A prediction model of community commitment and self-efficacy, using machine-learning: age-related differences in attitudes toward preventing social isolation among community-dwelling older adults

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Abstract

Purpose: We used machine learning to identify age-related differences in people's attitude concerning their community commitment and the community's self-efficacy for preventing social isolation among community-dwelling older adults.

Methods: Anonymous self-administered questionnaire surveys were conducted in 2013 (N=528), 2016 (N=888) and 2018 (N=810) to randomly selected local residents in a municipality, aged ≥20 years. The surveys included questions on personal attributes, a community commitment scale, and a self-efficacy scale for preventing social isolation among older adults. In the first phase, several machine-learning algorithms were applied to the responses from the <60-year and ≥60-year age groups for the 2013 and 2016 data to identify potential differences between the two age categories. In the second phase, the best-performing algorithm was applied to the 2018 data to predict the respondent's age group based on his/her responses.

Results: The first phase analysis indicated, for the community commitment scale, a classification accuracy of 0.60 for the best-performing algorithm and a kappa-value of 0.18. The accuracy and kappa-value for the self-efficacy scale were 0.62 and 0.24, respectively. Using the 2018 test data, the prediction accuracies for the ≥60-year age group were 0.61 and 0.65 for the community commitment scale and self-efficacy scale, respectively, and those for the <60-year age group were 0.60 and 0.60, respectively.

Conclusions: The results indicated awareness differences concerning community commitment and self-efficacy for preventing social isolation between residents aged <60 and ≥60 years. The responses of the residents aged ≥60 years showed slightly higher prediction accuracies, likely indicating more homogeneous responses.

Keywords : social isolation, frail elderly, machine learning, older adults

1. Introduction

In Japan, there have been accelerating trends in aging of the general population, nuclear families, single-person households, and elderly households in association with weakened familial and community relationships [1]. Community residents should be aware of the importance of coping with social issues and building engaged, confident, sustainable and inclusive communities.

Accordingly, the creation of personal relationships is important to facilitate mutual support among neighbors and building infrastructure is needed to allow local residents to live well. Older adults face challenges of loneliness and dementia, which can lead to isolation and mental problems. We believe that by watching over the elderly in the community, we can prevent their isolation and provide opportunities for communication. This will allow neighbors to support older adults, enhance the community commitment, including the sense of social belonging, and would facilitate the resolution

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of common issues in the community [2].

To prevent social isolation of community-dwelling older adults, public health nursing should facilitate contacts between residents, via providing a care-network, which includes community care professionals, local volunteers and residents. In the process of developing the community neighborhood watch, by community volunteers, for preventing social isolation of older adults, the community commitment and self-efficacy for preventing social isolation of older persons could be effective [3]. Community commitment refers to a person's awareness of being a member of the community and to his or her sense of community fellowship and belonging. This concept is useful to clarify community commitment and awareness of community welfare in local residents. Community commitment has been shown to be influenced by personal attributes of the community residents, including attachment and pride in personal relationships with other community residents that intensify with increasing years of residence; however community residents might lose mental support as their community relevance decreases with aging [4] [5]. Self-efficacy for preventing social isolation of older adults refers to one's sense of confidence that he or she is able to watch neighboring older persons and to perform community networking by himself or herself.

Neighborhood watch for preventing social isolation of older adults is conducted by local volunteer organizations, and they include a wide variety of activities such as personal safety confirmation and mapping [6]. A study titled "Report on the New-Generation Elderly 2017" (Research Institute for High-Life, 2017) revealed a difference in awareness of the actual status of living between older persons, aged ≥60 years, and younger persons, aged<60 years, as younger persons are more likely to prioritize their job or household affairs.

Machine learning could identify particular latent patterns in the data [7] and has evolved in the recent years as an artificial intelligence technique for automatic pattern recognition and knowledge acquisition. Previous studies have revealed various medical applications of machine learning, including assistance in medical diagnostic imaging [8], real-time predictions of blood glucose levels [9] and aging studies [10]. We therefore considered that it would be possible to obtain distinct insight into people's attitude to support the prevention of social isolation of older adults by using machine learning. Machine learning algorithms are highly likely to lead to the discovery of features and patterns that are difficult to extract using conventional analysis methods and help in creating more advanced prediction models.

