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Factors Affecting Professional Pilots' Intention to Leave Aviation Jobs: Supervised Machine Learning Algorithms

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Abstract
The objective of this study is to gain knowledge of the factors affecting the likelihood of Thai pilots leaving aviation jobs and classify the intention to leave outcomes using supervised machine learning algorithms derived from data science disciplines. The focus is on career success and job demand as key factors contributing to the intention to leave or not leave the airline. This multidisciplinary study follows a quantitative approach and relies on a sample of 610 Thai pilots listed in Thai Pilot Association. The results indicate that pilots holding the rank of pilot in command and an air transport pilot license with no other extra responsibilities such as check airman and instructor pilot have a lessor chance to leave aviation jobs. Moreover, the overall binary classification model developed by this method fits with empirical data. It is recommended that airlines respond to these risks by providing the job resources needed to maintain their pilots' morale and keep them on board. This research contributes to behavioral science disciplines by providing a classification model with moderate performance. Future research should broaden the sample to an international context and utilize a qualitative or a mixed methodology in order to obtain richer results.

Keywords*:* Aviation, Intention to Leave, Pilot, Pilot Rank, Supervised Machine Learning Algorithms

1. Introduction

The concept of human capital is widely cited as a valuable intangible asset even though it is not listed on an organization's financial report (Schultz, 1961; Kiker, 1966; Maneechaeye, 2021a). Human capital may be defined as the economic value of employees' skills and competencies, including qualification, training, intelligence to name a few (Kucharčíková, 2013). In the aviation business, pilots play a central role as, in this position, they are responsible for an airline's core service; flying aircrafts. In order to get a pilot ready to fly and be responsible for the safety of all the passengers and crewmembers onboard, a huge amount of money needs to be invested in this particular human capital. Indeed, airlines have no choice but to invest considerable funds to train them extensively, using among other devices costly simulator check rides. Such intensive training is necessary to ensure the proper skills, which this position's responsibility requires. It also provides the suitable professional pilot qualifications mandated by law to man commercial aircrafts. This entire process is estimated to take up to 2 years to complete with training costs ranging from USD50,000 to USD100,000. Clearly, pilot training is a significant investment, both in terms of time and money (Department of Employment, 2021). This brings to the fore an important issue. What will happen to all these investments in developing and training pilot if pilots feel unsatisfied with their current job demands and end up leaving the organization? This is a real issue the industry has to deal with as such investments may be made in vain (Maneechaeye, 2021b).

While a number of studies focus on the factors affecting turnover intention and burnout in various contexts (e.g. Federici, 2013; Tremblay & Genin, 2008), few studies really focus on how to predict the likelihood that some pilots will leave their job. This study focuses on this issue and, based on the above, seeks to address the following research question: Do pilot professional factors, namely pilot rank, pilot license, and pilot position significantly determine the likelihood of their leaving their aviation job? To answer this question, this study aims to develop a classification model using data science technique. More specifically, it aims to use supervised machine learning algorithms to determine the likelihood of leaving the company due to the three pilot professional factors to be considered in this study. It is expected that this classification model could be used by airlines to assess that likelihood and therefore develop a strategy designed to mitigate the risk of pilot turnover.

2. Literature Review

- *Supervised Machine Learning Algorithms*

Supervised machine learning algorithms are presently applied to analyze various contents in many fields of study (Burscher, Vliegenthart, & De Vreese, 2015). Computers quintessentially try to replicate the coding decision algorithms formerly coded by users. The intent is to automatically code a number of inputs into previously defined algorithms. Therefore, a set of pre-fitted predictions or a classification model for the content categories are the main preconditions of virtually all supervised machine learning models. In general, supervised machine learning involved three major steps (Burscher, Odijk, Vliegenthart, De Rijke, & De Vreese, 2014). Firstly, datasets are randomized into two sets, a train set and a test set, according to some predefined ratio that may range from 60/40 to 80/20 depending upon the nature of the dataset. This method, called holdout validation, is considered to be the simplest approach (Mahobia et al., 2010). Secondly, the train set is put into a prediction or classification model fitting, depending upon the objective of the study. As part of this process, an algorithm mathematically analyzes the features from each content category from the train set and generates a predictive or a classification model, depending on whether the research question is to predict or classify the target label outcome. Finally, after fitting a predictive or classification model by train set, the test set is put into a model to evaluate the prediction of classification performance. Supervised machine learning provides several advantages over legacy model development analysis. First and foremost, this it allows researchers to expand the scope of their analysis by determining the effectiveness of the predictions or their classification model by using test sets to evaluate the effectiveness of the fitted model (van Zoonen & Toni, 2016).

