



Dementia U-Care: Comprehensive Cognitive Screening Application for Seniors

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ABSTRACT

The prevalence of cognitive impairment increases with age, particularly impacting seniors as it advances to severe dementia. These conditions pose significant challenges for afflicted individuals and their caregivers, manifesting as profound impacts on daily life and imposing considerable emotional and financial burdens on families. Mild cognitive impairment (MCI) denotes an intermediate stage between normal cognitive function and dementia, signifying a decline in cognitive abilities while maintaining normal daily life activities. Identifying MCI early in seniors within the community is pivotal to preventing further cognitive decline.

In response to the challenge of traditional cognitive function assessments, which require trained healthcare professionals and take 20–30 minutes per case, we introduce “Dementia U-Care,” an innovative app designed to assist community health workers in screening, monitoring, and collecting cognitive data. Accessible on mobile devices, it allows seniors to respond through drawing and writing, simplifying data collection compared to paper forms. Dementia U-Care streamlines preliminary assessments, empowering professionals and reducing fatigue and errors. This tool enables prompt screening, minimizing test-related stress, with an average testing time of 13.06 minutes, ranging from 9 to 20 minutes. The evaluation indicates high satisfaction with Dementia U-Care, with a mean score of 9.37 ± 1.12 . Users are generally pleased with its quality and user experience, demonstrating its effectiveness in meeting their needs and providing a positive experience.

Article information:

Keywords: Dementia, Screening, Cross Platform Application

Article history:

Received: December 24, 2023

Revised: March 7, 2024

Accepted: April 18, 2024

Published: April 27, 2024

(Online)

DOI: 10.37936/ecti-cit.2024182.255205

1. INTRODUCTION

Dementia is a prevalent neurological disorder commonly observed among seniors, exhibiting a notable correlation with advancing age [1]. The expenses associated with caring for seniors dealing with dementia can be more than 2.5 times higher than for those without dementia, surpassing \$20,000 per senior annually and imposing a significant financial burden [2-4]. Every five years, the number of individuals grappling with dementia typically doubles, with women exhibiting a higher likelihood of being affected compared to men [5]. Furthermore, research indicates that 15% of individuals with dementia are at risk of developing more severe conditions, including Alzheimer’s disease. Additionally, they may experience other coex-

isting health issues such as hypertension, diabetes, and coronary artery disease [6-8]. Currently, there is no specific medication to eradicate dementia, but interventions can slow down or halt the progression of the disease. Achieving this goal requires a combination of activities and medical interventions, although attaining a complete resolution remains challenging [9-11].

Commonly utilized generic tools for screening cognitive decline include the Montreal Cognitive Assessment (MoCA) and the Mini-Mental State Examination (MMSE) [12-13]. In particular, MoCA effectively detects and distinguishes between normal and impaired cognitive function [12]. However, a limitation of MoCA is the necessity for assessors to undergo

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training in its usage and result evaluation. Furthermore, the evaluation process is time-intensive, averaging around 20–30 minutes per person. This extended time requirement poses a challenge for practical implementation in community settings due to the high resource demand, encompassing personnel and time. This method is a pragmatic solution, ensuring rapid and efficient identification and screening of individuals with cognitive impairment, particularly in areas where modern medical tools may not be universally accessible [14–15].

Considering the current trends in lifestyle and the accessibility of technology on mobile devices, healthcare professionals can utilize applications as service tools to screen for individuals with cognitive impairment [16–17]. Current screening methods often involve surveys with diverse questions and measurement criteria, making data collection, analysis, and retrospective searches challenging. This research aims to develop a screening application for cognitive impairment management, utilizing a format derived from a cognitive function test translated into Thai. The aim is to screen seniors for early-stage cognitive impairment and enhance the test format into a digital version, making data utilization for analysis, planning, and future medical management more accessible.

2. BACKGROUND AND RELATED WORK

The current medical tools for screening cognitive impairment come in two forms: 1) brain imaging scans and 2) survey-based assessments. The first method involves radiological brain scans, which can be costly and require significant investment. Additionally, it poses challenges in accessing seniors residing at a distance and is relatively expensive. On the other hand, survey-based assessments or questionnaires offer a cost-effective alternative. While they may be less precise than the imaging approach, they adhere to accepted standards for diagnostic evaluations with diagnosis by neurologists. However, it is crucial to have an expert supervise the administration of these tests.

In this context, survey-based assessments are particularly suitable for the Thai community [18–20]. The MMSE is a preliminary cognitive screening tool to differentiate individuals with cognitive impairment from those with normal cognitive function. Despite its limited sensitivity and quick screening time, the MMSE may include individuals with minor cognitive deficits within the standard group. Following this initial screening, the MoCA is utilized to further distinguish between those with normal cognitive function and those with mild cognitive impairment. The MoCA is employed in the standard group identified by the MMSE, providing a more detailed assessment and separating individuals with subtle cognitive impairments from those with normal cognitive function.

Diagnosis of cognitive impairment can be significantly enhanced by utilizing artificial intelligence (AI) in conjunction with MRI scan images. This collaborative approach increases diagnostic accuracy from 73.3% to 99%, employing machine learning algorithms [21]. The direct impact of machine learning on the success of dementia diagnosis is evident. Furthermore, mobile applications integrated with machine learning contribute to the early detection of Alzheimer's disease and prove effective in diagnosing various hazardous health conditions [22–23]. A study has been conducted to implement the Time Delay Neural Network architecture combined with the Hidden Markov Model (TDNN-HMM) for training acoustic models. This initiative aims to develop a robust Automatic Speech Recognition (ASR) system resistant to environmental noise and variations in received audio quality. The results reveal that the TDNN-HMM model, coupled with data augmentation using the lattice-free maximum mutual information (LF-MMI) objective function, achieves a word error rate (WER) of 41.30%. Notably, this study marks the first attempt to create an ASR system with Thai language support to automate the scoring system of the MoCA's language fluency assessment.

The MoCA test can effectively distinguish between individuals with normal cognitive function and those with mild cognitive impairment. It has been translated into multiple languages and utilized for widespread cognitive screening. Developed by Ziad S. Nasreddine and his team and translated for use in Thailand by Dr. Solaphat Hemrungronj, the MoCA test offers high accuracy and discriminative power [24]. Its international recognition makes it a preferred tool for diagnostic purposes, especially in screening for cognitive impairment. Notably, the MoCA test surpasses the MMSE test regarding precision in cognitive screening. MoCA Test form in the Thai language, comprising eight domains. These domains include Visuospatial/Executive functions, Naming, Memory, Attention, Language, Abstraction, Delayed Recall, and Orientation. Each domain assesses different aspects of cognitive function, contributing to the overall effectiveness of the test. The comprehensive nature of MoCA allows for a thorough evaluation of cognitive abilities, making it a valuable tool in research and clinical settings.

