

# A Job Recommendation Machine Learning Model Using Elderly Lifestyles

Nichamon Sithiponporn<sup>a</sup>, Uthai Tanlamai<sup>b</sup>, Achara Chandrachai<sup>c</sup>, Sipat Triukose<sup>d</sup>, <sup>a,c</sup>Technopreneurship and Innovation Management Program, Graduate School Interdisciplinary Program Chulalongkorn University, Thailand, <sup>b</sup>Department of Accountancy, Chulalongkorn Business School Chulalongkorn University, Thailand, <sup>d</sup>Research Group on Applied Computer Engineering for Medicine and Healthcare (ATM) Chulalongkorn University Big Data Analytics and IoT Centre (CUBIC) Chulalongkorn University, Thailand, Email: <sup>a</sup>[nsithiponporn@gmail.com](mailto:nsithiponporn@gmail.com), <sup>b</sup>[uthai@cbs.chula.ac.th](mailto:uthai@cbs.chula.ac.th), <sup>c</sup>[achandrachai@gmail.com](mailto:achandrachai@gmail.com), <sup>d</sup>[sipat.t@chula.ac.th](mailto:sipat.t@chula.ac.th)

One of the most significant social transformations nowadays is the aging society. The Baby Boomer generation is now becoming the majority segment of our society. This group seems to have different lifestyles and diverse characteristics from past generations of senior citizens. They tend to continue working into their older years. When recommending a job for this group, assessing their demographics may be insufficient. This paper suggests job recommendations, according to elderly lifestyles, using a machine learning process. Senior citizens living in Bangkok served as the sample for the study. The machine learning model was formulated in R programming language by a logistic regression algorithm to enhance accuracy. The model can recommend a job for seniors with 91.20% accuracy. The study provides the concept and empirical model for job recommendations for the elderly based on their background, lifestyles, and current quality of life norms.

**Key words:** *Ageing, Elderly, Job Recommendations, Lifestyles.*

## Introduction

Societies are rapidly aging throughout the world. Aging populations cannot be considered insignificant any more. The Bureau of Mental Health Strategy (2015) showed that Thailand has been an “Aged” society since at least 2013. In 2023, Thai people aged 60 years or older are expected to increase up to around 14 million, marking 21 percent of the Thai population. Thus, Thailand is transforming to “Complete Aging Society or Super-aged” over the coming

years (National Research Council of Thailand (NRCT), 2017). The fertility impact of World War II is evident, marking the period in which those born during the post-war baby boom have reached their old age (United Nations, 2015).

At the national level, the older a population is, the slower its economy grows (Kenan Foundation Asia, 2018). A shrinking labour force not only affects the number of insufficient workers but it also affects tax collection for public healthcare and social welfare. Therefore, the government and private sectors should find a way to keep people in the workforce. If people keep working and are able to take care of themselves, this would ease the governmental and societal burden. The United Nations Population Fund (2011) suggested improving the proportion of the aging population who remain economically active and receive support through work, to promote well-being among the elderly.

In the United States, Lohman, Byers-Connon, and Padilla (2017) found that the increasingly elderly population tended to continue working after retirement. Working after retirement is not only a hobby in their free time, but also increases their financial stability, and leads to a more desirable life. More social participation improves mental health, enhancing their quality of life. In 2017, quality of life issues among older persons were highlighted by the Ministry of Social Development and Human Security of Thailand (Whangmahaporn, Simmonds, & Whangmahaporn, 2019).

Aging worker trends in Thailand and the United States seem similar. A survey from the Poll and Centre for Aging Society Research at the National Institute of Development Administration (NIDA) pointed out that the majority of the Thai elderly still need to continue working to earn money for living. Some have to rely on family to support their living as they do not have any income (Netithanakul, 2015). Choorat, Sawangdee, and Arunraksombat (2012) found that older people did not need their children or society to take care of them, but rather they preferred to stay on their own feet, including maintaining their own earnings, their jobs, and their activities of daily living. Although they were retired, some were able to take care of themselves and do something useful for others. They believed that they had skills, abilities, and long experience, which are all beneficial to society.

Lohman et al. (2017) surprisingly found that senior citizens were among the most effective workers. Furthermore, older workers usually looked for a new field of work after retirement. They were keen to learn a new skill and have the ability to find a solution in any situation. Phijaisanit (2015) reported that, among the older Thai population, there were approximately 2.6 million people, or 37.55 percent, who refused to retire because they needed to continue working. Nevertheless, aging people who were willing to work after reaching 60 years of age had limited job opportunities in Thailand. The country lacks policies and infrastructure to

establish employment options to support senior workers, which encourage older people to maintain flexibility in their lives (Phijaisanit, 2015).

To build greater job opportunities for elderly workers, it is necessary to understand and provide job alternatives for seniors to work in all sectors. Using the generation concept as a demographic cohort, the people who became part of the Complete Aging Society were mainly born after World War II, from approximately 1946 to 1964. As Baby Boomers have entered their senior years, they have tended to possess different characteristics and demands from generations in the past. With particular social and historical experiences, all sectors need to understand their needs and job criteria that they require after retirement. Therefore, it is necessary to recommend a job that matches their needs. Hence, this study aimed to contemplate their lifestyles as one factor to recommend an appropriate job while taking into consideration the status of their current quality of life.

This study proposes the concept of job recommendations based on elderly lifestyles and the status of their current quality of life, elaborates on conceptual foundations, and provides supporting empirical evidence. The research aims to develop a machine learning model for a job recommendation system for the elderly. The study explores background profiles, job requirements, determinants of job criteria, and working conditions that are desirable by seniors, as well as examining respondents' lifestyles and quality of life, to model the classification of job recommendations.

## Literature Review

### *Elderly Lifestyle*

Lifestyle has always been interesting in terms of individuals' behaviour as well as feelings, attitudes, interests, and opinions. Myriam Töpfer and Bug (2015) pointed out that demography or geography alone do not give a complete picture of people. Psychographics, first introduced by Demby (1974), combines psychology with demographics. Psychographic or Lifestyle refers to individual activity, interest, and opinion. From a marketing standpoint, combining psychographics with demographic information gives a better understanding of the wants and needs of consumers (Rungsrisawat, Joemsittiprasert, & Jermisittiparsert, 2019; Saengchai, Thaiprayoon, & Jermisittiparsert, 2019; Phusalux, Jermisittiparsert, Saisama, & Wongjunyav, 2020). Plummer (1974) claimed that lifestyle patterns are the new construct which combines demographic and psychological benefits. Such richness and dimensionality tells things about users which other research cannot explain.

Wells and Tigert (1971) used a popular approach to measure lifestyle. They used rating statements about activities, interests, and opinions (AIO). Activity is an action taken on

various occasions and a living pattern, including work, hobbies, social events, vacation, entertainment, club membership, activity in the community, shopping, and sports. Interests focus on various issues, objects, events, and topics. Those issues are about surroundings, which could be family, home, job, community, recreation, fashion, food, media, and achievement. An opinion is a descriptive belief about themselves, social issues, politics, business, economics, education, products, future, and culture.

### ***Quality of Life (QOL)***

The World Health Organization (1997) was one of the earliest institutions that studied quality of life. The WHO defines quality of life as an individual's perception of their place of existence in a society with a cultural and valued context. Those include goals, expectations, standards, and their ideas. The concept of quality of life is influenced by physical health, mental health, personal belief, social relationship, and environment.

