Development of Elderly Life Quality Database in Thailand with a Correlation Feature Analysis

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Abstract: Understanding the context of the elderly is very important for determining guidelines that improve their quality of life. One problem in Thailand, in this context, is that each organization involved in caring for the elderly has its own separate data collection, resulting in mismatches that negatively affect government agencies in their monitoring. This study proposes the development of a central database for elderly care and includes a study of factors affecting their quality of life. The proposed system can be used to collect data, manage data, perform data analysis with multiple linear regression, and display results via a web application in visualizations of many forms, such as graphs, charts, and spatial data. In addition, our system would replace paper forms and increase efficiency in work, as well as in storage and processing. In an observational case study, we include 240 elderly in village areas 5, 6, 7, and 8, in the Makham Tia subdistrict, Muang district, Surat Thani province, Thailand. Data were analyzed with multiple linear regression to predict the level of quality of life by using other indicators in the data gathered. This model uses only 14 factors of the available 39. Moreover, this model has an accuracy of 86.55%, R-squared = 69.11%, p-Value < 2.2 × 10⁻¹⁶, and Kappa = 0.7994 at 95% confidence. These results can make subsequent data collection more comfortable and faster as the number of questions is reduced, while revealing with good confidence the level of quality of life of the elderly. In addition, the system has a central database that is useful for elderly care organizations in the community, in support of planning and policy setting for elderly care.

Keywords: quality of life system; data analysis; elderly monitoring system; elderly; multiple linear regression

1. Introduction

The elderly population of the world has increased to about 1.9 billion people or 22% of the global population and continues to grow [1]. Many countries have an aging society, with more than 10% being elderly [2]. Thailand is among the countries with an increasing proportion of the elderly, which causes changes in social structure. Statistics in 2019 show that the proportion of the elderly in the population is 16.13% [3], making Thailand an aging society (those aged 60 years and over are more than 10 percent of the population). At the same time, the percentage of young people and birth rates are declining. In an aging society, caregivers and government agencies need to pay more attention to utilities that support the life of the elderly [3]. Most of the elderly in Thailand need care from their family because they experience problems in daily life from frailty, and from chronic diseases...
such as respiratory diseases, cardiac disorders, diabetes, and cancer. However, most young family members in Thailand today need to leave home to work or study. Thus, they cannot take care of the elderly all the time. These problems decrease the abilities of the elderly to perform activities [4]. In Asia, the elderly who require physical exercise and group activities are more likely to join an activity center. The health problems of many elderly have also increased the demand for health related products and services. Government agencies play a key role in helping these seniors, highlighting the need for a system that supports and improves their quality of life. However, especially in rural village areas of Thailand, there is no system to compile quality of life databases that would be compatible with the multiple local government agencies. Thus, this study analyzed the quality of life of the elderly using machine learning with a multiple linear regression method and demonstrated such a unifying system.

Nowadays, technology can help improve the quality of life of the elderly [5–8]. Many studies have developed systems or devices to assist the elderly in a variety of areas, such as motion tracking [9–12], health monitoring [13–17], disease monitoring and predictions [18–23], smart homes [24–28], monitoring of alcohol consumption [29] or rehabilitation [30]. Their applications are multifaceted, including enhancement, care, compensation, research, and prevention. Most studies have focused on solving problems or caring for the elderly, rather than understanding the context of the elderly. However, if we can understand their context, we can search for problems and solutions, based on collecting their characterizing data and analyzing them using statistical tools. Usually, many agencies look after the elderly, with each agency collecting data separately and often incompatibly, manually converting paper forms into digital databases. This operation has an inherent long delay, and there may be human errors in the data recording process [4,7]. These processes can be replaced with web application technology to collect data, and save, analyze, and display results in near real-time. The web application also has the ability to provide visualizations in many formats, for users to quickly understand and adjust their views, based on graphs, maps, or street views.

