and mobility. Caregivers can also share their observations about residents' mood, sleep patterns, or behavioral changes, which can help detect potential issues early on. This is suitable for developing an ADL LINE-based monitoring system that is imperative to have the cooperation of care facilities, technology providers, and the Thai community. However, it is crucial to consider local cultural norms and address potential obstacles to ensure that the implementation is successful and responsible. This leads to earlier detection, improved interventions, and better health outcomes for individuals in long-term care facilities compared to traditional methods.

Collecting real-time ADL data detect functional decline early and provide personalized interventions, leading to more accurate care plans and efficient allocation of resources. It increases screening rates for mental health support, prevents the worsening of symptoms, and gains a deeper understanding of the relationship between ADL, stress, and others for necessary treatment adjustments. The support feedback has led to the development of experiments that integrate protocol functionality within this mobile application, allowing for remote consultations with doctors or specialists and improving access to healthcare. This study aims to develop a mobile healthcare (mHealth) application called "Long-Term Care" for measuring healthcare metrics for elderly individuals in the local Thai community. The application integrates the popular LINE platform with ADL (Activities of Daily Living) monitoring in long-term care facilities in Thailand to offer numerous benefits.

For our research, we have developed the "Long-term Care" mobile application on the popular LINE platform, with the aim of revolutionizing healthcare management for the elderly in Thailand. This innovative mHealth app monitors and analyzes daily activities to assess key health indicators such as ADL, mood, cognitive function, mobility, and fall risk (Figure 1). It provides personalized health advice tailored to Thai cultural beliefs and practices, fosters interactive communication for better understanding, and enables seamless sharing of health data with family members and caregivers.

2. Literature Review

2.1 How to Develop Long-Term Care Applications?

Technology has significantly improved the quality of life and care for individuals receiving long-term care. For instance, wearable devices and sensors can track vital signs, medication adherence, and activity levels, enabling healthcare providers to monitor patients remotely and offer virtual consultations. In Japan, they are developing an effective model to predict an individual's future long-term care demand using previous healthcare insurance claims data [2].

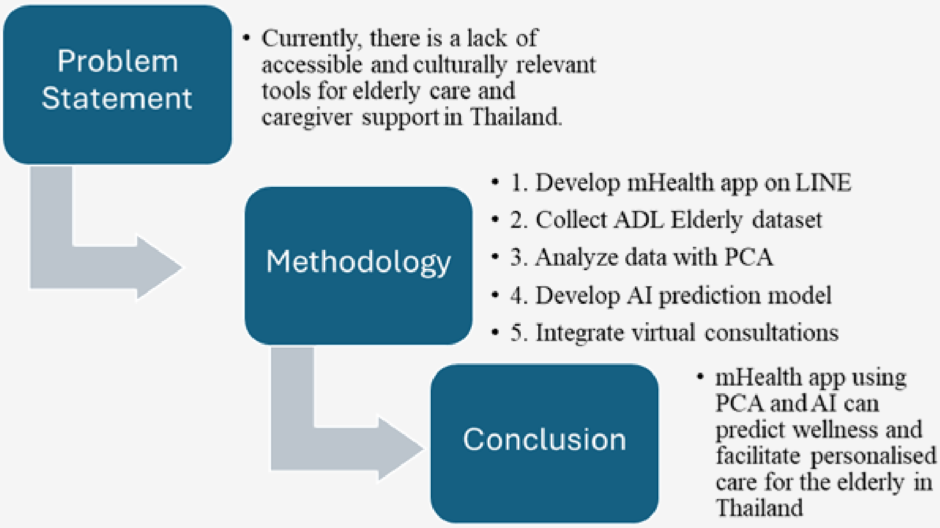

Figure 1: Conceptual design for LTH mHealth app research

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This model uses three learning algorithms with medical and long-term care insurance claims and enrollment records. Some health apps view medication as just one part of a larger strategy that includes other interventions and lifestyle changes to improve patient outcomes. The first systematic review of eHealth interventions for carers' wellbeing aims to provide a comprehensive analysis. The review identified 78 studies, which included 62 distinct interventions that aimed to improve carers' knowledge, self-efficacy, caregiving appraisal, and reduce health concerns. The studies revealed that dementia was the most researched area, accounting for 40% of all studies [3]. For example, the Transitional Care Assessment Tool in Long-Term Care (TCAT-LTC) is developed which consists of 2 themes, 12 categories and 63 items. Themes include organizational and financial aspects. Organizational aspects include categories such as communication, transfer of information, availability and coordination of resources, training and education of staff, education/support of the patient/informal caregiver, involvement of the patient/informal caregiver, telemedicine and eHealth, and social care. Financial aspects include primary care, hospital, and long-term care categories [4].

In the realm of mobile application development, a total of 328 apps were categorized. Out of these, 175 were developed for Android and 153 for iOS. The majority of these apps, 73% (11 out of 15), were developed by the software industry. In contrast, only 15% (3 out of 20) were co-developed by healthcare professionals. The remaining 2.1% (7 out of 328) were developed by academia [5]. Gamified apps and interactive platforms offer personalized exercises for cognitive stimulation and physical rehabilitation. These integrate information for coordinated care plans and progress tracking. Privacy and data security compliance are important. In Spain, it involves a combination of a smartphone application, an activity tracker wristband, and brief counseling, which is being compared to a group receiving only brief counseling. The goal is to evaluate the impact of the intervention on weight loss, body composition, physical activity, and caloric intake among Spanish sedentary adults who are overweight or obese [6].

Effective long-term care applications require collaboration between technology developers, healthcare professionals, caregivers, and patients. A study in Singapore used classification and regression tree analysis to find out why some patients and their caregivers didn't take up referred services [7]. Understanding the needs of those impacted by long-term care and leveraging technology thoughtfully creates impactful solutions that improve the quality of life for all involved. Four AI features - Recommendation, Conversational Agent, Recognition, and Prediction - are commonly used in seven health domains, including fitness, mental health, meditation and sleep, nutrition and diet, etc. [8]. For this study begins by establishing video conferencing platforms, such as Zoom, to connect patients from Ubon Ratchathani and Sisaket provinces with healthcare providers. This reduces social isolation and improves mental well-being. Then, it is being built on the LINE platform, which is cost-effective and offers benefits and also be used to monitor health and assess the effectiveness of mobile health intervention.