- *Human Capital Theory*

Human capital is a relatively new concept that replaces the legacy human resource concept. Human capital refers to the skills and ability that an individual attain to enhance his/her potential productivity and boost his/her career (Becker, 2007). High performance human capital such as pilots sends a signal to organizations that applicants deserve to be hired due to their accumulated skills and knowledge (Singer & Bruhns, 1991). The organization will acknowledge potential employees with the desirable professional attributes related to the organization's needs. A pilot job is considered to be a high investment career due to extensive flight training and the academic requirements that come in addition to practical training. Pursuing a pilot license thus changes an ordinary person into a competent licensed airman that can operate a complex flying machine and be responsible for the many souls on board a vessel. Therefore, given the huge human capital investment, airlines are often willing to pay high salaries and provide more resources to hire and retain proficient pilots (Swenson-Lepper, 2005).

- Career Success

Career success may be defined as positive work-related results or achievements accumulated as a result of one's past experiences (Judge, Cable, Boudreau, & Bretz Jr, 1995). Career success can be measured both subjectively and objectively. It is an individual's positive evaluation of his/her career. It is signalled by one's career satisfaction or job satisfaction. Objective career success is measured by one's salary and promotion (Boudreau, Boswell, & Judge, 2001). In the flying job context, rookie pilots holding a commercial pilot license start out as co-pilot so as to accumulate flight times and in-air experience together with problem solving skills. After passing certain flight times milestones and getting through several checks, their license will be upgraded to an air transport pilot license. Eventually, they will be extensively evaluated by check airmen or instructors and possibly be promoted to full-fledged pilots in command position or captains with more responsibilities and a bigger pay check. Such promotions are regarded as one of the most prestigious moments in a pilot life and considered as career success in the aviation industry, both subjectively and objectively.

- Job Demands

According to the job demands-resources theory developed by Demerouti, Bakker, Nachreiner, and Schaufeli in 2001, when job demands are high and job resources/positives low, stress and burnout increase. Conversely, a high number of job positives can offset the effects of high job demands. What job demands means is that the company expects employees to put efforts into their work (Bakker, Demerouti, & Verbek, 2004). As to job resources, it refers to the supporting work environment provided by an organization (Lesener, Gusy, & Wolter, 2019). Job demands may lead to physical and psychological stress and burnout problems at work (Maneechaeye, 2020). Whereas job demands are negative factors, well-provided job resources can possibly mitigate the negativity. Holding the highest position in the cockpit or being promoted as check airman or instructor pilot do not mean that there are no drawbacks though. Pilots holding extra positions apart from line flying, such as check airman or instructor position tend to face a high level of job demands that may add significant stress to their professional lives (Bauer & Herbig, 2019; Brezonakova, 2017; Carbone & Cigrang, 2001). Eventually, accumulated stress will lead to burnout, which may end up causing leaving the aviation job, thereby rendering past human capital investment useless (Brezonakova, 2017). Based on the above review of the relevant literature, the following hypotheses can therefore be developed:

H1: *Pilots holding the rank of Pilot in Command are less likely to leave their aviation job.*

H2: *Pilots holding an Air Transport Pilot License are less likely to leave their aviation job.*

H3: *Line pilots with no other extra duties are less likely to leave their aviation job.*

H4: *The binary classification model with the holdout validation method is fitted for empirical data.*

3. Methodology and Data Collection

This study utilizes a quantitative approach by adapting the supervised machine learning concept from data science disciplines.

- *Population*

The population in this study is Thai pilots registered with the Thai Pilot Association. The simple random sampling method was utilized to select them. Any Thai pilot registered with the Thai Pilot Association was considered to meet the inclusion criteria. The sample was drawn from seven major air carriers ranging from commercial airline and helicopter service companies. Only private air carriers were selected as military operations completely differ from civilian ones. According to the supervised machine learning concept, apart from fitting the classification model, model performance testing brought this methodology to new frontier of data analysis as not only the model was fitted but the performance of the model could be effectively evaluated by another set of data. Using the holdout validation methodology, the sample was randomly divided into 2 groups; a training set and a testing set along a 75/25 ratio.