This study aimed to develop an elderly monitoring system and to study the factors affecting their quality of life, with study areas in Moo 5, 6, 7, and 8, in Makham Tia subdistrict, Mueang Surat Thani district, and Surat Thani province, Thailand, comprising a total area of 2115 hectares. The total population is 1640, with 807 males and 833 females and 328 elderly persons. There are many factors in questionnaires to estimate the life quality of elderly, requiring time to complete the forms. For this reason, we propose using elderly related data to create multiple linear regression models using the R program to predict levels of quality of life. The resulting models make future data collection more effective and efficient, reducing time and confusion in answering questions by the elderly, because of a reduced set of questions. The results were shared with community organizations in the study area, to improve the quality of life of the elderly. The system also replaces the more cumbersome data collection method with a more efficient form and a centralized database that can be shared among many community organizations.

2. Background

Past research has shown the development of systems or tools for monitoring or tracking the elderly to facilitate better activities or improve their quality of life. Many studies have investigated factors that affect quality of life focusing on different issues, such as exercises [31,32], technologies [27,33], public services [34], and health services [35–37]. Segerståhl et al. [31] and Tajik et al. [32] proposed personal monitoring technologies to support exercise in order to help improve quality of life for the elderly. Supromin et al. [34] show that public services play an essential role in improving quality of life for the elderly. The authors studied the pattern of public services and the factors that influence the success of public services in Thailand in improving the quality of life of the elderly. Khosravi et al. [33] proposed assistive technologies as a solution in dealing with eight critical issues in aged care, namely, dependent living, falling risk, chronic disease, dementia,
social isolation, depression, poor wellbeing, and poor medication management. In addition, Liu et al. [27] and Lluch [36] have reviewed studies of the level of technology readiness of the elderly, as regards smart homes and health monitoring technology at home that supports the elderly with complex needs. The use of technology in healthcare services also needs to consider acceptance by user groups. For example, Deng et al. [35] compared acceptability among middle aged and old users in China, which helps to understand the attitudes of users as regards these technologies. Monitoring, in each area, is based on different information and factors, which constitute the goals of most research tasks that want to find suitable elements. For example, Urrunaga-Pastor et al. [38] studied factors affecting poor balance in the elderly living at high altitudes, utilizing a Poisson regression model with data on socio-demographic, medical, functional, and cognitive assessment. The analysis revealed factors that affect balance, such as alcohol consumption, fatigue, and walking speed. These results support the prevention of adverse events during work with the target group.

In 2017, Chen and Chen studied determinants of a critical quality of life, especially the risk for disability in older adults suffering from chronic diseases [39]. They used step-wise multiple regression analysis, and the model, overall, explained 49% of the variance in quality of life. The study indicated that social factors and the health conditions of elderly patients, the risk of disability in social isolation, and depression had negative relationships with quality of life. Paiva et al. [37] also found that environmental factors and self-government are important factors affecting health and quality of life.

Nowadays, “big data” are gathered from many people in the form of digital information. Herland et al. [40] discussed the infinite possibilities of big data analysis as a tool and methods for health data collected from many levels. Not long after that, Luo et al. [41] studied large data applications in medical research and healthcare between 2000 and 2015. They discussed the design and use of big data applications in the biomedical and healthcare domains’ large-scale data processing methods and discussed the effectiveness of methods using data mining techniques to analyze elderly data from sensors. Banaee et al. [42] have studied research related to the use of data mining to develop wearable sensors for health monitoring systems and present a review of the latest methods and algorithms used to analyze data from wearable sensors used for physiological examination in health services. These studies allow us to analyze and examine possible future tasks.

In summary, the previous works can improve elderly life quality by using monitoring systems to support decisions regarding activities and to show the factors affecting quality of life. Moreover, factors were studied to prevent and handle issues with health and quality of life. However, some studies have assessed both spatial data and important factors. Thus, this study also pursues spatial data analysis in the monitoring system, while also applying multiple linear regression to determine the main factors and provide a predictive model to estimate elderly life quality.

3. Materials and Methods

This study is related to system development, data collection, knowledge analysis, and presentation of results. We develop a system that can collect general information about the quality of life of the elderly to a central database provided to agencies in the community. Subsequently, we use the obtained data to analyze the relationships in the elderly data using multiple linear regression models, to achieve useful knowledge for prediction of the elderly quality of life. The main steps in the study are shown in an overview in Figure 1.