The objective of the present study was to identify the community commitment and community's self-efficacy for preventing social isolation among community-dwelling older adults, using machine learning applied to the data from a cross-sectional survey of randomly selected residents of a municipality, aged ≥20 years. In particular, we have investigated whether we can predict age-related differences in people's attitude towards preventing social isolation among older adults, by using as features (or explanatory variables) the responses to questionnaires concerning community commitment (Section 2.3.1) and community's self-efficacy (Section 2.3.2).

2. Methods

2.1 Design

This was a questionnaire-based community welfare planning survey in Matsubara that was implemented by the City of Matsubara government as a cross-sectional study on the awareness and actual status of community welfare of selected residents of Matsubara, aged ≥20 years.

Matsubara, a city with a population of approximately 110,000, has been developing as a commuter town. In 2017, various residents' associations, district welfare commissioners, child welfare commissioners, elderly clubs, and regional welfare councilors made periodical watching and greeting visits to 1129 older adults who needed support or wanted to be visited. Matsubara city is located in the southern part of Osaka prefecture, and the population growth rate over the past five years (2016-2021) is 0.39%. Furthermore, integrated community care support centers, social welfare councils, community social workers, and other entities collaboratively implemented security check visits on 2158 people, within the framework of their older people watch activities in 2017. Based on the security check results, activities were conducted to link older persons' care-related issues and other problems to public institutions [11].