The present study adopts the quality of life measures from the WHO. The Thai version, "WHOQOL-BREF-THAI", was developed from the WHOQOL-BREF quality of life assessment (World Health Organization, 1996) by Mahatnirunkul, Tuntipivatanaskul, Pumpisanchai, Wongsuwan, and Prommanajirangkul (1998). WHOQOL-BREF-THAI was developed and validated for its content validity and reliability at Cronbach's alpha coefficient of 0.84.

This tool measures the quality of life in Thai people using four elements as follows:

- 1) Physical health domain: daily activities, working ability, movement, and leisure.
- 2) Mental health domain: self-esteem, optimistic, pessimistic, personal beliefs, and learning.
- 3) Social relationship: personal relationship, and social support.
- 4) Environment: income, security, opportunity to learn new skills, and participation in a recreation activity.

### ***Job Recommendation***

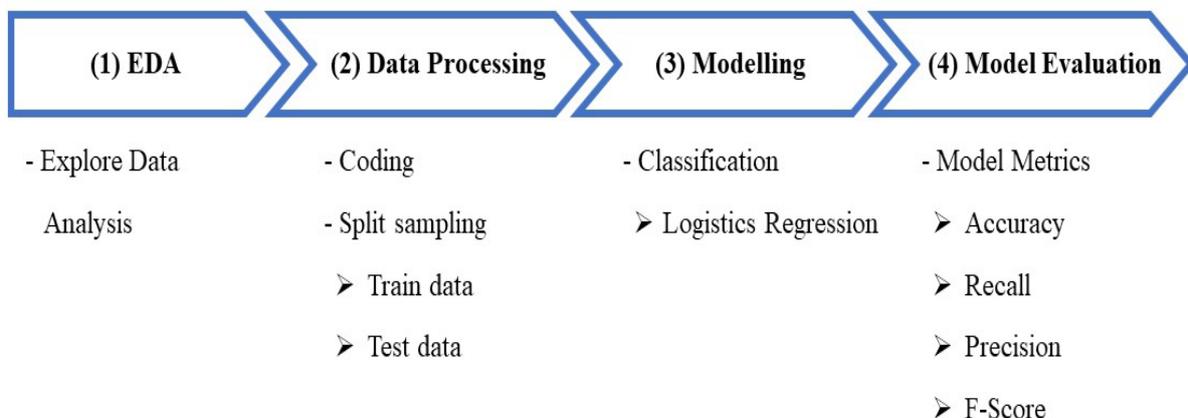
A survey of job recommendation services in Thailand found that services concern only demographics and geographic data. There is only one specific job recommendation service for senior citizens: The Department of Employment, of the Ministry of Labour, offers eight jobs for older people who require income, including teacher/coach, shop assistant, consultant, cooking/handicraft, service person, farmer, freelancer, business owner, and four social worker roles, including volunteer, community service, charity work, and sharing knowledge and skills, i.e. speakers. The elderly job recommendation service by this governmental unit is based solely on demographic data.

Sumalrot and Nochi Suksawai (2015) studied and recommended appropriate job characteristics for older adults. These include low-stress jobs and voluntary work. However, seniors believe that they can maintain their self-esteem and income at the same time. People of older ages show a decline in their life quality, including low self-esteem due to loss of social roles. In other words, losing such roles will negatively affect their self-esteem (Alotaibi, 2019). Consequently, senior workers should be encouraged to do the job they are keen to do, and not be limited to the job that people think that they should do. However, studies on job recommendations for aging people seem to be limited. Existing job recommendations focus on overall work conditions, based on demographic data only. While each person is likely to have different needs, past studies did not take individual differences into account for determining the right job. Therefore, this study proposed a job recommendation service concept which considered not only the personal background including demographics, but also considered elderly lifestyles and their current quality of life. There are various methods used for the job recommender system; for example, the Semantic matching process (Nilaphruek & Khanankhoaw, 2015), and the machine learning model with the Naïve Bayes algorithm developed by Malinowski, Keim, Wendt, and Weitzel (2006). The latter model provides a relatively accurate predictor when recommending a job. On the other hand, Lau (2011), who developed the recommendation system with various machine learning techniques, learned that logistic regression significantly outperformed Naive Bayes. Consequently, a machine learning model with logistic regression classification will be used to develop the job recommendation system in this study.

### ***Machine Learning Process***

The process for formulating machine learning comprised four main steps as shown in Figure 1: (1) EDA (Explore Data Analysis), (2) Data Processing, (3) Modelling, and (4) Model Evaluation (Hasan, Islam, Islam, & Hashem, 2019; Oswal, 2019).

**Figure 1.** Machine Learning process



### (1) EDA (Explore Data Analysis)

To perform any machine learning research, both exploratory data analysis and data observation are required (Hasan et al., 2019). Prior to processing the collected data, exploratory data analysis (EDA) is conducted to analyse the main characteristics of the data.

### (2) Data Processing

The data set is assigned by a numeric code. The data set is required to be split into two subsets: a train data subset for the training model and test data subset for evaluation purposes. The train data subset is run to train the algorithm, then the trained models are evaluated by the test data set (Hasan et al., 2019).

### (3) Modelling

Logistic regression is one of the most widely used generalised linear models for predicting probability, and has been widely used in many recommendation systems. (Wang et al., 2016) Logistics Regression is a classification algorithm for predicting a binary outcome such as Yes/No, True/False, given a set of independent variables. Logistic Regression generates a probability of occurrence of an event which is a value between 0 and 1 by fitting data to a logic function. However, to map a Logistic Regression possibility value to a binary category, a classification threshold or a decision threshold needs to be defined (Oswal, 2019).

ROC (Receiver Operator Characteristic Curve) is used for deciding the suitable threshold value for each model. ROC graph is generated by plotting the True Positive Rate on the y-axis against the False Positive Rate on the x-axis. The area under the ROC curve or Area under the Curve (AUC) is often used as a measure of probabilistic classifier quality. The higher the AUC, the better the model is at predicting (Vuk & Curk, 2006). Therefore, the classification threshold is selected from the value which contributes to the greatest AUC.

### (4) Model Evaluation

The Hosmer-Lemeshow test, or HL test, is a goodness of fit test for logistic regression and only used for binary response variables, i.e. yes or no. A goodness of fit test tells how well the data fits the model. Specifically, the HL test calculates if the observed event rates match with the expected event rates among population subgroups (Hosmer Jr, Lemeshow, & Sturdivant, 2013). The statistic for testing is Chi-square at a significant level of 0.05. The P-value must be more than 0.05 to accept  $H_0$  for a good fit of the model to the data.

The hypothesis test is:

**$H_0$ :** Model is fit

**$H_1$ :** Model is not fit

The significant level is at 0.05. (Hosmer & Lemeshow, 1980)

Next, the accuracy of the model needs to be determined. For Binary classifiers like Logistics Regression, when dealing with two-class classification problems, one class is labelled as a positive and the other one is labelled a negative. The test set consists of positive “P” and negative “N” examples. A classifier assigns a class to each of them. However, some of the assignments are wrong. To assess the classification results, the number of evaluation index is counted. Evaluation index comprises true positive (TP), true negative (TN), false positive (FP) (actually negative but classifies as positive) and false negative (FN) (actually positive but classifies as negative), as shown in Figure 2. The classifier assigned “TP + FP” exemplifies the positive class and “TN + FN” exemplifies the negative class (Kumar Ahuja, 2015; Vuk & Curk, 2006).

