EDUCATION QUARTERLY, December 2009, Vol. *67* (1), 3-20
U.P. College of Education

Predictive Models of Adult Distance Learners' Academic Performance: Comparative Analysis of Two Regression-based Models of Path Analysis

Maria Ana T. Quimbo
Institute of Community Education, College of Public Affairs
University of the Philippines, Los Baños

Abstract

Using two regression-based models, this study looked into factors that explain academic performance of adult distance learners. The efficiency and applicability of linear regression and logit regression procedures as statistical models for path analysis of mixed variables were compared along the criteria of model goodness-of-fit, predictive efficiency, and effect adequacy. Based on the criteria used, logit regression procedure has been shown to be a more efficient statistical tool than the classical linear regression procedure, when investigating pattern of causal relationships among variables at different levels of measurement. Implications of the study on distance education as a nontraditional mode of study and on achievement of adult distance learners were also presented.

Key words: distance education, achievement, mixed variables, path analysis, linear regression, logit regression

Causal modeling procedures provide social scientists with powerful methodological tools to examine complex causal relationships in sociological and educational investigations. These modeling techniques help simplify the enormity of events, relationships, and actions in the real world. Causal modeling has been used as the central framework that characterizes most empirical and mathematical approaches in social research (Bradley & Schaefer, 1998). Path analysis is one procedure that has gained popularity in the analysis of causal relations among variables in the social sciences even without experimentation.

Path analysis was introduced by social scientists to the field of behavioral and educational research in an attempt to reformulate verbal social theories in terms of empirically based language (Keeves, 1988). This technique provides a more rigorous

Correspondence should be sent to Maria Ana Quimbo. Email: anaquimbo@yahoo.com

mathematical, yet empirically verifiable, procedure. Path analysis is essentially a multivariate analytical technique. It yields an estimate of the magnitude of linkages between variables. It is not a method for discovering causes; rather, it is a tool intended to examine the underlying causal relationships of the variables in a causal model formulated by the researcher based on logic, common sense notions, existing knowledge, and theoretical considerations (Pedhazur, 1997).

Estimates provided by path analysis through linear regression procedure may be accurate and precise for some assumptions. However, they may also lead to quite unreasonable estimates such as when the dependent variable is a qualitative, categorical measure rather than a continuous, interval measure (Hagenaars, 1993). In social science and educational research, many of the variables of interest, including measures of attitudes and preferences, are qualitative or are measured in discrete number of categories (Agresti, 1990). More often, causal models in this type of investigations use mixed variables or a combination of variables at varying levels of measurement. What is needed for the analysis of mixed variables is a statistical technique that can be as efficient as the multivariate linear regression procedure but is not subject to its limitations when applied to qualitative variables.

One such technique is the loglinear modeling approach, which provides a new way of multivariate analysis of categorical data sets (Demaris, 1992). A special form of the loglinear model, the logit model, has become an important unifying framework for the multivariate analysis of categorical data (Eshima & Tabata, 1999). The regression-like application of the logit model requires the analysis of a categorical dependent variable as a function of a set of independent variables, which may be continuous, or categorical, or a mixture of the two (Knoke & Burke, 1988).

There have been studies designed to draw parallelisms to the application of linear regression and logit regression models to path analysis. One important study (Goodman, 1973) compared the two models using causal modeling of relationships among variables in a unidirectional or recursive manner. The Goodman study concluded that there is an obvious parallelism between the two procedures. This was later supported by Hagenaars (1993) who called the logit model a *modified* linear regression approach.

The main focus of this study was to compare the relative efficiency and applicability of linear regression and logit regression procedures as path analytic models used to examine underlying causal relationships among mixed variables. This study also served as an exploratory investigation of the determinants of academic achievement in distance education, which were identified and conceptualized in a causal model based on theoretical reviews and examination of related literature. It is important to know the determinants of achievement in distance education in order for educators to arrive at a better understanding of the meaning and nature of achievement in this nontraditional mode of study. Many of these factors may not be easily detected because they exist within the learners. Other important factors are embedded within the learning environment, but may have direct influence on the learner. An analysis of these factors, therefore, will help identify the variables that affect success of distance learners for the purpose of improving the delivery of this mode of instruction.

Conceptual framework

Three distinct types of variables were defined in the causal model which was specifically designed for this research (Figure 1). These were the exogenous, endogenous, and residual variables. An exogenous variable is influenced by factors outside the causal model but affects other factors within the causal model; endogenous variable is one whose variation is explained by other variables within the causal model; and a residual variable is not actually measured in the model but affects the endogenous variable in the causal model.

In the causal model, the predictors or independent exogenous variables are the nine dimensions of distance education; the endogenous variables that were used both as dependent and independent variables are persistence rate and achievement test scores (academic achievement at Time 1), and; finally, the endogenous dependent variable is GWA or general weighted average (academic achievement at Time 2). The *e'*s are the error terms, representing factors not actually measured in the causal model but affect the endogenous variables.