This research utilizes the wide user base of the LINE platform in Thailand, as well as its support for the Thai language and interactive capabilities, to develop a culturally relevant mHealth app that is easily accessible (Figure 2). The app can track activities of daily living (ADLs) and gather real-time data, enabling early identification of declines in functionality, customized interventions, and better health results.

2.2 Developing the Application to Support LTC?

The mobile Smart Care System (mSCS) conducted a study to evaluate the acceptance and usability of a mobile technology with focus groups. Participants reported that the application supported care coordination and communication with staff, and showed high technology acceptance among family caregivers in a long-term care setting. Facilitating conditions influenced acceptance, which should be optimized for technology uptake [13]. The health care sector has adopted digital technology to enhance patient care and clinical support, including the use of medical knowledge resources and monitoring quality care [14]. LINE is a widely used platform in Southeast Asia, which makes it easily accessible to a large population who may require long-term care support. As users are already familiar with the platform's interface and features, they can easily adopt and learn how to use it. For instance, LINE groups are useful for patients, family members, caregivers, and healthcare providers to communicate and coordinate with each other. They can share updates, schedule appointments, and discuss care plans together in a streamlined manner. It's important to note that while the LINE app can provide some long-term care support, it may not be a viable option for everyone. Its usage isn't as widespread as other apps, potentially leaving out certain segments of the population.

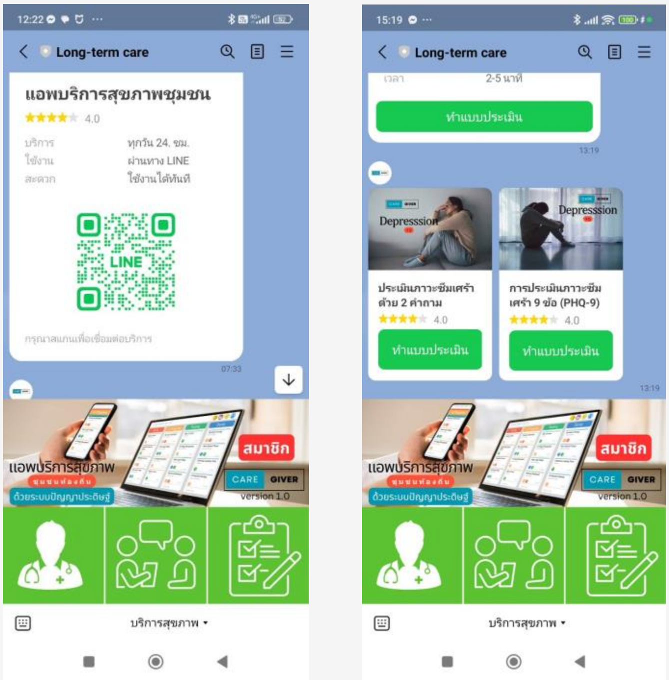

Figure 2: Long-term care” mHealth prototype

Additionally, digital literacy and device access must be considered, and the app may not have all the necessary features to provide comprehensive support. Therefore, integration with other specialized healthcare platforms and tools may be required. c, especially for those in rural areas or with limited connectivity, as they may not be able to fully benefit from the services. We plan to use the mHealth LINE application to gather data on the elderly and utilize Artificial Intelligence (AI) to identify suitable Machine Learning algorithms for predicting the ADL group in specific areas. However, it's important to note that previous studies have applied AI methods to identify appropriate datasets, yielding different results, as indicated in Table 1.

A long-term care developer recognizes the potential benefits of using LINE for communication, information sharing, and social engagement. However, it is crucial to address privacy concerns, ensure accessibility and digital inclusion, and consider integrating other healthcare tools for comprehensive support. This study has developed a LINE application that can serve as a centralized hub for remotely monitoring vital signs, medication adherence, and overall well-being. The application includes health self-assessments such as the ADL, stress, loneliness scales, and others. It also shares educational materials, health tips, and information about local resources for long-term care services and support. Therefore, it works as an open space to connect with others in similar situations, which can improve mental well-being and quality of life. This mHealth application is accessible and user-friendly for individuals with varying abilities and technology experience. It is crucial for the application to integrate with existing healthcare systems and platforms to ensure seamless information flow and care coordination.

2.3 Caregiver with LTC for Elderly Person Services

The pandemic has highlighted the importance of local healthcare for communities to access services easily. Specifically, long-term care services for the elderly are crucial to provide a range of assistance and support for older adults to live safely and comfortably as they age. In Taiwan, the study assessed variables for caregivers such as health, education level, job, income, and caregiving period. For care recipients, factors such as age, education level, living situation, and dependency level were assessed. Self-rated health was used to measure the health of both caregivers and care recipients [15].

Home nursing care was linked with better health for caregivers aged 65 or older, but not for those under 65. Caregiver employment, lower caregiving costs, and higher care recipient health improved the health of older caregivers. Daughters-in-law involvement and care recipient health were positively related to the health of younger caregivers. ICT was utilized to connect various groups including residents' families, hospitals, specialists, and general practitioners in the long-term care facilities [16].

Smartphone apps were created for both socializing and telemedicine. However, there was a lack of peer-to-peer social interaction among the elderly. As a result, this study aims to categorize LTC services in different settings such as at home, adult day care centers, assisted living facilities, or nursing homes based on their significance.

2.3.1 Essential services

The services mentioned below are crucial for meeting basic needs and maintaining safety. Personal care includes assistance with daily living activities like bathing, dressing, toileting, eating, and medication management. [17] Caregivers can help with errands, doctor appointments, and social outings, while also ensuring access to nutritious meals, particularly for those with dietary restrictions or difficulty cooking. They also help with housekeeping, laundry, and shopping to maintain a clean and comfortable living environment and check in regularly to ensure the elderly person's well-being and address any immediate concerns.