**Figure 2.** Confusion Matrix (Vuk & Curk, 2006)

		Actual Condition	
		Actual Positive	Actual Negative
Output of Classifier	Total Samples		
	Classify Positive	TP	FP
	Classify Negative	FN	TN

The most commonly used statistical metrics are precision, recall, accuracy, and F1-score (Villmann, Kaden, Lange, Stürmer, & Hermann, 2014). The following four values are used in these metrics: the definitions of precision, recall, F1-score and accuracy, as shown in Figure 3 (Pandhare & Shah, 2017). The precision metric expresses how precise or accurate the model is, out of those predicted positive results. The Recall metric is often denoted as a sensitivity test statistic describing the ability of the classifier to detect positive samples accurately. As a weighted average of the precision and the recall metrics, the F1-score is a widely used measure to evaluate a binary classification model.

**Figure 3.** Statistical Metrics (Liu, Ren, Song, & Li, 2015)

$$\begin{aligned} \textit{precision} &= \frac{TP}{TP + FP} \\ \textit{recall} &= \frac{TP}{TP + FN} \\ F1 &= \frac{2 \times \textit{precision} \times \textit{recall}}{\textit{precision} + \textit{recall}} \\ \textit{accuracy} &= \frac{TP + TN}{TP + FN + TN + FP} \end{aligned}$$

### **Research Method**

This research is a quantitative study that aims to develop machine learning for a job recommendation system using lifestyle and QoL. The research procedure included the research survey and empirical modelling for a job recommendation system. This section introduces the methods to develop a job recommendation system, including data and samples, survey tools, and machine learning processes.

### **Data and Samples**

In accordance with the Department of Older Persons (DOP) (2016), the number of Thais aged 60 years or above accounted for 16.47 percent of the total Bangkok population (936,865 people) in 2016. The sampling unit of the study was people from the “Baby Boomer generation”, born after World War II (from 1946 to 1964), who live in the Bangkok Metropolitan area. As a sampling frame was not available, this study applied non-probabilistic sampling. With purposive sampling, the 400 respondents aged between 55-73 years old who live in the Bangkok metropolitan area and are able to perform daily activities on their own were targeted.

The questionnaire was conducted and distributed both online and offline. The total number of respondents was 632 cases, of which 118 cases (18.7 percent) were from the offline channel and the remaining 514 cases (81.3 percent) were from the online survey.

### ***Survey Instrument***

The research survey comprised questions examining the samples' background, desirable jobs, quality of life, and their lifestyles. The questions were reviewed and adjusted as per two professors' suggestions. The 5-point rating scale answer was based on an interval scale (Likert, 1932).

The questionnaire consists of four sections as follows:

- Section 1: Demographic background - contains eight questions about demographics and geographic factors regarding gender, age, education, income, and expenditure.
- Section 2: Job - contains six questions about job preferences, determinants of job criteria and working conditions, and respondents' perception of work.
- Section 3: Quality of Life - contains 26 questions. There are 24 items for four domains which are physical (seven items), psychological (six items), social relationships (three items), and environment (eight items), and two independent items (overall QoL and satisfaction with own health), ranging from "not at all" to "extremely" to identify the level that the respondents feel during the past two weeks in each item.
- Section 4: Lifestyle – Activity (A) - contains 23 questions about psychographic factors regarding activities ranging from "always" to "never/rarely" to identify the frequency that the respondent participates in each activity.
- Section 5: Lifestyle – Interest (I) - contains 22 questions about psychographic factors regarding interest ranging from "Strongly interested" to "Strongly uninterested" to identify the level that the respondent is concerned with for each subject.
- Section 6: Lifestyle – Opinion (O) - contains 22 questions about psychographic factors regarding opinions ranging from "strongly agree" to "strongly disagree" to identify the level that the respondent agrees with each subject.

For lifestyle related questions, reliability was assessed by a Test-Retest technique calculated by Spearman's correlation coefficient. A total of 31 samples completed the questionnaire and the same group of samples repeated the same questionnaire after two weeks. Based on the 95% confidence of the Spearman's correlation coefficient estimated scores for indicating reliability included strong reliability (0.70 and above), moderate reliability (0.40-0.60), and weak reliability (0.30 and below) (Dancey & Reidy, 2007). Questions for the activity perspective have strong reliability at an average Spearman's correlation coefficient of 0.7007, while interest and opinion related reliability are at a moderate level, with an average Spearman's correlation coefficient of 0.6374 and 0.6379, respectively. Therefore, all items were acceptable and reliable in measuring the constructs. A content validity test was conducted by five professors to ensure each question about lifestyle was valid for the topic. Some questions were eliminated. The final questionnaire of activities, interests, and opinions contained 19, 16, and 17 questions, respectively.

### ***Ethics Statement***

As this study involved human participants, the research methods and instruments were evaluated and approved by the Research Ethics Review Committee for Research Involving Human Research Participants, Health Sciences Group, Chulalongkorn University. Prior to the survey, all respondents were informed about the aim of the study and gave their consent.

### ***Job Recommendation Model with Machine Learning Process***

#### **(1) Exploratory Data Analysis**

This study summarised data set by descriptive statistics of the samples. The data from the survey questionnaires were processed and analysed in SPSS software.

#### **(2) Data Processing**

In this study, the data set contained 465 cases, divided between 80 percent to the train data set, which accounted for 372 cases, and the remaining 20 percent to the test data set comprising 93 cases. The train data subset was run to train the algorithm, then the trained models were evaluated by the test data set (Figure 4). The data processing was done in R Programming.

Independent variables comprised data from demographic background, quality of life, and lifestyle (AIO). There were quite a few variables pertaining to AIO. Factor analysis was conducted for AIO to reduce the number of variables. According to Sithiponporn and Chandrachai (2019), who did a survey of lifestyles with identical survey instruments, exploratory factor analysis in SPSS Software was performed to identify the underlying dimensions of AIO. The results indicated a four-factor solution of each dimension. This study then applied lifestyle variables from Median and Standard Deviation (SD) of each AIO factor. The dependent variable was job preference. There were 12 job options for respondents to choose their jobs from, the first eight of which were paid jobs; the last four were charity works.

#### **(3) Modelling**

The logistic regression model was applied as a classification method in this study. Logistic regression generated a probability that predicts how many levels those jobs fit with seniors. Then, a classification threshold or a decision threshold was defined. The algorithm was defined as Binary Logistic Regression, to decide whether someone matches with each job. The classification threshold of each model was defined by AUC. After plotting the ROC graph, the area under the curve (AUC) was observed. The threshold was tested in each model in R Programming. Then, the threshold contributed to the best evaluation results for that model.

#### (4) Model Evaluation

Firstly, models were tested for goodness of fit. According to the HL test, the hypothesis test was as shown below. The P-value of each model was calculated in R Programming at a significant level at 0.05.

**H<sub>0</sub>:** Model 1 is fit, Model 2 is fit, ..., Model 12 is fit

**H<sub>1</sub>:** Model 1 is not fit, Model 2 is not fit, ..., Model 12 is not fit

To determine each's accuracy, the models in this study were evaluated by precision, recall, accuracy, and F-score. All four metrics of each model appeared in the R Programming. This study paid the most attention to the F-Score metric, as F-score is widely used to evaluate a binary classification model and balances precision and recall.

## Results

### *Exploratory Data Analysis*

The elderly living in Bangkok, the capital city of Thailand, served as the sample of the study. Among all 632 sample cases, there were 465 respondents, accounting for 73.58 percent who needed to continue working after retirement. The remaining 167 cases, or 26.42 percent, were not keen on working anymore. This corresponded to various research studies which found that a number of Thai senior citizens need to continue working (Choorat et al., 2012; Phijaisanit, 2015). Further analysis in this study will be based on those 465 respondents who prefer to work even after retirement. The descriptive statistics of survey data in each section were analysed in SPSS software as follows.

