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A Collaborative Framework With Artificial Intelligence for Long-Term Care

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ABSTRACT The trend of aging population among working families has made health care services for sub-healthy people more important. In Taiwan, caregivers are often hired by human resource agencies to provide long-term care, and they are the main supervisors responsible for the care of the sub-healthy people. However, most agencies only consider the cost of their caregivers and have insufficient staff to take care of the sub-healthy people, leading to the failure of the long-term care system. The lack of an effective collaborative framework for long-term care leads to sub-healthy people being at high risks. Existing frameworks for long-term care are still in the early stages of capturing suitability information dynamically. This paper proposes a new framework that includes all possible features suitable to support the needs of all sub-healthy people and provides a solution for the issue of determining suitable features for collaboration. This study applies association rules to long-term care to handle the mapping process and uses artificial intelligence technology to solve the issues of adjusting human variability dynamically based on the mapping result of sub-healthy people.

INDEX TERMS Artificial intelligence, collaborative framework, long-term care, sub-healthy people.

I. INTRODUCTION

One-ninth of the population of the world is 60 years of age or older, and the projected number of people over the age of 60 will reach 2 billion by 2050.[1] Sub-healthy people with chronic diseases are sometimes looked after by caregivers in nursing homes. However, most sub-healthy people live alone and frequently go outside as part of their daily activities. This implies that they would like to live a more independent life and need companionship, and they may possibly have a high risk of spiritual loneliness. This study uses the term sub-healthy to refer to older people who are capable of being independent under their residential aged care (RAC). Therefore, they have abilities to use state-of-the-art technologies such as smartphones to have their own social networks [1]–[3].

The long-term care system in RAC, sub-healthy people still need caregivers to accompany them to prevent spiritual alienation or accidents such as falls. Although caregivers including family members, friends, volunteers, nurses, and physicians are all possible candidates as home care workers. However, the main caregivers in charge of sub-healthy people under RAC are coming from care agencies [4]. Most agencies focus on decreasing their cost in hiring workers and always have insufficient staff, leading to the failure of the long-term care system [4]. This study proposes that caregivers could be sub-healthy people themselves to have a long-term collaboration with each other and can solve the issue of insufficient manpower. Sub-healthy people are often highly active, so it is necessary to consider their wills, backgrounds, or technologies to collaborate with. Sub-healthy people may have different political views or interests, so it is a challenge for long-term care to match their needs perfectly and to let the collaborative framework for long-term care work smoothly. The lack of an effective collaborative framework of long-term care will put sub-healthy people under unnecessary high risk. Therefore, the first research question is described as follows: RQ1: What are suitable features relevant to an effective collaborative framework for long-term care?

From the perspective of human or physical state variability, an effective framework should be able to learn and customize the association rules based on changing needs and preferences of sub-healthy people. However, it is a big challenge

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[1] https://www.ifa-fiv.org/

to face adjustments and manage human variability dynamically. People have different preferences and may change their behaviors even under the same conditions, which may influence the effectiveness of the collaborative framework. Therefore, the second research question is described as follows: RQ2: How to adjust data on human variability dynamically based on the features of sub-healthy people?

The main purpose of this study is to develop a collaborative framework for long-term care that is suitable for sub-healthy people and implement artificial intelligence to allow the mapping process of the collaboration to be both suitable and reliable. The next section presents literature reviews and is followed by a description of the proposed framework and research model. The fourth section presents the design of the experiment, and it is followed by the last section that concludes with some important contributions, limitations, and future prospects of the study.

