Multinomial Regression Model for In-service Training

Hsieh-Hua Yang, Hung-Jen Yang, Jui-Chen Yu, and Wen-Jen Hu

***Abstract*—**In-service training is education for employees to help them develop their professional skills in a specific discipline or occupation. This training takes place after an individual begins work responsibilities. On-line technology is supporting our learning in many ways. Both credit and degree pursuing are formal developing program. There is a need to developing a model of in-service training for a certain professional group so can illustrate their group behavior. The purpose of this study was to present how to develop a model of in-service training by using multiple logistic regressions. Based on literature review, a theory model was first identified. An investigating was conducted to collect data to evaluate the designed model. The model consist two factors, one is the learners' age and the other is the learning styles. Two models were establish to explore both credit training and degree training courses. The resulted model then was further discussed to reveal in-depth of in-service needs.

***Keywords*—**In-service Training, Multiple Logistic Regression.

I. Introduction

Multinomial Logistic Regression is useful for situations in which you want to be able to classify subjects based on values of a set of predictor variables. For distinguish relationships among researched factors, designing a model to verify theory become a important processes[1-4]. This type of regression is similar to logistic regression, but it is more general because the dependent variable is not restricted to two categories

In-service training is education for employees to help them develop their professional skills in a specific discipline or occupation. This training takes place after an individual begins work responsibilities. In-service training is important because of the fast changing professional working requirement. Without progresses in personal professional knowledge, those knowledge workers could be easily lost behind in their professional line. The out of date know how wont help any if the changes were expected. In-service training is the core solution of coping with changing in a professional career[2, 5-10].

The desire for greater in-service trainees' satisfaction is an important motive in the decision making process of an in-service training program. This study uses the national vocational high school teacher sample to examine the in-service training model.

II. Theory Frame

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In order to provide teacher in-service more effectively, teacher education want to predict what type of delivery is

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likely to take.

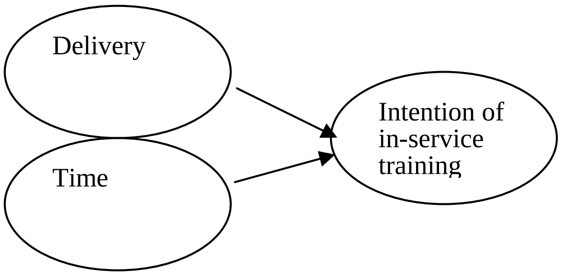

Figure 1 Conceptual model of in-service training

In-service training is education for employees to help them develop their skills in a specific discipline or occupation. In-service training takes place after an individual begins work responsibilities. Most typically, in-service training is conducted during a break in the individual's work schedule[5, 11, 12].

Trainees need practical experience before they can or will benefit from the intended training.

The possible benefit is that the trainees can draw from their work experience. On the other hand, the possible disadvantage of in-service training is that the trainee is already responsible for and engaged in a task or program and may be easily distracted from training activities.

There were two factors in the theory model. The first one is the way of course delivery. On-line course, mix course, and face to face course are those three types of delivery. The conceptual model is shown in figure 1.

III. METHODOLOGY

The data for this study were drawn from a larger project titled "Taiwan National In-service Training needs Investigation"[13, 14]. The projects investigate nation wide teachers from elementary through high school including vocational high school teachers about their preference of in-service training. After creating survey instruments, the national surveys were delivered in 2006 to all teachers. For the vocational high school track, there were total 25,077 teachers. A total 3,664 teachers completed questionnaires were obtained, for an overall response rate of 15 percent.

Two different types of mobility propensity served as dependent variables. Those are preferred delivery method and course time schedule. A measure of preferred delivery method was measured by selecting one of those three different delivery methods, 1). on-line, 2). Mix, 3). Face to face in general classroom.

The course time schedule was measured by selecting one of those time 1). Holidays 2). Weekend, 3). Workdays. Intention to take in-service training was measured by a question about the likelihood that the respondent will take any in-service training course (code as 3=Degree, 2=Degree Credit, intention, 3=Credit).