In Figure 1, we divide this research into two main phases: system development and knowledge discovery. The first phase was designed to provide elderly information for partners by exploring user requirements from the partnership. The partnership consists of 5 officers from Makhantia Sub-District Health Promotion Hospital, 20 officers from Village Health Volunteer, 1 head of Elderly Club, 4 officers from Office of the Village Headman, and 1 officer from Ministry of Social Development and Human Security. The user requirements were surveyed to develop a system based on a web application. Next, elderly data were
collected by using the developed web application. The obtained data were manipulated by partners and caregivers. The caregivers for the elderly are responsible for the elderly information and update the information in the system to reflect the current conditions. Village Health Volunteer is an assistant in using the system for some elderly who cannot use the system due to health problems or do not have a caregiver. Our partners responsible for elderly care can verify the accuracy or correct the information; for example, Makhantia Sub-District Health Promotion Hospital can check the health status, and Village Headman checks the address information. The data checking process is essential, because some elderly may be confused about their health conditions or medical history and ultimately affect the use of the information for those who help in case of emergency. They can check the information against the legacy system or with the corresponding summary document of each topic. If any topic has an inconsistent number of elderly, then one has to identify the cause of the misinformation. The agency staff regularly visits the area every month in the elderly meeting or village meeting, and update the information. After recording the data, the system uses these data to calculate the level of elderly quality of life by providing data visualizations for ease of use and interpretation. Moreover, the user can export the summarized data to a hard copy report for further analysis. The system uses these data to calculate the level of elderly quality of life. The final step will be illustrated with data visualizations that are easy to use and understand, regarding both elderly details and summary data on questions.

**Figure 1.** Overview of the proposed system.

The second phase in Figure 1 is knowledge discovery from the elderly information derived from the first phase, where multiple linear regression was applied to create prediction models. We are interested in finding the factors that determine the level of elderly quality of life, to supplement the original data in the previous phase.

3.1. Phase 1: System Development

The development process used the system development life cycle (SDLC). SDLC is a thought process in the development of information systems to solve business problems and meet the requirements of users. The SDLC process consisted of 7 stages of system development: planning, system analysis and requirements, system design, development, integration and testing, implementation, and operations and maintenance. For the first two stages above, planning and analysis, user requirements were collected from the partners. Next, the system was designed in the form of a web application that uses both a web page and mobile application and runs on any operating system, as shown in Figure 2.
Users or those involved in taking care of the elderly can access data and quickly track the information in the system via the internet. Initially, the system received information from the elderly or their caregivers. The data are stored on the server of the system, which can be accessed by web applications. Additionally, we designed the web applications with a responsive web that is compatible and easily accessible on all devices.

![Use case diagram of the proposed system.](image)

**Figure 2.** Use case diagram of the proposed system.

In development stage, the system was designed for three user groups: caregivers or elderly, partnership, and administrator, illustrated with interface structure designs in Figure 3. The first group is caregivers or the elderly, who can respond and recheck their questionnaire. The users in this group can manage their profiles. The obtained elderly data were used to analyze their quality of life and to display it to appropriate parties. The second group is the local authorities partners, who also have access to this information. They can view overall and personal data on the elderly in the forms of text, maps, and graphs, and can export the data in .xlsx and .csv file formats that are useful in the government agencies. Additionally, they can manage their profile data in a sign in system. The last group is the administrators, who can manipulate overall information in the system. They are primarily responsible for monitoring and granting users access to the system to protect the personal information of the elderly. All users need to be logged in as a member of the system because the personal information of the elderly cannot be distributed publicly. The users can apply for membership by specifying their official status or as care givers who are interested. Registered users have to wait until they have passed the verification from the system administrators or staff of the partner agencies. Afterwards, if the registered users are verified as responsible or relevant to the elderly, then they will be authorized to access the system and access the information, as appropriate. The security system with a personal inspection makes it impossible for persons unrelated to an elderly to access or use their information. Thus, this system is only available to those who are staff members of an agency that deals with elderly care, while elderly caregivers can access information of only those elderly in their care.