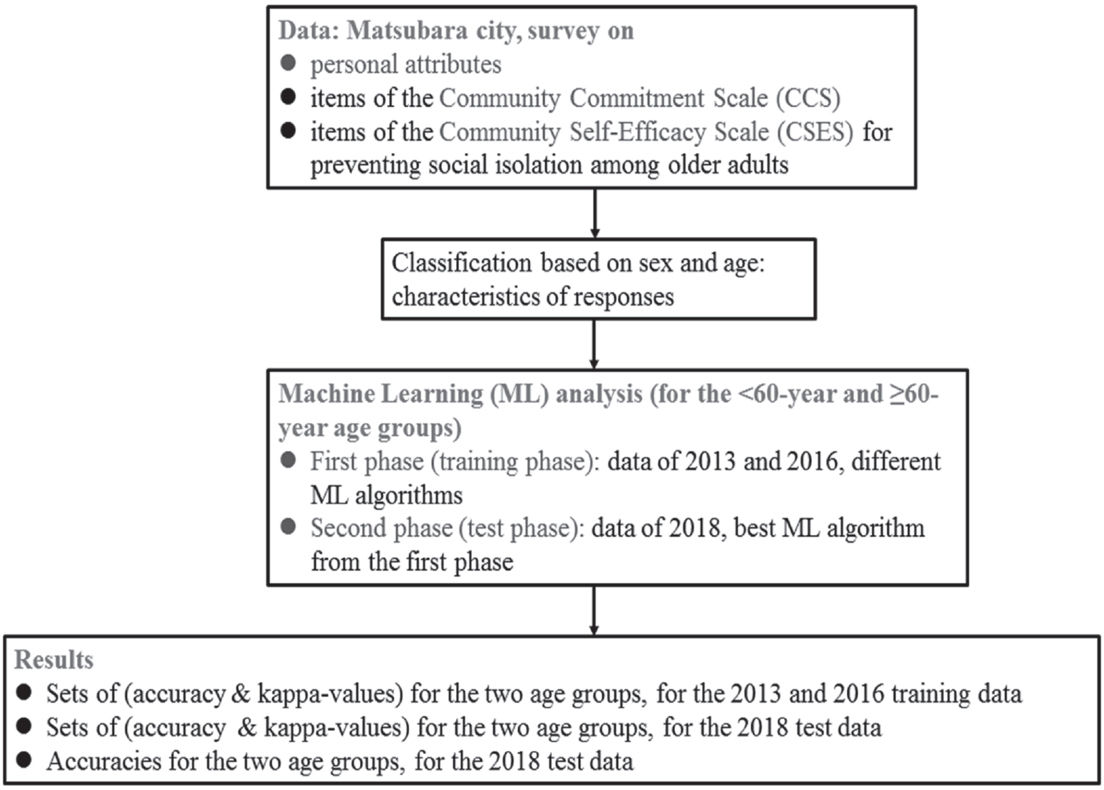


Figure 1. Schematic representation of the analysis flow used in this study

2.2 Sample

Anonymized self-completion questionnaire forms were sent by mail to 1500 residents in June and July 2013 and to 3000 residents in September 2016 and in June and July 2018. Completed surveys were recovered from 651 (43.4%) respondents in 2013, 1038 (34.6%) respondents in 2016, and 964 (32.1%) respondents in 2018. Respondents with no missing age or sex data were selected: 528 (35.2%) respondents in 2013, 888 (29.6%) respondents in 2016, and 810 (27.0%) respondents in 2018.

2.3 Measures

Demographic characteristics were analyzed by age and sex. The subjects were stratified by age as follows: 20–29 years, 30–39 years, 40–49 years, 50–59 years, 60–69 years, and ≥70 years.

2.3.1 Community commitment

Community commitment was evaluated using a previously established Community Commitment Scale (CCS), with confirmed reliability and validity [12]. As already mentioned, community commitment refers to a person's awareness of community fellowship and belonging, and this concept is useful in evaluating their awareness of community welfare. Eight questions under two headings were asked: four on fellowship, including "people in this community habituate themselves to mutual consideration and greetings," and four on belonging, including "community fellowship is annoying." Responses were evaluated using a four-grade scoring system: "completely agree" (3 points), "slightly agree" (2 points), "slightly disagree" (1 point), and "completely disagree" (0 points). The total score ranged from 0 to 24 points, with higher scores indicating higher levels of community commitment.

2.3.2 Community's self-efficacy for preventing social isolation among community-dwelling older adults

Community's self-efficacy for preventing social isolation among community-dwelling older adults was measured using a community self-efficacy scale (CSES) developed by Tadaka et al. (2016) [13]. Eight questions in two categories were asked: four questions on community networks, including "able to create a place where nearby residents gather at ease" and four questions on neighbor watching, including "greet any older neighbor who is absent a few days." Responses were evaluated using a four-grade scoring system: "fully confident" (3 points), "slightly confident" (2 points), "slightly unconfident" (1 point), and "completely unconfident" (0 points). The total score ranged from 0 to 24 points, with higher scores indicating higher self-efficacy.

2.4 Analytic strategy

Data on the subjects' attributes were analyzed using descriptive statistics. For community commitment and self-efficacy for older adults' watch, the mean and standard deviation were calculated on each lower scale, and normality was confirmed. The data were then statistically tested by two-way layout analysis of variance. A *p*-value exceeding 5% was considered to indicate a significant difference.

Machine learning [14] can be roughly divided into three types, according to its data feed and pattern recognition methodology: supervised learning, unsupervised learning and reinforcement learning. In this study we employ supervised machine learning, which uses labeled datasets to train algorithms to classify data or predict outcomes accurately. Machine learning-based prediction/classification models were developed using algorithms included in the R caret package. Responses on the CCS and CSES were handled as "features," and predictions of classification by age stratum were handled as "targets". "Targets" were predicted/classified using "features." Two age strata were established: 20–59 years (<60-year age group) and ≥60 years (≥60-year age group). For training the machine-learning algorithms, seven models were applied to the data obtained in 2013, 2016 ("learning" datasets) and the best-performing algorithms were used with the 2018 data ("test" data) (see the flow-chart of analysis in Figure 1). A linear discriminant analysis algorithm was used as a first model. As nonlinear models, a decision tree algorithm known as the classification and regression tree [15] and a classification method known as the k-nearest neighbors' algorithm [16] were used for analysis. More complex nonlinear algorithms were also used to model the data: learning vector quantization [17], random forest [18], Gradient Boosting Machine (GBM) [19], and Support Vector Machine (SVM) [20]. Accuracy and kappa values were calculated to quantify the classification ability of the machine-learning algorithms. The accuracy and level of agreement (kappa value) are said to be higher as they approach 1. Data were statistically analyzed using R version 3.0.1 (R Foundation for Statistical Computing, Vienna, Austria) and SPSS Statistics version 25 (IBM Corp., NY, USA).

$$\text{Accuracy} = \frac{\text{number of accurate predictions}}{\text{total number of predictions}}$$

$$\text{Kappa value} = \frac{\text{accuracy} - \text{expected precision in random prediction}}{1 - \text{expected precision in random prediction}}$$

2.5 Ethical considerations

This study was approved by the Institutional Review Board of the Kio University. (December 6, 2018 approval No.30-5-1).