### **Section 1: Demographic background**

As shown in Table 1, males and females were at almost the same proportion. Considering the age, most respondents, from 264 cases, or 56.8 percent, were 60-64 years old. The majority were relatively highly educated (204 cases / 43.9 percent) who graduated with a Master's degree or above. In terms of revenue per month, about half respondents earned more than THB 50,000 a month, and about half of the respondents spent no more than THB 30,000 per month.

**Table 1:** Descriptive statistics of samples

<i>Respondents</i>	<i>Frequency (%)</i>	<i>Respondents</i>	<i>Frequency (%)</i>
<b>Gender</b>		<b>Revenue (Baht/month)</b>	
Male	225 (48.4%)	<= 10,000	63 (13.5%)
Female	240 (51.6%)	10,001-20,000	86 (18.5%)
		30,001-40,000	43 (9.2%)
<b>Age</b>		40,001-50,000	50 (10.8%)
55-59 years old	122 (26.2%)	50,001-100,000	108 (23.2%)
60-64 years old	264 (56.8%)	> 100,000	115 (24.7%)
65-69 years old	55 (11.8%)		
70-73 years old	24 (5.2%)	<b>Expenditure (Baht/month)</b>	
		<= 10,000	75 (16.1%)
<b>Education</b>		10,001-20,000	78 (16.8%)
Below Vocational Diploma	38 (8.2%)	20,001-30,000	90 (16.4%)
Vocational Diploma or Equivalent	32 (6.9%)	30,001-40,000	59 (12.7%)
Bachelor's degree or Equivalent	191 (41.1%)	40,001-50,000	53 (11.4%)
Master's degree or above	204 (43.9%)	50,001-100,000	65 (14.0%)
		> 100,000	45 (9.7%)

## Section 2: Job

In this section, questions enabled multiple responses. As shown in Table 2, most of the respondents at 27.6 percent were retirees, and 24.2 percent were self-employed. To work after retirement, most respondents preferred being a business owner, a consultant, or a teacher or coach, at 20, 17.1, and 15.2 percent respectively. Another 10 percent would prefer to work as a volunteer, and 8.4 percent prefer to share their knowledge and skills with society for charity. Concerning the workplace, more than one-third of the samples preferred being self-employed and working at home; however, up to around 28 percent would like to work for an enterprise community. Retirees preferred continuing work because they expected to spend their free time wisely, to build their self-esteem, and to gain income at 17.2, 16.1, and 14.3 percent, respectively. The primary concerns for choosing a job after retirement depended on their preference at 24.3 percent, and working hours and commutation issues at 20.8 percent.

The job preference dataset was found to be imbalanced. The class imbalance issue is one of the obstacles to performing a good classifier by Machine Learning algorithms (Batista, Prati, & Monard, 2004). The dataset was balanced by the resampling method in section 4.2 and Binary Logistics Regression algorithms were formulated from both the original dataset and the balanced dataset, to compare and select the best models.

**Table 2:** Descriptive statistics of samples – Job

<i>Respondents</i>	<i>Multiple Response (%)</i>	<i>Respondents</i>	<i>Multiple Response (%)</i>	<i>Respondents</i>	<i>Multiple Response (%)</i>
<b>Current Occupation</b>		<b>Job Preference</b>		<b>Expectation</b>	
Unemployed/Retired	139 (27.9%)	Teacher/Coacher	105 (15.2%)	Spend free time	354 (17.2%)
Self-employed	120 (24.2%)	Shop Assistant	21 (3.0%)	Build self-esteem	332 (16.1%)
Employee	99 (20.0%)	Consultant	118 (17.1%)	Revenue	294 (14.3%)
Freelance	78 (15.7%)	Cooking/Handicraft	34 (4.9%)	Support society	279 (13.6%)
Government officer	48 (9.7%)	Service person	27 (3.9%)	Get friend	201 (9.8%)
State enterprise	11 (2.2%)	Farmer	24 (3.5%)	Enjoyment	200 (9.7%)
Volunteer	3 (0.6%)	Freelance	9 (1.3%)	Exercise	200 (9.7%)
		Business owner	138 (20.0%)	Social participation	197 (9.6%)
		Volunteer	69 (10.0%)		
<b>Previous Occupation</b>		Community service	37 (5.4%)	<b>Criteria to choose job</b>	
Employee	201 (38.3%)	Charity work	51 (7.4%)	Job preference	346 (24.3%)
Government officer	115 (21.9%)	Sharing knowledge & skills	58 (8.4%)	Commutation	296 (20.8%)
Self-employed	103 (19.6%)	<b>Workplace Preference</b>		Working hour	296 (20.8%)
Freelance	55 (10.5%)	At home/ Self-employed	239 (39.0%)	Aptitude	276 (19.4%)
State enterprise	28 (5.3%)	Community Enterprise	172 (28.1%)	Revenue/Benefits	207 (14.5%)
Unemployed/Retired	23 (4.4%)	Private Sector	128 (20.9%)	Others	4 (0.3%)
		Public Sector	68 (11.1%)		
		Others	6 (1.0%)		

### Section 3: Quality of Life (QoL)

In terms of assessing the quality of life (QoL) status of all respondents, over 71 percent had good QoL, while only 0.4 percent QoL were not good. Pertaining to each domain, the majority of the samples considered their physical, psychological, and environmental condition in a good status. Around the same proportion of respondents had moderate and good social relationships, at 48.8 and 48.6 percent, respectively (Table 3).

**Table 3:** QoL Scores

<i>Respondents</i>	<i>Frequency (%)</i>		
	Not Good	Moderate	Good
<b>Quality of Life</b>			
Physical domain	0.4%	38.3%	61.3%
Psychological domain	0.2%	28.4%	71.4%
Social Relationships	2.6%	48.8%	48.6%
Environment	0.6%	35.3%	64.1%
Overall QOL	0.4%	27.7%	71.8%

#### **Section 4-6:** Lifestyles

The responses of activities, interests, and opinions (AIO) were segmented by factor analysis and cluster analysis tools (Sithiponporn & Chandrachai, 2019). Sithiponporn and Chandrachai (2019) claimed that activities, interests, and opinion aspects of the 465 baby boomer respondents in this study could be identified by six distinct lifestyle segments: sociable, healthy living, homemaker, self-reliant, modernist, and introvert. The first segment was named “sociable”, comprising 24 percent of the samples, or 110 cases. The following segment was “healthy living”, comprising 50 respondents, or 11 percent. Surprisingly, only four percent (20 cases) segmented as “homemakers”, which may contrast the stereotype of older people. Among 465 cases, 19 percent were “self-reliant” (88 cases). The main segment was unexpectedly “modernist”, accounting for one-fourth of the total samples. The remaining 18 percent (83 cases) were classified as “introverts”.