The integration and testing stage of SDLC involved systems integration and system testing, typically carried out to determine if the proposed design meets the initial set of goals. Testing was repeated individually to find errors, bugs, and inter-operability issues. This testing was performed until the end-users found the results acceptable. Another part of this phase was verification and validation, both of which helped ensure successful
project completion. The test consisted of two parts: the test by the developer and the test by the elderly. The test format was divided into two main sections: software testing and hardware testing. Its final two steps involved the actual installation and maintenance of the developed system. The system was installed on the server along with the actual data from the sample population. This step provided a user guide to the users. In addition, system performance and user satisfaction were assessed by using a questionnaire.

Figure 3. The interface structure design of the system.

3.2. Phase 2: Data Analysis to Discover Knowledge

At this stage, the data are subjected to machine learning or statistical algorithms. Data modeling was used to find the relationships between the input variables from the questionnaire. Practically, the knowledge discovered will be processed as a data analysis life cycle with six steps, as follows [43].

3.2.1. Discovery

Understanding the quality of life of the elderly is essential to finding ways to improve that quality, and generally relies on measuring the quality of life with available measuring tools. The questionnaire developed by the World Health Organization is widely used as such tool [44] in demographic surveys by country, in which the user needs to adapt the tool to the context of the specific population [6,7]. Moreover, the questionnaire, based on the Barthel index [45], is applied to estimate the ability to carry out the daily life activities of elderly. In this study, we improved the assessment questions together with our partners to adapt them for use in the study area. There are four domains in the questionnaire: physical (9 items), psychological (9 items), social relationship (12 items), and environmental (7 items). The details of each domain are shown in Table 1. Total scores for quality of life (37 questions each with 1–5 points) ranged from 37 to 185, with higher scores indicating a better life quality. Factors related to social and economic aspects were assessed to study their influences on quality of life [46]. In fact, it was found that females tend to have a better quality of life than males in Brazil [47]. Health related factors can also be associated with life quality, and a perception of good health and a small number of chronic diseases contribute positively to quality of life [39].

This step aims to specify the research questions to discover knowledge by defining study issues from data obtained, which can be classified into three categories: general data (15 questions), quality of life (37 questions), and assessment of the ability to carry out daily activities (10 questions). General information for older people includes personal information such as gender, age, blood type, education level, occupation, and illnesses.
For the quality of life questionnaire, the details are as shown in Table 1. Questions for assessing ability to perform daily activities are about ability to help oneself, including eating, grooming, toilet use, mobility, dressing, stairs climbing, bathing, bowel, and bladder function. Following this assessment, the research question was designed as follows:

Table 1. The details of the quality of life questionnaire.

| Domain         | Details                                                                                                                                 |
|----------------|-----------------------------------------------------------------------------------------------------------------------------------------|
| Physical       | The perception of the physical condition of a person that affects everyday life consists of the level of the perceived health of one’s overall self, the level of the perceived health condition affecting daily life, the level of satisfaction with rest and sleep, the level of satisfaction with the activities that can be performed daily, the level of satisfaction with the ability to work as before, the level of ability to move by oneself, the level of ability to perform daily activities by oneself, the level of satisfaction for treatment/physical examination, and the level of acceptance of body changes. |
| Psychological  | The perception of one’s mental state consists of the level of happiness overall, the level of acceptance of one’s actions, the level of self-satisfaction, the level of acceptance of a changed appearance, the level of acceptance of psychological/emotional change, the level of good/cheerful feeling, and the level of satisfaction with the progress of children. |
| Social         | The perception of one’s relationships with others consists of the level of satisfaction with being friendly with other people, the level of satisfaction with the help that has been received in the community, the level of satisfaction in being respected by others, the level of satisfaction in counseling others, the level of satisfaction with the assistance from local government organizations, the level of satisfaction in exercise/recreation, the level of relationships with family members, the level of relations with relatives/neighbors, and the level of unity of the family/relatives. |
| Environmental  | The perception of the environment that affects lifestyle consists of the level of the safety of life in the community, the level of satisfaction in the community exercise facilities, the level of satisfaction in the place of residence, the level of satisfaction in the environment around the residence, the level of community self-reliance, the level of satisfaction in the place used for mental relaxation/for religious activities, and the level of satisfaction with overall wellbeing. |

Research Question: Which factors from the elderly information can predict the quality of life of the elderly?