Linear regression is not appropriate for situations in which there is no natural ordering to the values of the dependent variable. In such cases, multinomial logistic regression may be the best alternative.

$$\pi_{ik} = \frac{e^{z}{}_{ik}}{e^{z}{}_{i1} + e^{z}{}_{i2} + \ldots + e^{z}{}_{iK}}$$

where

p_{ik} is the probability the i^{th} case falls in category k

z_{ik} is the value of the k^{th} unobserved continuous variable for the i^{th} case

For a dependent variable with K categories, consider the existence of K unobserved continuous variables, Z1, ... ZK, each of which can be thought of as the "propensity toward" a category. In the case of a packaged goods company, Zk represents a customer's propensity toward selecting the kth product, with larger values of Zk corresponding to greater probabilities of choosing that product (assuming all other Z's remain the same).

Mathematically, the relationship between the Z's and the probability of a particular outcome is described in this formula.

$z_{ik}=b_{k0}+b_{k1}x_{i1}+b_{k2}x_{i2}+\ldots+b_{kJ}x_{iJ}$ where

x_{ij} is the j^{th} predictor for the i^{th} case

b_{kj} is the j^{th} coefficient for the k^{th} unobserved variable

J is the number of predictors

Zk is also assumed to be linearly related to the predictors

$$\pi_{ik}(\text{with constants added to } z\text{'s}) = \frac{e^{z_{ik}+c}}{e^{z_{i1}+c}+e^{z_{i2}+c}+\ldots+e^{z_{iK}+c}} = \frac{e^{z_{ik}}e^{c}}{e^{z_{i1}}e^{c}+e^{z_{i2}}e^{c}+\ldots+e^{z_{iK}}e^{c}} = \frac{e^{z_{ik}}}{e^{z_{i1}}+e^{z_{i2}}+\ldots+e^{z_{iK}}} = \pi_{ik}$$

As it stands, if you add a constant to each Z, then the outcome probability is unchanged. This is the problem of non-identifiability. To solve this problem, ZK is (arbitrarily) set to 0. The Kth category is called the reference category, because all parameters in the model are interpreted in reference to it. It's a good idea (for convenience sake) to choose the reference category so that it is the "standard" category to which others would naturally be compared.

The coefficients are estimated through an iterative maximum likelihood method.

By performing a Multinomial Logistic Regression, the studio can determine the strength of influence a person's delivery preference and, time schedule preference, has upon the intention of taking in-service training. A multinomial logistic model is fit for the full factorial model or a user-specified model. Parameter estimation is performed through an iterative maximum-likelihood algorithm.

In order to further examine the determinant of a more advanced course member grouping, age was serve as covariate variable.

IV. Results

The results would be reported according to both description of in-service training model and in-service training multinomial regression model.

A. Description of in-service training model

Descriptive results of dependent and independent variables were reported in Table 1.

Table 1 Processing summary of in-service training model

		N	Marginal Percentage
intention	Credit	910	24.8%
	Degree Credit	794	21.7%
	Degree	1960	53.5%
Time	holiday	2446	66.8%
	weekend	646	17.6%
	workdays	572	15.6%
delivery	face to face	565	15.4%
	mix	1094	29.9%
	on-line	2005	54.7%
Valid		3664	100.0%
Missing		0	
Total		3664	

Subpopulation	9

In Table 2 as following, the highest frequency is pursuing degree by using online delivery style with 1286 counts. The lowest is degree credit course by using face to face delivery style with 115 counts.

Table 2 Cross table of intension and delivery

		delivery			Total
		face to face	mix	on-line	
intention	Credit	272	271	367	910
	Degree Credit	115	327	352	794
	Degree	178	496	1286	1960
Total		565	1094	2005	3664

In Figure 2, the bar chart illustrated the distribution of frequency counts according to intention and delivery.