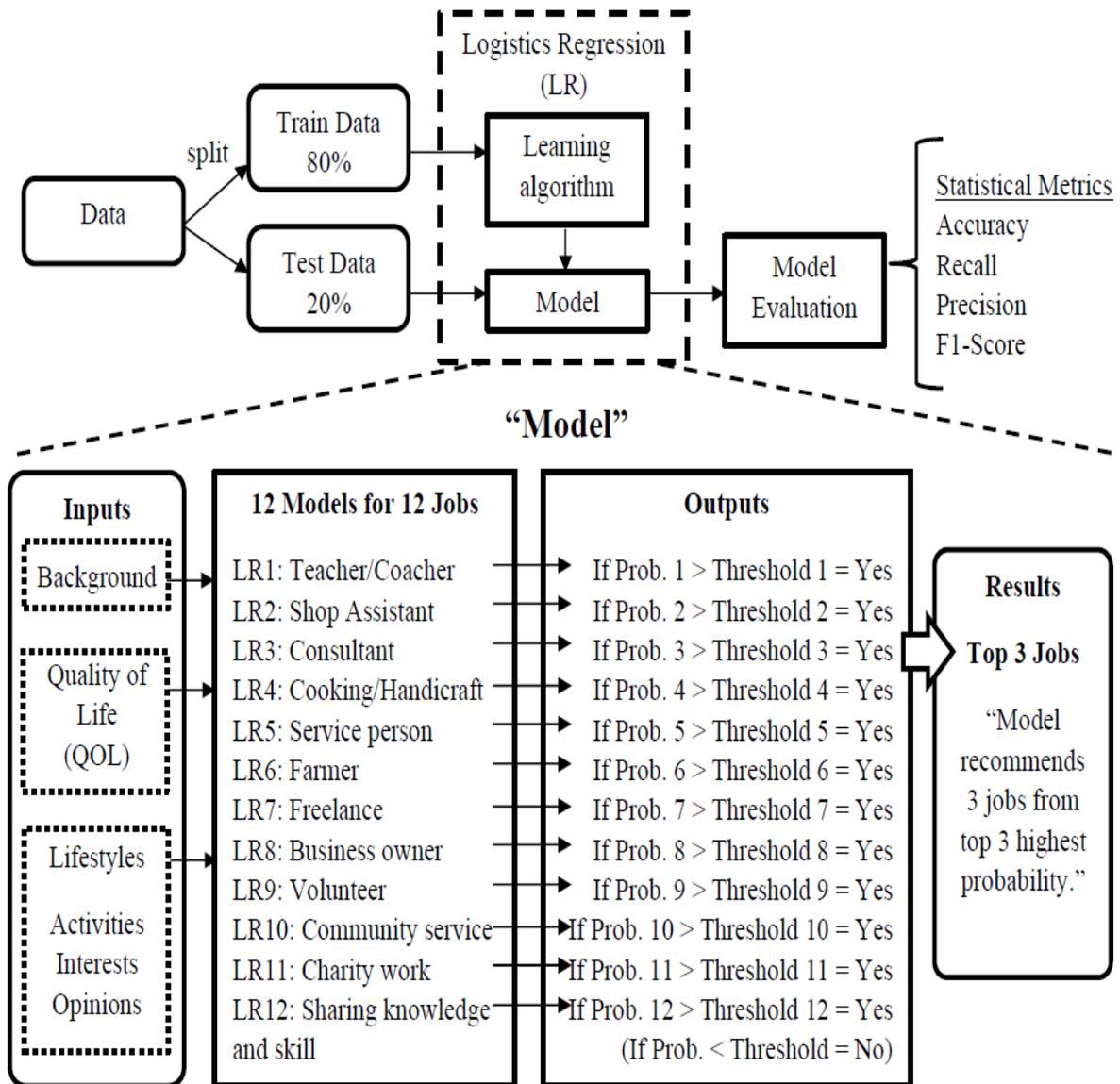
#### **Job Recommendation Models**

There were 12 job options for seniors in the market - teacher/coach, shop assistant, consultant, cooking/handicraft, service person, farmer, freelancer, business owner, volunteer, community service, charity work, and sharing knowledge and skills (i.e. speaker). Thus, twelve models of Binary Logistic Regression were formulated in R programming. The process and the twelve “models” are summarised in Figure 4. The logistic regression model returned a probability as an output. Then this study converted the returned probability to a binary value as “yes” or “no”, to suggest that those jobs match with the participants. If the probability was greater than the defined threshold value, then the model categorised that job to “yes.”

According to data exploration, the dependent variable “job preference” was imbalanced. Some sample classes were significantly above than the others. For example, the majority of classes were teacher/coach (105 responses), consultant (118 responses), and business owner

(138 responses), while minority classes were freelancer (9 responses), shop assistant (21 responses), farmer (24 responses), etc. Imbalanced datasets required the resampling method for binary classification. This technique can help to increase the size of the minority class called over-sampling, and simultaneously decrease the majority class called under-sampling (Díez-Pastor, Rodríguez, García-Osorio, & Kuncheva, 2015). The random over-sampling method aims to balance class distribution, through a random replication of the minority class datasets from the original. On the other hand, with random under-sampling, samples are randomly removed from the original dataset until a predetermined balance ratio is reached (Cateni, Colla, & Vannucci, 2014). The job preference dataset contained 691 responses. The balance ratio was determined at 58 samples per class. The random over-sampling method was applied in R Programming for job preference data set which had responses below 58 samples, including shop assistant, cooking/handicraft, service person, farmer, freelancer, community service, and charity work. The random under-sampling method was implemented to teacher/coach, consultant, business owner, and volunteer, to balance the dataset as 58 responses only. Job-sharing knowledge and skills did not require any resampling, as responses were at 58 samples. Then the proportion of each job was balanced at around 8.4%, or 58 samples. This dataset is called the balanced dataset. Then twelve models of Binary Logistic Regression were formulated in R programming from the balanced dataset. This study evaluated and compared model metrics, between the models formulated from the original dataset and the balanced dataset in section 4.3.

**Figure 4.** Data Processing, Modelling, and Model Evaluation process



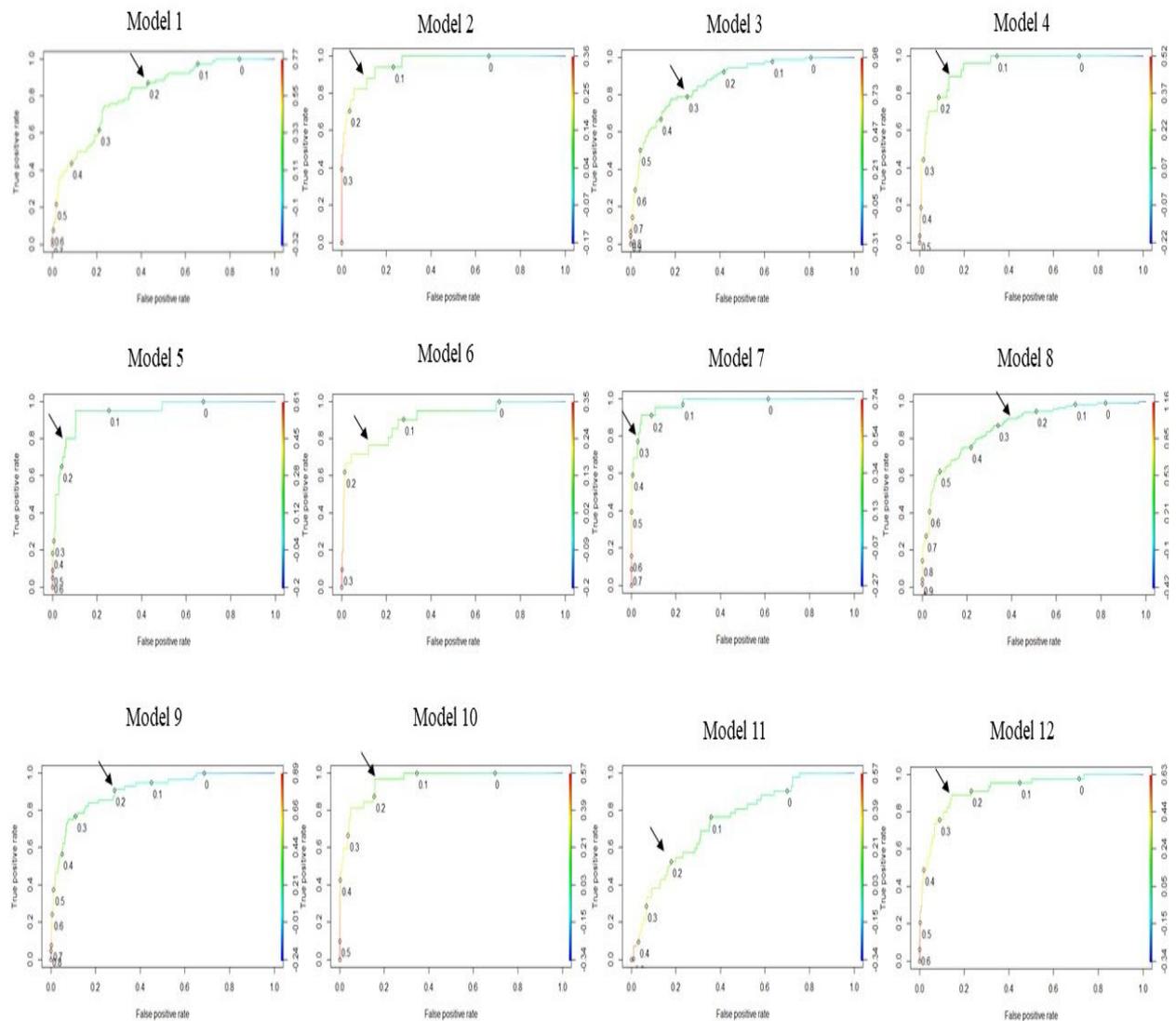
The classification threshold of each model was defined as shown in Table 4. After plotting the ROC graph, the area under the curve (AUC) was observed. The classification threshold was selected from the value which contributed to the greatest AUC as indicated with an arrow in each model in Figure 5 (original dataset) and Figure 6 (balanced dataset).