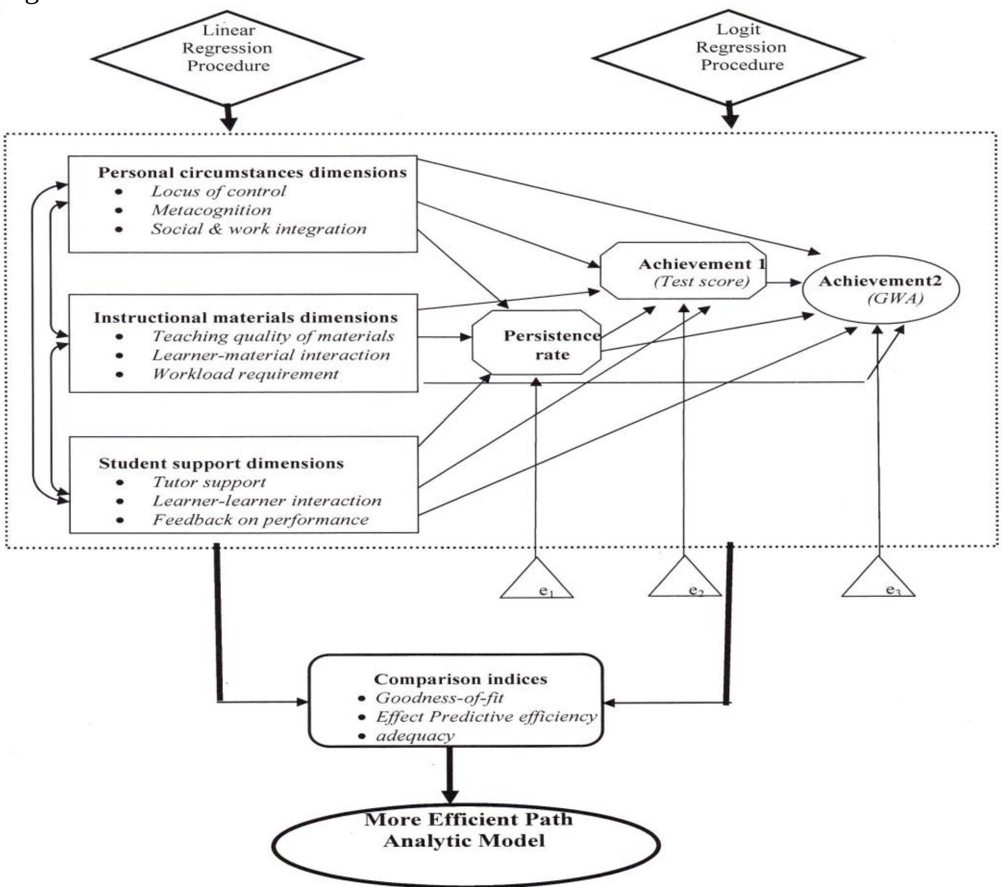

Figure 1
Conceptual framework

Specifically, the nine dimensions of distance education are social and work integration, locus of control, and metacognition (personal circumstances subsystem), teaching quality of materials, learner-material interaction, and workload requirements (instructional materials subsystem), and tutor support, learner-learner interaction, and feedback on performance (student support subsystem). Persistence rate was measured in terms of the percentage of assignments submitted and examinations completed, averaged per semester. Finally, achievement at Time 1 and achievement at Time 2 indicate measures of formative assessment and summative assessment, respectively.

The relationships among the variables of interest are graphically presented in a causal model or path diagram displayed in the middle section of Figure 1. As shown in the path diagram, the direct straight arrows indicate causal effects while the curved two-headed arrows imply correlation. The correlations between exogenous variables, represented by the two-headed arrows, are not given causal interpretation in path analysis. In particular, the distance education dimensions are the exogenous variables in this study. Moreover, the variable to which an arrow points is the dependent variable, and the variable from which an arrow originates is an independent variable.

The adequacy of a model built upon path analytic procedures is a function of the extent to which confidence may be placed on the model as a reflection of the relationships of the variables in the real world. In educational research practice, three criteria have stood out as indicators of the usefulness and significance of a model. These three criteria are model goodness-of-fit, predictive efficiency, and effect adequacy. They are operationally defined in this study as *adequacy* of the statistical model to the obtained data, *power* in prediction, and ability to generate *significant* association patterns among variables in the causal model, respectively. Ultimately, the procedure that indicated *better* model fit, *higher* predictive efficiency, and *more significant* association patterns among the variables of interest was determined as the more efficient and appropriate path analytic model for mixed variables.

Methods

Respondents

Respondents were taken from the roster of students enrolled during the second semester of AY 2005-2006 in the teacher education programs offered by the Faculty of Education of a state-owned distance learning institution. At the time of the completion of the study in February 2006, all respondents were actively engaged in the teaching profession, either as teachers or trainors, at all levels of the educational ladder from pre-school to college level.

Among the 250 student-respondents who were selected using simple random sampling technique, only 213 had complete data and were actually included in the study. Of these, 154 (72.3%) were females and 59 (27.7%) were males. Greater number of female respondents was observed across the five degree programs included in the study. These degree programs were the ladderized Diploma/Master of Arts in Education (major in Language Studies), Diploma in Mathematics Teaching, Diploma in Social Studies Education, Diploma in Science Teaching, and Doctor of Philosophy in Education (major in Science Education). Mean age of respondents was 36 years, with a range of 24 to 57 years. Majority of respondents belonged to the younger age groups; 77 (36.2%) were below 31 years and 54 (25.3%) were between 31 to 35 years. Fewer were older; 33 (15.5%) were between 36 to 40 years and 49 (23.0%) were above 40 years.