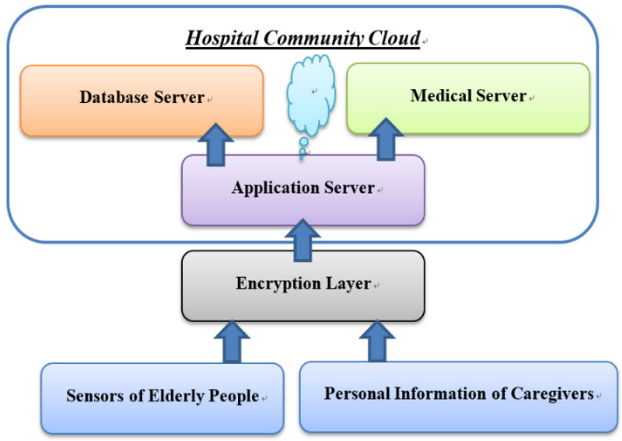

FIGURE 1. One of the existing frameworks for long-term care [9].

II. LITERATURE REVIEW

Existing studies state that many sub-healthy people, especially those with chronic diseases, do not cooperate well in maintaining their long-term care once back home from the hospital. This is associated with patients coming home to an empty house and not having adequate home-care services [5]–[7]. There is a developed centralized health record management architecture to support cooperative works for sub-healthy people [5], [6]. The architecture is based on the Collaborative Filtering (CF) theory, which compares sub-healthy people with others when they buy the same type of products. However, the current studies retain some serious misgivings about the adequacies of this system since it does not consider its suitability for sub-healthy people. Besides, the common limitation of those approaches is the lack of adjusted abilities that can provide a shred of underlying evidence or framework to increase information related to sub-healthy people.

The basic idea of the suitability of human resource agencies is that optimized services should consider all human resources and be dynamic to adjust their needs. However, in existing studies, for example, Zhang *et al.* [8] they may only consider some medical factors, such as pathology, radiology, and endoscopy. To achieve the identification of the suitability factors, actors should be assigned as having one or more roles or factors, such as the risk levels or demography categories, as well as patients need to be able to selectively interact with a good healthcare system. Some sub-healthy people may prefer to take care of themselves as if they were high-risk level people because of the higher level of interaction or empathy they receive.

One of the existing frameworks (Figure 1) consists of a server, user interface, remote base station and community cloud [9]. The hospital community cloud has a hierarchical framework with two modes: in-patient and out-patient, which provide connectivity to the hospital community cloud from their local servers. With the help of the centralized cloud system, caregivers can help their patients connect their devices to the server. In Figure 1, the first layer consists of comprehensive sensors (e.g., time and location sensors) and personal information, though it fails to focus on the factors relevant to the characteristic of long-term care. The second layer is responsible for encrypting data, yet there is no documentation that provides instructions to decrypt the data. The ideal application layer should cover the issue of identifying sub-healthy people, but this is not highlighted in the existing framework. Although existing studies understand the potential of building collaborative frameworks, they do not fully realize it in practice due to a variety of challenges. Further research is required to address the issues of long-term care. As most existing approaches do not solve the research questions mentioned above, their practical feasibility and level of user acceptance are uncertain. This framework is not appropriate to guide the design of long-term care systems.

To return to the second research question, what kind of technologies are helpful that can dynamically adjust to human variability based on the features of sub-healthy people? From a novel perspective, one of the major challenges that researchers are facing in this field is to explore a process innovation [10] in search of this answer.

In this study, I addressed the above issue by building an effective framework to utilize artificial intelligence to operate a mapping process by computing all possible suitable features across all sub-healthy people. The mapping process would use association rules for the joining and the pruning phases by reducing the number of candidates of sub-healthy people before using classification algorithms for support counting. Sub-healthy people could also view the candidates related to them anytime and then decide whether the process could continue to move on to the next step. This research applies artificial intelligence to the proposed collaborative framework of long-term care to solve the issues of finding suitable features and adjusting human variability dynamically based on the features of sub-healthy people.

III. RESEARCH METHODOLOGY

Existing frameworks for long-term care are still in the infancy stage due to the difficulty of building collaborative frameworks that can represent the characteristics suitable for capturing relevant features dynamically. Therefore, there is great potential to develop a new framework that could facilitate and guide the design of an effective long-term care system. The proposed collaboration is not to fail to provide or connect the health care workers from care agencies or hospitals by replacing the current long-term care system, oppositely, the novel method is trying to support the current system to solve the issues of insufficient manpower and spiritual loneliness.

