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The Development of Turnover Intention Prediction Model for Out-of-Office Workers in Thailand

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Abstract

The study of the development of turnover intention prediction model for out-of-office workers in Thailand aims to investigate the factors affecting probability of turnover intention and to develop the most suitable turnover intention prediction model for out-of-office workers by using binary logistic regression approach. This is a quantitative social science survey research. The population of the study are professional employees that are assigned to work outside the office, including but not limited to salespersons, financial auditors, management consultants, medical representatives, real estate agents and other professional jobs that often work outside an office. Research tools are questionnaires and rating scales. A convenience sampling method was applied. Self-administrative questionnaires both hard copy and electronic form were directly distributed to various out-of-office workers in Thailand. In this study, 420 sample size was collected and separate into 67% of training set and 33% of test set. The well-fitted turnover intention prediction from binary logistic regression approach for out-of-office worker can be deliberately developed and fitted with empirical data. It is obvious and clear that all thelegacy negative work-related factors are still relevant and contribute to the prediction of turnover intention of employees. Organizations should utilize any possible countermeasures to mitigate these risks. For future research, qualitative research should be done so as to gain more insights regarding turnover intention.

Introduction

Nowadays, there are several professions where there is not a need to be in an office. These fields of work are mostly related to jobs that require employees to be at the client site or customer office. In a modern working world, mobile technology and innovation focused on the internet of things are dynamic and are used by those who work outside the office as a method to get their jobs done even though they are not at the company's headquarters. The digital disruption has gradually encouraged modern day employees to work outside an office. In Thailand, teleworking plays an important role in various fields of work including financial auditors in finance and accounting industry, medical representatives in healthcare industry, real estate agents in real estate industry and management consultants in business consulting industry.

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Past studies confer that teleworking plays a crucial role in benefits and advantages on relevant working environment (Baruch, 2000; Pratt, 1984).

There are several differences between working in the office and working remotely outside the office. Autonomy is the obvious aspect among these two paradigms. By working remotely, employees are able to manage work schedule at their own pace while working in the office is subjected to office time and office discipline. Apart from autonomy, however, isolation is not a problem of office workers but this can be an issue for teleworkers. But personal life conflict due to improper work-life balance can be problematic for both fields of work (Gajendran & Harrison, 2007). Due to these differences, teleworking context is worth studying.

Even today, a high-quality human capital is costly. With the continuous development of competitive working world, the development of human resource has certainly become a crucial factor assisting to drive an organization goal, especially for those who work outside the office. An organization has to invest in each employee and train employees well to ensure they work efficiently and effectively; not only for a company but also to meet and exceed client expectation. What if all those expensive investments have gone in vain by a high rate of employee turnover as these types of employee are isolated from their team member and supervisor (Knight & Leimer, 2010). A lack of essential communication and cooperation can be expected, and this can be considered as a main problem that might lead to job dissatisfaction and finally to a decision to leave a company.

Job demands and resources theory (JD-R) had been divided into 2 separated components which are job demand and job resource. These two generic components could be found in any field of professions and leads to two possible physical and psychological outcomes which are motivational process and health impairment. While job demands means that the organization requires employee to put an effort both physically and mentally into assigned works or engagements, job resource, on the other hand, means supporting environments related to work that help employees reach targets and goal at work (Bakker & Demerouti, 2014). The job demand leads to both physical and mental fitness problems at work. Nevertheless, the job resource is a helping hand in this situation as it could help support workers and mitigate work-related problems in their everyday working routine. Moreover, a well-planned job resource provided by an organization to each employee leads to a professional development in their career. Job demands and resources theory are widely cited as the reference model to study on work-related problems in various entities both private and public organizations and this model could be applied to any type of employee.

According to Cognitive Evaluation Theory by Ryan (Ryan & Deci, 2000), basic psychological needs lead to intrinsic motivation and brings out a behavior. These needs comprise of need for autonomy, need for competence and need for relatedness. Autonomy plays an important role in working behavior and job satisfaction as autonomy is a freedom of employee to act, manage, decide or determine on what they should have done on their assignment. Autonomy is widely known to have a positive effect on employee's job performance as they perceive that the organization puts a confident trust on them. This positive perception toward organization leads to an increasing level in a work-related intrinsic motivation which finally results in a high work performance (Narayanan, Menon, & Plaisent, 2017).