As shown on the ROC graph of 12 models from the original dataset in Figure 5, various thresholds with range  $\pm 0.05$  were tested in each model for the appropriate metrics. In model 2, for example, the ROC graph showed the threshold value could be between 0.1-0.2. Then threshold value 0.1, 0.15, and 0.2 were tested for Model 2 in R Programming. Finally, the

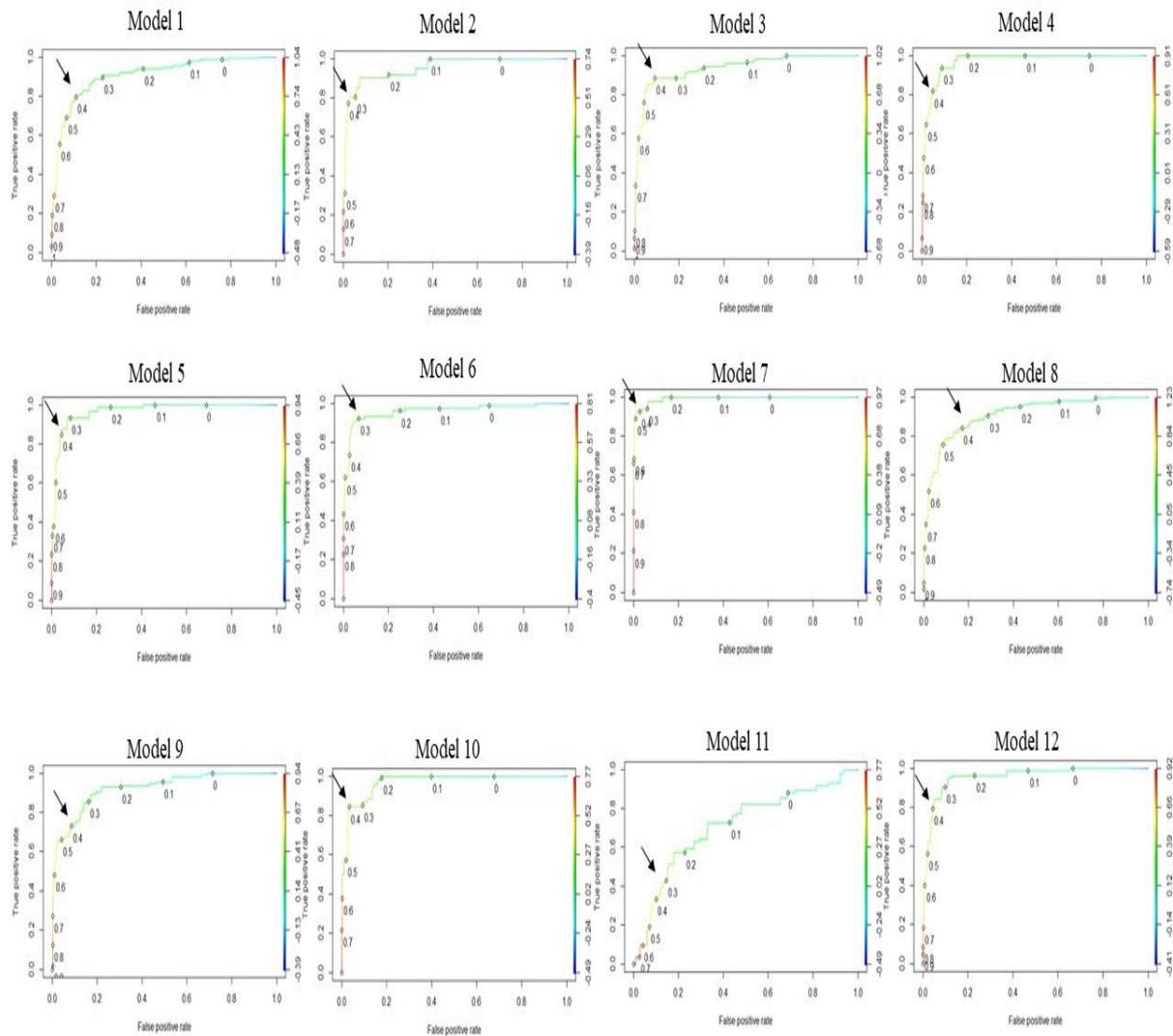
threshold of 0.15 contributed to the best evaluation results. Therefore, the classification threshold was set at 0.15 for Model 2.

Exploring all ROC graphs of 12 models from the balanced dataset in Figure 6, the threshold seemed to be around 0.3-0.5 range. Thresholds at 0.3, 0.4, and 0.5 were tested in each model for the appropriate metrics in R Programming. The threshold contributed to the best F-score result selected for each model. The majority of the models generated the best F-score metric with a threshold at 0.4, and the classification threshold was set at 0.40, except for Model 6 and 7 which contributed to the best F-score at 0.3 and 0.5 thresholds, respectively.

**Figure 5.** ROC graph of twelve models from the original dataset



**Figure 6.** ROC graph of twelve models from the balanced dataset



### Model Metrics

According to the HL test for the P-value of each model, the P-value of the twelve models from the original dataset and twelve models from the balanced dataset were all above 0.05. Therefore, the hypothesis “ $H_0$ : Model is fit” was accepted. The results indicated a significant statistical fit of all models.

Precision, recall, accuracy, and F-score were calculated in R Programming. They are reported in Table 4. The overall model’s metrics showed that the recommendation system from the original data was 82.12% accurate. In other words, the system predicted correctly at 82.12 times out of 100 total predictions. Based on a balanced score between precision and recall, F-score was only 54%, while an algorithm trained by the balanced data predicted correctly up to

91.20% which outperformed the algorithm trained by the original data. In terms of F-score, the models from the balanced dataset significantly exceeded the F-score of the models from the original data to 78.22%. In addition, most of ROC graphs showed that the models by balanced data in Figure 6 had a greater area under the curve that the graph from the model by original data in Figure 5.