Table 1: A comparison table summarizing previous research

Study	Dataset	Methodology	Results
Development and validation of a prediction model for cognitive impairment among disabled older adults [9].	Chinese Longitudinal Healthy Longevity Survey (CLHLS), eighth wave (2017-2018), seventh wave (2014), and sixth wave (2011).	LASSO regression for variable selection, logistic regression (LR), support vector machine (SVM), random forest (RF), and XGBoost for model development	LR exhibited the best predictive performance with an area under the curve (AUC) of 0.875. A nomogram based on LR using five predictors (age, ADL score, IADL score, HI, and VI) demonstrated good discrimination in internal (AUC = 0.871) and external (AUC = 0.825 and 0.863) validation sets.
Development and evaluation of a machine learning algorithm to identify functional impairment using electronic health record (EHR) data[10].	EHR data from 6484 patients	Unsupervised learning (K-means and t-SNE) for patient classification, supervised learning (Extreme Gradient Boosting) to predict functional status states.	High accuracy in predicting functional status states (AUROC 0.92, 0.89, and 0.87 for normal function, mild/moderate impairment, and severe impairment, respectively). Age, falls, hospitalization, home health use, labs, comorbidities, and social determinants of health were key predictors.
Prospective cohort study of internal medicine wards in a tertiary care hospital in China to develop a machine learning model that predicts delirium risk in geriatric internal medicine inpatients [11].	40 hospital admissions with a median (IQR) age of 84 (79-87) years, 527 (71.2%) were men, and 101 (13.6%) with delirium.	Decision tree model trained on 70% of the data with five-fold cross-validation, under-sampling to address class imbalance, and evaluation on the remaining 30%.	The model achieved an AUC of 0.950 and F1 score of 0.810 on the test set, with 93.3% sensitivity, 94.3% specificity, 71.8% positive predictive value, 98.9% negative predictive value, and 94.1% accuracy.
A two-step hybrid machine learning model to explore the onset of depression in home-based older adults [12].	Depression data (collected in 2011, 2013, 2015, and 2018) of home-based older Chinese (n = 2,548) recruited in the China Health and Retirement Longitudinal Study	Step 1: Long short-term memory network (LSTM) to identify risk factors in 2015 using the first two waves of data. Step 2: Three ML classification algorithms (gradient boosting decision tree, support vector machine, and random forest) evaluated with 10-fold cross-validation and AUROC metric to estimate depression outcome.	Time-varying predictors of depression successfully identified by LSTM (mean squared error = 0.8). Mean AUCs of the three predictive models ranged from 0.703 to 0.749. Top five important variables: self-reported health status, cognition, sleep time, self-reported memory, and ADL disorder.

2.3.2 Supportive services

These services focus on enhancing the quality of life, promoting independence, and addressing specific needs. Caregivers provide opportunities for conversations, socialization, and activities to combat loneliness and isolation. They engage in various activities such as brain games, exercise programs, and creative pursuits to maintain cognitive function and physical health. Additionally, they offer counseling, support groups, and access to mental health professionals to address anxiety, depression, or any other mental health concerns. In Thailand, elderly citizens are often provided with social care assistance. Caregivers help with tasks such as managing finances, navigating benefit programs, and making legal decisions related to aging. As Thailand is a Buddhist country, many individuals in the community connect with religious or spiritual communities and practices to address spiritual needs and find comfort.

2.3.3 Advanced services

These are specialized services that cater to individuals with more complex medical or cognitive needs. Caregivers who are trained nurses provide medical care such as wound care, medication administration, and pain management. Physical, occupational, and speech therapy are also provided to help regain or maintain functional abilities after illness or injury. Palliative care and support are also provided for terminally ill individuals and their families.

2.4 Mobile Application for Caregivers

Developing an application for caregivers to assist the elderly with long-term care services is a wonderful initiative. It has the potential to significantly improve the lives of both caregivers and those they care for. For example, a mobile application was used to assess the effect of an electronic medical record-integrated mobile app for personalized diabetes self-care. The focus was on the self-monitoring of blood glucose and lifestyle modifications on glycemic control in patients with type 2 diabetes mellitus [18].

This idea is addressing a critical need because there is a growing demand for innovative tools and support systems for caregivers, especially with the increasing elderly population. The application utilizes LINE's accessibility and familiarity to reach caregivers effectively and offer valuable functionalities. It provides resources, education, and connections to ease the burden of caregivers and improve the quality of care by assisting with tasks such as medication reminders, appointments, and access to information (Figure 3).

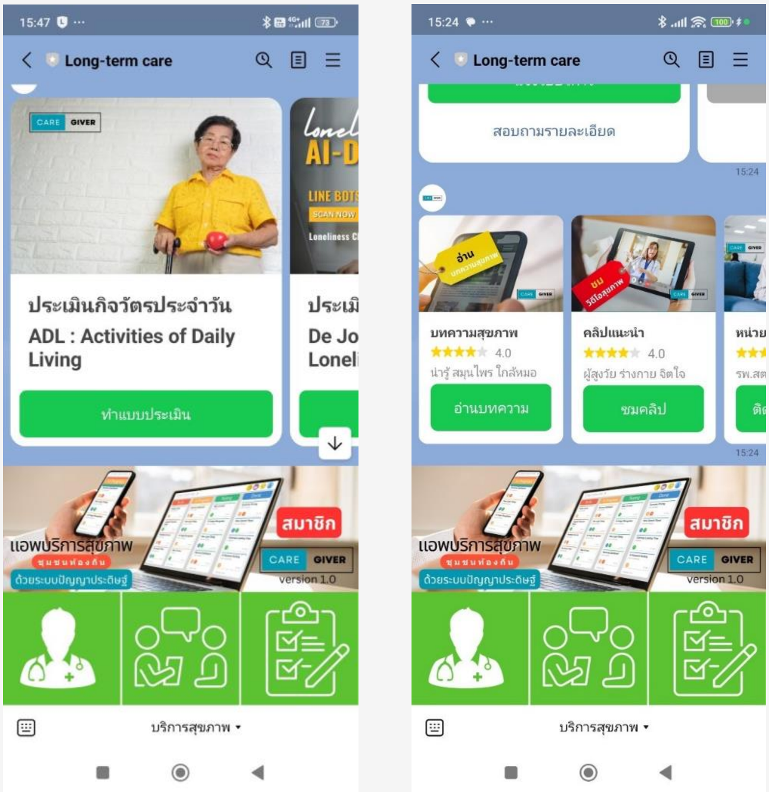

Figure 3: Self-Assessment and Services in mHealth “long-term” care applications

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The application also promotes elderly independence and well-being. In essence, this application serves as a healthcare notebook for community members to conveniently collect their health-related activities and information. iREST is an mHealth example that aims to develop and assess the usability of a Just in Time Adaptive Intervention application platform. [19] It was highly usable and easily implemented across different smartphone platforms. This information can be easily accessed by doctors or healthcare units to track progress, identify potential problems, and monitor the completion of behavior-related tasks.

