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Information Economy and Educational Opportunities: A Latent Variable Model of Learning Skills

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***Abstract* - As internet economic forces are transforming traditional companies and jobs, colleges are attempting to foster in their students transferable skills that will improve their chances in the digital workplace, where employers look for potential employees not only possessing technical expertise, but who are also capable of and personally responsible for continually refreshing their knowledge base to keep pace with rapid technical change. In this paper a latent variable model is constructed to analyze the direct and indirect relationships between learning skills, educational performance, collaboration, family environment and personal stress of sophomores in applied informatics, economic and business sciences. While the obtained maximum likelihood estimates show significant dependencies between collaboration and learning, they strongly reveal a non-skill oriented educational system. It seems to reward lack of learning skills with success. This work underlines an urgent need to reform the curricula and the fundamental teaching and grading methodologies.**

Index Terms - Educational performance, Latent Variable Modeling, Learning skills

INTRODUCTION

In today's information society, professionals face demanding requirements. Increasing use of information technology, the growing proportion of knowledge intensive work and a new organization of work, based on networks and teams, have extended the range of abilities needed. What employers expect of their employees is not only a strong grasp of relevant knowledge, but diversified social, communication and cooperation skills, ability to critically select, acquire, and use knowledge. A characteristic of today's working life is rapid change. Experts are required to continuously construct and reconstruct their expertise in a process of lifelong learning. These requirements pose considerable challenges to educational systems, which are expected to produce not only academic intellectuals and researchers but also experts for working life of the future.

It has been suggested [1] that the general purposes of higher education include:

- Providing a general educational experience of intrinsic worth in its own right,
- Preparing students to produce, apply and disseminate knowledge,
- Preparing students for a specific profession, and
- Preparing students for general employment.

It can be said that general educational experience includes the development of critical thinking skills and the ability to think conceptually. Production, application and dissemination of knowledge require deep understanding of the subject matter, its methodology and training to produce new knowledge. Preparation for a specific profession requires acquisition of theoretical and practical knowledge before professional skills can be acquired. Preparing students for general employment involves practical experiences and competencies to learn and reflect, equipping them with essential skills to enable them to continue learning and sourcing relevant information on their own or in collaboration throughout their working lives. It also involves the development of communication skills like oral presentation and report writing, as well as the use of foreign languages.

Although these types of skills are widely recognized as aims of higher education in today's digital era, inertia is not a phenomenon to which academic institutions are immune. Universities have not kept pace with the current demand for these prerequisites of professional expertise [2]-[4]. It has been noted that in traditional forms of university instruction students often acquire inert knowledge [5]. Such knowledge cannot be useful in today's digital economy because it cannot be transferred into complex problem solving of working life.

The main purpose of this paper is to investigate the relationship between learning skills, collaboration, personal stress, family psychological support and educational performance. To achieve this purpose, a latent variable model is constructed, identified and estimated. The empirical application of the model is based on the databank DATED [6], which contains 300 variables, mainly on motivation, learning skills, socio-economic factors, score achievements and self-assessment of sophomores.

The maximum likelihood estimates of the model reveal a non-skill oriented educational system. It can be argued that the system as it stands is designed to produce consumers of professional services rather than professionals, or, instead of producing experts, this system produces a host of consumers of expertise [3].

The paper is structured in five sections. The next section develops a theoretical learning-skill model. The third section discusses the data used. The fourth section includes the

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empirical application and the last section discusses the results and concludes the paper.

THE THEORETICAL LEARNING-SKILL MODEL

Latent Variable Modeling (LVM) has been used in social sciences and economics to resolve successfully the problem of statistical and econometric analysis of phenomena, which cannot be accurately expressed in a quantitative dimension only [7]. The LVM approach has been developed mainly by Joreskog and Sorbom [8], Hayduk [9] and Bollen [10], and further discussed and extended by these and other scientists and researchers. LVM uses the analysis of variance-covariance to study the complex path structure of direct and indirect interdependencies of observed factors and their influence on the latent phenomena under investigation.