A. THE PROPOSED FRAMEWORK

Physiology is the study of the functions and mechanisms of human body systems such as the respiratory, muscular, cardiovascular, and skeletal systems, which are underpinned by the concept of homeostasis [11]. The study identifies the physiological components to be abstract and measurable functions. For example, sub-healthy people may use sensors (e.g., wearable devices) or mobile phones that can measure their physiological data, such as heart rate, body temperature, oxygen saturation, and blood pressure [12]. In case of an emergency, such as a fall or a heart problem, wearable devices can automatically report their health condition to doctors, caregivers, or families. Some sensors through a smart home design could be useful to assist older people to remain in their home and extend independence [13]. In addition, people can share the information recorded by the devices with their friends, or post them on social media through social networking applications [12]. Therefore, physiology is one of several important features to be included while building a collaborative framework [14].

Assessing risk levels is an important process during diagnosis, treatment, and rehabilitation. Because of the complexity and seriousness of the consequences of a risk, it is critical that not only hospitals but also some government departments implement sound risk management mechanisms that can provide timely warning or macro administration such as levels of dependence. The risk levels in this study implies that dynamic environment context or interactions with others such as falls. Falls are significant concerns across the residential aged care sector, with half of the older population falling annually [15], [16]. Although fall prevention in RAC may enable sub-healthy people to maintain their independence, enhance their wellbeing, and sustain their quality of life. Family members or caregivers may only contact sub-healthy people frequently through mobile phones out of concern when they are enjoying outdoor activities, but it is difficult for caregivers to be fully aware of their current contexts for fall prevention [17]. In Taiwan, we usually use the Barthel score,[2] which can be categorized into several levels, as a measurement index for the risk levels from the Ministry of Health and Welfare.[3] The risk levels are also one of the important features to be included when building a collaborative framework because it can help identify, assess, analyze and mitigate potential risks [18]. The risk levels can be categorized into four levels: low, moderate, high, and very high [19].

Medical records are the systematic documentation of a single patient's medical history, including details such as chronic disease and surgical reports [5], [6], [8], [9]. Medical records are sometimes regarded as static management of signs and symptoms such as heart failure reports [20]. This study focuses on sub-healthy people who are under RAC and can collaborate with some active and energetic people. To achieve the identification of the suitable features, medical records are one of the more important factors because such information (e.g., pathology, radiology, and endoscopy) could provide cues to prevent infection or improper eating habits related to chronic diseases such as diabetes. Features selection should be assigned according to similar characteristics, such as medical records, and patients need to be able to selectively interact within a good mutual collaboration [21]. Some older people may prefer to manage their health as if they have the chronic disease because of the higher level of interaction or empathy they receive.

Demography is the statistical study of populations such as education, nationality, religion, and ethnicity. A good mutual collaboration should have participants from similar backgrounds and common interests, which may have cues from characteristics such as education, nationality, and religion. Therefore, demography corresponds to detailed background information. Although there may be some serious misgivings about the adequacies of this mutual collaboration since it not only considers the features themselves but instead can cover whole societies or groups defined by criteria in order to offer optimized services based on the decentralized system.

The proposed collaborative framework (Figure 2) defines the process for long-term care, including factors of suitability, long-term care application, and artificial intelligence technology. Data on the risk levels, physiology, medical records, and demography are collected to check the suitability of the sub-healthy people. The suitability information must be represented in a structured, uniform, and interchangeable format. The long-term care application is a process of logically selecting and integrating information that is relevant only to long-term care and transferring that data as transformed by the computing process to become meaningful information. The artificial intelligence technology provides more accurate services encapsulated in the form of a dynamic network that allows all users to interact with it through different methods, such as association rules and classification algorithms. The proposed framework of this study aims to facilitate the system by allowing designers or programmers that could devote their time to meeting some requirements, rather than dealing with more standard details of providing some working systems, thereby improving overall time for development.