3.2.2. Data Preparation

Data from the population registered on the date of collection shows that there were 1640 people, 807 males, 833 females, and 328 elderly people (aged 60 years or more). There are 134 attributes of elderly characteristics from questionnaires of life quality. The data may be incomplete, missing, inconsistent, and noisy due to the vast size and potentially incorrect results. The data was prepared for further analysis by removing unnecessary columns for each analysis, such as I.D., phone number, and I.D. on the personal card. Missing values were handled by truncating the data in that record. Afterwards, the data were consolidated into forms appropriate for data analysis. Finally, we stored the output data in .csv format for the next step. From the data preparation, we have 240 elderly (112 males and 128 females) remaining for analysis, due to incomplete entries.

3.2.3. Model Planning

This step aims to plan the process and methodology of model building for data analysis. We compared machine learning models for classifying the data on quality of elderly life, as shown in Figure 4. From this experimental comparison among machine
learning models, multiple linear regression was selected to predict quality of elderly life, due to its accuracy.

Figure 4. An accuracy comparison among machine learning models.

We divided the data on quality of elderly life into training and test data, as shown in Figure 5. The training data was used to fit (or identify) models with multiple linear regression in the R-3.5.1 environment for Windows and RStudio version 1.1.456. The modeling provided linear equations to predict the quality of life. The next step is to evaluate the accuracy of the models with test data. The test data set is used to evaluate predictive accuracy. However, this work applied the round function to estimate the class label. We use the confusion matrix function to assess predictive accuracy. This provides accuracy, kappa, and \( p \)-values to evaluate the performance of the model. The obtained predictive models are used to predict the life quality for new future cases.

Figure 5. Step of model planning.

3.2.4. Model Building

This step implements the model planning to determine the relationships of input variables with outcome variables to answer the research questions in discovery stage. Multiple linear regression was applied.

Multiple linear regression models are linear relationships between a dependent variable and one or more independent variables. The dependent variables are sometimes called responses, and the independent variables are predictors or regressors [48]. These models consider the effects at a specified time point, as follows [49].
\[ y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_j x_j + \cdots + \beta_p x_p + \epsilon, \]  

(1)

where

- \( y \) is the outcome variable;
- \( \beta \) are the regression coefficients in the model;
- \( \beta_0 \) is the value of \( y \) when all \( x_j \) equal zero;
- \( \beta_j \) is the change in \( y \) based on a unit change in \( x_j \), for \( j = 1, 2, \ldots, p \);
- \( x_j \) are the input variables, for \( j = 1, 2, \ldots, p \); and
- \( \epsilon \) is a random error term (error or residual) that represents the difference between the linear model output and the observed value for \( y \).

The model is obtained from a system of equations that can be expressed in matrix notation as follows.

\[ Y = X\beta + \epsilon, \]  

(2)

where \( Y \) is an \((n \times 1)\) vector of the dependent variable or response, \( X \) is an \((n \times (p + 1))\) matrix of the levels of the \( p \) independent variables, \( \beta \) is a \(((p + 1) \times 1)\) vector of the regression coefficients, and \( \epsilon \) is an \((n \times 1)\) vector of random errors. This method assumes that the expected value of the error term is zero, so if \( E(\epsilon) = 0 \), the variance is \( V(\epsilon) = \sigma \), and the errors are uncorrelated.