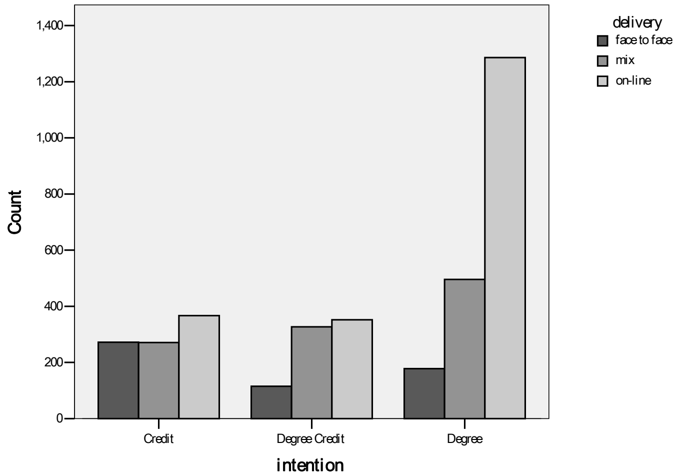

Figure 2 Frequency counts of intension and delivery in Bar chart form

In Table 4 since the significant level is less than 0.05, there exits difference among cells.

The chi-square test measures the discrepancy between the observed cell counts and what you would expect if the rows and columns were unrelated. The two-sided asymptotic significance of the chi-square statistic is less than 0.05, so it's safe to say that the differences are not due to chance variation, which implies that each in-service course offers differently according to the delivery methods. Since this value is less than 0.05, it can be concluded that the relationship observed in the cross tabulation is real and not due to chance.

Table 3 Chi-Square tests of intension and delivery

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	315.382(a)	4	.000
Likelihood Ratio	296.582	4	.000
Linear-by-Linear Association	256.410	1	.000
N of Valid Cases	3664		

a 0 cells (.0%) have expected count less than 5. The minimum expected count is 122.44.

In Table 5 as following, the highest frequency is pursuing degree by time scheduled on holiday with 1285 counts. The lowest is degree credit course by time scheduled on workdays with 94 counts.

Table 4 Cross table of intension and time

		Time			Total
		holiday	weekend	workdays	
intention	Credit	653	110	147	910
	Degree Credit	508	192	94	794
	Degree	1285	344	331	1960

Total	2446	646	572	3664

In Figure 3, the bar chart illustrated the distribution of frequency counts according to intention and time.

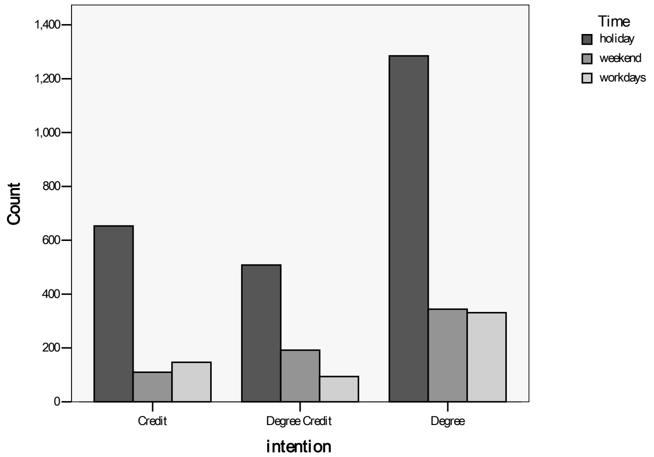

Figure 3 Frequency counts of intension and time in Bar chart form

In Table 7 since the significant level is less than 0.05, there exits difference among cells.

Table 5 Chi-Square tests of intension and time

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	49.391(a)	4	.000
Likelihood Ratio	49.893	4	.000
Linear-by-Linear Association	5.488	1	.019
N of Valid Cases	3664		

a 0 cells (.0%) have expected count less than 5. The minimum expected count is 123.95.

The two-sided asymptotic significance of the chi-square statistic is less than 0.05, so it's safe to say that the differences are not due to chance variation, which implies that each in-service course offers differently according to the time schedules. Since this value is less than 0.05, it can be concluded that the relationship observed in the cross tabulation is real and not due to chance.

B. Multinomial Logistic Regression of In-service Training

The in-service training model was completed by adding the measure of intension in the model to delivery method and time schedule. To examine the in-service training model, the model fits first been tested.