Research instruments

Two types of instruments were developed and used in the study, namely; Evaluation Questionnaire for Distance Education and Distance Education Achievement Test for Teachers. The *Evaluation Questionnaire for Distance Education* (EQDE) is a two-part self-administered instrument. The first part was used to collect information about the respondents' general profile. The second part contained items which describe the nine dimensions of distance education. These items were a combination of 90 positive and negative statements, on a 5-point Likert-type scale. Respondents were asked to indicate their general perceptions (i.e. degree of agreement and disagreement) on the dimensions of distance education. The *Distance Education Achievement Test for Teachers* (DEATT), on the other hand, was developed with the help of three subject matter specialists, one for each of the subject areas crucial to, or common among, the teacher education programs. These subject areas are Pedagogy (teaching principles and strategies), Educational Foundations (Educational Psychology and Philosophy, and Socio-Cultural Foundations), and Measurement and Evaluation.

The initial version of the achievement test consisted of 187 items measuring the content of the areas as presented and discussed in the course materials used by the students. Content validation of the achievement test was performed by the researcher with the assistance of a measurement expert by making sure that items matched the Tables of Specifications based on the course materials prescribed for the three subject areas. After content validation, the instrument was pilot tested to the same group used for the EQDE.

Pilot test data were used to perform both item reliability and item analyses of the achievement test. Reliability of test items was determined using the Kuder-Richardson (KR) 21' procedure, an internal consistency measure. Internal consistency of the entire test was quite high, with a reliability coefficient of 0.89. By subtest, Measurement and Evaluation was the most reliable (r=0.72), followed by Educational Foundations (r=0.70) and Pedagogy (r=0.68).

Data analysis procedure

Mean scores and standard deviations were used to describe perceptions of the EQDE items as well as persistence rate, achievement test scores, and GWA of students. The *t* test was used to examine if significant differences in achievement (test score and GWA) between male and female exist. Finally, *F* test was employed to determine significant differences in achievement across age groups and degree programs. Tukey's Honestly Significant Difference (HSD) Test was applied for significant *F* values obtained.

Persistence rate scores, achievement test scores, and GWA values were transformed to four categories each, for the application of logit regression procedure as required by this analysis. Specifically, persistence rate scores were categorized as “high”, “moderate”, “low”, and “very low”. On the other hand, achievement test scores and GWA values were categorized as “high”, “average”, “low”, and “very low”. Persistence rate and achievement test score categories were determined by dividing the persistence rate and achievement test scores of respondents into quartiles. These categories were defined as follows: a) for persistence rate, *high* (90-100%); *moderate* (77-89%); *low* (61-76%); and *very low* (26-60%); and b) for achievement test score, *high* (58-78%); *average* (50-57%); *low* (42-49%); and *very low* (27-41%). The GWA categories were determined using the generally accepted University Graduate School grading system, in which a grade of 2.0 is used as the cut-off grade between high and low academic performers. These categories were defined in this study as: *high* (below 1.50); *average* (1.50-2.00); *low* (2.01-2.50); and *very low* (above 2.50).

The major statistical procedures of the study were multiple linear regression and multinomial logit regression to derive path analytic models expressed in terms of regression functions. Three regression functions were evolved from each of the regression procedures, one function for each endogenous variable used as dependent variable in the causal model, namely, persistence rate, achievement test score, and GWA. Linear regression functions use continuous dependent variables while logit regression models use categorical dependent variables. Hence, pertinent variables were transformed into categories, as described in the previous paragraph. The same set of independent variables was used in both regression procedures. The list of variables for each regression function derived from the two procedures is summarized in Table 1.

In applying the linear regression model, *F test* of statistical significance was used as an index of *model fit* to evaluate the adequacy of the contribution of the independent variables to the model; R^2 as the measure of *predictive efficiency* to estimate the proportion of variance in the dependent variable explained by the independent variables in the regression model; and *beta coefficient* as the indicator of *effect adequacy* to explain the relative importance of the individual independent variables in predicting the dependent variable. In using the logit regression model, *Model Chi-square* statistic was used as an index of *model fit*; *pseudo-*R^2 as the measure of *predictive efficiency*; and *logit coefficient* as the estimate of *effect adequacy*. Other measures of the indicated criteria were not used.

Table 1

Measurement of variables used in the causal model

Regression Functions (RF)/ Variables	Linear Regression	Logit Regression
RF #1		
DV:		
• Persistence rate	• Continuous *(Persistence rate in %)*	• Categorical *(High, moderate, low, & very low)*
IV:		
• Dimensions of DE	• Continuous* *(Likert scale score)*	• Continuous* *(Likert scale score)*
RF #2		
DV:		
• Achievement test score	• Continuous *(Test score)*	• Categorical *(High, average, low, & very low)*
IV:		
• Dimensions of DE	• Continuous* *(Likert scale score)*	• Continuous* *(Likert scale score)*
• Persistence rate	• Continuous *(Persistence rate in %)*	• Continuous *(Persistence rate in %)*
RF #3		
DV:		
• GWA	• Continuous *(Average grade in all courses)*	• Categorical *(High, average, low, & very low)*
IV:		
• Dimensions of DE	• Continuous* *(Likert scale score)*	• Continuous* *(Likert scale score)*
• Persistence rate	• Continuous *(Persistence rate in %)*	• Continuous *(Persistence rate in %)*
• Achievement test score	• Continuous *(Test score)*	• Continuous *(Test score)*

* Note: Variables measured using attitudinal scale are commonly treated as continuous. They are, in fact, categorical (ordinal) but are assumed to have an underlying continuous distribution.