- *Instrument*

After being granting permission, 650 self-administered survey questionnaires in a soft copy format were distributed via intra-office email by the researcher. Questions regarding feature variables or independent variables were dichotomous and those regarding personal information and demographics were both dichotomous and continuous. After a process of data exploration and preprocessing (cleaning duplicated data, detecting outlier, imputation for missing value, and deleting noisy data), 610 respondents qualified for the statistical analysis. All the questionnaires were administrated according to Thai social norms, and local traditions. All measurements were in Thai language. Sample sizes were calculated by infinite population mean formula as the exact number of population was unknow (Cochran, Mosteller, & Tukey, 1954). The number of sample size was calculated as Equation (1):

$$n = \frac{p(1-p)z_{\alpha/2}^2}{d^2} \qquad (1)$$

Where proportion (*p*) is 0.5, error (d) is 0.05, alpha is 0.05, and Z at 0.975 is 1.96. Therefore, the minimum number of samples would be 385 or more in accordance with the calculation.

This research utilized a self-developed questionnaire based on the aforementioned related literature with dichotomous answers for each question. For example, the choice of answers to the question "What is your pilot rank?" was either "Pilot in Command" or "Second in Command." For the question "What is your pilot license type?" the two possible answers were "Commercial Pilot License" or "Air Transport Pilot License." The choice could also be a simple "yes" or "no" as was the case with the following question "Apart from line flying, do you have extra responsibilities such as check airman or instructor pilot?" ("Yes or No).

- *Data Analysis*

The screened data of 610 samples were analyzed by using a supervised machine learning classification algorithms to test the hypothesis of the study. The reason behind the adoption of this technique is that it allows for the classification of feature and label variables (Angsuchote et al., 2011). The statistical method used in this study was entirely computed by R (R Core Team, 2021).

4. Results and Discussion

Table 1 shows the descriptive statistics for nominal data relating to the classification model. The largest sample is pilot in command (51.30%) followed by holding commercial pilot license (46.70%). Most of the pilots worked as line pilot (73.90%). The rest of them held either check airman or instructor pilot positions (26.10%). 94.60 percent of the population sampled was males. 75.60 percent of them held a bachelor degree. Moreover, 75.60 percent of them piloted fixed wing aircraft and 60percent had been flying for more than 10 years.

Table 1: Descriptive Statistics for Nominal Demographic Data

Feature Variables (N = 610)	Frequency	Percentage
1. Pilot Rank (RNK)		
- Pilot in Command (PIC)	313	51.3
- Second in Command (SIC)	297	48.7
2. Pilot License (LIC)		
- Commercial Pilot License (CPL)	285	46.7
- Air Transport Pilot License (ATP)	325	53.3
3. Pilot Position (POS)		
- Line Pilot with Check Airman or Instructor Position (LPC)	159	26.1
- Line Pilot Position Only (LPO)	451	73.9

Before fitting a binary logistic regression classification model, all features variable were put into chi-square test of independence in order to determine whether which variable would be considered to input in the classification model. Independent variables that had a significant relationship with intention to leave aviation job were retained for inclusion in the model. The results of the chi-square test of independence indicate that all the variables were statistically significant with $p < .001$. This implies that pilot rank, pilot license, and pilot position significantly classified intention to leave aviation job and these also implied that all independent variables were suitable for fitting a binary logistic regression classification model as shown in Table 2.