The research of Marshall, Michaels, & Mulki, (2007), found work-related isolation means a lack of socially and emotionally interaction with team members at work and can possibly lead to a feeling of loneliness. This might lead to a work-related relationship among colleagues within an organization. In the context of a teleworking environment, this definitely leads to a lack of interaction and communication with team members and supervisor. The lack of human contact at work could possibly lead to social isolation. An employee that normally works outside the office usually face a communication problem with team members and by this issue, can naturally lead to a stressful situation regarding work due to the job demands.

In general, burnout is a word that is used to describe the physical and mental exhaustion at work faced by employee as a direct outcome of stress from over-work. This can damage both mental and physical fitness of employees. Burnout is latent. The continuing process of it can deteriorate individuals' mental and physical health from prolonged exposure to work-related stress. To summarize, burnout is a mental and physical state of exhaustion caused by excessive and prolonged stress occurring especially when employees feel negatively overwhelmed and unable to meet employers' expectation. As this situation continue, they start to lose motivation and interest at work and this leads to poor job performance and burnout also minimizes productivity and energy of employees which leaves them feeling cynical and resentful at work (Simha, Elloy, & Huang, 2014).

In the past, if employees feel satisfied in their job, it will lead to an intention to stay in an organization (Bannister & Griffeth, 1986). Nowadays, this finding should be reconsidered as there are many factors affecting intention to leave an organization even though they feel satisfy in their job. Moreover, in a previous study, public sector employees had a less probability of leaving the company due to job security (Akova, Cetin, & Cifci, 2015). However, there are few research that scrutinize this in the context of Thailand. Factors mentioned earlier are worth studying as to whether these could possibly lead to a probability of turnover intention. According to a review of related literature, the objective of the study is to develop the suitable turnover prediction model by using data science technique which separates main dataset into train set to fit the model and test set to evaluate prediction performance. It can be hypothesized that employees with high autonomy, less isolation, less burnout and working for public sector might have a less chance of turnover intention.

As a result of these negative factors, as mentioned above, organizational investments might be done in vain. There were several published works that study factors affecting turnover intention from time to time. Nonetheless, there are few research that studied on how to predict turnover intention, especially on an out-of-office profession.

Objective

Objective of this study is to develop the turnover intention model by using binary logistic regression approach in teleworking context.

Conceptual framework

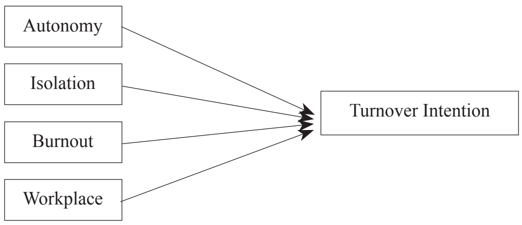

Figure 1 Conceptual framework

Research methodology

1. Population and samples

The population of this study are professional employees that are always assigned to work outside the office, including but not limit to salespersons, financial auditors, management consultants, medical representatives, real estate agents and other jobs that often work outside an office. This is a social science survey research. Hence, a convenience sampling method was applied. In this research, 500 questionnaires were sent and whereas 420 samples were qualified for analysis. This study used questionnaires which were classified into six parts, autonomy, work-family conflict, isolation, burnout, turnover intention and general demographic data. Self-administrative questionnaires both hard copy and electronic form were directly distributed to various out-of-office workers in Thailand including those who were working in the field of financial auditing, medical representatives, real estate agency and management consulting. The questionnaires were administrated according to actual situation and local culture. All the measures were translated and back-translated from English to Thai.

2. Research instrument

Burnout scale contains 5 items from the Maslach Burnout Inventory or MBI (Maslach, Jackson, Leiter, Schaufeli, & Schwab, 1986) a tool to measure burnout (Cronbach's Alpha = .920). Isolation contains a 5 item scale from Golden (Golden, Veiga, & Dino, 2008) to measure individual level of isolation at work (Cronbach's Alpha = .880). The autonomy scale contains 5 items from Van den Broeck (Van den Broeck, Vansteenkiste, De Witte, Soenens, & Lens, 2010) to measure individual level of autonomy (Cronbach's Alpha = .897).