While the data collected in the form is highly accurate, its efficiency for practical applications is limited. The data collection process requires combining scientific and artistic skills to extract information from the document form. Test administrators, or data collectors, must possess practical communication skills and precision in calculating scores based on test evaluation criteria. Such demands may result in fatigue among experts involved in data collection, given the time-consuming nature of the survey, which takes approximately 20 minutes per individual, depending on

the responder's knowledge and the test administrator's proficiency [25-26].

Furthermore, the MoCA test should be utilized under the supervision of medical professionals or neurology specialists to ensure accurate assessment results. The complexity of score calculation and test result interpretation, particularly in certain test activities, may require extended processing times and intricate analytical procedures. Continuous data collection from questionnaire responses, where data collectors must simultaneously record and verify the accuracy of responses, adds another layer of complexity. This process involves cross-checking to ensure responses are consistent and not repetitive compared to previous answers.

These challenges pose issues for immediate result delivery or situations requiring rapid reporting. Developing an application incorporating the MoCA test could be a promising avenue to address some of these challenges. Such an application could streamline the test administration and scoring processes, ensuring quick and accurate result retrieval. This technology help identifying cognitive decline in community environments.

3. OVERVIEW OF DEMENTIA U-CARE

The development concept of the DEMENTIA U-Care application consists of two main components: 1) the application itself and 2) cloud-based database management. The process begins with training healthcare professionals or volunteer community health workers in the community to use the dementia screening application. They record basic information about the senior individuals who will undergo the screening test. Subsequently, the senior individuals take the screening test using the application on a tablet or smartphone. A qualified healthcare professional or trained personnel facilitates the testing process. The input data from seniors may include spoken words, images, drawings, or various activities captured through the tablet. The application processes the test results for each question and provides an analyzed score, which is then sent to healthcare professionals or volunteer community health workers for confirmation before storing the data in the cloud-based database.

The application serves as an assistant that provides decision-support information by evaluating preliminary scores based on the test criteria. It also offers diagnostic information to healthcare professionals or volunteer community health workers, including scoring criteria. This functionality allows healthcare professionals or volunteers to access test results and historical data in personalized reports, leveraging provided diagnostic information and scoring criteria. Figure 1 illustrates the application's development concept.

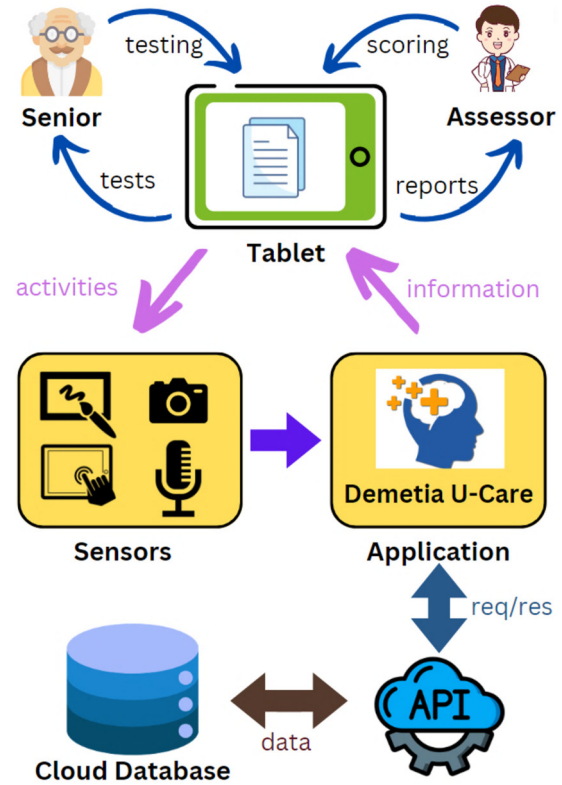


Fig.1: The design concept of the Dementia U-Care application.

4. METHODOLOGY

Research on developing Dementia U-Care cognitive screening application involves a systematic approach focusing on the design thinking process to ensure high-quality outcomes. The research process consists of the following steps: 1) user requirements study, 2) design and development of application prototypes, 3) expert evaluation of prototypes, 4) refinement and application deployment, 5) implementation, and 6) evaluation and technology transfer. By adhering to these steps, the research aims to prioritize user needs, ensure adequate design, and produce a cognitive screening application for dementia that is technically robust and user-friendly. The iterative nature of the process allows for continuous improvement and adaptation to address better the dynamic requirements of both users and experts in the field. This approach ultimately contributes to developing a high-quality, impactful solution for dementia care.

4.1 User Requirement Study

In the empathize and define stages of the design thinking process, we collected data from ten participants, including five community health volunteers, five system analysts, app designers, and general users. This diverse group was engaged in activities such as

brainstorming and silent brainstorming to ensure a variety of perspectives in the development of the application. The participants consisted of both volunteers and members of the community. This process aimed to understand the work practices and user testing requirements for individuals with cognitive impairment. The data collection involved administering the MoCA test, a survey-style paper-based test requiring participants to draw pictures and answer various questions. The questionnaire included diverse questions; the testing duration ranged from 20 to 30 minutes.

Field visits were conducted to collect data in each community, spanning several days due to an average of 30-40 senior participants in each community. Different criteria for measuring results were applied to each question in the survey, leading to potential errors in the scoring process. Additionally, the survey's paper format made it challenging to conduct retrospective data searches. The data collected in paper form hinders the analysis and utilization of information for other purposes.

4.2 Design and Prototype Development

The ideation stages in the design thinking process were employed to generate various ideas, incorporating previously gathered concepts and new out-of-the-box ideas. This was achieved through the use of personas representing the target user group. These personas provided diverse perspectives on the identified problems, detached from the individual identities of the group members. The outcomes of this process form the application's user interface and serve as the basis for developing the application prototype.

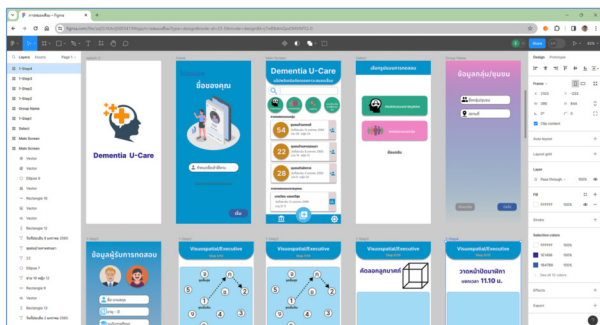


Fig.2: Mockup Created Using Figma.

This transition leads to the prototype development stage, further divided into three sub-steps: wireframe creation, user interface or mockup design, and application prototype development. The wireframes serve as a skeletal framework, outlining the basic structure of the application. Following this, mockups are created, which involve designing the user interface or interactive models. Finally, the application prototype is developed, providing a functional representation of the application based on the previously established

design concepts, as shown in Figure 2.