Beta coefficients for linear regression and logit coefficients for logit regression can either be positive or negative indicating the positive and negative effect, respectively of the independent variable on the dependent variable. Variables found to have significant beta and logit coefficients at alpha .05 were retained as important predictors. The causal paths or direct effects as well as indirect effects of significant predictors for linear regression and logit regression models were examined and are presented in separate fitted path diagrams for each regression model as shown in Figures 2 and 3.

Results

Dimensions of distance education

As a result of the validity and reliability analyses conducted on EQDE items, 19 items were retained in the personal circumstances subsystem, 20 in the instructional materials subsystem, and 19 in the student support subsystem. Of the three subsystems, respondents gave the most favorable rating to personal circumstances, moderately favorable rating to instructional materials, and quite favorable rating to student support (Table 2).

Table 2
Means and Standard Deviations of Ratings in the EQDE Items

Subsystems and Dimensions of Distance Education	Means	Standard Deviation
Personal Circumstances Subsystem		
• Social and work integration	3.70	0.92
• Locus of control	4.27	0.86
• Metacognition	4.02	0.85
Subsystem Average	4.00	0.89
Instructional Materials Subsystem		
• Teaching quality	4.10	0.86
• Learner-material interaction	3.84	0.96
• Workload requirements	3.15	0.93
Subsystem Average	3.70	0.91
Student Support Subsystem		
• Tutor support	3.53	1.12
• Learner-learner interaction	2.70	1.11
• Feedback on performance	3.30	1.12
Subsystem Average	3.18	1.12

Note: Score closer to “5” indicates more positive attitude

More specifically, respondents expressed highly affirmative perceptions on locus of control and metacognition dimensions. The results imply the respondents’ strong belief in their control of the various aspects of their learning situation. They were also confident of their own abilities to enable them to acquire relevant knowledge and skills that have direct application to them. Respondents also gave quite a high rating on their present circumstances as working, adult learners. This is an evidence of their competence and ability to attend to the requirements posed by work, family, and social obligations in addition to the demands of their studies.

The respondents had a positive attitude toward the teaching quality of materials and the quality of learner-material interaction. The findings suggest that distance learners generally perceived the course materials as well-designed and carefully developed to satisfy the materials’ main intent as instruments for effective instruction. Moreover, the course materials were considered user-friendly, providing a sense of "interpersonal relationship" between the learner and the material, making them good substitutes for the face-to-face interaction in the traditional classroom. However, there was a general feeling among respondents that the course materials created a heavy workload in terms of time and effort required from the students.

Distance learners expressed dissatisfaction with the lack of help obtained from fellow distance learners. However, there was a quite favorable perception of the quality of support provided by tutors. Distance learners who had a chance to interact with tutors perceived that tutors were a big help in encouraging high achievement among students, in explaining requirements and objectives of the course, and in encouraging free expression of student ideas. Finally, feedback dimension was given a nearly neutral rating, to which respondents indicated that timeliness of feedback provided by tutors and faculty-in-charge (FIC) was quite poor.

Persistence and achievement of DE students

<u>*Persistence rate*</u>

Persistence rate of distance learners was examined in terms of the percentage of assignments submitted and examinations completed, averaged per semester. Variations in persistence rate according to gender and age groups were too small to yield significant differences. On the other hand, significant differences were found across degree programs, F (4, 212) = 14.02, p = .00. High persistence rates were observed among language studies (85%), social studies (81%), and PhD students (78%), while low persistence rates were exhibited by science teaching (55%) and mathematics teaching (61%) majors. Lower variability in persistence rates was also observed among the more persistent students, namely language studies (SD = 9.6), social studies (SD = 14.3), and PhD (SD = 13.1) students. Science teaching majors significantly differed from all other students with respect to persistence rate. Homogenous subgroups formed using Tukey's HSD Analysis showed that language studies, social studies, and PhD programs clustered as one group, while science teaching and mathematics teaching programs formed another group.

Using the categories of "high", "moderate", "low", and "very low", more than 27% of the respondents had very low persistence rate. Widest dispersion (SD = 10.8) in persistence rates was also observed among the very low persistent students.

<u>*Achievement test score*</u>

Item reliability and item analyses conducted on the achievement test resulted in the retention of 125 items from the original pool of 187 items. Average score (i.e. percent correct answers) for the entire achievement test was a little more than one-half or 51 percent. The highest mean score by subject area was observed in Measurement and Evaluation (56% correct answers), followed by Pedagogy (50%) and by Educational Foundations (46%). Greatest dispersion of test scores was obtained in Measurement and

Evaluation, indicating that there was a wider spread of test scores among examinees in this subtest compared to the other two subtests.

Differences in test scores according to gender and age groups were not significant. However, analysis of variance for degree programs indicated significant differences in test scores, F (4, 212) = 3.72, p = .01, with language studies, social studies, and PhD students obtaining the highest scores. On the average, PhD students obtained 61% correct answers, followed by language studies majors with 58%, and social studies majors with 53% for the entire test. Mathematics teaching students, who had the highest variability in achievement test scores, achieved slightly lower score (58% correct answers). The poorest test performance was exhibited by science teaching majors (46%). Pairwise comparison of means using Tukey's HSD test revealed significant differences between the means of science teaching students and those of language studies and PhD students.

Achievement test scores were categorized as "high", "average", "low", and "very low". Most (28.3%) of the examinees were low scorers. The most heterogeneous group (SD = 7.6) was the high scorers while the most homogeneous group (SD = 2.0) was the *average* group.