3. Collection of data

This research used a self-administrated questionnaire to collect the data. Self-administered 500 survey questionnaires were distributed and classified into 3 parts, burnout, isolation, autonomy and demographic information. After performing data reduction, detecting outlier, imputating missing value and deleting duplicated information, only 420 samples were qualified for the statistical analysis.

For the number of samples (Cochran, Mosteller, & Tukey, 1954), infinite population mean formula was calculated as follows:

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

In this formula, proportion (p) is 0.5, error (d) was 0.05, alpha was 0.05 and Z at 0.975 was 1.96. Therefor the minimum number of samples would be 385 or more as per calculation.

4. Data analysis

The screened data of 420 samples were analyzed by using a binary logistic regression approach to test the hypothesis of the study. The reason behind the adoption of this technique was that it allows for testing multiple predictors as well as to predict a dichotomous target dependent variable. The datasets were separated into two sets in the ratio of 67 % of training set and 33 % of test set. First, the binary logistic regression model was fitted by using a training dataset and after diagnosing fitness of the model by various statistics method. Second, according to the research objective, the model was tested by using an unseen data or testing set to determine a prediction accuracy by using a classification evaluation of the confusion matrix. The entire analysis process from data preprocessing to model classification evaluation was conducted by using R language (R Core Team, 2020).

Results

Regarding the data analysis, the results were separated into 2 parts consisting of descriptive statistics for both nominal and continuous demographic data and inferential statistics.

A total of 420 samples were screened. After filling in a missing value by column average, smoothing out noisy data, identifying and screening outlier, resolving duplicated data and correcting inconsistency, the clean dataset was put into the analysis. According to Table 1, descriptive statistics for nominal demographic data, shows that most of the sample are female (56.9 %), holding a degree above bachelor degree (55.2 %), working in the public sector (50.5 %), holding an operational level position (59.5 %) and single (63.8%). Moreover, Table 2, shows that the mean age of the sample at 37.22 years with standard deviation of 11.27, the average current work tenure at 9.42 years with standard deviation of 10.45, the average work experience at 13.84 years with standard deviation of 11.07, the average estimated salary per month at THB 52,503.83 with standard deviation of THB 43,621.53.

For binary logistic regression model analysis, the most essential condition prior to conducting an analysis is to check predictors multicollinearity (Midi, Sarkar, & Rana, 2010). This could be accomplished by calculating Variance Inflation Factor (VIF). Generally, VIF should not exceed 2 to ensure that there was no multicollinearity among predictors. Moreover, normality of predictor should be expected. Based on Skewness and Kurtosis, each predictors should not exceed plus or minus 2. According to Table 3, all VIFs were less than 2 and Skewness and Kurtosis of all predictors were within range of plus or minus 2. Therefore, the data are suitable for binary logistic regression.

Table 1 Descriptive statistics for nominal demographic data

Demographic Data (n = 420)	Frequency	Percentage
1. Sex		
- Male	18	43.1
- Female	239	56.9
2. Education		
- Bachelor degree	188	44.8
- Above bachelor degree	232	55.2
3. Workplace		
- Private sector	208	49.5
- Public sector	212	50.5
4. Current Position		
- Operational	250	59.5
- Managerial	170	40.5
5. Marriage		
- Single	287	63.8
- Married	133	31.7

Table 2 Descriptive statistics for continuous demographic data

Demographic data (n = 420)	Mean	S.D.
1. Age (Year)	37.22	11.27
2. Current workplace tenure (Year)	9.42	10.45
3. Total work experience (Year)	13.84	11.07
4. Estimated monthly salary (Baht)	52,503.83	43,621.53

Table 3 Variance inflation factors, skewness and kurtosis

Variables	VIF	Skewness	Kurtosis
Autonomy (ANM)	1.134	-0.305	-0.454
Isolation (ISL)	1.159	-0.124	-0.009
Burnout (BOT)	1.253	-0.075	-0.565
Workplace (WORK)	1.075	-0.018	-2.000
Turnover Intention (TURN)	-	-0.648	-1.582

According to Table 4, most predictors are statistically significant except for Autonomy and Isolation that shows significant at significant level of 10%. In this analysis for the criterion variable, turnover intention, code 0 mean intent to turn over and code 1 mean 'NOT' intent to turn over. The private sector workplace was coded as 0.