The ideal caregiver application should prioritizes functions that address everyday challenges caregivers face, such as scheduling, coordinating care plans, and accessing relevant resources. The interaction design of the application should priorities user-friendliness and accessibility, making it intuitive and easy to navigate for caregivers of all ages and tech literacy. For example, the application should feature large fonts for accessibility and connect with local healthcare providers, community organisations, and delivery services to provide comprehensive support. Importantly, data security measures should be in place to protect user information and ensure adherence to relevant data privacy regulations. It is also important to provide training for both caregiver associations and senior centers to promote adoption and offer training workshops for effective app utilization.

2.4.1 Potential LTC mobile application features

There is a study on technology acceptance to compare mHealth research treatment with models, identify gaps, and clarify acceptance process [20]. In developing as a mobile application, it based on the concepts of ease and effectiveness. It is especially designed for task management, scheduling and organizing daily routines, medication schedules, and appointments as tools to connect with family members, healthcare providers, and other caregivers through calls, video chat, and messaging platforms. There are various support applications such as Google Meet, Zoom, Microsoft Teams, or LINE that allow caregivers and the community to work together by using features such as emergency alerts and location sharing for immediate assistance and peace of mind. These applications also provide accessibility to local services, support groups, and educational materials on elder care. With the help of mobile devices, caregivers can monitor the progress of care, medication adherence, and overall well-being of the elderly, which helps them in making informed decisions (Figure 4).

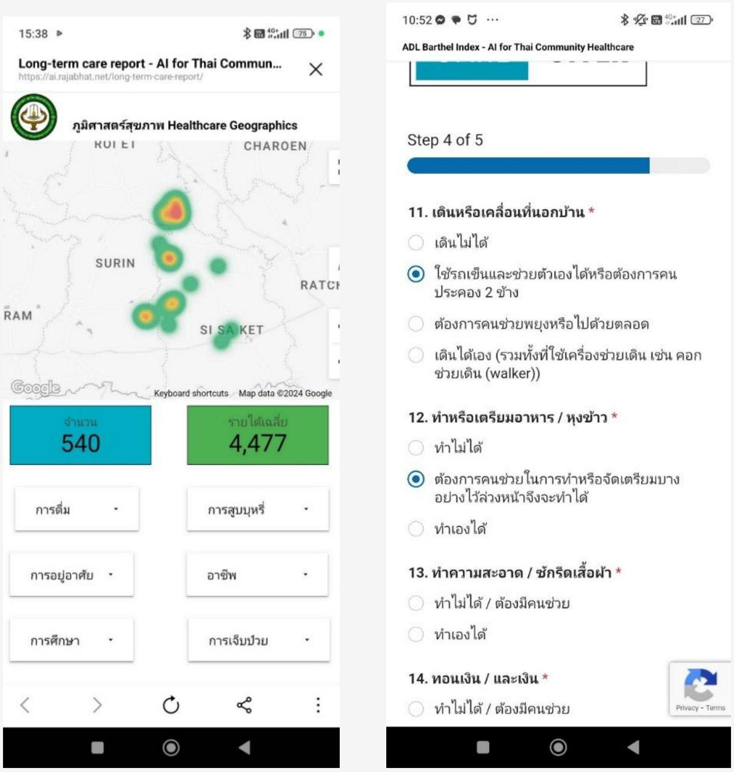

Figure 4: Healthcare Geographics and ADL questionnaire in “Long-term care” mHealth

To summarize, there is a huge potential in developing an application for caregivers who are supporting the elderly in long-term care. By prioritizing user needs, accessibility, and providing comprehensive support, it creates a valuable tool that can make a real difference in the lives of both caregivers and the elderly receiving care.

3. Methodology

This study aims to utilize a mobile application for real-time surveys, such as Activities of Daily Living (ADL) monitoring, stress screening and others. This leads to earlier detection, improved interventions, and better health outcomes for individuals in long-term care facilities compared to traditional methods. By collecting frequent and objective data on ADL, early detection of functional decline can be achieved. This is more effective than relying on periodic surveys or observations. Real-time data insights can enable personalized and timely interventions to address specific ADL challenges, leading to improved effectiveness. Therefore, it utilizes a three-phase approach base on mHealth prototype (Figure 5):

Self-Assessment: Users assess their health by using interactive tools and questionnaires, which helps in developing datasets.

Machine Learning Analysis: Machine learning algorithms analyze user data to predict health needs and offer personalized recommendations.

Consultant: Users can now easily connect with healthcare professionals for virtual consultations, improving care coordination and access to healthcare.

It developed an AI-powered Long-term care app with three phases to analyze user data and track health progress. The first phase is the Self-Assessment phase, which provides interactive tools and questionnaires for users to assess their general health, identify potential concerns, and track progress. This phase is the beginning of dataset development. The second phase of the healthcare process involves the use of machine learning algorithms to analyze user data, such as their symptoms and health measurements. In this particular mHealth application, the ADL dataset is collected from local healthcare units. The dataset is then divided into two separate sets for training and testing. The accuracy of healthcare predictions is determined by a confusion matrix, which takes into account several factors including precision, recall, F1 score, sensitivity, and specificity. Sensitivity refers to the true positive rate, while specificity refers to the true negative rate.