[2] https://en.wikipedia.org/wiki/Barthel_scale

[3] https://www.mohw.gov.tw/np-108-2.html

FIGURE 2. The collaborative framework for long-term care.

Existing frameworks create a cooperative platform with human resource agencies that provide long-term care. These agencies may provide information on the availability of caretakers in advance to provide a "window period" if they are not ready to receive a patient or a task related to them. However, few studies combine artificial intelligence technologies and long-term care together with the integration of suitability and older people [22]. In addition, existing methods retain some issues of insufficient suitability after applying artificial intelligence applications into the collaborative platform [23]. In RAC, although an ideal collaborative framework should try to put relevant factors as much as possible, the proposed framework still has some limitations. Current caregivers in the long-term care system should pass some professional training, but the proposed framework cannot reveal this part. In addition, we still cannot ignore the importance of face-to-face interaction for a health assessment, even we apply artificial intelligence into the framework to increase the ability of self-learning to lead to better performance of the system. In sum, the proposed solution is based on a dynamically changeable context to involve relevant factors, which can be grouped into the suitability. In addition, the framework can be used for different kinds of long-term care applications, such as mobile agent systems. Importantly, the proposed adaptive service will automatically respond to sub-healthy people.

B. THE ALGORITHM TO LONG-TERM CARE

The proposed algorithm is referred to as the Apriori algorithm. This algorithm is one of the most popular methods used for mining frequent items through a transactional process. The algorithm uses multiple-pass and generation-and-test frameworks to comprise the phases of joining and the pruning for improving the number of candidates before scanning the dataset for support counting [24] (Table 1).

TABLE 1. The steps of the algorithm.

Given support and confidence index in four steps:
Step 1: Compute collaborative records based on the proposed framework
Step 2: Consider seed people to meet minimum threshold support
Step 3: Compute collaborative records where P2 is selected after P1
Step 4: Consider seed people to meet minimum threshold confidence

The algorithm of the collaborative framework demonstrates the initialization of parameters from older people, setting up supporting groups such as threshold requirement, computing confidence to let the system operate effectively, and adding collaboration to let the systems adjust dynamically.

The Algorithm of the Collaborative Framework

Require: Initialization of parameters: getRecords, getOlderPeopleID
Set up support groups:
for support (index ← threshold)
groups (getOlderPeopleID) ← records (getOlderPeopleID)
end for
Compute confidence:
for confidence (index >= threshold)
confidence (getOlderPeopleID) ← groups (getOlderPeopleID)
end for
Build collaboration:
if probability (candidate (getOlderPeopleID)) >= probability (confidence (getOlderPeopleID)) then
collaboration (getOlderPeopleID) ←
candidate (getOlderPeopleID)
end if

C. THE RESEARCH MODEL

This study follows the proposed research framework of suitability, which provides practical guidelines for building an innovative research model and an effective manner to solve a problem in this field. Based on extant approaches and their limitations, this model not only integrates different data from diverse features but also considers utilizing artificial intelligence to increase accuracy dynamically.

One of the research questions was to identify factors relevant to building an effective collaborative framework for long-term care. User perceptions such as perceived ease of use, perceived usefulness, user satisfaction, and user intention are popular for evaluating a system or framework [25], [26]. Perceived usefulness is measured by how much a potential user thinks a system will help them enhance their daily performance. Even if potential users believe that the system or framework is useful, they may simultaneously feel that the system or framework is too difficult to use and that the benefit