Autonomy odd ratio shows 1.342 implying that if the average score of autonomy increased by 1 point, the chance of 'NOT' intent to turn over will increase by time 1.342. This implies that the higher an autonomy, the less chance of resigning from the company.

Table 4 Fitting a binary logistic regression model

Predictor	Estimated	Standard Error	Z value	*p*-value	Odd Ratio	Variable Important
Y-intercept	1.945	0.885	2.198	.027*	6.995	-
Autonomy (ANM)	0.294	0.158	1.861	.062	1.342	1.860
Isolation (ISL)	-0.389	0.201	-1.937	.052	0.677	1.937
Burnout (BOT)	-0.571	0.168	-3.39	.000**	0.564	3.389
Workplace (WORK)	1.345	0.293	4.594	.000**	3.841	4.593

$* p < 0.05$, $*** p < 0.000$

Isolation odd ratio shows 0.677 implying that if the average score of work-related isolation increases by 1 point, the chance of 'NOT' intent to turn over will increase by time 0.67 or decrease by time 1.49 (1/0.677). This means that the higher a work-related isolation, the higher chance of resigning from an organization.

Burnout odd ratio shows 0.564 implying that if average score of burnouts increases by 1 point, the chance of 'NOT' intent to turn over will increase by time 0.564 or decrease by time 1.77 (1/0.564). This implies that the higher a burnout, the higher chance of turnover intention.

Workplace odd ratio shows 3.841 implying that public sector workers had a higher chance of 'NOT' intent to turn over more than private sector workers by time 3.841. This implies that the public sector workers had a less chance of resigning from the organization.

In reference to variable important (Nathans, Oswald, & Nimon, 2001), the best predictor to predict a chance of turnover intention was Workplace with Variable Important of 4.593 and followed by Burnout with Variable Important of 3.389 and the worst predictor to predict a chance of turnover intention is Autonomy with Variable Important of 1.860 which is congruent with its significant level at only 10% compared to other predictors (Liaw & Wiener, 2002). According to the analysis mentioned above, the turnover intention prediction model for out-of-office workers can be developed as follows:

$$\text{Logit (TURN)} = 1.945+0.294(\text{ANM})-0.389(\text{ISL})-0.571(\text{BOT})+1.345(\text{WORK})$$

After developing a well-fitted prediction model, model evaluation and diagnosis are put into a consideration as to whether the model was fitted with empirical data and was valid in predicting outcome (Archer & Lemeshow, 2006). There are several measures to evaluate and diagnose the model as to the goodness of fit which are absolute measures like Likelihood Ratio Test, Pseudo R-square and Hosmer and Lemeshow Test and relative measures like Wald Statistics. According to Table 5, all test statistics indicate a good fit of the model. Relative fit measure as Wald tests both F-test and Chi-squared test were significant and Log Likelihood Ratio test are also significant. Hosmer and Lemeshow Test is not significant indicating a good fit.

Table 5 Goodness of Fit: Wald Test and Log Likelihood Ratio Test and Hosmer-Lemeshow Test

Test statistics	df	Statistics	*p*-value
Wald Test (F-test)	-4	10.535	.000***
Wald Test (Chisq)	-4	42.139	.000***
Log Likelihood Ratio (Chisq)	-4	56.224	.000***
HL Test (Chisq)	8	7.451	.488

$*** p < 0.000$

In accordance with model fit statistics mentioned in Table 6, this can be implied that the model has a good fit. For instance, Nagelkerke Pseudo R-square was 25 %.