After the twelve definitive models were finalised, this paper proposed the machine learning algorithm to rank and recommend a job. The algorithm ranked the job in which binary value was “yes”, and then recommended jobs based on the top 3 probabilities in the ranked job list for seniors.

**Table 4.** Model Evaluation Metrics – Original vs Balanced dataset

Model	Job options	Classification Threshold	Train dataset (80%)				Test dataset (20%)				Dataset
			Accuracy	Recall	Precision	F-Score	Accuracy	Recall	Precision	F-Score	
1	Teacher/Coacher	0.2	63.4%	87.2%	35.1%	50.0%	49.5%	77.8%	33.9%	47.2%	Original
		0.4	86.2%	79.6%	73.8%	76.6%	84.2%	64.9%	66.7%	65.8%	Balanced
2	Shop Assistant	0.15	89.8%	82.4%	28.6%	42.4%	84.9%	25.0%	8.3%	12.5%	Original
		0.4	95.2%	77.0%	82.5%	79.7%	95.0%	76.2%	76.2%	76.2%	Balanced
3	Consultant	0.3	75.8%	78.9%	50.0%	61.2%	63.4%	82.1%	44.2%	57.5%	Original
		0.4	89.9%	88.6%	73.6%	80.4%	82.0%	85.2%	48.9%	62.2%	Balanced
4	Cooking/ Handicraft	0.15	82.3%	88.9%	27.6%	42.1%	78.5%	42.9%	15.8%	23.1%	Original
		0.4	92.5%	81.7%	77.6%	79.6%	94.2%	55.0%	84.6%	66.7%	Balanced
5	Service person	0.2	94.4%	65.0%	48.1%	62.0%	93.5%	42.9%	60.0%	67.7%	Original
		0.4	93.0%	83.3%	78.1%	78.9%	92.8%	60.9%	77.8%	70.7%	Balanced
6	Farmer	0.15	88.2%	71.4%	28.3%	40.5%	83.9%	33.3%	7.1%	11.8%	Original
		0.3	92.6%	92.1%	68.6%	99.2%	92.8%	85.0%	63.0%	72.3%	Balanced
7	Freelance	0.3	96.0%	77.3%	63.0%	69.4%	98.9%	75.0%	100.0%	85.7%	Original
		0.5	97.1%	89.0%	94.8%	91.8%	94.2%	66.7%	84.2%	74.4%	Balanced
8	Business owner	0.25	68.0%	91.5%	49.5%	50.0%	53.8%	85.7%	31.0%	47.2%	Original
		0.4	82.9%	84.1%	67.6%	76.6%	85.6%	85.7%	62.5%	65.8%	Balanced
9	Volunteer	0.2	74.2%	89.3%	35.7%	50.1%	63.4%	53.8%	20.0%	49.4%	Original
		0.4	87.3%	73.2%	68.3%	76.3%	87.1%	77.8%	58.3%	76.2%	Balanced
10	Community service	0.15	78.8%	96.9%	28.4%	44.0%	67.7%	100.0%	14.3%	25.0%	Original
		0.4	94.6%	84.3%	78.7%	81.4%	92.8%	66.7%	76.2%	71.1%	Balanced
11	Charity work	0.3	88.4%	57.1%	49.0%	52.7%	88.2%	55.6%	41.7%	47.6%	Original
		0.4	91.0%	82.1%	68.3%	74.6%	92.1%	78.3%	66.7%	72.0%	Balanced
12	Sharing knowledge and skill	0.25	86.3%	84.4%	46.3%	59.8%	76.3%	61.5%	32.0%	42.1%	Original
		0.4	92.8%	79.3%	76.5%	77.8%	88.5%	68.8%	44.0%	53.7%	Balanced
<b>Total score Overall Model</b>			<b>82.4%</b>	<b>83.2%</b>	<b>40.2%</b>	<b>54.2%</b>	<b>75.2%</b>	<b>69.5%</b>	<b>29.5%</b>	<b>41.4%</b>	Original
			<b>91.2%</b>	<b>82.8%</b>	<b>74.2%</b>	<b>78.2%</b>	<b>89.7%</b>	<b>73.1%</b>	<b>64.2%</b>	<b>68.3%</b>	Balanced

This study also formulated a binary logistic regression model, with different independent variables. Then metrics between the models were compared. Table 5 clearly shows that the model with all three groups of independent variables has the highest accuracy, precision, recall, and F-Score, compared with the models which either independent variables group applied. The results confirmed as per Demby (1974) indicated that combining psychographic with demographic information enhanced a better understanding of elderly needs. However, this study also found that demographics are still an important factor to put the right man on the right job, as the metric showed that demographic background alone model achieved an F-score around 39%, with accurate recommendation approximately 76% outperforming the model from QoL and lifestyles variables.

**Table 5:** Model Evaluation Metrics – Different independent variables

Independent Variables	Overall Model's Metrics			
	Accuracy	Recall	Precision	F-Score
I. Demographics Background ii. Quality of Life (QoL) iii. Lifestyles (AIO)	82.44%	83.25%	40.17%	54.19%
I. Demographics background	76.04%	60.96%	28.71%	39.04%
ii. Quality of Life (QoL) iii. Lifestyles (AIO)	74.39%	55.48%	25.88%	35.29%

### Conclusion and Recommendation

This paper proposed the concept of job recommendations for senior citizens, based on their backgrounds, lifestyles, and current status of quality of life. Through extensive experiments on a real dataset from 465 respondents, the machine learning of the binary logistics regression algorithm was developed for the job recommendation system. The method was observed to be able to achieve good evaluation metrics including accuracy, recall, precision, and F-score in the job recommendation scenario. Job recommendation by machine learning model using lifestyles was shown to be able to recommend a job for seniors with 91.20% accuracy. Still, demographic background was shown to one of the important factors. However combining it with psychographic information was proven to enhance job recommendation performance. This result aligns with various research works, which highlights that demographic information alone is not sufficient; psychographics bring about better solutions (Demby, 1974; Myriam Töpfer & Bug, 2015).

This study also recommended data exploratory as essential. Prior to modelling, the dataset should be observed. If there are imbalanced dataset issues, this should be overcome to enhance a good classifier by machine learning algorithms. In this case, the balanced dataset



improved the model's accuracy and F-score from 82.12% to 91.20% and 54.19% to 78.22%, respectively.

In conclusion, this paper contributes to empirical evidence of a reasonably accurate machine-learning algorithm that recommends a job based on background, lifestyle, and quality of life. Such an algorithm should be able to be leveraged as a feature in a job recommendation system, for employment after retirement.

However, the proposed job recommendation system did not take into consideration work location nor working hours. Behind job preference, which is the most important criterion when baby boomers choose a job after their retirement, commutation and working hours were found as the second most important criteria. Future work should consider location and working hours, for retirees' job recommendations.

### **Acknowledgment**

This study is supported by a CU. Graduate School Thesis Grant.