Design Information from the Mockup has been utilized in developing the Flutter prototype. Flutter, a cross-platform development framework, is the primary tool for creating applications that can operate on both iOS and Android operating systems. It employs the Dart programming language. Developed by Google, Flutter empowers developers to create aesthetically pleasing and user-friendly applications easily. This capability is crucial in shaping the functionality of the Dementia U-Care application, ensuring convenience and user-friendliness for senior users. This development has refined the testing process to align with mobile devices, describing all eight assessment domains.

4.2.1 Visuospatial/Executive Functions Domain

This domain involves a testing characteristic where participants are instructed to draw images comprising three types: 1) Continuous line drawing in the sequence, starting with numbers and alternating with letters; 2) Drawing a cube shape; and 3) Drawing a clock face indicating 11:10. The research team has designed a UX/UI that supports senior users in drawing images directly on mobile devices or tablets, along with voice command functions to assist those with speech difficulties. Participants may use a stylus pen instead of a finger touch on the screen. The design also incorporates familiarity-building features for senior users. Functions include the latest drawing undo (Undo) and reset (Reset) functions to clear all actions on the screen for a fresh start, presented in icon button format, as shown in Figure 3.

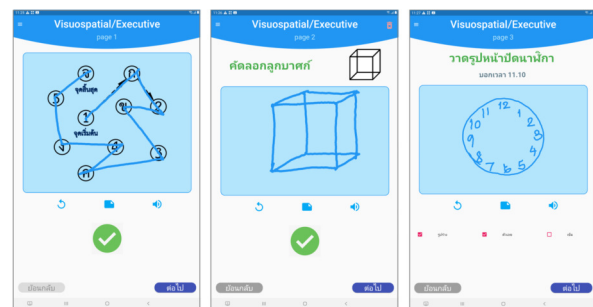


Fig.3: Prototype design for the Visuospatial/Executive functions domain.

After test takers have completed the test or activities for each item, volunteer community health workers must score the test taker's performance. The research team has specified that the application should display information in the form of an AlertDialog to provide scoring criteria. Additionally, Machine Learning (ML) techniques assess the scoring, and the predicted scores are displayed. This functionality enables volunteer community health workers to confirm the test results. If the community health worker believes that the scores differ from what the ML has pre-

dicted, they can manually adjust the scores to ensure accuracy or cancel the scoring to allow for a retest, as illustrated in Figure 4.



Fig.4: Displaying scoring criteria, predicted scores, and result confirmation using AlertDialog.

4.2.2 Naming domain

The Naming domain is responsible for examining the language usage of individuals undergoing testing to screen for cognitive impairment. It assesses whether the person still possesses the ability to recognize vocabulary and describe the meaning of words and objects. The research team utilized images from the original Thai version of the MoCA test to gather data from test-takers. The Speech to Text technique was employed, where images of animals were presented one by one, and participants were prompted to use spoken language to answer questions about the animal's identity in each image. The spoken responses were then converted into text for storage in the database and displayed on the screen for result analysis, as illustrated in Figure 5. Once again, community health officials are responsible for verifying the test scores.

4.2.3 Memory

The Memory domain is a test where the test-taker is presented with spoken words or a set of words to memorize. Subsequently, the test-taker is required to recall and repeat those words verbally. To facilitate this process, the research team has developed an

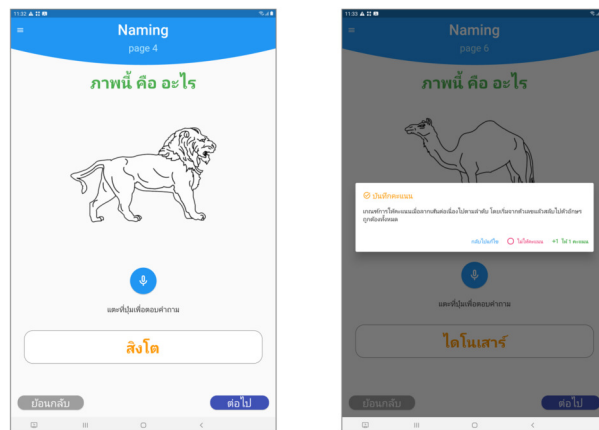


Fig.5: Prototype design for Naming domain: (Left) a text generated from converted speech, and (Right) confirms the recording scores.

application with a function to play audio files that narrate the word sets, serving as an alternative to actual speech production. This design aims to reduce the fatigue of community health workers during their operational duties, as illustrated in Figure 6.

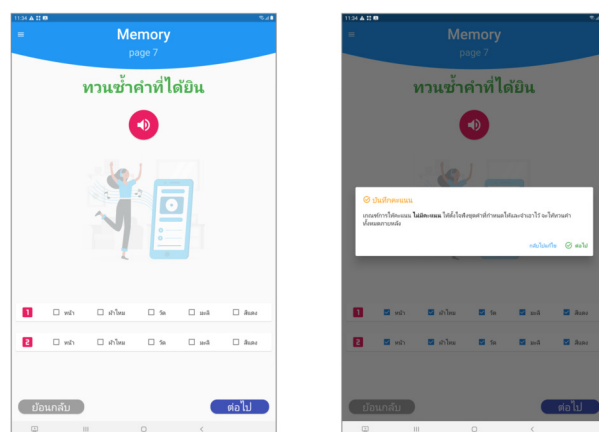


Fig.6: Prototype design for the Memory domain: (Left) a screen for play audio, and (Right) confirms the recording scores.

Once the test-taker has repeated the specified words, community health workers can mark the words in the list, creating a record of the vocabulary items. This procedure is repeated twice. It is crucial to note that no scoring is assigned for test confirmation in this domain. The primary objective is for the test-taker to memorize the word sets, anticipating subsequent recall during later stages of questioning.

4.2.4 Attention domain

The Attention domain assess the ability to identify and perceive crucial information in the surrounding environment or ongoing situations. The testing format within this domain is diverse. It includes 1) Sequential forward and backward verbal recall, 2) The

ability to detect changes, and 3) Sequential deletion of numbers. The research team has designed an application to assist community health workers in their tasks by incorporating features such as playing audio files and recording repeated verbal responses, as depicted in Figure 7 (a).