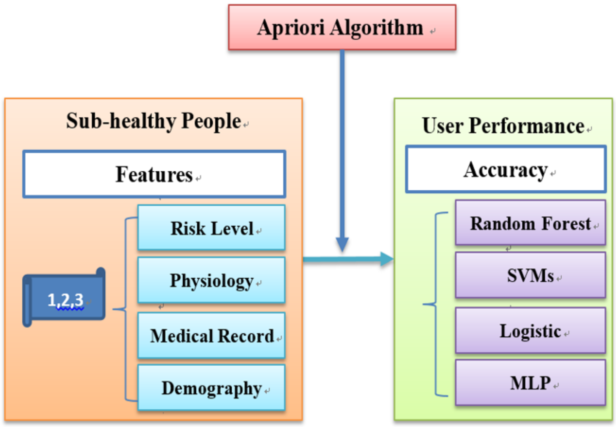

FIGURE 3. The research model.

in usage is outweighed by the effort of using the system; this is called perceived ease of use [25], [26]. Therefore, to return to answer the first research question (RQ1), I have made the hypothesis that in order for it to be considered to be suitable, the proposed framework must include the risk levels, physiology, medical records, and demography to improve the users' (a) perceived usefulness, (b) ease of use, (c) satisfaction, and (d) need for and intention to use long-term care.

The research model described uses machine learning algorithms, such as support vector machines (SVMs) to deal with any challenges involved in learning orientation [27]. SVMs are widely-used powerful algorithms that consider empirical error and structural risk minimization [28], [29]. The random forest algorithm is suited if there are many classification trees without overfitting problems, for it classifies a new object from an input vector, and puts the input vector down each tree in the forest [29]. Therefore, this study uses association rule by finding frequent features and then building classification methods of sub-healthy people to create a collaborative model. This study aims to address the problem of finding out suitable features and adjusting human variability dynamically based on the features of sub-healthy people. The research model is depicted in Figure 3.

In the research model, the features of sub-healthy people include the risk levels, physiology, medical record, and demography, which have their domain knowledge and can form a long-term collaboration structure. This research model, combined with the proposed framework addresses the research questions of suitability and human variability of sub-healthy people. To return to the second research question (RQ2), the second hypothesis examines whether the accuracy of the best classification model is higher than the collaboration without the association rules. The next section conducts a design of experiments based on association rules and classification algorithms by using a set of sub-healthy people who have different features to accomplish certain goals or tasks in a given setting.

IV. EXPERIMENTAL DESIGN

This study adopts quantitative methods to measure two hypotheses. The first hypothesis is to examine user perceptions of the proposed framework. The independent variable is the proposed framework, which includes the risk levels, physiology, medical record, and demography components. Dependent variables include perceived ease of use, perceived usefulness, user satisfaction, and user intention to use. The second hypothesis is to examine whether the accuracy of the best classification model is higher than the collaboration without the association rules. Therefore, the independent variable is the level of the association rules used in a collaborative framework, which is operationalized by two levels: using the association rules and not using it. The dependent variable is the accuracy of the suitability, which is associated with the second research question.

The different components of the experiment are the risk levels, physiology, medical record, demography, and a cross-section of people who belong to different groups. It is important to ensure that the members of the groups selected contain all the features needed to accomplish the next tasks in this given setting. This sample data is used in the experiment for checking users' suitability randomly, as well as for eliciting users' volatility on system design. Therefore, it offers great potential for developing a new framework that could facilitate and guide the design of an effective long-term care system.

A. ASSOCIATION RULES

The suitability data of the sub-heathy people are shown in Table 1. Therefore, it offers great potential for developing a new framework that could facilitate and guide the design of an effective long-term care system.

As shown in Table 2, data on sub-healthy people have a variety of combinations that determine whether they are suitable for the mapping process. The mapping process of sub-healthy people is shown in Figure 4. The Apriori algorithm mines all the features in collaborative people, where each person Si contains a set of people called collaborative people. The collaborative people consist of "s" users and are called the s-users and its length is s. The left table in the figure called Cs represents the candidate users of length s. The right table in the figure called Ls is frequent if its support, which is at least specified minimum support: the number is two. In the first phase, Cs is generated by joining Ls-1 through the Apriori algorithm, and then counts supports of the Cs. The purpose is to determine the scanning of the dataset based on s-th of Ls. This algorithm fails towards the end when there is no Cs. For the second phase, the table is used for arranging Cs with support counting. The candidate could continue pruning for sub-healthy people by using the downward closure property. It is effective for the user if the length is larger than number two, and then it can begin in the third phase.