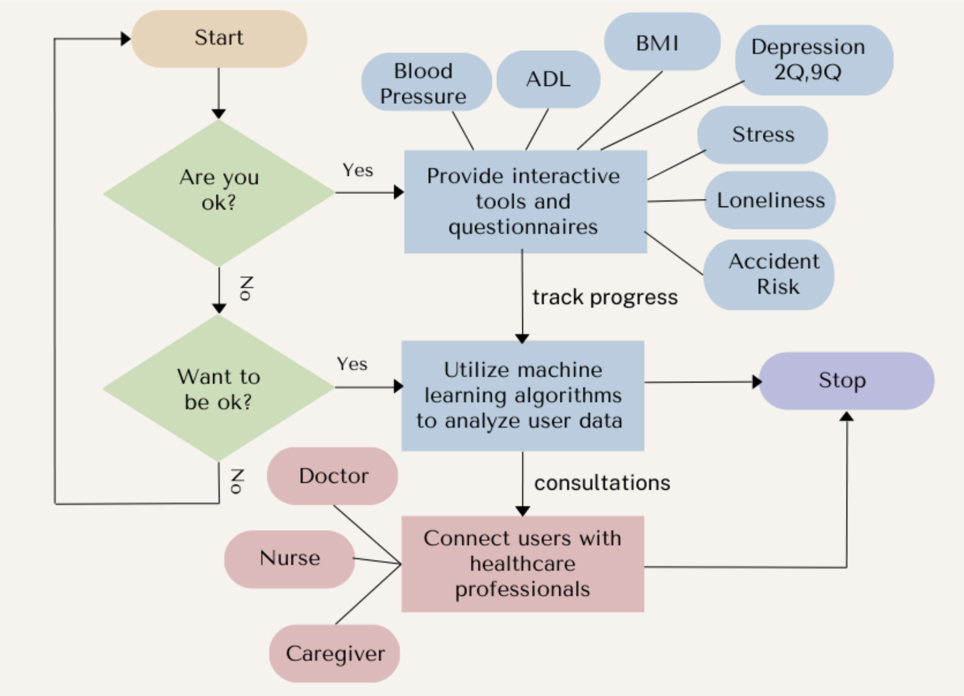

Figure 5: Long-term care mHealth prototype

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Table 2: ADL categories

ADL	ADL Level	Focus	Activity
B3	Independent Level Score >=12	Maintaining independence and promoting self-management.	Encourage individual performance of ADLs like bathing, dressing, eating, toileting, and mobility.
B2	Needing Assistance Level 5>=Score <= 11	Supporting individuals to safely complete ADLs while maximizing their participation.	Assist with specific tasks or offer modified approaches (e.g., using adaptive equipment, providing step-by-step instructions).
B1	Dependent Level 0 >= Score <= 4	Ensuring comfort, safety, and dignity while providing complete care for ADLs.	Perform ADLs for the individual, prioritizing their well-being and addressing specific needs.

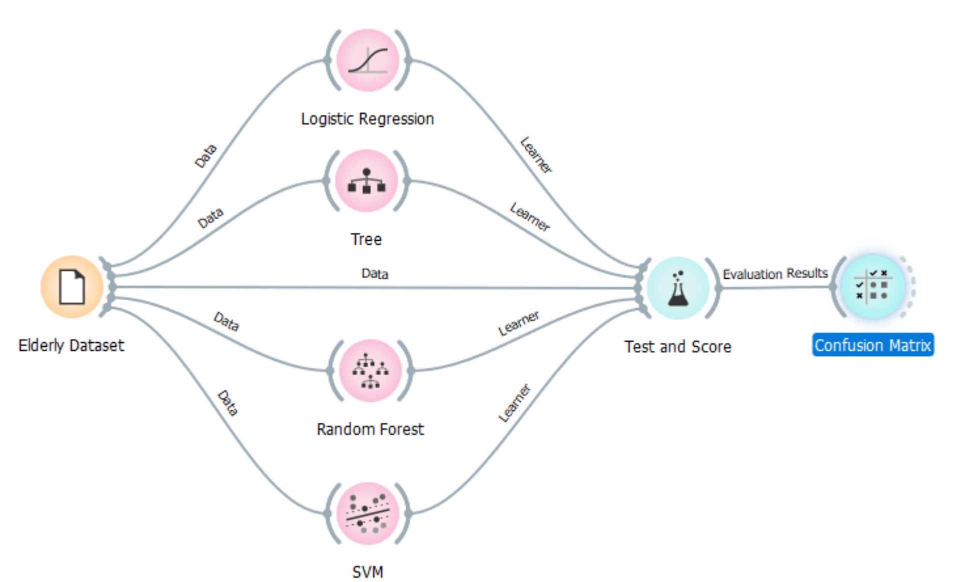

Figure 6: Teaching/Learning the "Long-term care" mHealth prediction algorithms

The third phase of this study is known as the Consultant phase. In this phase, users are connected with healthcare professionals, such as doctors, nurses, or specialists, for virtual consultations through chat, video calls, or secure messaging. This feature is designed to help caregivers develop interventions for their community. For the experiments, we collected a dataset of 913 samples from Ubon Ratchathani and Sisaket provinces. Descriptive analysis revealed that the majority of individuals were self-sufficient in their activities of daily living (ADLs), and a decline in self-sufficiency was observed with increasing age. Each level of Activities of Daily Living (ADL) requires different activities to support and take care of an individual. AI can recommend suitable actions based on an individual's screening, which can help caregivers reduce their intervention guidelines by categorizing appropriate activities. This prototype application analyzes user data to predict healthcare reports for personal and community sections. Each level of Activities of Daily Living (ADL) requires different activities to support and take care of an individual (Table 2). AI can recommend suitable actions based on an individual's screening, which can help caregivers reduce their intervention guidelines by categorizing appropriate activities.

3.1 Machine Learning Model Development and Evaluation

To predict healthcare needs and wellness in the elderly population, we developed a machine learning model using the collected ADL dataset. The dataset was divided into training and testing sets. Various machine learning algorithms were explored (Figure 6), including Logistic Regression, Support Vector Machine (SVM), Random Forest and Trees.

This is a standard machine learning workflow for training and evaluating various classification algorithms using a dataset related to the elderly. The Elderly Dataset serves as the initial data source and contains information about the elderly population, including relevant features for the target prediction such as ADL scores and demographic information. The dataset is divided into two subsets (Figure 8):

Training Data: This subset is used to train the machine learning models.

Testing Data: Used to evaluate the performance of the trained models on unseen data.

In this study, we are using different machine learning algorithms to identify the most suitable model for predicting ADL (Activities of Daily Living) levels based on the provided samples. Logistic Regression is a straightforward yet effective algorithm for binary classification tasks, such as predicting whether an individual is independent or needs assistance with ADLs. Random Forest and Decision Tree are ensemble learning methods that combine multiple decision trees to improve prediction accuracy and robustness. Support Vector Machine (SVM) is a powerful algorithm for classification and regression tasks and can handle complex data relationships. The model selection process involved evaluating each algorithm's performance on the testing set using the following metrics (Figure 7):

- **Accuracy:** The overall proportion of correct predictions.
- **Precision:** The proportion of true positives among all optimistic predictions.
- **Recall (Sensitivity):** The proportion of true positives among all actual positive instances.
- **F1 Score:** A balanced measure combining precision and recall.
- **Specificity:** The proportion of true negatives among all actual negative instances.