LVM is based on the following three-fold postulation:

1. Formulation of the hypothesis to be investigated as a causal structure among a set of latent variables.
2. Detection of a set of observed factor-variables, which can be used as proxies of the latent variables. Such observed variables are called indicator variables.
3. Specification of the latent variables as functional combinations of the indicator-variables and measurement errors in a causal chain of observed and non-observed variables.

The general form of the model includes the following three matrix equations:

$$\eta = B\eta + \Gamma\xi + \zeta \quad (1)$$

$$y = \Lambda_y \eta + \varepsilon \quad (2)$$

$$x = \Lambda_x \xi + \delta \quad (3)$$

η and ξ are random vectors of latent dependent and independent variables, respectively, B and Γ are coefficient matrices, and ζ is a random vector of disturbance terms. The elements of B represent direct causal effects of η-variables on other η-variables and the elements of Γ represent direct causal effects of ξ-variables on η-variables. The vectors η and ξ are not observed but instead vectors y and x are observed, such that the two measurement models represented by (2) and (3) hold. Λ_y and Λ_x are coefficient matrices, and ε and δ are vectors of errors of measurement in y and x, respectively.

The observed vectors y and x contain indicator variables for the unobserved or latent variables η and ξ, respectively. The latent variables correspond to theoretical constructs or variables measured correctly. For this reason, they may be called "true" variables. The structural equation model represented by (1) specifies the causal relationship between the "true" or latent variables η and ξ. The measurement models represented by (2) and (3) specify how the latent variables, or hypothetical constructs η and ξ, are measured in terms of the observed variables y and x, respectively. It is emphasized that ζ in (1) is a vector of classical disturbances, including all random discrepancies that emerge between the actual values of η and the values that would be obtained by the corresponding exact or, in the case of no disturbances, stable functional relationship. Such random discrepancies may be accounted for by the omission of variables from the model, or to some "intrinsic" randomness in elements of vector η, which cannot be explained anyway, or to any other non-systematic influence on vector η, which cannot be captured by the right-hand part of (1) no matter how elaborate it is. What ζ does not include is measurement errors, which are instead cast into the vectors ε and δ in (2) and (3). For the model (1)-(3) the following classical assumptions are made:

a. The error terms ζ, ε and δ have zero mean values. ζ is uncorrelated with the vectors ξ and η. ε and δ are uncorrelated with the corresponding vectors η and ξ, respectively.
b. The matrix B has zeroes in the diagonal, and
c. The matrix *(I-B)* is non-singular.

Assumptions (a) ensure that (1)-(3) are well specified including all the important determinants of the dependent variables. Regarding assumption (b), the elements of matrix B are assumed not to depend on themselves. Assumption (c) is required for estimation purposes, i.e. the inverse of matrix $(I-B)$ or $(I-B)^{-1}$ must exist.

Following the LVM methodology, the theoretical learning-skill model can be formulated as follows:

$$\begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix} = \begin{bmatrix} \beta_1 & \beta_2 \\ \beta_3 & \beta_4 \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix} + \begin{bmatrix} \gamma_1 & \gamma_2 & \gamma_3 \\ \gamma_4 & \gamma_5 & \gamma_6 \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \end{bmatrix} \quad (4)$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix} = \begin{bmatrix} \lambda_1 & \lambda_2 \\ \lambda_3 & \lambda_4 \\ \lambda_5 & \lambda_6 \\ \lambda_7 & \lambda_8 \\ \lambda_9 & \lambda_{10} \\ \lambda_{11} & \lambda_{12} \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{bmatrix} \quad (5)$$

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} \lambda_{13} & \lambda_{14} & \lambda_{15} \\ \lambda_{16} & \lambda_{17} & \lambda_{18} \\ \lambda_{19} & \lambda_{20} & \lambda_{21} \\ \lambda_{22} & \lambda_{23} & \lambda_{24} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \end{bmatrix} \quad (6)$$

Variables y_1-y_2 represent two indicators of educational performance and variables y_3-y_6 represent four indicators of learning skills. Variables x_1-x_4 represent indicators for collaboration, family psychological support and personal stress. The next section discusses the data used.