TABLE 2. The suitability data of sub-healthy people.

ShP	Risk Level	Physiology	Medical Record	Demography	Collaboration
S1	2	2	1	2	Y/N
S2	2	3	1	3	Y/N
S3	2	3	1	1	Y/N
S4	2	1	2	1	Y/N
S5	3	3	1	3	Y/N

If the confidence of probability is set to 80%, then the result of the mapping process would be S1 → S2, S1 → S3, etc. as shown in Figure 4. According to the features of related association rules, the two candidates for sub-healthy people could be combined into one dataset for further classification analysis of their features.

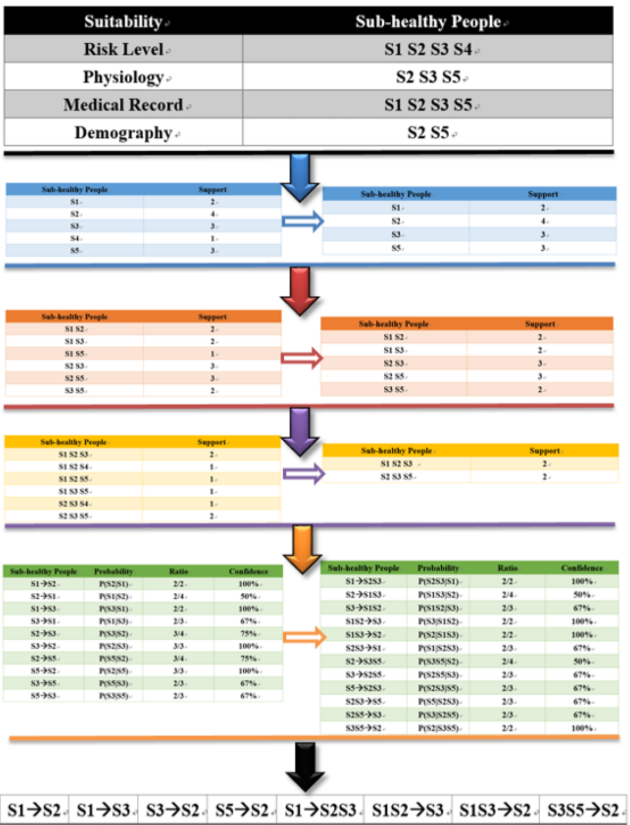

FIGURE 4. The mapping process of sub-healthy people.

B. CLASSIFICATION MODELS

The set of relevant features of sub-healthy people include the users numbered in sequence RL1, Phy1, MR1, Dem1, RL2, Phy2, MR2, and Dem2, which are (2, 1, 2, 2, 3, 1, 3) and shows the risk levels, physiology, medical record, and demography of the first and second candidate, respectively. The dataset of the suitability based on the result of the mapping process is shown in Table 3.

TABLE 3. The mapping process of sub-healthy people.

ShP	RL1	Phy1	MR1	Dem1	RL2	Phy2	MR2	Dem2	Col
S12	2	2	1	2	2	3	1	3	Y
S13	2	2	1	2	2	3	1	1	Y
S14	2	2	1	2	2	1	2	1	N
S15	2	2	1	2	3	3	1	3	N
S23	2	3	1	3	2	3	1	1	N
S24	2	3	1	3	2	1	2	1	N
S25	2	3	1	3	3	3	1	3	Y
S34	2	3	1	1	2	1	2	1	N
S35	2	3	1	1	3	3	1	3	N
S45	2	1	2	1	3	3	1	3	N

In the classification algorithm, the evaluated output includes true positive (TP), true negative (TN), false positive (FP), and false negative (FN), which are based on the results of classifiers with observations of candidates. The terms of the positive and negative could indicate the prediction of the classifier, and the terms of the true and false could refer to whether the prediction could correspond to the observation. In Figure 5, TP indicates collaborations correctly identified as having suitability; TN shows that observations without collaboration are correctly identified as not having suitability; FP represents that observations without collaboration are incorrectly identified as having suitability; FN means that observations with collaboration are incorrectly identified as not having suitability. The accuracy is the number of correct predictions divided by the total number of predictions (i.e., accuracy = (TP + TN) / (TP + TN + FP + FN)).