Hyperparameter tuning was performed to optimize each model's performance. The final model was chosen based on its overall performance across the selected metrics, with a focus on achieving a good balance between sensitivity and specificity. The diagram illustrates the workflow for evaluating and selecting a machine learning model to predict health outcomes in the elderly population. The workflow begins with the "Elderly Dataset," which serves as the input for three different machine learning algorithms: Logistic Regression, Support Vector Machine (SVM), and Random Forest. Each algorithm is trained on the dataset using a "Learner" component, which adjusts the model's parameters to fit the data. The trained models are then evaluated using a "Test and Score" component, which measures their performance on a separate portion of the data that wasn't used for training. This evaluation process involves generating "Predictions" and comparing them to the actual outcomes, resulting in "Confusion Matrices" and "Evaluation Results" for each model. The "Confusion Matrix" provides a detailed breakdown of the model's predictions, showing the number of true positives, true negatives, false positives, and false negatives. These values are used to calculate evaluation metrics like accuracy, precision, recall, and F1-score. The "Evaluation Results" likely include these performance metrics, as well as other relevant statistics, helping researchers assess the effectiveness of each model. The "Tree" component connected to the Random Forest algorithm suggests that this particular model is based on a decision tree structure, which can be used to understand how the model makes predictions.

Model	AUC	CA	F1	Prec	Recall	MCC
SVM	0.503	0.948	0.923	0.900	0.948	0.000
Random Forest	0.546	0.944	0.922	0.900	0.944	0.018
Tree	0.452	0.939	0.921	0.906	0.939	0.060
Logistic Regression	0.684	0.948	0.923	0.900	0.948	0.000

Figure 7: Teaching results for finding the Machine Learning algorithms

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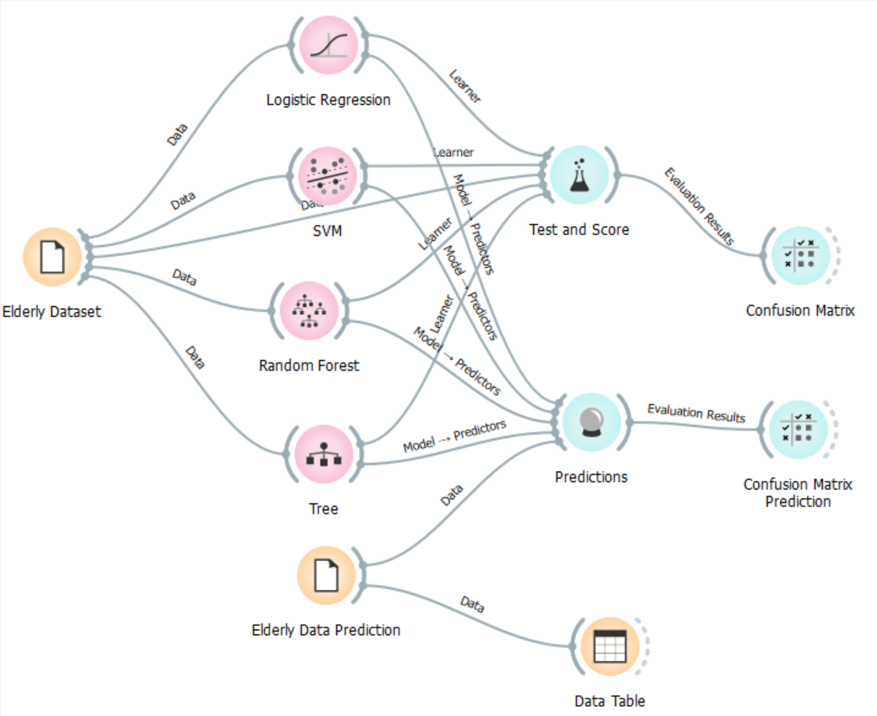

Figure 8: Long-term care mHealth prediction diagram

	Tree	error	Random Forest	error	SVM	error	Logistic Regression	error	ADL Group	Gender	Age
1	0.02 : 0.96 → 3	0.037	0.00 : 1.00 → 3	0.000	0.04 : 0.95 → 3	0.050	0.04 : 0.94 → 3	0.056	3	2	72
2	0.50 : 0.50 → 2	0.500	0.47 : 0.52 → 3	0.533	0.02 : 0.96 → 3	0.975	0.26 : 0.70 → 3	0.741	2	2	94
3	0.33 : 0.67 → 3	0.333	0.35 : 0.65 → 3	0.351	0.04 : 0.95 → 3	0.052	0.10 : 0.87 → 3	0.126	3	2	82
4	0.02 : 0.96 → 3	0.975	0.00 : 1.00 → 3	1.000	0.04 : 0.95 → 3	0.961	0.02 : 0.97 → 3	0.983	2	1	70
5	0.02 : 0.96 → 3	0.037	0.00 : 1.00 → 3	0.000	0.04 : 0.95 → 3	0.051	0.01 : 0.98 → 3	0.024	3	1	68
6	0.02 : 0.96 → 3	0.037	0.00 : 1.00 → 3	0.000	0.04 : 0.95 → 3	0.049	0.01 : 0.99 → 3	0.012	3	1	59

Show perfomance scores Target class: (Average over classes)

Model	AUC	CA	F1	Prec	Recall	MCC
Tree	0.688	0.833	0.815	0.867	0.833	0.632
Random Forest	0.688	0.667	0.533	0.444	0.667	0.000
SVM	0.500	0.667	0.533	0.444	0.667	0.000
Logistic Regression	0.750	0.667	0.533	0.444	0.667	0.000

Figure 9: Testing the “Long-term care” mHealth prediction diagram

Finally, the "Elderly Data Prediction" component appears to represent the final selected model, which is used to generate predictions for new, unseen data (Figure 9). These predictions are then stored in a "Data Table" for further analysis and use in the mHealth application. In summary, the diagram provides a clear and comprehensive overview of the machine learning methodology used in the study. It shows how the researchers explored multiple algorithms, evaluated their performance, and ultimately chose a model to predict health outcomes in the elderly population based on their dataset.

AUC (Area Under the Curve): A measure of the model's ability to distinguish between classes. The Tree and Random Forest models have the highest AUC (0.688), suggesting better discrimination than SVM (0.500). Logistic Regression has the best AUC (0.750) among all the models.

CA (Classification Accuracy): The proportion of correct predictions. The Tree model outperforms the others with the highest CA (0.833).

F1 Score: A balanced measure of precision and recall. The Tree model again excels with the highest F1 score (0.815).

Precision: The proportion of true positives among predicted positives. The Tree model demonstrates the best precision (0.867).

Recall: The proportion of true positives among actual positives. All models except the Tree model have a recall of 0.667.

MCC (Matthews Correlation Coefficient): A measure of the quality of binary classifications. The Tree model has the highest MCC (0.632), indicating the best overall performance.