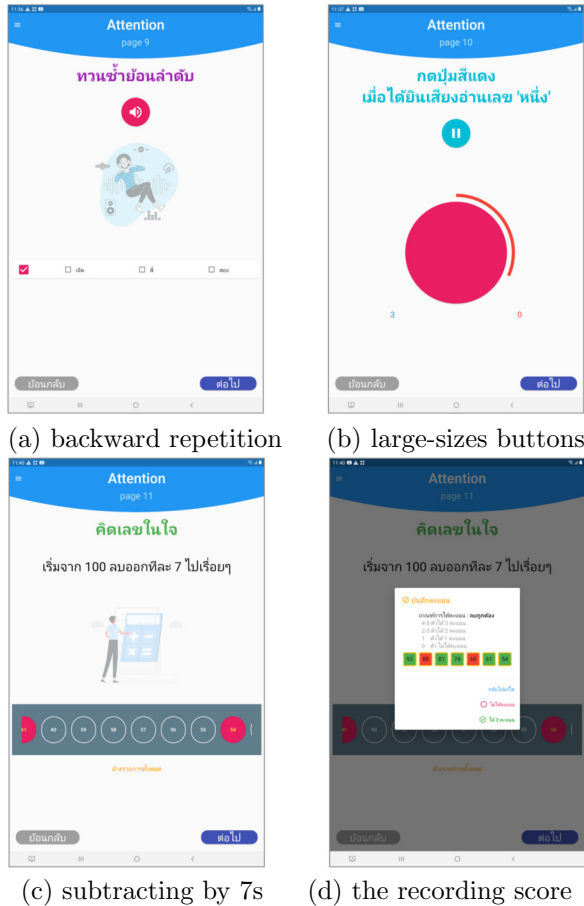


Fig.7: Prototype design for the Attention domain.

For the subsequent testing phase, the interface displays large-sized buttons with the functionality to play audio of digit sequences. Test-takers must press the button continuously when they hear “1.” The application reads the numbers sequentially, one at a time, and checks whether the test-taker pressed the button corresponding to the audible number “1.” The button must be pressed within a designated time frame of 1 second. Once the 1-second interval is complete, the application proceeds to read the next digit, repeating this process until the entire set of commands is covered. Points are deducted for not pressing the button when the number is heard and again if the button is pressed when the spoken number is different. The deduction is limited to a maximum of 2 points. Scoring details are presented on the screen, as illustrated in Figure 7(b).

In the final screen of this domain, participants engage in mental subtraction. They are instructed to verbally state the number obtained by subtracting 7, starting from 100, and repeating this process five

times. The application utilizes a horizontal bar with numbers from 100 to 50 (in reverse order) that community health workers can slide horizontally. When the test-taker states a number, the community health worker records it by tapping on the corresponding number displayed on the bar, as shown in Figure 7(c). The application calculates scores based on correct responses, with a maximum score of 3 points (3 points for correct responses of 4-5, 2 points for 2-3, 1 point for 1, and 0 points for 0). This scoring criterion, although intricate, provides convenience for data collection and calculation when transitioning to the use of this application. The application will notify the scoring criteria and summarize the obtained scores to enable community volunteers to verify the score recording, as illustrated in Figure 7(d).

4.2.5 Language

In the Language domain testing, the focus is on language skills and proficiency, encompassing various language usage aspects such as reading, writing, speaking, and listening. Test participants are required to listen to a text or conversation and respond to questions or speak their answers. The evaluation emphasizes understanding the heard content, language use in responses, and proficiency in speaking.

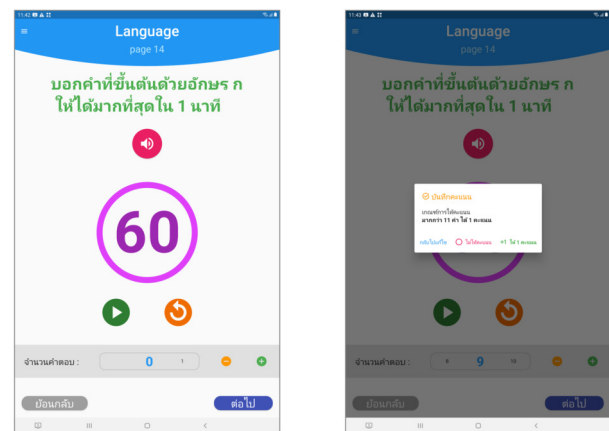


Fig.8: Prototype design for the Language domain: (Left) countdown timer, and (Right) confirms the recording scores.

To address this, the research team has designed an application in the form of a timed game, as depicted in Figure 8. The interface displays a countdown timer resembling a stopwatch set for 60 seconds. It consists of three buttons: 1) play button: instructs the test-taker to articulate words starting with a specified consonant within a given timeframe of 60 seconds 2) countdown timer start button: initiates the countdown timer and transforms into a temporary pause button, displaying a giant countdown clock indicating the remaining time, and 3) time reset button: resets the timer to the initial 60 seconds for a fresh start.

The assessment and scoring in the Language domain involve community health volunteers overseeing the screen. They use the “+” button to add points when the test-taker correctly pronounces words and the “-” button to deduct points for mistakes. No points are awarded if a word is repeated, lacks meaning, or does not meet the specified consonant conditions. Scoring involves earning 1 point for correctly pronouncing more than 11 words.

4.2.6 Abstraction

Testing in the Abstraction domain focuses on measuring the ability to distinguish significant features or crucial information from the overall data. Test participants are asked to identify similarities between two things, for example, banana - orange. The test-taker should respond that both are related as they are fruits. The research team has designed an application incorporating an interactive audio-command and description function to enhance user engagement and reduce fatigue. This function aims to standardize the process of describing items that questionnaire respondents must practice. The application also includes a Checklist Scoring section, assessing how many points the test-taker can score by identifying similarities between two items, as illustrated in Figure 9.

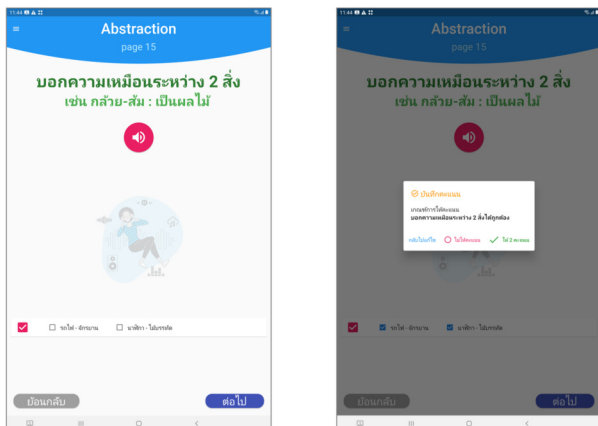


Fig.9: Prototype design for the Abstraction domain. (Left) checklist scoring; (Right) confirms the recording scores.

4.2.7 Delayed Recall

The Delayed Recall domain assesses the ability to remember information after a certain period following its presentation. Test participants are evaluated based on their capability to recall information received in the initial stage. If the test-taker can recollect or remember the information well after it has been presented, it indicates a good capacity for Delayed Recall. As illustrated in Figure 10, the application interface encompasses a design featuring the play sound command button and a checklist scoring mechanism. This checklist records test-takers responses,

indicating their ability to recall and remember words from the Memory domain.