In the research question, the outcome variable is the level of quality of life, which is divided into levels 1–5 (5: excellent level, 4: good level, 3: medium level, 2: fair level, 1: level should be improved). The R environment was used to fit the models at a 95% confidence interval. There were 111 candidate attributes that were subjected to feature selection. These variables were tested in the \texttt{lm} function to exclude the nonsignificant factors where \( \text{Signif} > 0 \). The process was repeated until the third cycle, leaving only 14 correlated variables affecting the quality of life level, and the results are shown in Equation (3).

\[
\text{QoL\_Level} = 0.051 \times \text{No}_1 - 0.194 \times \text{No}_2 + 0.269 \times \text{No}_3 - 0.261 \times \text{No}_4 - 0.234 \times \text{No}_5 + 0.104 \times \text{No}_6 + 0.377 \times \text{No}_7 + 0.126 \times \text{No}_8 + 0.098 \times \text{No}_9 + 0.095 \times \text{No}_{10} + 0.076 \times \text{No}_{11} + 0.156 \times \text{No}_{12} + 0.156 \times \text{No}_{13} + 0.005 \times \text{No}_{14} + 1.401, 
\]

(3)

where

- \( \text{QoL\_Level} \) is the quality of life level;
- \( \text{No}_1 \) is education level (0–8);
- \( \text{No}_2 \) is deafness (0 = no, 1 = yes);
- \( \text{No}_3 \) is having an eye disease (0 = no, 1 = yes);
- \( \text{No}_4 \) is urinary / kidney disease (0 = no, 1 = yes);
- \( \text{No}_5 \) is heart disease (0 = no, 1 = yes);
- \( \text{No}_6 \) is still having to treat the disease (0 = no, 1 = yes);
- \( \text{No}_7 \) is have income from savings (0 = no, 1 = yes);
- \( \text{No}_8 \) is the ability to wear clothes (0–2);
- \( \text{No}_9 \) is satisfaction in perceived overall health (1–5);
- \( \text{No}_{10} \) is health status has affected lifestyle (1–5);
- \( \text{No}_{11} \) is satisfaction with rest and sleep (1–5);
- \( \text{No}_{12} \) is satisfaction from each day (1–5); and
- \( \text{No}_{13} \) is receiving body changes (1–5) and \( \text{No}_{14} \) is the age of the elderly.

This model has an accuracy of 86.55%, R-squared = 69.11%, \( p\)-Value < 2.2 \times 10^{-16}, and Kappa = 0.7994 at 95% confidence interval. Moreover, we found that the future questionnaire can be reduced to only 14 model input attributes. The coefficients of each factor indicate the level and direction of their relationship with the level of quality of life. For example, education level has a coefficient of 0.051 in the positive direction, meaning
that obtaining a higher level of education leads to a better quality of life. In addition, most illness questions have a negative coefficient, meaning that having that disease reduces the quality of life.

3.2.5. Communicating Results

After model identification, the test data were used to assess the model accuracy indicators shown in Table 2.

Table 2. The results from testing accuracy of the model.

| Question              | Accuracy | R-Squared | $p$-Value | Kappa |
|-----------------------|----------|-----------|-----------|-------|
| Research Questions    | 86.55%   | 69.11%    | $<2.2 \times 10^{-16}$ | 0.7425 |

The results show that the proposed model can predict the quality of life relatively well. Moreover, we discovered that the survey questionnaires could be reduced, excluding several attributes, to match the identified models, saving time and space required to store the elderly data in the future. We communicated the results to our partners to show the critical attributes that affect the quality of elderly life. The partners can apply the knowledge discovered in this work to improve the quality of elderly life and the data collection method.

3.2.6. Operationalizing New Knowledge

In the final step, we communicated the benefits of the results more broadly and deployed the developed web application to the elderly in the villages. We used 240 elderly in the village areas 5, 6, 7, and 8, in Makham Tia subdistrict, Muang district, Surat Thani province, Thailand. In the future, we encourage agencies that care for the elderly to use systems and models to collect data and to predict level of quality of life.

4. Results and Discussion

In the previous sections, we considered system development and knowledge discovery. This section describes the results and discusses system development and knowledge discovery as regards implementation and accuracy, respectively.