Therefore, the Tree model demonstrates superior performance in predicting ADL group membership compared to Random Forest, SVM, and Logistic Regression, as evidenced by its higher AUC, CA, F1 score, precision, and MCC. However, Logistic Regression exhibits the best discrimination of classes based on its AUC value. These findings suggest that the Tree model may be the most suitable for predicting ADL levels in this specific context, although further analysis and validation might be necessary to confirm its generalizability. This application uses user data to predict the healthcare needs of the elderly population and facilitate support from local healthcare units. This dataset contains 913 samples collected from Ubon Ratcha Thani and Sisaket provinces in Thailand. The Likert-type scale for ADL items ranges from 1 (Unable) to 4 (Independent) in Table 3. The dataset was used for descriptive analysis, principal component analysis, and machine learning model development.

Table 3: Elderly dataset description

Feature	Description	Data Type	Measurement Scale	Range/Values
Age	Participant's age in years	Numerical (Integer)	Ratio	19-98
ADL Level	Assessment of Activities of Daily Living (ADL)	Categorical	Ordinal	B1 (Dependent), B2 (Needing Assistance), B3 (Independent)
Feeding	Ability to feed oneself	Ordinal	Likert-type (1-4)	1 (Unable), 4 (Independent)
Grooming	Ability to maintain personal hygiene (e.g., brushing teeth, combing hair)	Ordinal	Likert-type (1-4)	1 (Unable), 4 (Independent)
Transfer	Ability to move from one position to another (e.g., bed to chair)	Ordinal	Likert-type (1-4)	1 (Unable), 4 (Independent)
Toilet Use	Ability to use the toilet independently	Ordinal	Likert-type (1-4)	1 (Unable), 4 (Independent)
Mobility	Ability to walk and move around	Ordinal	Likert-type (1-4)	1 (Unable), 4 (Independent)
Dressing	Ability to dress oneself	Ordinal	Likert-type (1-4)	1 (Unable), 4 (Independent)
Stairs	Ability to climb stairs	Ordinal	Likert-type (1-4)	1 (Unable), 4 (Independent)
Bathing	Ability to bathe oneself	Ordinal	Likert-type (1-4)	1 (Unable), 4 (Independent)
Bowels	Ability to control bowel movements	Ordinal	Likert-type (1-4)	1 (Unable), 4 (Independent)
Bladder	Ability to control bladder function	Ordinal	Likert-type (1-4)	1 (Unable), 4 (Independent)
Others	(Additional features may include stress, loneliness scales, and other health-related measurements)	Varies	Varies	Varies

4. Experiments and Design Results

The focus of this study is to use mobility services to aid caregivers and the local community in accessing healthcare services. To achieve this goal, there is a need for tools that can improve the provision of services and support from the local government. Moreover, if these tools can predict or estimate the impact of elderly individuals on healthcare services, it can help the healthcare center plan for the necessary intervention protocols, considering the number of caregivers available to support the community. Descriptive analysis results from 913 samples of 3 districts and 4 sub-districts in Ubon Ratch Thani and Sisaket provinces. This report provides a summary of the descriptive analysis of the relationship between age and ADL (Activities of Daily Living) levels present in the data in Table 4. The findings indicate that most individuals (94.74%) belonged to age group B3, representing an independent level of ADL. The remaining individuals were distributed in age groups B2 (3.83%), which means a need for assistance, and B1 (1.42%), which represents a dependent level. Additionally, the average age for all groups was 69.95 years old, ranging from 19 to 98 years old.

As per the Age and ADL Level analysis, there was a noticeable pattern of declining independence with advancing age. Individuals in the independent group (B3) were generally younger than those in the group needing assistance (B2) and the dependent group (B1). The group needing help (B2) had the highest standard deviation, indicating more significant age variability within this group than the others. This analysis provides a basic understanding of how age and ADL levels are related. Further investigation is needed to draw more definitive conclusions and identify potential factors influencing ADL performance as a histogram. The histogram (Figure 10) shows a skewed distribution towards the older age groups, which is consistent with the following:

X-axis: Age groups ranging from 20-24 to 80-84 years.
Y-axis: Probability, likely ranging from 0 to 0.2 (20%).

For the AI data-driven, the additional questions that could be explored such as what factors besides age might influence an individual's ADL level.

Table 4: Descriptive analysis of ADL by age

		Frequency	%	Mean	Std. Deviation	Variance	Minimum	Maximum
Age	B3	865	94.74%	69.99	8.22	67.57	19	96
	B2	35	3.83%	77.6	11.32	128.25	56	113
	B1	13	1.42%	75.38	10.92	119.26	58	98

B3: Independent Level B2: Needing Assistance Level B1: Dependent Level

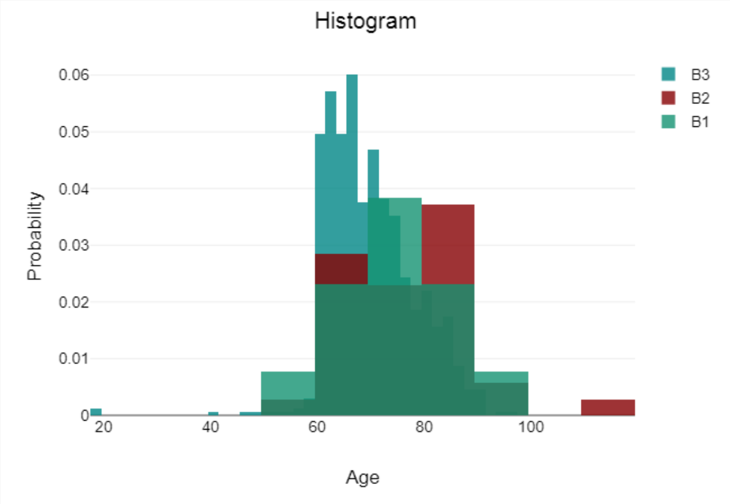

Figure 10: ADL histogram probability and age

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This study aims to gain deeper insights into the relationship between age and Activities of Daily Living (ADL) performance by addressing certain questions and considering potential limitations. The study utilizes Principal Component Analysis (PCA) with Varimax rotation on a dataset assessing ADL performance to identify underlying factors that explain the interrelationships between different ADLs. The results of this study will be used to develop features for an AI model that predicts wellness in the local community.

This table (Table 5) presents a correlation matrix summarizing the relationships between ten activities of daily living (ADLs): feeding, grooming, transferring, toilet use, mobility, dressing, stairs, bathing, bowels, and bladder. The values in the table represent the correlation coefficients between each pair of ADLs, ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation). Most correlations are positive, indicating that individuals who perform well in one ADL tend to also perform well in others. The strength of these correlations varies, with some activities exhibiting stronger relationships than others. Transferring, toilet use, mobility, and dressing show the strongest positive correlations (coefficients above 0.75), suggesting they share a common underlying factor related to physical movement and independence.