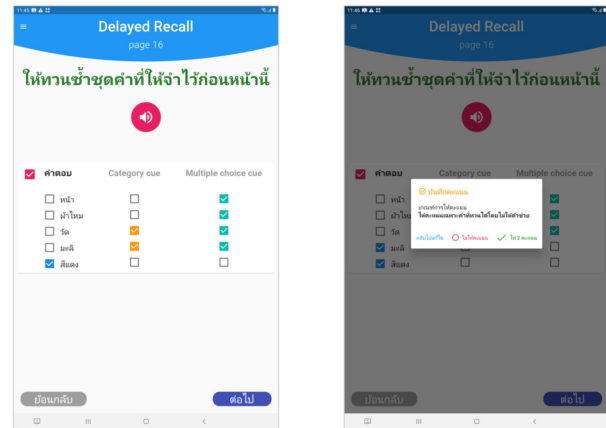


Fig.10: Prototype design for the Delayed Recall domain. (Left) checklist scoring; (Right) confirms the recording scores.

4.2.8 Orientation

The Orientation domain is a test that focuses on evaluating an individual's awareness and understanding of time, place, and people in the surrounding environment. As depicted in Figure 11, the research team has designed it to be straightforward, featuring a button-play sound command function and a Checklist Scoring system. With these features, test-takers can accurately record responses to questions regarding current date and time information and correct place names.

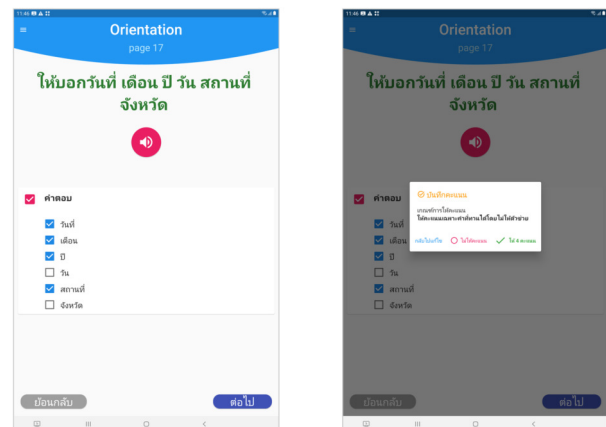


Fig.11: Prototype design for the Orientation domain. (Left) checklist scoring; (Right) confirms the recording scores.

4.3 Expert Evaluation of the Prototype

Prototyping assessment by domain experts involves measuring and evaluating the suitability for use before deployment or dissemination. The test participants in this research phase comprise three

medical professionals, five application design and development experts, ten senior individuals, and five general users, forming a sample population of 23 users for the prototype application. Evaluation is conducted using the System Usability Scale (SUS), a tool designed to assess system and application efficiency. The usability testing questionnaire comprises ten evaluation questions, with scores calculated using odd-numbered and even-numbered questions. Odd-numbered questions constitute a positive evaluation, while even-numbered questions represent a negative assessment. The resulting proportional usability score reflects user satisfaction with the developed application's usability.

Table 1: Expert Evaluation Results of the Prototype.

No.	Question	Mean	S.D.
1	I think that I would like to use this system frequently.	3.65	0.70
2	I found the system unnecessarily complex.	2.70	0.75
3	I thought the system was easy to use.	4.04	0.81
4	I think that I would need the support of a technical person to be able to use this system.	1.17	0.48
5	I found the various functions in this system were well integrated.	4.57	0.50
6	I thought there was too much inconsistency in this system.	1.35	0.56
7	I would imagine that most people would learn to use this system very quickly.	4.35	0.48
8	I found the system very cumbersome to use.	1.65	0.87
9	I felt very confident using the system.	4.30	0.62
10	I needed to learn a lot of things before I could get going with this system.	1.65	0.56

Table 1 shows the satisfaction results of the prototype of the Dementia U-Care screening application. Equation 1 calculates the total score for odd-numbered questions (x), while Equation 2 calculates the total score for even-numbered questions (y).

$$x = \sum_{i=1,3,5,7,9} Q_i - 5 \quad (1)$$

$$y = \sum_{i=2,4,6,8,10} 25 - Q_i \quad (2)$$

Where ' x ' stands for the sum of scores for odd-numbered questions, ' y ' represents the sum of scores for even-numbered questions, ' i ' represents the sequence of the question, and ' Q ' represents the question's score at sequence ' i '.

The values of x and y obtained from calculations are 15.91 and 16.48, respectively. When plugged into Equation 3, it results in a System Usability Scale (SUS) score of 80.98 out of a maximum of 100 points. The standard deviation is 6.71, indicating an excellent level of usability.

$$SUS = (x, y) \times 2.5 \quad (3)$$

The expert evaluation results have provided additional suggestions for refining the prototype application:

1) Visualization of ML-Based Assessment in Visuospatial/Executive Domain: The ML-generated real-time predictions during drawing tasks, such as continuous lines drawing, cube shape drawing, and clock face drawing, should not be displayed. This is because the ML processing provides real-time predictions, potentially influencing the test-taker by giving hints or making them aware that their drawing is incomplete during the test. This interference could significantly impact the accurate assessment of the individual's actual abilities during the test.

2) Animation and Progress Bar in Attention Domain: The animation showing a progress bar around the red circular button in the Attention domain, indicating the remaining time for the test-taker to press the button, was distracting. It led to increased excitement and may have diverted attention from the primary task of pressing the button within the specified time. Additionally, it is recommended not to display scores for correct and incorrect button presses, as this unnecessary information introduces distractions to the user interface.

In summary, these recommendations aim to enhance the accuracy and reliability of the prototype application by addressing issues related to real-time ML-based feedback during drawing tasks and minimizing distractions caused by animations and unnecessary scoring information during user interactions. These adjustments are crucial for ensuring that the assessment accurately reflects the cognitive abilities of the test-taker without undue influence or distraction.

5. MACHINE LEARNING MODEL

Machine learning is employed in developing the Dementia U-Care application to assist in predicting the accuracy of outcomes from the Visuospatial/Executive Domain. This application is developed using the Flutter Framework. A key aspect of developing applications in this domain is creating a machine learning model to ensure the accuracy and precision of predictions suitable for application use. Additionally, it must utilize the resources of mobile devices sparingly. Therefore, the research team opted for the TensorFlow Lite machine learning model, a set of tools that facilitates on-device machine learning, allowing developers to execute their models on mobile and embedded devices. The steps involved in creating the model are as follows:

5.1 Data Set Selection

The research team chose a dataset from the Visuospatial/Executive domain, which had been collected from prior research. It includes 128 samples, presented with expert evaluations in document format, as depicted in Figure 12. This dataset will be processed in the subsequent steps for training purposes in three models, namely 1) Continuous Line Model, 2) Cube Shape Model, and 3) Clock Face Model.