3. Results

3.1 Characteristics of participants

The characteristics of participants in this study, according to each fiscal year cohort, are shown in Table 1. Approximately 60% of the respondents were women (Fiscal Year [FY] 2013 = 58.3%, FY2016 = 59.3%, FY2018 = 60.5%). Persons aged ≥60 years accounted for approximately 50% of the respondents (FY2013 = 46.6%, FY2016 = 56.8%, FY2018 = 53.7%).

3.2 Changes in community commitment and self-efficacy for preventing social isolation for community-dwelling older adults

Changes in community commitment and self-efficacy for older adults' watch are shown by gender and age stratum according to each fiscal year cohort in Table 1. The mean CCS score was 11.72 ± 2.91 points in 2013, 11.91 ± 2.91points in 2016, and 11.82 ± 2.56points in 2018; no significant difference was found. The mean CSES score was 7.18 ± 4.75points in 2013, 7.08 ± 4.63points in 2016, and 6.91 ± 4.78points in

Table 1. Subjects' attributes and Changes in community commitment and community's self-efficacy for preventing social isolation among community-dwelling older adults

		FY2013 n=528		FY2016 n=888		FY2018 n=810		
		n	(%)	n	(%)	n	(%)	
Gender	Men	220	(41.66)	361	(40.65)	320	(39.51)	
	Women	308	(58.33)	527	(59.35)	490	(60.49)	
Age, years	20–29 years	40	(7.58)	57	(6.42)	53	(6.54)	
	30–39 years	68	(12.88)	65	(7.32)	76	(9.38)	
	40–49 years	89	(16.86)	126	(14.20)	110	(13.58)	
	50–59 years	85	(16.10)	136	(15.31)	136	(16.79)	
	60–69 years	133	(25.19)	216	(24.32)	170	(20.99)	
	≥70 years	113	(21.40)	288	(32.43)	265	(32.72)	
Family composition	Living alone	45	(8.52)	107	(12.04)	102	(12.59)	
	Couple only	143	(27.08)	274	(30.85)	276	(34.07)	
	Two parent–child generations	277	(52.46)	387	(43.58)	356	(43.95)	
	Three parent–child generations	44	(8.33)	61	(6.90)	62	(7.65)	
	Others	19	(3.60)	59	(6.64)	14	(1.73)	
		M	±SD	M	±SD	M	±SD	*p*
CCS†	Overall	11.72	±2.91	11.91	±2.91	11.82	±2.56	.560
	Men	11.50	±2.98	11.92	±2.79	11.59	±2.38	.124
	Women	11.87	±2.91	11.90	±2.91	11.96	±2.55	.958
	20–29 years	11.90	±3.18	11.72	±2.46	11.77	±2.77	.642
	30–39 years	11.68	±2.93	11.86	±2.68	12.36	±2.24	.106
	40–49 years	12.01	±2.24	12.40	±2.48	12.15	±2.79	.414
	50–59 years	11.56	±3.05	12.43	±2.41	11.75	±2.21	.112
	60–69 years	11.59	±2.67	11.69	±2.72	11.53	±2.29	.886
	≥70 years	11.42	±3.54	11.65	±3.33	11.70	±2.66	.820
CSES†	Overall	7.18	±4.75	7.08	±4.63	6.91	±4.78	.530
	Men	7.46	±4.82	7.26	±4.86	7.56	±5.17	.792
	Women	6.99	±4.69	6.69	±4.49	6.49	±4.48	.222
	20–29 years	5.78	±4.43	4.21	±3.72	4.75	±4.23	.231
	30–39 years	5.66	±4.84	5.05	±3.48	4.66	±4.33	.436
	40–49 years	6.23	±4.36	6.15	±4.29	5.96	±4.49	.757
	50–59 years	6.92	±4.61	7.11	±4.36	6.21	±4.23	.228
	60–69 years	8.13	±4.13	7.43	±4.81	7.66	±4.44	.154
	≥70 years	8.48	±5.34	8.26	±4.74	8.23	±5.11	.893