General weighted average

The student's general weighted average or GWA was computed by averaging the student's grades in all subjects taken in at least a 4-semester period of study. On the other hand, the grade in each subject was based on student performance in tutor-marked assignments, faculty-marked assignments, and faculty-graded examinations.

GWA, a longitudinal measure of achievement was used to complement the achievement test, which is a one-time measure of achievement. GWA is considered a summative indicator of achievement since it measures student performance not only on selected courses, as what the achievement test determined, but on *all* courses completed over a period of time. The intention of having a second measure of achievement was to gain a better understanding of the nature and meaning of achievement and to find out what factors could bring about achievement, as measured in this study in two different ways.

Differences in GWA across gender and age groups were not significant. On the other hand, differences in GWA across degree programs were significant, F (4, 212) = 16.53, p = .00, with social studies, language studies, and PhD students showing higher GWAs than the rest. Social studies and language studies majors both obtained mean GWA of 1.89, followed closely by PhD students with mean GWA of 1.96. Lowest academic performance was among the majors of science teaching (M = 2.48, SD = 0.32) and mathematics teaching (M = 2.37, SD = 0.53).

These findings were similar to those found earlier for achievement test scores. Students with high achievement test scores also obtained high GWA (DLST, DSSE, and PhD); those with low achievement test scores also obtained low GWA (DMT and DST).

Wide dispersions in GWA were observed among mathematics teaching and science teaching majors just like in achievement test.

Pairwise comparison of mean GWA across degree programs using Tukey's HSD Test showed significant differences between the mean GWA of science teaching students and those of the students in the other degree programs. This is not surprising because the mean GWA of science teaching students was extremely low (*M* = 2.48) compared to those of students in other degree programs. This was further confirmed by Tukey's HSD which displayed only two homogeneous subgroups, the science teaching students and the rest.

On the basis of the "high", "average", "low", and "very low" groupings, majority (36.2%) of distance learners had low GWA. This is because the overall GWA was 2.03, which falls into the *low* category. Greatest variability in GWA (*SD* = 0.26) was observed among students with very low GWA.

Application of Linear Regression and Logit Regression as Path Analytic Models

<u>*Goodness-of-fit*</u>

All indices of model fit were significant, which indicates *adequate* fit for all regression functions for both linear and logit regression procedures (Table 3). Given the combined effects of the independent variables used in the study, both the linear regression and logit regression procedures provided good predictions of the dependent variables. Thus, both regression procedures can be used to adequately predict the actual relationships between the independent and dependent variables.

<u>*Predictive efficiency*</u>

Results revealed that in terms of *power in prediction*, logit regression procedure was more efficient compared to linear regression since there was much more variability in the dependent variables accounted for by the independent variables in the logit regression models than in the linear regression models (Table 3). The predictive efficiency measures generated by linear regression and logit regression procedures did not only explain the proportion of the variation in the dependent variable that was accounted for by the model. These measures also determined the amount of variation in the dependent variable that was *not* accounted for by the model, also called the unexplained variations or $1\text{-}R^2$.

To arrive at a more predictive efficient model, it is important that *explained* variation, i.e. the difference between unexplained variation and total variation, be as *large* a value as possible. This concept of predictive efficiency is related to the proportional reduction in error (PRE) interpretation of R^2 which is the difference between unexplained variation and total variation divided by the total variation explained by the model.

Table 3
Measures of Model Fit and Predictive Efficiency

Regression Functions	Model Fit			
	Linear Regression		*Logit Regression*	
	F	*p*	*Model* χ^2	*p*
Regression Function 1	4.19	.000	67.66	.000
Regression Function 2	9.22	.000	104.44	.000
Regression Function 3	80.06	.000	302.16	.000
	Predictive Efficiency			
Regression Function 1	0.14		0.33	
Regression Function 2	0.35		0.56	
Regression Function 3	0.84		0.93	

Notes:
Regression Function 1: Dependent Variable – Persistence rate; Independent Variables – DE dimensions
Regression Function 2: Dependent Variable – Achievement test score; Independent Variables – DE dimensions and persistence rate
Regression Function 3: Dependent Variable – GWA; Independent Variables – DE dimensions, persistence rate, and achievement test score

For instance, R^2=0.84 for linear regression function means that there was a proportional reduction of 84% in the probability of error of prediction by relying on the independent variables used in the model than by not relying on them. Similarly, pseudo R^2=0.93 for logit regression function implies that there was a proportional error reduction in prediction of as much as 93%. Thus, regression functions derived through linear regression procedure had *poorer* predictive efficiency than those derived through logit regression because of the greater unexplained variance (or lower explained variance) in these functions, which eventually led to lower indices of predictive efficiency.

Effect adequacy

In the fitted path diagram (Figure 2) for linear regression, *learner-learner interaction* and *feedback on performance* were the significant independent variables for the dependent variable persistence rate; *metacognition* and *persistence rate* for achievement test score; and *metacognition*, *teaching quality of the material*, *learner-material interaction*, *learner-learner interaction*, *persistence rate*, and *test score* for the dependent variable GWA. With regard to indirect effect, *metacognition*, for instance, has an indirect effect on *GWA* through *achievement test score*. The application of linear regression procedure produced a total of 10 significant independent variables with direct effects and six with indirect effects on the dependent variables.