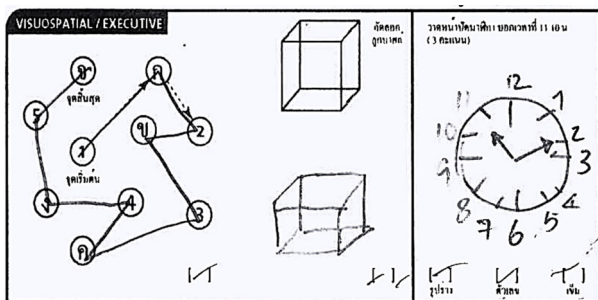


Fig.12: Data Set and the evaluation results by experts.

5.2 Data Preparation

Data preparation involves transforming and enhancing the data to a suitable format for model training. The data obtained from the MoCA Test field data collection is in the form of handwritten paper documents, needing more clarity, compromising the data set's effectiveness as a model training prototype. Despite efforts to enhance image quality through adjustments in lighting and contrast, the research team decided to employ an image cloning technique to obtain the most transparent and representative images from the original data set. This approach ensures sharpness and likeness while maintaining a more user-friendly digital file format.

5.3 Model Creation

Model creation involves importing the prepared data into the training process, resulting in a model file that can be utilized in the application. The research team opted for Google Teachable Machine, a user-friendly tool for machine learning that is accessible to those who are learning. The creation process involved generating three models, as depicted in Figure 13.

The first model pertains to continuous line drawing, with two predicted classes: “correct” and “incorrect.” Similarly, the cube drawing model consists of “correct” and “incorrect” classes. The final model for clock drawing encompasses five classes: 1) shape, 2) shape+numbers, 3) shape+hands, 4) shape+numbers+hands, and 5) incorrect. The outcomes derived from this research’s models or prediction results are presented in the Softmax function to

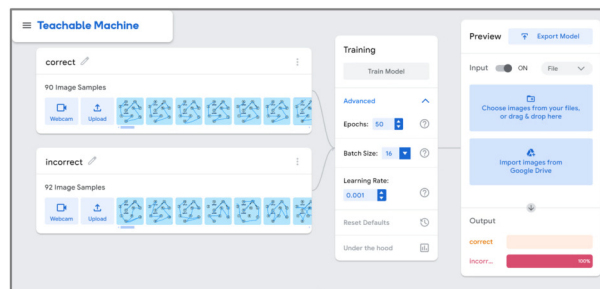


Fig.13: Continuous Line Model Creation in Teachable Machine Program.

normalize the prediction outputs into probabilities. This presentation method facilitates a more straightforward interpretation of the model’s results. Once the trained models are ready, they will be exported in TensorFlow Lite format for seamless integration into mobile applications, ensuring optimal usability on portable devices.

6. EXPERIMENT AND EVALUATION

Based on feedback received from experts’ evaluations, the research team has refined and improved the application to ensure its readiness for real-world use. Subsequently, the application has been published on the Play Store, enabling users to access it on the Android operating system. Following this, the team proceeded to conduct screenings for individuals with cognitive impairment in the Hua Don sub-district, Mueang district, Ubon Ratchathani province. In order to facilitate the testing process, researchers recruited a volunteer sample group of 80 individuals from the population residing in the vicinity of the Hua Don Sub-district Health Promotion Hospital. These volunteers came from four villages and were chosen for their proximity to the hospital, streamlining their participation in the testing activities. The testing location was provided by the Hua Don Sub-district Health Promotion Hospital.

The research protocol required that volunteers meet certain criteria. Specifically, individuals aged 50 years and above who could read and write and had not undergone cognitive assessment or screening within the past year were eligible to participate.

6.1 Research Tools

The tools used for on-site research include 1) Samsung Galaxy Tab A, a 10.1-inch model with an Octa-core processor (2x1.8 GHz Cortex-A73 & 6x1.6 GHz Cortex-A53) and 3 GB of RAM, 2) Dementia U-Care application installed on the tablet, 3) User manual for the Dementia U-Care application prepared for knowledge transfer to healthcare personnel at Hua Don Sub-district Health Promotion Hospital, and 4) User satisfaction questionnaire for app usage.

6.2 Data Collection

Participants undergoing evaluation will take a test administered by community volunteer staff or brain health experts overseeing and participating in scoring and activity verification. The population involved in the assessment consists of 80 senior individuals, as depicted in Figure 14.



Fig.14: Usage of the Dementia U-Care Application: (Left) Button pressing in the Attention domain. (Right) Drawing a cube in the Visuospatial/Executive domain.

6.3 Results Evaluation

The evaluation involves two components: a user satisfaction questionnaire and app usage data stored on the cloud. This data includes database records and images generated from drawing activities in the Visuospatial/Executive domain. It can be utilized to analyze the efficiency of the machine learning model.

6.4 Technology Transfer

Technology transfer involves conveying knowledge gained from developing and using the Dementia U-Care application. The process starts with explaining and transferring the assessment method for cognitive impairment using the MoCA evaluation. Participants then undergo training in using the application, including installation, registration, and a demonstration through the tablet. The training involves ten individuals, including doctors, healthcare staff from Hua Don Sub-district Health Promotion Hospital, and community volunteers. Participants are encouraged to ask questions throughout, and once they understand and complete the training, they proceed to use the application.

7. RESULTS AND DISCUSSION

Results from the overall research indicate the practical implementation of the Dementia U-Care application for screening cognitive impairment in seniors. This collaboration involved voluntary senior participants from Huadon Sub-district, Mueang District, Ubon Ratchathani Province, Thailand, who met the essential screening criteria set by the research, totaling 80 individuals.

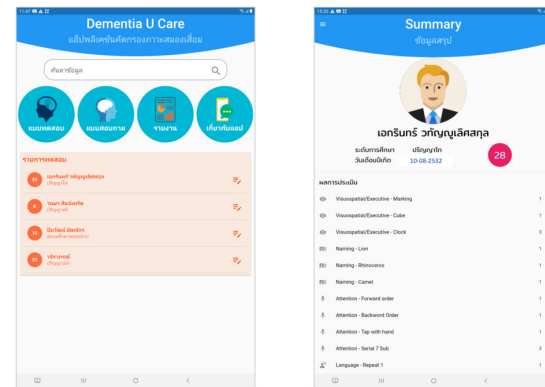


Fig.15: Main Screen Design for Dementia U-Care Application: (Left) List of individuals screened (Right) Personal assessment report.