FY, fiscal year; CCS, Community Commitment Scale; CSES, Community self-efficacy scale.
†Total score ranged from 0 to 24 points.

2018; significant difference was not found. The CCS or CSES scores according to Gender are as follows. For Men, the mean CCS score was 11.50 ± 2.98 points in 2013, 11.92 ± SD2.79 points in 2016, and 11.59 ± 2.38 points in 2018. For Women, the mean CCS score was 11.87 ± 2.91 points in 2013, 11.90 ± 2.91 points in 2016, and 11.59 ± 2.55 points in 2018. There was no significant difference for all CCS items in 2013 and for all CCS items and all CSES items in 2018.

3.3 Machine learning-based prediction/classification models

Seven machine learning models were applied to the 2013 and 2016 observation data in the form of "learning" datasets (or training datasets). For community commitment, the levels of agreement of the various models for predicting "targets" from "features" are shown in Figure 2a. SVM proved to be the best model for the data, with accuracy of 0.59 and a kappa value of 0.17 (random chance would correspond to a kappa value of 0.0). Data on community's self-efficacy for preventing social isolation among community-dwelling older adults are shown in Figure 2b. GBM proved to be the best model for the data, with an accuracy of 0.63 and a kappa value of 0.27. Data on community commitment and community's self-efficacy for preventing social isolation among community-dwelling older adults are shown in Figure 2c. SVM proved to be the best model for the combined data, with an accuracy of 0.64 and a kappa value of 0.28.

To quantify the prediction/classification capability, "independent" observation data (i.e., data not used in the learning stage), known as test data, are required. When using the test data (2018 data), the accuracy and kappa value of the best machine learning model were 0.60 and 0.18 for community commitment, 0.62 and 0.24 for self-efficacy for older adults watch, and 0.64 and 0.28 for the combined community commitment and self-efficacy for older adults watch, respectively. We can compute prediction accuracies for the two age groups separately. For the ≥60-year age group, the accuracy was 0.61 for community commitment and 0.65 for self-efficacy for older adults' watch. For the <60-year age group, the accuracy was 0.60 for community