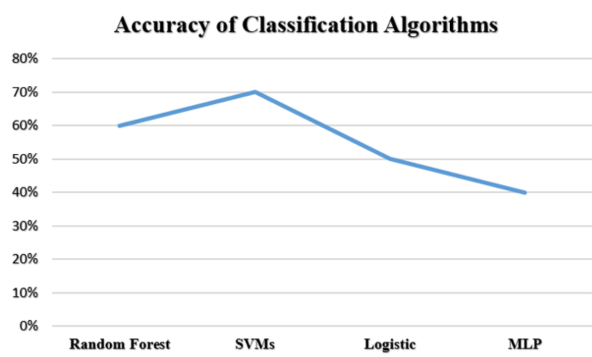

FIGURE 5. Accuracy of classification algorithms.

This study uses the classification algorithms, SVMs, random forests, logistic, and multi-layer progression (MLP), with 10-fold cross-validation to obtain the accuracy of the suitability prediction of collaboration. For example, the first candidate is randomly partitioned into ten equal subsamples with 10-fold cross-validation. A subsample is retained as the validation data for testing, and the remaining subsamples are regarded as training data. All observations are set for both training and testing, and each observation can be used exactly once for validation. Those algorithms are chosen because they are popular machine learning algorithms and have been widely used. The accuracies of classification algorithms are 60%, 70%, 50%, and 40% using random forests, SVMs, logistic, and MLP, respectively. The SVMs achieves the highest accuracy.

A prototype system of long-term care (Figure 6) was developed by using the Android Studio software, which was using Java programming and Android SDK. Based on the mobile application services (APPs) type, participants could have a specific way to understand the proposed framework, which includes the risk levels, physiology, medical record, and demography. In order to evaluate the first hypothesis effectively, 68 participants participated in the online survey to do the questionnaire that whether or not the proposed framework will improve users' (a) perceived usefulness, (b) ease of use, (c) satisfaction, and (d) intention to use of long-term care. Participants were not selected based on certain demographics. All participants were over 18 years old. Among them, 37 participants were under 30 years old, 17 were between 31-40 years old, and 14 participants were more than 40 years old. 32 participants were female. A five-point Likert scale [30] was used to measure the survey questions, with the number one indicating "strongly disagree," the number five indicating "strongly agree," and the number three indicating "neutral."

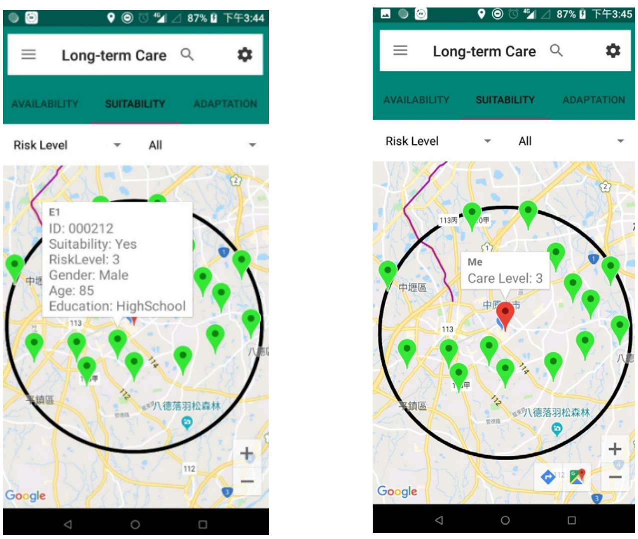

FIGURE 6. The prototype system of long-term care.