The goodness-of-fit table presents two tests of the null hypothesis that the model adequately fits the data. If the null is true, the Pearson and deviance statistics have chi-square distributions with the displayed degrees of freedom. Its value is greater than 0.05, so the data are consistent with the model assumptions.

Table 6 Goodness of fit of in-service training model

	Chi-Square	df	Sig.
Pearson	21.076	8	.07
Deviance	21.947	8	.05

This is a likelihood ratio test of the model against one in which all the parameter coefficients are 0 (Null). The chi-square statistic is the difference between the -2 log-likelihoods of the Null and Final models.

Table 7 In-service training model fitting information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	451.647			
Final	121.877	329.770	8	.000

Since the significance level of the test is less than 0.05, you can conclude the model is outperforming the Null.

The likelihood ratio tests check the contribution of each effect to the model as shown in Table 8.

Table 8 likelihood ratio tests of in-service training model

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	121.877(a)	.000	0	.
Time	155.065	33.188	4	.000
delivery	401.754	279.877	4	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.
a This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

For each effect, the -2 log-likelihood is computed for the reduced model; that is, a model without the effect. The chi-square statistic is the difference between the -2 log-likelihoods of the Reduced model from this table and the Final model reported in the model fitting information table.

If the significance of the test is small (less than 0.05) then the effect contributes to the model.

V. Conclusion

Using the Multinomial Logistic Regression Procedure, you have constructed a model for predicting teacher choice of in-service training. The teacher educators can then slant the promotion of a particular intention toward a group of teachers likely to take in-service training.

In Table 9, the classification table shows the practical results of using the multinomial logistic regression model.

Table 9 Predicted classification of in-service training model

Observed	Predicted			
	Credit	Degree Credit	Degree	Percent Correct
Credit	272	0	638	29.9%
Degree Credit	115	0	679	.0%
Degree	178	0	1782	90.9%
Overall Percentage	15.4%	.0%	84.6%	56.1%

Of the cases used to create the model, 272 of the 910 people who chose the credit in-service training are classified correctly. 0 of the 794 people who chose degree credit in-service training are classified correctly. 1782 of the 1860 people who chose cereal are classified correctly.

Overall, 56.1% of the cases are classified correctly. This compares favorably to the "null", or intercept-only model, which classifies all cases as the modal category.

According to the case processing summary, the modal category is degree in-service training, with 53.5% of the cases. Thus, the null model classifies correctly 53.5% of the time.

The parameter estimates table summarizes the effect of each predictor in Table 10.. The ratio of the coefficient to its standard error, squared, equals the Wald statistic.

If the significance level of the Wald statistic is small (less than 0.05) then the parameter is different from 0.

Parameters with significant negative coefficients decrease the likelihood of that response category with respect to the reference category. Parameters with positive coefficients increase the likelihood of that response category.

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Table 10 Parameter estimates table of in-service training model

intention(a)		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Credit	Intercept	-1.212	.108	124.801	1	.000			
	[Time=1]	.004	.114	.001	1	.975	1.004	.802	1.255
	[Time=2]	-.292	.152	3.707	1	.054	.747	.554	1.005
	[Time=3]	0(b)	.	.	0	.	.	.	.
	[delivery=1]	1.649	.114	208.983	1	.000	5.199	4.158	6.502
	[delivery=2]	.663	.096	47.419	1	.000	1.941	1.607	2.344
	[delivery=3]	0(b)	.	.	0	.	.	.	.
Degree Credit	Intercept	-1.584	.124	163.505	1	.000			
	[Time=1]	.258	.130	3.958	1	.047	1.295	1.004	1.670
	[Time=2]	.610	.150	16.547	1	.000	1.841	1.372	2.471
	[Time=3]	0(b)	.	.	0	.	.	.	.
	[delivery=1]	.892	.135	43.561	1	.000	2.441	1.873	3.181
	[delivery=2]	.849	.094	82.098	1	.000	2.337	1.945	2.809
	[delivery=3]	0(b)	.	.	0	.	.	.	.

a The reference category is: Degree.
b This parameter is set to zero because it is redundant.

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