THE DATA

The empirical investigation is based on the authors' Databank on Education DATED [6], which contains data mainly from the authors' statistical surveys and additional information as well. The data used in this paper refer to the University of Macedonia. A sample of 50 students was selected by random stratification of the sophomore population of all eight Departments. The sample covers the 3.6% of the population and has the same balance of the sexes as the whole year's student intake. The survey lasted three weeks in October 2002. Students were invited to a meeting and the purpose of the survey was explained to them. Several meetings followed where confidentiality issues and the questionnaire were presented and discussed. Finally, in the last meeting the selected students completed the questionnaire.

The purpose of the survey was the introduction of a learning skill program within a planned major educational reform promoted by the European Union. The students were very enthusiastic and responded favorably paying the appropriate attention to the completion of the questionnaire, which was structured in 11 major sections with closed and open questions. The sections included were the following:

- General personal and family details
- Motivation (13 questions)
- Effectiveness of lectures (4 questions)
- Committing information from lectures to long-term memory (7 questions)
- Effective use of books and journals (5 questions)
- Book reading strategy (7 questions)
- Committing information from books and journals to long-term memory (5 questions)
- Writing skills (8 questions)
- Oral skills (5 questions)
- Use of English (10 questions)
- Comments and opinions 7 open questions)

It is noted that all above sections include questions on collaboration and personal stress. Achievement scores and success factors were also collected from the secretariats of each Department for all sampled students individually.

The completed questionnaires were used to construct indicator variables for learning skills, collaboration, stress, and family support. These indicator variables are used to estimate the empirical model.

THE EMPIRICAL MODEL

The empirical model is presented in the following path diagram.

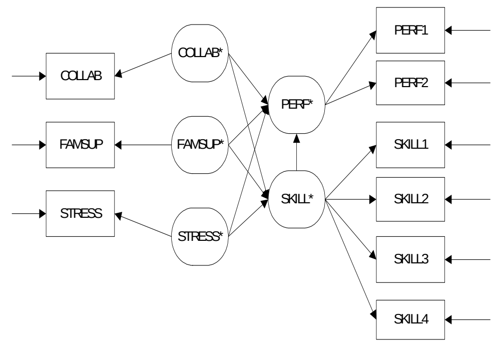

FIGURE 1
PATH DIAGRAM OF THE EMPIRICAL MODEL

Conceptual variables, denoted by a star, are pictured as circular shapes and observed variables are represented by rectangles. COLLAB denotes collaboration, FAMSUP denotes family support, PERF1 and PERF2 are two indicators of educational performance, and SKILL1-SKILL4 denote four different areas of learning skills. PERF* denotes the conceptual variable of educational performance. PERF* is represented by the two indicator-variables PERF1 and PERF2, which are two indexes constructed by the authors in order to express the measured educational achievements. SKILL* is also a conceptual variable represented by the four indicator-variables, SKILL1-SKILL4, which are four indexes constructed by the authors to express measured skills in four different learning areas. The data used for the index compilation are included in the databank DATED. The above model can be written in the following matrix form.

$$\begin{bmatrix} PERF* \\ SKILL* \end{bmatrix} = \begin{bmatrix} 0 & \beta_1 \\ \beta_2 & 0 \end{bmatrix} \begin{bmatrix} PERF* \\ SKILL* \end{bmatrix} + \begin{bmatrix} \gamma_1 & \gamma_2 & \gamma_3 \\ \gamma_4 & \gamma_5 & \gamma_6 \end{bmatrix} \begin{bmatrix} COLLAB* \\ FAMSUP* \\ STRESS* \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \end{bmatrix} \tag{7}$$

$$\begin{bmatrix} PERF1 \\ PERF2 \\ SKILL1 \\ SKILL2 \\ SKILL3 \\ SKILL4 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \lambda_1 & 0 \\ 0 & \lambda_2 \\ 0 & \lambda_3 \\ 0 & \lambda_4 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} PERF* \\ SKILL* \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{bmatrix} \tag{8}$$

$$\begin{bmatrix} COLLAB \\ FAMSUP \\ STRESS \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} COLLAB* \\ FAMSUP* \\ STRESS* \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \tag{9}$$

The empirical model (7)-(9) is overidentified. It has 45 moments and 25 free parameters to be estimated. These are the two β's, the six γ's, the four λ's, the variances of the error terms and the variance-covariance matrix of the exogenous indicator variables COLLAB, FAMSUP and STRESS. The model (7)-(9) is estimated by using the LISREL software

[11]. The following table shows the maximum likelihood estimates of the model.