7.1 Application Development Results

The Dementia U-Care application used in this research has been improved to function effectively in real-world scenarios. The adjustments were made based on recommendations from experts and individuals with experience in screening individuals with cognitive impairment. The result is an application capable of recording data and assessing the outcomes of those screened for cognitive impairment, as depicted in Figure 15 (left). This interface serves as the main page and features a top menu, including buttons for creating new tests (screening), satisfaction surveys, displaying reports, and accessing settings. The top bar facilitates item retrieval alongside a data list section presenting information on individuals who underwent screening. Notably, this information is visible only to the respective public health community volunteer who recorded the screening data and is inaccessible to other personnel.

Figure 15 (right) represents individualized reports on the screening outcomes for individuals with cognitive impairment. These reports display scores for each assessed domain and basic information about the evaluated individuals.

7.2 Application Usability Results

The performance evaluation of the Dementia U-Care application revealed an average testing time of 13.06 minutes, with a minimum usage time of 9 minutes and a maximum of 20 minutes. Additionally, user satisfaction scores were obtained through assessments within the application, covering five aspects, each with a maximum score of 10 points. All aspects received high satisfaction levels, except for the time-related factor, as illustrated in Table 2.

The table presents the mean scores, standard deviations (S.D.), and corresponding satisfaction levels for various criteria in the user satisfaction evaluation of the Dementia U-Care application. The results indicate high to very high levels of satisfaction across dif-

Table 2: User Satisfaction Evaluation Results for Dementia U-Care Application.

Criteria	Mean	S.D.
1. Appropriateness of Assessment Duration through the Application	8.98	1.35
2. User-Friendliness of the Application	9.34	1.19
3. Clarity and Audibility of Sound in the Application	9.45	0.99
4. Suitability of Equipment Used	9.50	1.15
5. Overall System Suitability	9.54	0.90
Average	9.37	1.12

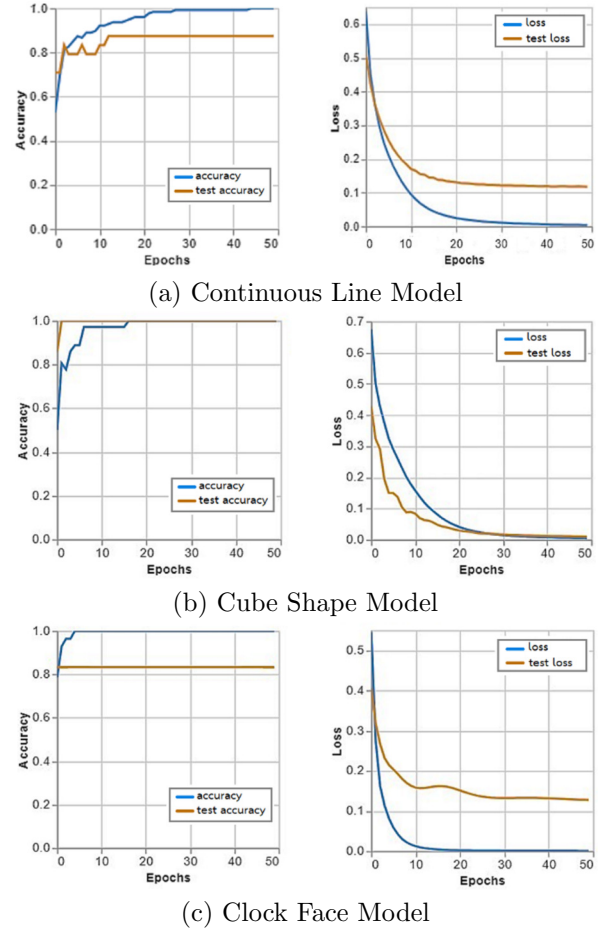
ferent aspects, with particularly noteworthy ratings for the ease of use and the clarity of sound within the application.

7.3 Model Performance Evaluation Results

The data collected, intended for training with a set of 128 samples across all three models, will undergo training processes in the Teachable Machine. This research has set the training rounds to 50 epochs, with a learning rate fixed at 0.001 and a batch size set to 16 for effective cross-validation. Following the prescribed training rounds, it was found that all three models achieved an accuracy and loss value of 1.00 and 0.00, respectively. Upon evaluating the model's performance through accuracy test and loss test metrics, it was observed that the Cube Shape Model demonstrated superior stability and efficacy, with an accuracy test score of 1.00 and a loss test score of 0.01. Meanwhile, the Continuous Line Model and Clock Face Model showed similar evaluation levels, with accuracy test scores of 0.87 and 0.83 and corresponding loss test scores of 0.12 and 0.13, respectively. As detailed in Figure 16, these findings affirm the feasibility of deploying these trained models for real-world application development.

After successfully training the machine learning models for use in the application, the research team deployed the application in the field to screen for individuals with cognitive impairment. This involved recruiting a total of 80 voluntary participants and utilizing data collected from the application database to evaluate the real-world performance of the system within the Visuospatial/Executive domain using a Confusion Matrix. From the results depicted in Figure 17(a), it was observed that the machine learning model correctly predicted 29 images of continuous lines as true positives, 45 images as true negatives, three images as false positives, and three images as false negatives, resulting in an overall accuracy of 92.5%.

Regarding the prediction of cube shape drawings, as detailed in Figure 17(b), the model correctly predicted seven images as true positives, 64 images as true negatives, one as false positive, and eight as false negatives, achieving an overall accuracy of 88.75%.

**Fig.16:** Accuracy and Loss per epoch for Visuospatial/executive functions domain.

In the case of predicting clock face drawings, as this model has five prediction classes, evaluating its overall performance can be achieved by calculating the sum of true positives across all classes divided by the total number of predictions. This yields a value of $(28+15+4+14+9)/80$, resulting in an overall accuracy of 87.50%.

Table 3: Model performance evaluation results.

Measure	Continuous Line Model	Cube Shape Model	Clock Face Model
Accuracy (%)	92.50	88.75	87.50
Sensitivity (%)	90.63	87.50	95.24
Specificity (%)	93.75	88.89	52.94
Precision (%)	90.63	46.67	88.24
F1-score (%)	90.63	60.87	91.60

Table 3 reveals that the Continuous Line Model exhibited superior overall performance with an accuracy of 92.50%. It demonstrated robust sensitivity (90.63%) and specificity (93.75%), indicating its proficiency in detecting positive and negative instances. The precision and F1-score were equally commendable at 90.63%, showcasing a balanced precision-recall trade-off.