4.1. Implementation and Evaluation

The results of system development include the form of data collection, data management, and data visualization. We use mobile applications to collect data directly for convenience also in taking pictures and identifying geolocation. These data can be used to display the elderly data and various analysis results on an online map for spatial visualization, which is not practical with the traditional paper form. In addition, the photo or geolocation is useful to the staff of the elderly care agencies who want to visit the elderly, or to rescuers in the community to help in an emergency. However, the elderly or caregiver is the decision-maker who chooses the recording of various data in the system. The staff of the elderly care agency and caregiver are the only ones with access to the elderly’s information. Those who want to use the system must register and be assigned login information, then wait for profile review and appropriate access to each information to be assigned. Therefore, staff will have access to elderly information in their own area (Village/Sub-district) and caregivers will only have access to the elderly in their care. Moreover, we designed user inputting of elderly data with a web application that supports all screen sizes (see, for more details: https://www.parasystem.org/Elderly/html/ltr/index.php, accessed on 1 January 2022). An example of page screens on mobile is shown in Figure 6.
Figure 6. An example of screens on mobile.

An overview of the results from this study of the elderly is shown in Figure 7. This figure summarizes the general data on 240 elderly people in the system after the data preparation process regarding gender, age range, blood type, education level, work, and chronic diseases. The data show that, among the elderly, there are more females than males and most are between the ages 60 and 69. As regards education, 84% of the elderly studied have been educated at least to the early elementary school level. In addition, of the elderly, 65% have an underlying disease, which indicates a high level of health problems in the studied elderly population.

For data management, the system was designed to manage data on the elderly, member data, replies to the questionnaire, and so on, by user groups, as described in Section 3.1. Each user can manage data, based on access rights, such as view, add, edit, and delete, using an interface designed to display a preview, as in Figure 8.
From experimental data collection, we received data on the elderly for 328 people in 4 villages (100% of the elderly in those four villages). The data are displayed in visualizations that are easily understood, with examples in Figure 9.

We use an online map to show the spatial relationships between data obtained from questionnaires and analysis. The elderly data on the online map used Google Maps API combined with databases and web development. The user can view the elderly’s location, data description, filter, and download the data. An example of an online map screen is shown in Figure 10.
Moreover, the system uses Google Street View services, which makes it possible to view the home of an elderly, as in Figure 11. This reduces the problems with finding the address of the elderly for any agencies involved in elderly care. The proposed system allows different departments to receive different benefits. The Health Promotion Hospital at Makham Tia Subdistrict can see the distribution of elderly patients by disease, along with other information of the elderly in the community. The office of Social Development and Human Security in Surat Thani Province can inspect the welfare of the elderly and obtain in depth information on individual seniors, along with the population density in each area, to improve the quality of life. The Makham Tia Subdistrict Administration Organization has insights into individual elderly people and accesses summaries of elderly information. They can use this information to plan policies. For example, after seeing the density of the number of elderly people from the presented data, this organization may also plan to establish units or subcenters to provide quick and comprehensive access to the elderly care. The Village Headman receives factual information from the elderly, and can go to the area to inspect the status. In addition, the information is used as a guideline for activities for the elderly. The Village Health Volunteer was able to obtain accurate information on the home
location of the elderly and see overall information, as a guideline for the development of various projects for the elderly. It is also useful for new volunteers to obtain information about the elderly quickly, with the picture, location, and personal data of the elderly in the system.

**Figure 11.** An example of Google Street View services.

Besides, based on results from the questionnaire to the elderly, we find that most of the elderly have good levels of quality of life, followed by an excellent level and a small number of other levels, as in Figure 12.

**Figure 12.** Summary of the levels of quality of life.

### 4.2. Accuracy of Knowledge Discovery

Regarding the research questions, we find that the elderly data can be used to create a linear model to predict with Equation (3). The models have selected inputs from the candidate predictors and the test results with the test data are also shown in Table 3.