It is also apparent that other independent variables affecting the dependent variables were not accounted for by the causal model. This is indicated by the path coefficients of the error components (e_s) or residual variance, which are factors not actually measured in the model but do affect the endogenous variables. Figure 2 shows that the path coefficients of error components in the linear regression model are e_1=0.93

for persistence rate, e_2=0.81 for achievement test score, and e_3=0.40 for GWA. The coefficient 0.93 means that $(0.93)^2$ or approximately 86% of the variance in persistence rate is not explained by the combined effects of the independent variables within the causal model affecting it. For achievement test score, the coefficient 0.81 suggests that $(0.81)^2$ or approximately 66% of the variance in achievement test score is not explained by the combined effects of the independent variables within the causal model affecting it. Finally, for GWA, the coefficient 0.40 suggests that $(0.40)^2$ or approximately 16% of the variance in GWA is not explained by the combined effects of the independent variables within the causal model affecting it.

For logit regression, the fitted path diagram (Figure 3) shows that *social and work integration*, *learner-material interaction*, *tutor support*, and *learner-learner interaction* were the significant independent variables for *high* persistence rate; *metacognition*, *locus of control*, *teaching quality of the materials*, *feedback on performance*, and *persistence rate* for *high* achievement test score; and *learner-material interaction, workload requirement*, *persistence rate,* and *test score* for *high* GWA. As for the indirect effect, *locus of control*, for example, has an indirect effect on *GWA* through *achievement test score.* The logit path analysis also revealed the presence of other independent variables *outside* the causal model that do affect the dependent variables. As in the linear regression path analysis, this is indicated by the path coefficients for the residual (unexplained) variance or error terms, e_1=0.82 for persistence rate, e_2=0.66 for achievement test score, and e_3=0.26 for GWA. These coefficients indicate that about 67% $(0.82)^2$ of the variance in persistence rate is not explained by the combined effects of the independent variables within the causal model, about 44% $(0.66)^2$ in achievement test score, and only about 7% $(0.26)^2$ in GWA.

It is also interesting to note that of the independent variables in the three logit regression functions, *learner-material interaction* and *learner-learner interaction* were the strongest predictors of high persistence rate, *metacognition* and *teaching quality of the materials* of high test score, and *learner-material interaction* and *workload requirement* of high GWA. These results showed instructional material as a very important factor in predicting *high* achievement in distance education. This relates to an earlier finding showing instructional material as providing the basic foundation in distance learning, being a substitute for the traditional classroom interaction that takes place between the student and teacher and having been designed primarily to "do the teaching itself" (Moore & Kearsley, 1996).

The application of logit regression procedure generated a total of 13 variables with direct effects and 13 with indirect effects on the dependent variables. The findings also reveal that the logit regression procedure captured all the exogenous, independent variables within the causal model, thus contributing to the significant prediction of the three dependent variables, both in direct and indirect manner. Hence, with regard to *affect adequacy criterion*, the logit regression model is more efficient than the linear regression model.