Table 2: Chi-square Test of Independence – Cross Tabular

Feature Variables (N = 610)	Intention to Leave Aviation Job	No Intention to Leave Aviation Job	Chi-square Test of Independent
1. Pilot Rank (RNK)			
- PIC	74	278	$\chi2(1) = 12.374$
- SIC	73	185	$p < .000$***
2. Pilot License (LIC)			
- CPL	85	200	$\chi2(1) = 9.859$
- ATP	62	263	$p < .000$***
3. Pilot Position (POS)			
- LPC	53	106	$\chi2(1) = 10.027$
- LPO	94	357	$p < .000$***

Note. PIC = Pilot in Command, SIC = Second in Command, CPL = Commercial Pilot License, ATP = Air Transport Pilot License, LPC = Line Pilot with Check Airman or Instructor Position, LPO = Line Pilot Position Only, *** $p < .001$

As Table 3 below shows, by applying a maximum likelihood estimation, a binary logistic regression model was developed from the training set, which was randomized and derived from 75 percent of total dataset. In this classification model, a binary logistic regression classification model was fitted to assess the impact of pilot rank, pilot license, and pilot position on the likelihood that participants would be determined to leave their aviation job and all feature variables or predictor variables including intercept were statistically significant. Crude and adjusted odds ratios were described and shown significant in all of the feature variables. Adjusted odds ratios were used to determine one dependent and more than one independent variables by eliminating confounding effects by other independent variables within the same classification model. For variable importance from the random forest concept (Nathns, Oswald, & Nimon, 2001), this value signified the importance of the classification ability, the more the number, the better the classification ability. In this classification model, pilot position was the most important variable classifying intention to leave aviation job with a variable importance value of 3.87.

Table 3: Fitting a Binary Logistic Regression Classification Model Based upon 457 Training Samples

Feature Variable	*EST*	Crude OR (95% CI)	Adj. OR (95% CI)	*p*-value	*VI*
Intercept	-1.51	-	-	.000***	-
Pilot Rank (RNK)	-0.62	0.70 (0.45, 0.98)	0.54 (0.31, 0.92)	.024*	2.26
Pilot License (LIC)	0.61	2.18 (1.40, 3.38)	1.85 (1.16, 2.96)	.001**	2.58
Pilot Position (POS)	1.07	2.17 (1.37, 3.43)	2.93 (1.70, 5.05)	.000***	3.87

Note. *EST*. = model coefficients; *Crude OR* = crude odd ratio; *Adj. OR* = adjusted odd ratio; 95% CI = 95% confident interval from range estimation; *p*-value = Wald's Test *p*-value; *VI* = variable importance; reference class (coded as 1) = pilot in command (RNK), commercial pilot license (LIC) and line pilot with check airman or instructor position (POS) respectively; Significant codes: * $p < .05$, ** $p < .01$, *** $p < .001$

The pilot rank significant adjusted odds ratio was 0.54, implying that the likelihood of pilots with command rank leaving their aviation job was 1.85 (1/0.54) times. This means that second in command pilot rank had significantly higher chance of leaving their aviation job. The pilot license significant adjusted odds ratio was 1.85, implying that the likelihood of pilots holding a commercial pilot license leaving their aviation job was 1.85 times higher than that of pilots holding an air transport pilot license. The likelihood of pilots holding a commercial pilot license to leave their aviation job is therefore significantly higher. Finally, the pilot position significantly adjusted odds ratio was 2.93, implying that the chance for line pilot with check airman or instructor position to leave their aviation job was 2.93 times higher than that of those holding a line pilot position only. This means that line pilots holding a check airman or an instructor position have a significantly higher chance of leaving their aviation job. Thus, Hypotheses 1 to 3 were accepted.

After developing a classification model, the model evaluation and diagnosis were tested to see if the model was fitted with empirical data and was valid in terms of classification ability (Archer & Lemeshow, 2006). There are several measures to evaluate and diagnose a model goodness of fit. They include both absolute measures of fit, such as the Likelihood Ratio Test, the Pseudo R-squared, and the Hosmer and Lemeshow Test, and relative measures of fit such as the Wald Statistics. As an absolute fit indice, the Pseudo R-squared imitates regular R-squared; the higher its value, the more absolute the fit. As Tables 4 and 5 show, all tested statistics pointed to a good fit and good model fit statistics. As relative measures of it, Wald Statistics, which include both the F-test and Chi-squared test, were significant. As to absolute measures of fit, the Log Likelihood Ratio test was also significant, indicating a good fit with empirical data. Moreover, Hosmer and Lemeshow Test was not significant, also pointing to a good fit with empirical data. Therefore, Hypothesis 4 was supported.