C. RESULTS

To test the first hypothesis, the Cronbach's Alphas for the user perception was 0.794, which reveals that the consistency of the questionnaire is reliable. To test the first hypothesis, the one-sample t-test is used to evaluate whether the average user perception is equal to three (indicating neutral), which is the middle value of the five-point Likert scale [31]. Results of one-sample t-test analysis on user perception reveal significant differences between using the suitability including the risk levels, physiology, medical record, and demography on the proposed framework compared to not using the suitability. If the output of the one-sample t-test significantly exceeds three, the user could be satisfied with the proposed framework. The main effects of perceived usefulness (mean difference $= 1.39$, $p < 0.01$), perceived ease of use (mean difference $= 1.43$, $p < 0.01$), user satisfaction (mean difference $= 0.85$, $p < 0.01$), and user intention to use (mean difference $= 1.23$, $p < 0.01$) are significant. The user perception is significantly higher when using the suitability as part of the proposed framework when compared to not using it (Figure 7). Therefore, the first hypothesis is supported.

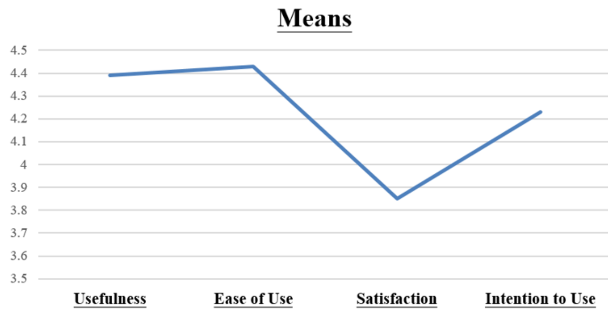

FIGURE 7. Means of user perceptions of the proposed framework.

To test the second hypothesis, the collaboration is built randomly as usual ten times and the mean of SVMs is compared to 70%, which is created by the association rules. The result of the one-sample t-test analysis on the comparison between using and not using the rule reveals significant differences. The main effect of the association rules based on the research model (mean difference $= -14$, $p < 0.01$) is significant. The accuracy of the best classification model (SVMs) is higher than the collaboration without the association rules. Therefore, the second hypothesis is supported.

V. CONCLUSION

This study has made several significant contributions to collecting and using data on long-term care. First, it has shown that existing collaborative frameworks for long-term care mainly focus on specific needs through centralized agencies that match home care workers and sub-healthy people. However, this method only considers the cost of their caregivers and cannot solve the issue of insufficient workers to determine suitable features relevant to the effective collaborative framework of long-term care. This paper proposes a new framework with all possible features of the suitability across all sub-healthy people and can solve the first research question. Second, the proposed framework applies artificial intelligence to solve the issues of adjusting data on human variability features of sub-healthy people dynamically, thus addressing the second research question. Third, this study applies association rules to long-term care. To the best of our information, this is the first study in the field that offers an applicable algorithm while building the mapping process.

In order to refine the result and properly address the human variability issue, this research builds classification models using random forests, SVMs, logistic, and MLP.

There are few limitations to this study. First, the current mapping process was based on small samples and all users did not respond to long-term care immediately. So it is necessary to perform more studies with larger samples of sub-healthy people. Therefore, we were unable to get the best accuracy from the collaboration. In the future, it is worth enlarging data to overcome the limitation regarding the accuracy of the classification results. Second, regarding relevant features categorized on the suitability, the detailed sub-items (e.g., physiology 1, 2, and 3) are not incorporated in the description of experimental design due to privacy issues. To guide practical insights into a long-term care system, the sub-items category with detailed descriptions should be identified clearly and the issue of revealing the information needs to be solved. The research of the collaborative framework for sub-healthy people is still in a preliminary stage, and this study offers a referential direction to further research.

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