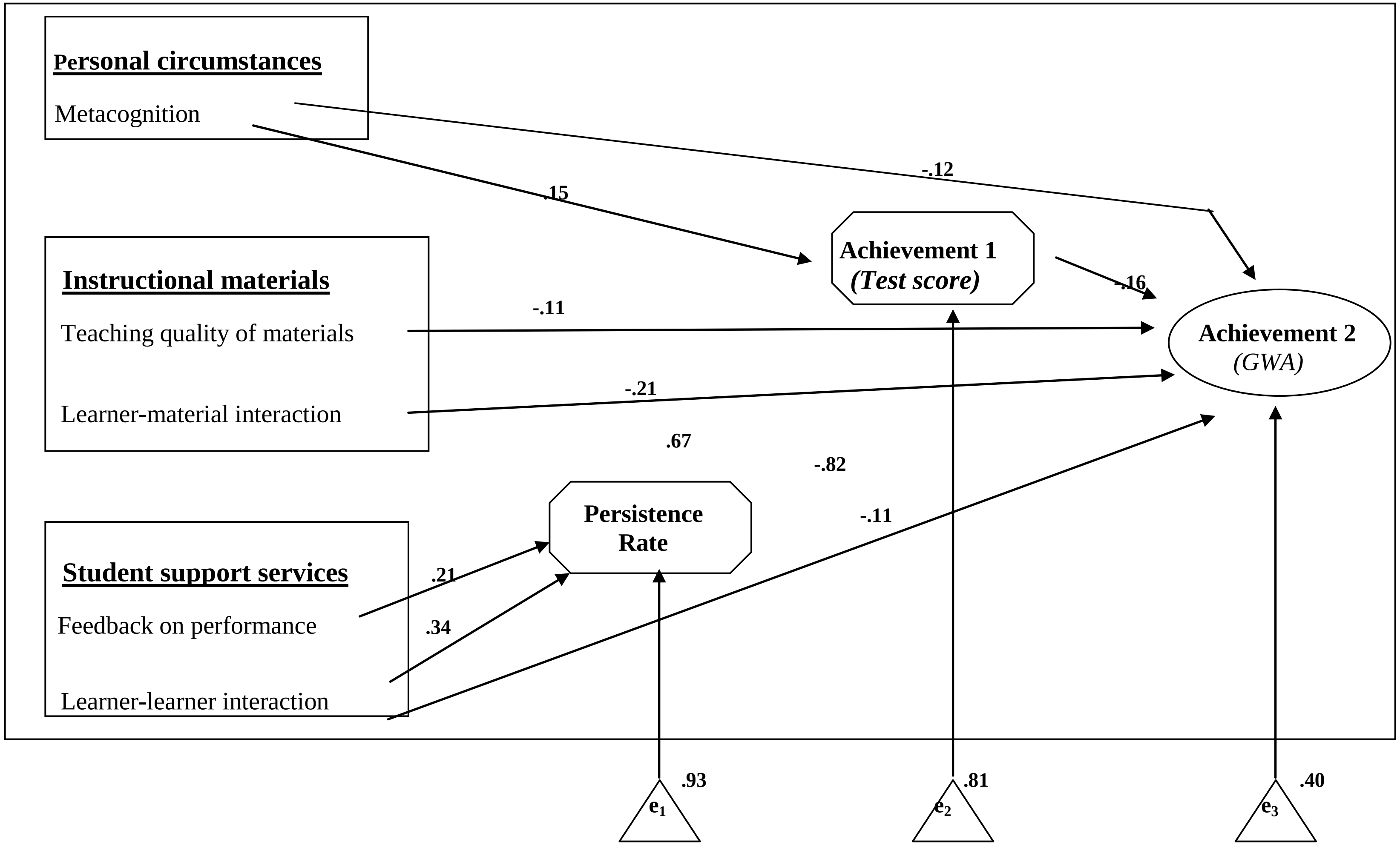

Figure 2
Fitted Path Diagram Showing Significant Paths Using Linear Regression

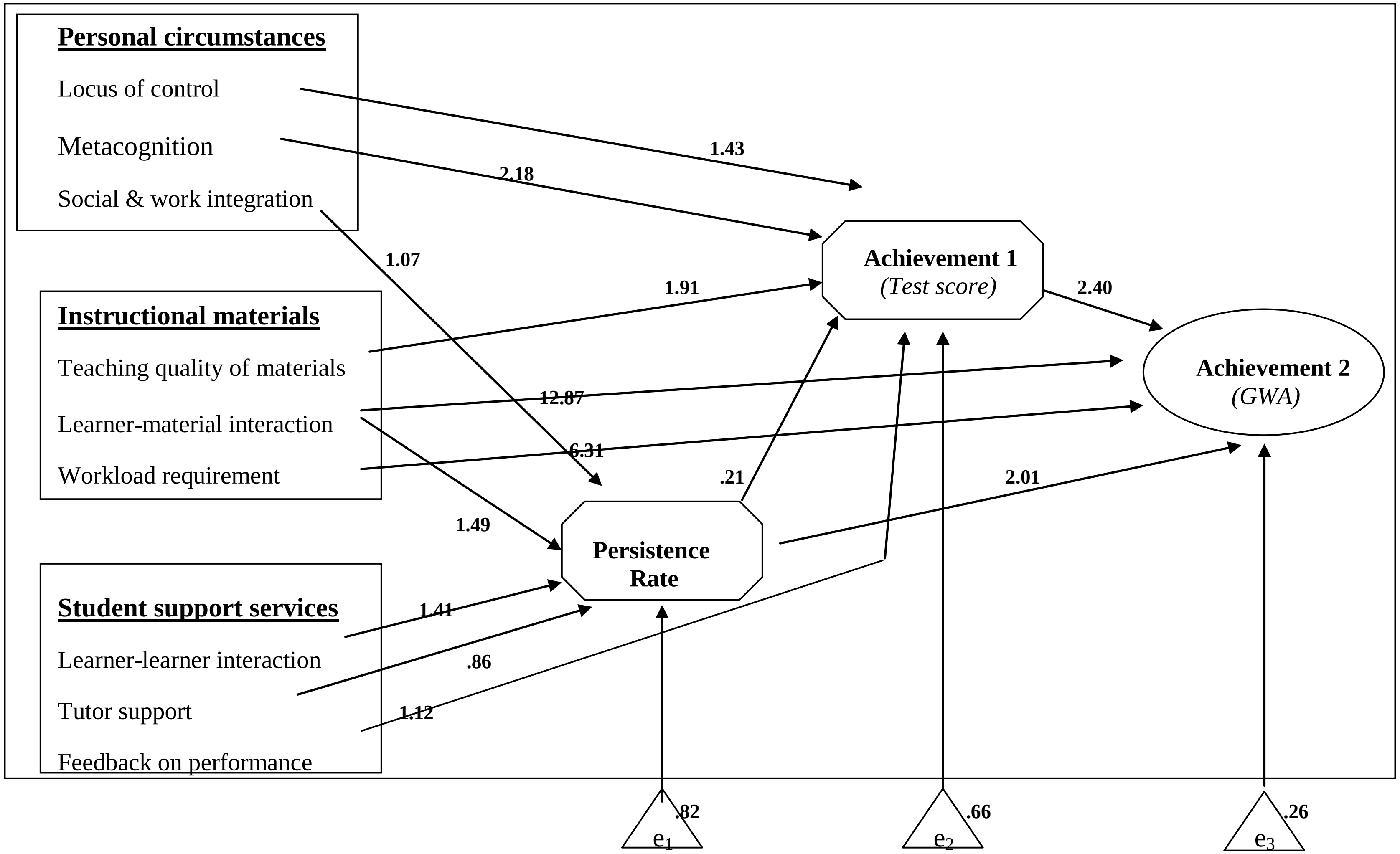

Figure 3
Fitted Path Diagram Showing Significant Paths Using
Logit Regression

Conclusion, implications, and recommendations

All indices of *model fit* for linear and logit regression procedures yielded significantly *good fit* to the data for all regression functions examined, indicating that *both* regression models can adequately predict the actual relationships between the independent and dependent variables. With regard to *power in prediction*, logit regression was the more superior model compared to linear regression since regression models derived through logit procedure accounted for the greater variation in the dependent variables than those derived through linear regression procedure. As for *effect adequacy*, logit regression procedure was more efficient than linear regression procedure given the fact that logit procedure generated greater number of significant association patterns among the variables in the causal model and allowed more statistically significant independent variables to enter the regression model compared to linear regression procedure. Based on the three criteria of goodness-of-fit, predictive efficiency, and effect adequacy, there is sufficient evidence to support the research hypothesis of this study that logit regression is a better path analytic procedure compared to linear regression in explaining underlying causal relationships of *mixed* variables or variables measured at varying levels of measurement. Although there is no difference between the two procedures in terms of model fit, logit regression procedure has greater predictive power than linear regression, has produced more significant association patterns among independent and dependent variables in the causal model and has indicated greater reduction in prediction error.

Logit regression procedure has an excellent application in educational research and practice where numerical values of continuous quantitative variables are often converted to categories. For example, student performance is usually measured in quantitative terms such as test score but teachers transform these to qualitative categories such as “high”, “average’, and “low”. There is hardly any meaningful distinction made between a grade of 89 and 90, for instance, except if 89 is “average” achievement and 90 is “high” achievement. In actual practice then, academic performance and achievement while measured as continuous variables are more meaningfully described and reported in terms of distinct categories.

Similarly, the reliability and criterion validity of a test are determined using quantitative procedures that yield coefficients that range from 0 to 1.0. However, psychometric measurement experts, for instance, do not make minute numerical distinction between two different tests that may have reliability coefficients of say, 0.85 and 0.87. To convey meaning to readers, these numerical coefficients are transformed into meaningful categories such as “high”, “moderate”, and “low” reliability. Such categorical descriptions are thus used to indicate the worth and effectiveness of the test.

In actual practice, the quantification of variables is a good way of making the measurement of variables objective and unbiased. However, these numerical distinctions become more useful if meanings, such as categorical descriptions are attached to them. This then makes qualitative interpretations of variables necessary and essential to quantitative measures.