Table 4: Classification Model Diagnosis: Goodness-of-Fit Test

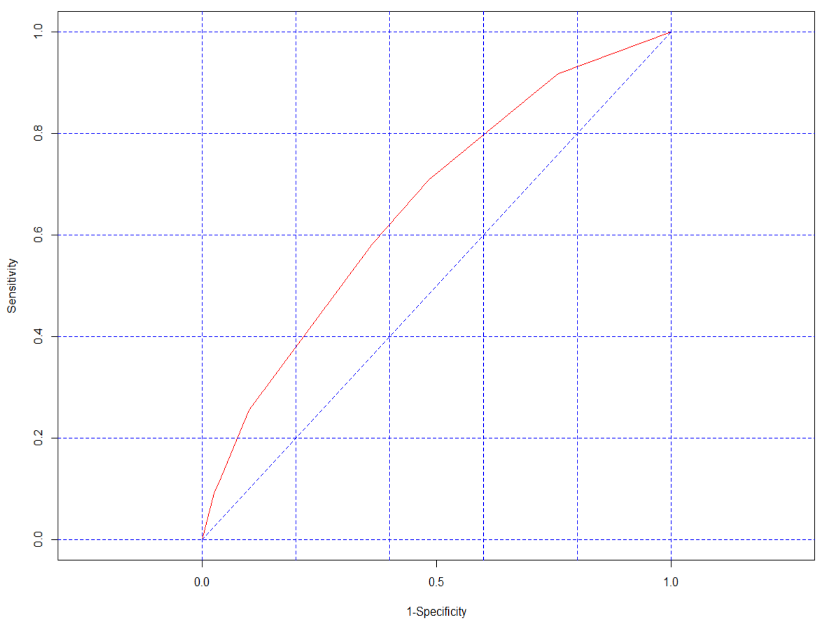
Test Statistics	*df*	Statistics	*p*-value
Hosmer and Lemeshow Test (χ^2)	4	0.73	.98
Likelihood Ratio Test (χ^2)	-3	28.09	.000***
Wald Test (χ^2)	-3	25.62	.000***
Wald Test (F-test)	-3	8.54	.000***

Significant codes: ***$p < .001$

Table 5: Classification Model Diagnosis: Model Fit Statistics

Model Fit Statistics	Value
Log-likelihood: Intercept Only	-252.21
Log-likelihood: Full Model	-238.16
Deviance (-2LL)	476.33
Cox and Snell Pseudo R^2	0.060
Cragg-Uhler (Nagelkerke) Pseudo R^2	0.089
McKelvey and Zavoina Pseudo R^2	0.099
AIC = 484.334; BIC = 500.833; Likelihood Ratio = 28.090; *p*-value < .001***	

To evaluate the classification performance at all possible thresholds, the Receiver Operating Characteristic Curve (ROCC) was analyzed to determine the model accuracy performance using two parameters; true positive rate (sensitivity) and false positive rate (1-specificity). The Area under ROCC Curve (AUC) measured the total two-dimensional areas under the entire ROCC through an integral calculus paradigm that provided an aggregate measure of classification performance across all possible thresholds. As shown in Figure 1, the classification model AUC was 65.6 percent, indicating a moderate classification performance.



(AUC) = 0.656 with sensitivity and specificity are equal as cut-off value

Figure 1: Receiver Operating Characteristic Curve showing Area Under ROCC Curve
(The visualization was developed by the author using R)

Finally, the model was put through classification experimental testing by inputting one sample from unseen data and having a model classified outcome. In this case, as shown in Table 6, if a subject were in a pilot in command position, held an air transport pilot license, and were a line pilot with a check airman or instructor position, the model would classify this subject as having no intention of leaving his/her aviation job.

Table 6: Binary Logistic Regression Classification Result from One Unseen Data

Feature Variable	One Record of Unseen Data Input
Pilot Rank (RNK)	Pilot in Command (1)
Pilot License (LIC)	Air Transport Pilot License (0)
Pilot Position (POS)	Line Pilot with Check Airman or Instructor Position (1)
Intention to Leave Aviation Job	No (Predicted Value = 0.257, less than 0.5 cut-off value)

Note. Reference class = pilot in command (RNK), commercial pilot license (LIC) and line pilot with check airman or instructor position (POS) respectively. Reference class would be labeled as 1.