Table 6 Binary Logistic Regression Model Fit Statistics

Model fit statistics	Value
Log-likelihood: Intercept Only	-181.083
Log-likelihood: Full Model	-152.971
Deviance	305.941
McFadden's Pseudo R-square	.128
Cox & Snell Pseudo R-square	.181
McKelvey & Zavoina's Pseudo R-square	.268
Nagelkerke Pseudo R-square	.250

According to the research objective which was to develop the most suitable prediction model, the model needed to be tested and evaluated for prediction performance. In order to effectively evaluate the prediction, the evaluation was based on an unseen dataset or test set that was derived from the 33% or 139 samples of the main datasets. Confusion matrix is an evaluation tool that was utilized as a prediction evaluation as this matrix could describe accuracy, no information rate and its p-value, Kapa, Mcnemar's test, sensitivity and specificity. The detail of confusion matrix that was based on unseen dataset is shown in Table 7.

Table 7 Confusion Matrix: prediction evaluation based on 139 sample of unseen dataset

Confusion matrix		Intention to turnover	No intention to turnover
	Predicted	Actual	
Intention to turnover		23	12
No Intention to turnover		25	79

According to Table 8, the model prediction accuracy was 73.3%. No information rate is the most possible best guess in case there was no information beyond the overall distribution of the predicted class, which was, in this case shown at 65.4% which was less than accuracy. Mcnemar's test provided strong evidence for a statistically significant for prediction effect. Kappa co-efficient shows 0.371 with a moderate level of consistency in agreement. True positive percentage (Sensitivity) is 0.479 and true negative rate (Specificity) was 0.868.

Table 8 Confusion matrix statistics

Reference class	Intention to turnover
Accuracy	.733
95% Confident Interval	(0.652,0.805)
No Information Rate	.654
p-value [Accuracy > No Information Rate]	.028*
Kappa	.371
Mcnemar's Test p-value	.048*
Sensitivity	.479
Specificity	.868

* $p < 0.05$

Finally, to determine the proportion of correctly classification to incorrectly classification, Pearson's Chi-squared test with Yates' continuity correction was calculated and significantly shows that the proportion of correctly classification to incorrectly one is significant as shown in Table 9.

Table 9 Pearson's Chi-squared test with Yates' continuity correction

Test statistics	df	Statistics	*p*-value
Chi-squared Test	1	18.318	0.000***

*** $p < 0.000$

All in all, after fitting the prediction model on train dataset and testing its performance on test or unseen dataset, all research presumptions are accepted as employees with high autonomy, less isolation, less burnout and working for public sector who have a less intention of leaving their job, according to the analysis result.

Discussion

According to the proposed turnover intention prediction model for out-of-office workers mentioned above, it has clarified that the most obvious factor affecting a chance to leave an organization is the workplace and followed by burnout. The result was interpreted in the same manner as the previous study of Chen, Ran, Zhang, Yang, Yao, H., Zhu, & Tan (2019) Moreover, burnout is the main factor that has a direct affect to an organization. Burnout significantly reduces the job performance and leads to health problems of employees and ultimately, leads to an intention to leave an organization. In this study, work-related isolation also contributed to a higher chance to leave. These are all negative factors that impact employees intention to leave. However, autonomy is considered as a factor that negatively affects a chance to leave as normally, autonomy would lead to job satisfaction. When people feel satisfy in their job, there is a small probability that they will decide to leave a company. Finally, public sector employees had a less chance of leaving compared to their private counterpart (Akova, Cetin, & Cifci, 2015). This result is congruent with Eliot (Hammer & Van Tassell, 1983) as public sector employees always have a higher level of extrinsic motivation than the private sector (Demoussis & Giannakopoulos, 2007). It is obvious that all the legacy negative work-related factors are still relevant and contribute to turnover intention of employees and this research once again confirm those findings. An organization should utilize any possible countermeasures to mitigate this risk.

Suggestion

Ultimately, there are two major limitations and recommendations for future study. Firstly, this research is quantitative style. In order to receive a deeper understanding of each employee's mind about turnover intentiona future study should apply qualitative research method so as to gain more insights regarding turnover intention in teleworking context. Secondly, this study scrutinizes on work-related negative factors affecting turnover intention. Future research should study on several positive work-related factors such as career satisfaction or job satisfaction as these factors might also predict intention in teleworking environment.

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