The study also has important implications to distance education. While there are a number of significant predictors of achievement from the nine dimensions identified, metacognition, learner-material interaction, and learner-learner interaction appear to have the greatest influence on achievement in distance education. With regard to metacognition, distance learning institutions can administer psychological tests to obtain students' psychological profile, which may include aspects like readiness to distance mode of study, learning style, and work habits. The results of these psychological tests can be used in designing specific student intervention programs that capitalize on the strengths of the students while addressing their weaknesses.

As to learner-material interaction, distance learning institutions should ensure that the contents of the distance learning materials are more user-friendly, easy to comprehend, and less burdensome in terms of allowing the learners to extract the necessary information from the materials. A regular post-course assessment should be instituted to determine the general perception of the students on the volume, difficulty level, and pacing of academic work as presented in the course material. All these could provide effective quality education without defeating the purpose of learning through distance education.

As for learner-learner interaction, distance learning institutions should determine the feelings of isolation experienced by distance learners and address them appropriately. Students in this study have expressed the minimal support from tutors and the lack of support from fellow learners. The implementation of online delivery of courses could have contributed to the feeling of isolation among students. Distance learning institutions may have to supplement this technological innovation with occasional group meetings between faculty and students and among students themselves.

References

Agresti, A. (1990). *Categorical data analysis*. New York: John Wiley & Sons.

Bradley, W.J. & Schaefer, J.C. (1998). *The uses and misuses of data and models: The mathematization of the human sciences.* London: Sage Publications.

Demaris, A. (1992). *Logit modeling: Practical applications*. Quantitative Applications in the Social Sciences. Series no. 07-086. Newbury Park, California: Sage Publications.

Eshima, N. & Tabata, M. (1999). Effect analysis in loglinear model approach to path analysis of categorical variables. *Behaviormetrika,* 26(2), 221-233.

Goodman, L.A. (1973). The analysis of multi-contingency tables when some variables are posterior to others: A modified path analysis approach. *Biometrika*, 60, 179-192.

Hagenaars, J.A. (1993). *Loglinear models with latent variables*. Quantitative Applications in the Social Sciences. Series no. 07-095. Newbury Park: Sage Publications.

Keeves, J.P. (1988). Path analysis. In J.P. Keeves (Ed.), *Educational research, methodology and measurement. An international handbook* (pp. 723-730). New York: Pergamon Press.

Knoke, D. & Burke, P.J. (1988). *Loglinear models.* Quantitative Applications in the Social Sciences. Series no. 07-020. Newbury Park, California: Sage Publications.
Moore, M. G. & Kearsley, G. (1996). *Distance education: A systems view*. Belmont, California: Wadsworth Publishing.
Pedhazur, E.J. (1997). *Multiple regression in behavioral research* (3rd ed.). Fort Worth, Texas: Harcourt College Publishers.

Date received: June 2008

Maria Ana T. Quimbo is associate professor at the Institute of Community Education, College of Public Affairs, University of the Philippines, Los Baños. She is also college graduate programs coordinator in the same institution.