As to the research objective, which was to develop the most suitable binary classification model, the model needed to be tested and evaluated for classification performance. In order to effectively evaluate the classification ability, the evaluation was based on a test set that was derived from the 25 percent or 153 samples of the main data sets. Table 7 shows the result of classification performance evaluation based on the confusion matrix.

Table 7: Confusion Matrix: Classification Performance Evaluation
(Based upon 153 Unseen Samples)

Confusion Matrix		Intention to Leave	No Intention to Leave
		Actual	
Intention to Leave	Predicted	1	3
No Intention to Leave		36	113

As shown in Table 8, to determine the classification performance on the basis of the test set classification results from the confusion matrix, the model classification accuracy was 74.5 percent. The True Positive Rate (Sensitivity) was 2.7 percent and the True Negative Rate (Specificity) 97.4 percent. Sensitivity or True Positive Rate refer to the proportion of those who met the conditions that gave rise to a positive result from the model classification. Conversely, specificity or True Negative Rate refer to the proportion of those who do not have the condition that received a negative result from the model classification. Accuracy should be more than 0.5 in order to ensure better classification performance than just flipping a coin. Recall that the goal of the test was to accurately identify pilots having the intention (or meeting the conditions) to leave. The number of false positives should be very low, which requires a high Specificity or True Negative Rate, that is to say, pilots who do not have the intention (or do not meet the conditions) to leave are highly likely to be excluded by the model classification results. The classification performance as measured by the test set revealed a very high Specificity or True Negative Rate of 97.4 percent, which indicated that this classification model had a high classification performance.

Table 8: Classification Performance Resulted from Test Set

Classification Performance Index	Results
Accuracy	0.745
Sensitivity or True Positive Rate	0.027
Specificity or True Negative Rate	0.974

The results of the analysis indicate that pilot rank, pilot license, and pilot position play a critical role in assessing the likelihood of Thai pilots leaving their aviation job. These variables were impacting factors that significantly determined the likelihood of leaving aviation job. Finally, as shown in Table 9, in this study, all hypotheses were supported.

Table 9: Summary of Hypothesis Testing Results

Hypothesis	Result	Explanation
H1	Supported	Pilots holding a rank of Pilot in Command are less likely to leave aviation job.
H2	Supported	Pilots holding Air Transport Pilot License are less likely to leave aviation job.
H3	Supported	Line pilots with no other extra duties are less likely to leave aviation job.
H4	Supported	The binary classification model with the holdout validation method is fitted with empirical data.

5. Conclusion and Recommendations

This study contributes to the growing academic literature on Thai pilots' intention to leave aviation job. A practical contribution from this study is the finding that job demands play the most influential role in determining the likelihood that a pilot will leave the organization. This is in keeping with previous studies conducted in various contexts on the same issue (Hoonakker, Carayon, & Korunka, 2013; Jourdain & Chênevert, 2010). Training a pilot is costly by nature. It is therefore advisable that airlines make an effort to support their pilots by providing adequate job resources and keep their flying morale high in order to retain them on board. Moreover, airlines should pay attention to lower rank pilots with commercial pilot license and provide more suitable career plan to those pilots since, according to the results of this study, pilots with second-in-command rank holding commercial pilot license have the higher chance of leaving aviation jobs. In addition, since, as the results indicate, pilots with extra duties have a higher chance of leaving aviation jobs, airlines should allocate adequate job resources to those pilots in order to mitigate stressful work-related situation stemming from job demands. Moreover, in order to maintain an acceptable level of flight crew members in operation, airlines should enhance their recruitment marketing strategies so as to attract potential flight crew members to join the fleet and help mitigate pilot shortage risk (Wangyuenyong, 2017).

Another academic contribution of this study is the harmonious utilization of data science discipline approach in the behavioral sciences context. Compared to legacy techniques, a classification model fitted with train set and evaluated by test sets provides more insightful results in terms of classification and reduces the chance of overfitting the model (Kotsiantis, Zaharakis, & Pintelas, 2007). However, even though adapting a classification model from data sciences discipline helped to clarify answers to problems in behavioral science, there were limitations. First, samples were collected from Thai pilots. Thereby, the result from this study might apply to those flying in Thailand. Future studies should extent the samples to an international context. Second, this study is quantitative. Future research should be qualitative as this method allows for deeper and richer results (QRCA, 2021).

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