## REFERENCES

- Alotaibi, N. B. (2019). Prerequisites of Enhancing Life Quality for the Elderly People in the Saudi Community. *International Journal of Innovation, Creativity and Change*, 9(3), 56-84.
- Batista, G. E., Prati, R. C., & Monard, M. C. (2004). A study of the behavior of several methods for balancing machine learning training data. *ACM SIGKDD explorations newsletter*, 6(1), 20-29.
- Bureau of Mental Health Strategy. (2015). *Strategic plan of Department of Mental Health in the Twelfth National Economic and Social Development Plan (2012 - 2016)*. In. Retrieved from <https://dmh.go.th/ebook/view.asp?id=375>
- Cateni, S., Colla, V., & Vannucci, M. (2014). A method for resampling imbalanced datasets in binary classification tasks for real-world problems. *Neurocomputing*, 135, 32-41.
- Choorat, W., Sawangdee, Y., & Arunraksombat, S. (2012). Factors Influencing the Risk of Having Mental Health Problems of Thai Elderly. *Thai Population Journal*, 3(2).
- Dancey, C. P., & Reidy, J. (2007). *Statistics without maths for psychology*: Pearson Education.
- Demby, E. (1974). Psychographics and from whence it came. *American Marketing Association*, 9(30).
- Department of Older Persons (DOP). (2016). *Statistics of ageing population in Thailand 2016*. Bangkok: Ministry of Social Development and Human Security Retrieved from [http://www.dop.go.th/upload/knowledge/knowledge\\_th\\_20170707092742\\_1.pdf](http://www.dop.go.th/upload/knowledge/knowledge_th_20170707092742_1.pdf).
- Díez-Pastor, J. F., Rodríguez, J. J., García-Osorio, C., & Kuncheva, L. I. (2015). Random Balance: Ensembles of variable priors classifiers for imbalanced data. *Knowledge-Based Systems*, 85, 96-111. doi:<https://doi.org/10.1016/j.knosys.2015.04.022>
- Hasan, M., Islam, M., Islam, I., & Hashem, M. M. A. (2019). Attack and Anomaly Detection in IoT Sensors in IoT Sites Using Machine Learning Approaches. 100059. doi:10.1016/j.iot.2019.100059
- Hosmer, D. W., & Lemeshow, S. (1980). Goodness of fit tests for the multiple logistic regression model. *Communications in statistics-Theory and Methods*, 9(10), 1043-1069.
- Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (Vol. 398): John Wiley & Sons.



- Kenan Foundation Asia. (2018). Aging Society – The Global Trend, its Consequences, and the Role of Technology. Retrieved 31 December 2019, from Kenan Foundation Asia <https://www.kenan-asia.org/aging-society-the-global-trend/>
- Kumar Ahuja, D. G. (2015). Evaluation Metrics for Intrusion Detection Systems-A Study. *International Journal of Computer Science and Mobile Applications*, 11.
- Lau, C. W. (2011). News Recommendation System Using Logistic Regression and Naive Bayes Classifiers.
- Likert, R. (1932). A technique for the measurement of attitudes. *Archives of psychology*.
- Liu, Q., Ren, J., Song, J., & Li, J. (2015). Co-occurring atomic contacts for the characterization of protein binding hot spots. *PLoS ONE*, 10(12).
- Lohman, H., Byers-Connon, S., & Padilla, R. (2017). *Occupational Therapy with Elders - eBook: Strategies for the Occupational Therapy Assistant*: Elsevier Health Sciences.
- Mahatnirunkul, S., Tuntipivatanaskul, W., Pumpisanchai, W., Wongsuwan, K., & Prommanajirangkul, W. (1998). Comparison of the WHOQOL100 and the WHOQOL-BREF (26 items). *Journal of Mental HealthThailand*, 5, 4-15.
- Malinowski, J., Keim, T., Wendt, O., & Weitzel, T. (2006). *Matching people and jobs: A bilateral recommendation approach*. Paper presented at the System Sciences, 2006. HICSS'06. Proceedings of the 39th Annual Hawaii International Conference on.
- Myriam Töpfer, & Bug, P. (2015). *Classical Consumer Lifestyle Segmentation Methods*. Retrieved from Reutlingen:
- National Research Council of Thailand (NRCT). (2017). National Research Strategies (2017). Retrieved 1 November 2017 <http://sci.uru.ac.th/rmu/doc/strategy-thai-y.pdf>
- Netithanakul, A. (2015). Public Policy in Healthcare Utilization of the Elderly: Evidence from Kanchanaburi DSS, Thailand. *International Journal of Crime, Law and Social Issues*, 2(1), 15-22.
- Nilaphruek, P., & Khanankhoaw, R. (2015). The Enhancement of Efficiency in e-Recruitment System using Semantic Matching Technique. *Science and Technology RMUTT Journal*, Vol 5, 83-99.
- Oswal, N. (2019). Predicting Rainfall using Machine Learning Techniques. *arXiv preprint arXiv:1910.13827*.
- Pandhare, K. R., & Shah, M. A. (2017). *Real time road traffic event detection using Twitter and Spark*. Paper presented at the 2017 International conference on inventive communication and computational technologies (ICICCT).



- Phusalux, J., Jermstittiparsert, K., Saisama, C., & Wongjunyav, N. (2020). Impact of Social Media Marketing on Consumer Buying Behaviour of Youth. *International Journal of Psychosocial Rehabilitation*, 24(7), 1304-1331. DOI: 10.37200/IJPR/V24I7/PR270120.
- Phijaisanit, E. (2015). How can promoting desirable elderly employment opportunities alleviate the shortfalls of Thailand's ageing society?
- Plummer, J. T. (1974). The Concept and Application of Life Style Segmentation. *Journal of Marketing*, 38(1), 33-37. doi:10.2307/1250164
- Rungsrissawat, S., Joemsittiprasert, W., & Jermstittiparsert, K. (2019). Factors Determining Consumer Buying Behaviour in Online Shopping. *International Journal of Innovation, Creativity and Change*, 8(8), 222-237.
- Saengchai, S., Thaiprayoon, K., & Jermstittiparsert, K. (2019). Sensory Marketing Cues and Behavioural Intention: An Application of Stimulus Organism Response Model in the Hospitality Industry of Thailand. *Journal of Computational and Theoretical Nanoscience*, 16(11), 4748-4756.
- Sithiponporn, N., & Chandrachai, A. (2019). The study of elderly lifestyle segmentation in Thailand. *Manuscript submitted for publication*.
- Sumalrot, T., & Nochi Suksawai, H. (2015). AGING IN THE WORLD OF WORK: BIOPSYCHOSOCIAL PERSPECTIVES. *Panyapiwat Journal*, 7(1), 242.
- United Nations. (2015). World Population Ageing 2015ST/ESA/SER.A/390(ST/ESA/SER.A/390), ST/ESA/SER.A/390. Retrieved from [https://www.un.org/en/development/desa/population/publications/pdf/ageing/WPA2015\\_Report.pdf](https://www.un.org/en/development/desa/population/publications/pdf/ageing/WPA2015_Report.pdf) doi:ST/ESA/SER.A/390
- United Nations Population Fund. (2011). Impact of Demographic Change in Thailand. Retrieved from
- Villmann, T., Kaden, M., Lange, M., Stürmer, P., & Hermann, W. (2014). *Precision-Recall Optimization in Learning vector quantization classifiers for improved medical classification systems*. Paper presented at the 2014 IEEE Symposium on Computational Intelligence and Data Mining (CIDM).
- Vuk, M., & Curk, T. (2006). ROC curve, lift chart and calibration plot. *Metodoloski zvezki*, 3(1), 89.
- Wang, Y., Feng, D., Li, D., Chen, X., Zhao, Y., & Niu, X. (2016). *A mobile recommendation system based on logistic regression and Gradient Boosting Decision Trees*. Paper presented at the 2016 International Joint Conference on Neural Networks (IJCNN).



Wells, W. d., & Tigert, D. J. (1971). Activities, Interests and Opinions. *Journal of Advertising Research*, 11(4), 27-35.

Whangmahaporn, P., Simmonds, P., & Whangmahaporn, B. (2019). *Care-for-the-Older Person-at-Home Volunteers's Citizenship Affecting Participation in the Older Persons Care of Thailand*.

World Health Organization. (1997). *WHOQOL: Measuring Quality of Life*: Division of Mental Health and Prevention of Substance Abuse, World Health Organization.