Grooming, bathing, and dressing also have relatively strong correlations (around 0.65), potentially reflecting shared aspects of self-care and personal hygiene. The components represent these underlying factors, and the percentages in the "Total % of Variance" column indicate their relative importance in explaining the overall variations observed in the ADL data in Table 6.

Table 5: Correlation matrix

Feature	Feeding	Grooming	Transfer	Toilet use	Mobility	Dressing	Stairs	Bathing	Bowels	Bladder
Feeding	1	0.57	0.69	0.62	0.68	0.65	0.62	0.54	0.41	0.41
Grooming	0.57	1	0.66	0.62	0.66	0.68	0.53	0.66	0.39	0.37
Transfer	0.69	0.66	1	0.79	0.84	0.79	0.72	0.64	0.52	0.52
Toilet use	0.62	0.62	0.79	1	0.81	0.82	0.76	0.72	0.52	0.49
Mobility	0.68	0.66	0.84	0.81	1	0.79	0.75	0.68	0.53	0.48
Dressing	0.65	0.68	0.79	0.82	0.79	1	0.77	0.75	0.55	0.55
Stairs	0.62	0.53	0.72	0.76	0.75	0.77	1	0.59	0.53	0.52
Bathing	0.54	0.66	0.64	0.72	0.68	0.75	0.59	1	0.4	0.43
Bowels	0.41	0.39	0.52	0.52	0.53	0.55	0.53	0.4	1	0.77
Bladder	0.41	0.37	0.52	0.49	0.48	0.55	0.52	0.43	0.77	1

Table 6: Total of variance

Component	Total	Variance (%)	Accumulated (%)
1	6.63	66.27	66.27
2	1.05	10.45	76.72
3	0.53	5.29	82.01
4	0.46	4.59	86.6
5	0.34	3.39	89.99
6	0.28	2.76	92.75
7	0.23	2.33	95.08
8	0.19	1.88	96.96
9	0.17	1.66	98.62
10	0.14	1.38	100.00

Additionally, the first component explains the largest portion of the variance (6.63%), suggesting it captures the most significant underlying factor influencing ADLs in this dataset. The remaining components contribute progressively smaller portions of variance, implying they represent less prominent but potentially still relevant factors. By the 10th component, the accumulated explained variance reaches 100%, indicating that all the relevant information from the original data is captured by these ten components. This table shows three components that help to classify different activities of daily living (ADLs) based on their importance for physical independence and functional ability (Table 7). Component 1 has high positive loadings (above 0.7) for most basic ADLs, such as feeding, grooming, transfer, toilet use, mobility, dressing, stairs, and bathing. This suggests that it captures a general factor related to overall physical independence and functional ability for basic ADLs. On the other hand, component 2 shows moderate positive loadings for bathing (0.38) and grooming (0.4), along with a negative loading for bowels (-0.65). This might indicate a factor associated with personal care and hygiene, potentially influenced by dexterity and upper body movement to some extent.

Finally, component 3 has high positive loadings for both bowels (0.68) and bladder (0.66), suggesting it isolates a distinct factor specifically related to elimination functions. In summary, these components help to understand the importance of different ADLs for physical independence and functional ability, as well as the factors that influence personal care and hygiene and elimination functions. Finally, the results obtained from Varimax are presented as follows (Table 8):

Component 1: Overall Physical Independence (0.61 - 0.78)
This component has high positive loadings for most ADLs (feeding, transfer, toilet use, mobility, dressing, stairs), suggesting it captures a general factor related to overall physical independence and functional ability for basic ADLs.

Component 2: Elimination Functions (0.8 - 0.91)
This component demonstrates high positive loadings for both bowels and bladder, indicating that it isolates a distinct factor that is specifically related to the management of urinary and bowel functions.

Component 3: Personal Care and Hygiene (0.8 - 0.82)
This component has high positive loadings for grooming and bathing, suggesting it represents a factor associated with self-care and personal hygiene, potentially involving aspects of upper body movement and coordination.

Table 7: Component matrix

Feature	**Components**		
	1	**2**	**3**
1. Feeding	0.77	-0.16	-0.32
2. Grooming	0.76	-0.26	0.4
3. Transfer	0.89	-0.1	-0.13
4. Toilet use	0.89	-0.12	-0.06
5. Mobility	0.9	-0.13	-0.11
6. Dressing	0.91	-0.07	0.04
7. Stairs	0.84	0	-0.28
8. Bathing	0.79	-0.22	0.38
9. Bowels	0.68	0.65	0.05
10.Bladder	0.66	0.66	0.1

Table 8: Rotated Component Matrix (Varimax)

Feature	Components		
	1	2	3
1. Feeding	0.78	0.2	0.25
2. Grooming	0.32	0.18	0.82
3. Transfer	0.72	0.34	0.43
4. Toilet use	0.68	0.33	0.5
5. Mobility	0.72	0.32	0.47
6. Dressing	0.61	0.39	0.56
7. Stairs	0.76	0.39	0.26
8. Bathing	0.35	0.24	0.8
9. Bowels	0.22	0.9	0.16
10. Bladder	0.17	0.91	0.19

5. Conclusion and Future Works

This study has successfully developed mobile health technology (mHealth) that utilizes principal component analysis (PCA) as a data-driven approach. However, to design effective and ethical intervention protocols for caregivers who support older adults in their activities of daily living (ADL) needs, it is essential to combine the insights obtained from PCA with clinical expertise and individual considerations. It highlights that while mHealth can be a useful tool that cannot replace the human touch, empathy, and judgment of a caregiver. The study's success lies in the mHealth application that uses the LINE platform to bridge the gap between caregivers and local healthcare units in the community. This application establishes a direct connection with participants, making it convenient for the government and community to track and monitor community wellness. It is important to note that recommendations such as healthcare promotion or intervention protocol should be evaluated and adapted carefully based on the individual's unique situation.

In future works, the identified features will be used to determine suitable services for interventions aimed at improving the well-being of the local community. The insights gained from analyzing the ADL dataset using techniques like PCA can provide valuable information for developing targeted and comprehensive interventions to enhance the well-being of the local community. By addressing the various factors that affect ADLs and adopting a holistic approach, communities can create a supportive environment that promotes independence, dignity, and overall well-being for their residents.

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