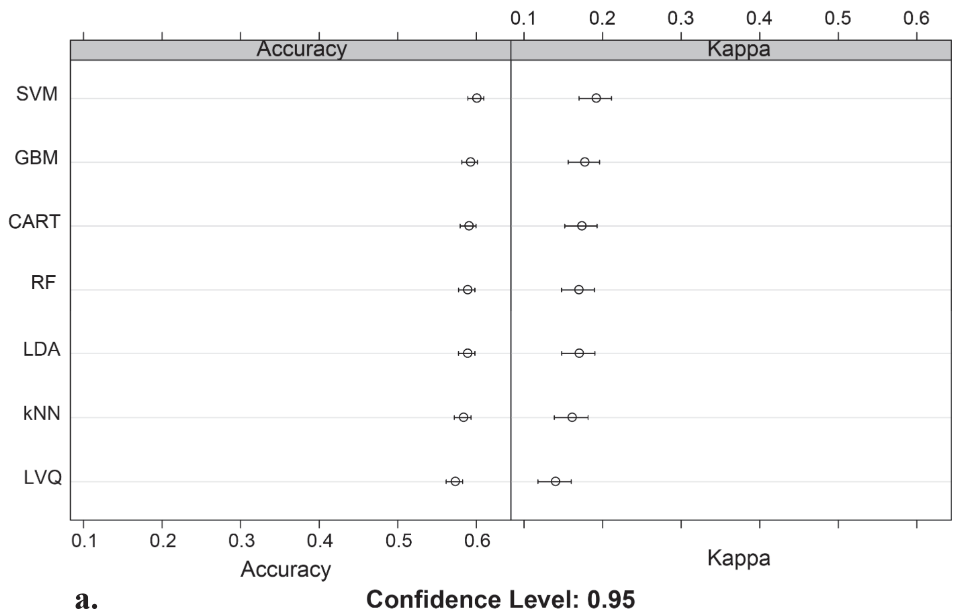
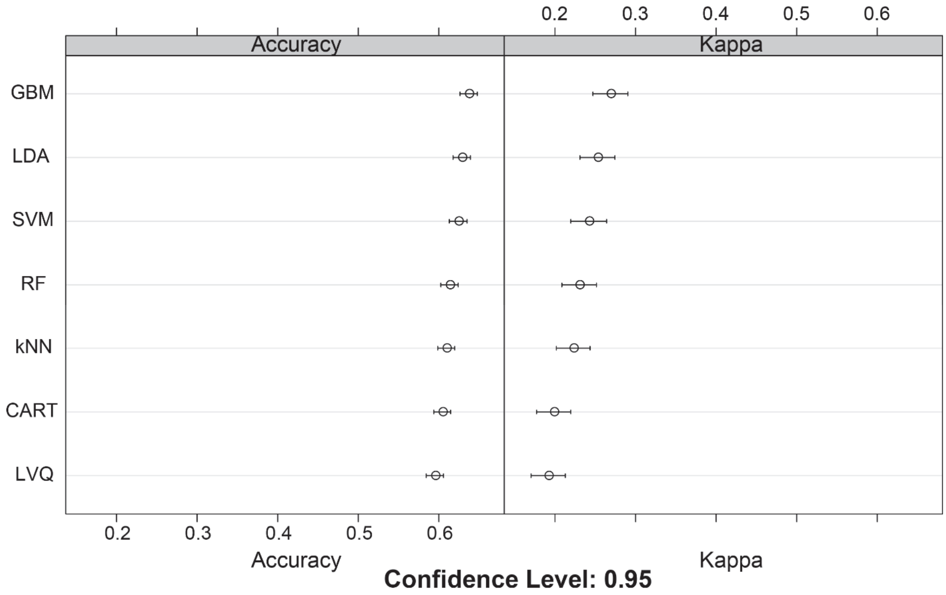


Figure 2a. CCS prediction model (accuracy: approximately 0.6, kappa value: approximately 0.2). CCS, community commitment scale; SVM, support vector machine; GBM, gradient boosting machine; CART, classification and regression tree; RF, random forest; LDA, linear discriminant analysis; kNN, k-nearest neighbors; LVQ, learning vector quantization. **b**. CSES prediction model (accuracy: approximately 0.65, kappa value: approximately 0.27). Symbols have same meaning as in (**a**). **c**. CCS-CSES mixed prediction model (accuracy: approximately 0.65, kappa value: approximately 0.2). Symbols have same meaning as in (**a**) and (**b**).



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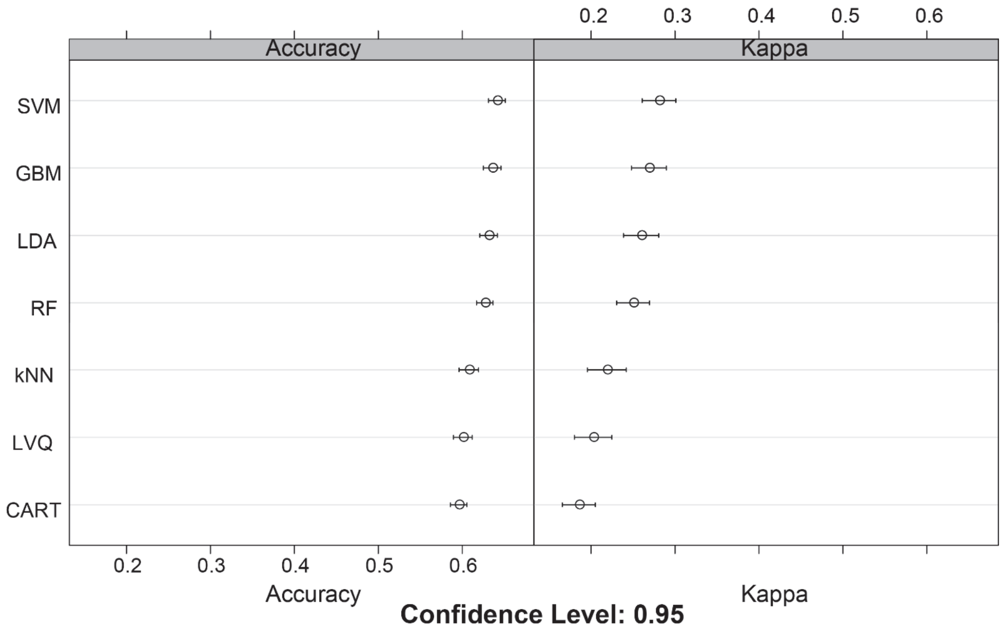