		Actual Values	
		Positive	Negative
Predicted Values	Positive	29	3
	Negative	3	45

(a) Continuous Line Model

		Actual Values	
		Positive	Negative
Predicted Values	Positive	7	1
	Negative	8	64

(b) Cube Shape Model

		Actual Values				
		shape	shape+numbers	shape+hands	shape+numbers+hands	incorrect
Predicted Values	shape	28	0	0	0	2
	shape+numbers	2	15	0	1	0
	shape+hands	0	1	4	0	0
	shape+numbers+hands	0	2	2	14	0
	incorrect	0	0	0	0	9

(c) Clock Face Model

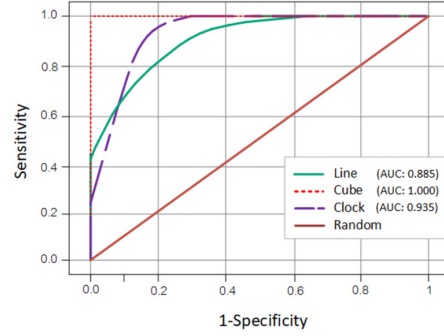
Fig.17: Confusion Matrix for Visuospatial/executive functions domain.

The Cube Shape Model exhibits a precision level of 88.75%, significantly lower than the Continuous Line Model, with a precision value as low as 46.67%. However, its sensitivity, specificity, and F1-score remain relatively accurate, at 87.50%, 88.89%, and 60.87%, respectively.

The Clock Face Model, boasting an accuracy of 86.25%, showcased robust sensitivity at 88.24%, rendering it proficient in clock drawing detection. A precision of 95.24% significantly contributes to a remarkable F1-score of 91.60%, emphasizing its efficacy in optimistic instance prediction.

Figure 18 represents the three machine learning models: the Continuous Line Model, Cube Shape Model, and Clock Face Model, employed in the research study. The area under the ROC curve (AUC) was utilized as a metric to assess the performance of these models. Upon plotting the ROC curves and calculating the AUC values, the following results were obtained:

Cube Shape Model: The AUC value of 1.000 suggests that this model achieved perfect classification performance, indicating that it could perfectly discriminate between the classes without any false positives or false negatives. This exceptional performance is noteworthy and suggests that the Cube Shape

**Fig.18:** Receiver operator characteristic curves: (green) Continuous Line Model, (red) Cube Shape Model, (purple) Clock Face Model (brown) Random Classifier.

Model may be highly suitable for the task at hand.

Clock Face Model: With an AUC value of 0.935, the Clock Face Model demonstrates discriminative solid power. Although not perfect like the Cube Shape Model, its high AUC value indicates that it can effectively differentiate between positive and negative instances with a high degree of accuracy.

Continuous Line Model: The AUC value of 0.885 is lower than the Cube Shape and Clock Face Models, but it still indicates good discriminative performance. The Continuous Line Model may achieve a different level of perfection than the Cube Shape Model, but it still demonstrates a solid ability to distinguish between classes.

Overall, the experimental results suggest that all three models show promise in their ability to classify instances effectively. However, the Cube Shape Model stands out with its perfect classification performance, followed closely by the Clock Face Model. These findings highlight the importance of choosing the appropriate machine learning model based on the specific requirements and characteristics of the dataset and task at hand.

7.4 Volunteer Rights Protection

This research has undergone ethical approval for human research from Ubon Ratchathani Rajabhat University, Thailand, adhering to the principles outlined in the Declaration of Helsinki and the International Conference on Harmonisation of Good Clinical Practice (ICH GCP) guidelines under the reference number HE651006. The researcher informed volunteers about the research project through Hua Don Sub-district Health Promotion Hospital, and before the commencement of the study, the researcher explained the objectives and research procedures and allowed volunteers to decide freely. Data collected through the application will be kept confidential with signed-in usernames and passwords for electronic mail, and access will only be granted to the system designer to protect volunteers' privacy. General infor-

mation records will utilize numerical codes, and access to this data will be password-protected for analysis purposes only. All data will be securely destroyed after the conclusion of the research.

8. CONCLUSION AND FUTURE WORK

The research successfully implemented the Dementia U-Care application, employing a comprehensive design and prototype development process. The design thinking approach, guided by ideation stages and user personas, contributed to a user-friendly interface. The prototype development utilized Flutter, a cross-platform framework, ensuring compatibility with iOS and Android operating systems.

The application's testing process, focusing on eight cognitive domains, demonstrated innovative features to accommodate senior users. The Visuospatial/Executive Functions domain incorporated touch-screen drawing and voice commands, addressing challenges in motor skills and speech. The Naming domain utilized the Speech to Text for language assessment, enhancing accuracy and efficiency. Memory testing integrated audio playback to alleviate the burden on community health workers, and the Attention domain employed interactive features for sequential tasks. The Language domain introduced a timed game for language proficiency evaluation, promoting engagement.

Furthermore, the Abstraction domain implemented an audio-command description function, enriching the evaluation process. The Delayed Recall domain assessed memory retention over time, while the Orientation domain gauged awareness of time, place, and people.

Results indicated the successful application of the Dementia U-Care in real-world scenarios, with high user satisfaction and usability scores. The machine learning models exhibited commendable performance, with the Continuous Line Model standing out for its balanced precision-recall trade-off.

Overall, the Dementia U-Care application represents a significant advancement in cognitive impairment screening. It provides a valuable tool for community health workers and contributes to the well-being of senior individuals. Future enhancements may focus on refining sensitivity in specific domains and expanding the application's adaptability for diverse user groups.

In the upcoming phases of this project, the research team will focus on enhancing and releasing the application on the Play Store. A pivotal aspect of this endeavor involves integrating Docker technology to reinforce the project's infrastructure. Docker encapsulates the software and its dependencies within containers, ensuring the creation of reproducible and consistent environments throughout various development and deployment stages. This strategic implementation optimizes the deployment process, foster-

ing scalability and seamless integration. The research team anticipates heightened efficiency in deploying the application across a diverse range of Android devices through Docker, ultimately contributing to a more reliable and enduring user experience. This deliberate utilization of containerization aligns with contemporary software development practices, promoting agile development and facilitating a smooth transition from testing to real-world deployment. Moreover, Docker's adaptability is expected to address compatibility challenges, further ensuring a streamlined deployment experience for users.

ACKNOWLEDGEMENT

The research team would like to express gratitude to the director of Hua Don Sub-district Health Promotion Hospital, Khueang Nai District, Ubon Ratchathani Province, for providing facilities and facilitating the research. Additionally, appreciation is extended to the assistant researchers in the community who serve as volunteer staff in the research area.

AUTHOR CONTRIBUTIONS

Conceptualization, E.W., and P.K.; methodology, E.W., and P.K.; software, E.W.; validation, E.W., P.K., and B.D.; formal analysis, E.W., and B.D.; investigation, P.K.; data curation, B.D.; writing—original draft preparation, E.W.; analysis and Interpretation, E.W., and B.D.; writing—review and editing, E.W., P.K., and B.D.; visualization, E.W., and B.D.; supervision, P.K.; funding acquisition, P.K. All authors have read and agreed to the published version of the manuscript.

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