**Table 3.** Reducing the number of factors in models.

| Question       | Candidate Attribute Count | Selected Attributes | Accuracy  |
|----------------|---------------------------|---------------------|-----------|
| Research Question | 111                       | 14                  | 86.55%    |
Table 3 shows the candidate attribute count for training the model and the count of selected attributes used to predict the level of the quality of life. Previously, we used 37 attributes to assess the level of quality of life, but the first model uses only 14 attributes. In addition, the obtained results from the statistical evaluation in some values cannot show statistically significant values. For this reason, we evaluated the model using the confusion matrix to find weaknesses and ways to improve the model. In this approach, we compare the results of using the proposed models from elderly data analysis and using the original calculation from collecting questionnaires mentioned in Section 3.2. We have demonstrated the efficiency of model by assessing the confusion matrices in Table 4.

Table 4. The confusion matrix of the proposed model to predict the level of the quality of life.

| Class          | True Excellent | True Good | True Medium | True Fair | True Should Improve | Class Precision |
|----------------|----------------|-----------|-------------|-----------|---------------------|-----------------|
| Pred. Excellent| 67             | 7         | 0           | 0         | 0                   | 90.54%          |
| Pred. Good     | 12             | 131       | 6           | 0         | 2                   | 86.75%          |
| Pred. Medium   | 0              | 4         | 10          | 0         | 0                   | 71.43%          |
| Pred. Fair     | 0              | 0         | 0           | 1         | 0                   | 100.00%         |
| Pred. Should improve | 0 | 0 | 0 | 0 | 0 | 0.00% |
| Class Recall   | 84.81%         | 92.25%    | 62.50%      | 100.00%   | 0.00%               |

For Table 4, we used the model of Equation (3) to predict the quality of life for each elderly in this research, while the true values are quality of life as determined by officers. Class recall value is a measurement of model accuracy by considering class by class, while class precision value is the measurement of data accuracy by considering class by class. For this model, the precision of all classes was higher than 71.43%, but the recall of classes was high for some classes only, except for a level that should be improved as it has no value. This is caused by the collected data being clustered in some classes in the study areas, and to calculating the overall accuracy by means of the confusion matrix, giving the high 87.10% classification accuracy. The model shows factors related to the quality of life of the elderly, although some levels are less accurate because the amount of information is too small for training at that level, resulting in less learning. However, this table shows that the development of models that provide predictive efficiency at all levels requires sufficient training data at all levels, while the elderly in the case study had a fair quality of life and only very few need improvements.

Additionally, this model can easily be developed as a functional condition in a web application. When used in conjunction with our developed data collection system, it can instantly analyze the level of quality of life. However, the elderly in different areas may have different factors affecting their quality of life. Therefore, models based on information on the elderly can differ by the target area. This proposed model development process can also be used with other age group or demographic data, to find models that answer questions the researcher poses to available data.

Presently, our system is now in use, having replaced the original practices of the local authorities that were our partners. We share knowledge and information together. The partner uses information and the system to plan public policies and to understand the elderly in the community. After using the system, they evaluated the usability of the
system using a satisfaction assessment form. We had a sample of 100 people, or more than 25% of the number of our partners and elderly representatives, whose population size is approximately 300 people. Assessment results showed a very satisfactory level from 70% of responders and the most satisfactory from 30%.

5. Conclusions

Information on the elderly is essential for promoting and improving their quality of life. This study developed and demonstrated a personal elderly monitoring system, and knowledge discovery from collected data. This system is used for data collection, data management, and data visualization for the care of the elderly, with the presentation of information in the forms of text, graphs, and online maps for easy and interesting comprehension. The development involved the participation of partner organizations to ensure that the system supports the actual needs of users. Furthermore, we analyzed knowledge by multiple linear regression, thus fitting the model to predict the level of quality of life, with feature selection reducing the needed input information. The model uses 14 attributes of the 37 candidate attributes, to predict the level of quality of life with an accuracy of 86%. This model suggests reduced questionnaires for the convenience of the elderly. Moreover, the system and discovered knowledge have been shared with the partners involved with elderly care. This information can be used in policy planning and to understand the context of the elderly in the community, especially to improve their quality of life.

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