c.

commitment and 0.60 for self-efficacy for older adults' watch.

With regard to classification by machine learning, the kappa values indicated the predictive performance of a machine learning model (here either SVM or GBM) compared with a random model (random estimation of "target values"). Kappa values of 0.21 to 0.40 indicate "slightly good" prediction levels [21]. Notably, when the machine-learning algorithm was applied using other combinations of age strata (e.g., age ≥50 years and age <50 years), the classification results were not statistically significant.

4. Discussion

The present study was based on a panel survey of community residents, in Matsubara, aged ≥20 years: 528 residents in 2013, 888 residents in 2016, and 810 residents in 2018. The data were analyzed using a new approach, known as machine learning, to characterize the study population by age stratum in terms of community commitment and community's self-efficacy for preventing social isolation among community-dwelling older adults.

As shown in Section "3.3 Machine learning-based prediction/classification models" and Figures 2a, b and c, the SVM and GBM algorithms provided the best prediction performances. We speculate that this is mainly due to their ability to handle non-linearity in the data [22].

The prediction accuracy was higher for the ≥60-year age group than for the <60-year age group. These results indicate that the learning algorithms of this study were able to predict age-related differences in community commitment and community's self-efficacy for preventing social isolation among community-dwelling older adults.

As implied by the accuracy results, the ≥60-year age group showed more uniform responses (i.e., same pattern of responses–easier to classify/predict). For community commitment and community's self-efficacy for preventing social isolation among community-dwelling older adults, it is suggested that awareness was different between the <60-year age group and the ≥60-year age group. With regard to the awareness of "community commitment" and "self-efficacy for older adults' watch" ,the ≥60-year age group showed more uniform responses, whereas the <60-year age group showed lower accuracy values than the ≥60-year age group and hence non-uniform responses. The statistical significance of the differences in accuracies should be further tested in future studies.

We consider that machine learning can be used for future support, by recognizing patterns of residents' awareness from the information that has been compiled as empirical knowledge by health welfare workers to date. Machine learning is reportedly used in a wide variety of fields, including the development of robots that promote mutual support of older adults in the community setting and systems for monitoring older adults electric power consumption patterns [12] [13]. A large data from surveys by governmental entities, including a broad range of information on daily activities and long-term care, are expected to be used proactively to enable the identification of early-detection patterns and improve community activities to cope with dementia, falls, and other issues.

The results of the present study suggest that the public health nursing strategy should consider age-related differences among older adults to facilitate attitudes towards preventing their social isolation, in particular for those residents dwelling in a community through organizational empowerment based on PHN's social capital [23]. These efforts should be part of a broader strategy of building a community-based comprehensive care system.

5. Conclusions

The results from a questionnaire-based community welfare planning survey of 528 (35.2%) respondents in 2013, 888 (29.6%) respondents in 2016, and 810 (27.0%) respondents in 2018 were analyzed to determine age-related differences in community commitment awareness between the <60-year age group and the ≥60-year age group. Data analysis by machine learning showed age-related awareness differences among the two age groups, characterized by classification accuracies of about 0.6 and level of agreement (kappa-values) of around 0.2.

Data Availability Statement

The data that support the findings of this study are available on reasonable request from the Matsubara city, Osaka Prefecture, Japan.

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