TABLE I
MAXIMUM LIKELIHOOD ESTIMATES OF MODEL (7)-(9)

Parameter	Estimate	T-value
β_1	-16.458	-3.93
β_2	-0.018	-3.64
γ_1	45.493	2.95
γ_2	6.031	0.54
γ_3	5.119	2.16
γ_4	2.244	4.30
γ_5	0.482	1.08
γ_6	0.186	2.02
λ_1	0.023	2.79
λ_2	0.612	10.32
λ_3	0.358	3.49
λ_4	0.306	3.39
χ^2	18.14, degrees of freedom=20	
R^2	0.8863	

As Table I shows, the fit of the model is satisfactory as can be seen from the chi-square statistic, as well as from the coefficient of multiple determination of the whole system of equations. Moreover, the estimated variance-covariance matrix of the exogenous indicator-variables is very close to the observed variances and covariances, giving an additional indication of the good fit of the model as a whole.

As Table I also shows, family support has an insignificant effect on both performance and skill development. The relationship between skills and educational performance is negative and significant. Moreover, a collaborative environment has a significant and positive direct influence on performance and skill development. Similarly, personal stress affects performance and skill development significantly. However, the estimated total (direct and indirect) effects of collaboration, family support and stress on performance and skill development show a marked difference. The following tables present the estimated total effects with the corresponding t-values in parentheses.

TABLE II
ESTIMATED TOTAL EFFECTS OF KSI ON ETA

	COLLAB*	FAMSUP*	STRESS
PERF*	8.5596 (0.59)	-1.9018 (-0.148)	2.0659 (0.79)
SKILL*	2.2441 (4.30)	0.4820 (1.08)	0.1855 (2.02)

TABLE III
ESTIMATED TOTAL EFFECTS OF ETA ON ETA

	PERF*	SKILL*
PERF*	---	-16.4580 (-3.93)
SKILL*	-0.0178 (-3.64)	---

As the above tables show, the estimated total effects of collaboration, family support and personal stress on educational performance are insignificant, while collaboration and stress affect the estimated total effect of skill development significantly. At the same time, the estimated total relationship between skill development and educational performance is significant and negative. The implications of these estimates will be discussed in the next final section.

CONCLUDING REMARKS

The main findings of this paper can be summarized as follows:

- Skill development and educational performance are related negatively.
- Collaboration and stress affect skill development, but they do not affect educational performance.

These findings may be explained by a sequel questionnaire to explore the effects of Greece's educational system on the working lives of her young generations. Education has traditionally been, and continues to be, characterized by a passive learning process, where students are almost "forced" to absorb enormous quantities of new knowledge without critical thinking. Parents are anxious to "give" a university degree to their children, it being a pre-requisite for a position in the public sector. Thereafter, a pervasive clientalism continues to stifle all attempts, mainly EU inspired, to introduce meritocracy. While this remains the case students are persuaded that learning skills acquisition has little to do with entry into, or advancement in, the public sector. Our findings show that the present university regime enables good grades to be achieved, by last minute cramming for example, without the acquisition of learning skills. Steps are being taken to validate the existing questionnaire by applying it to students in a university in a completely different culture, and then to evolve means to elicit corroboration or otherwise of the assertions made in this paper.

The result of such a mentality is that students with intelligence above average may not care to struggle to acquire learning skills, which are not taught at the university or have not been taught at any previous school. Given that student evaluation and assessment is generally based only on the exams at the end of the semester, these students have the ability to obtain high educational achievements in terms of scores by preparing for the exams just one or two weeks ahead. The rest of less fortunate of them have to struggle to acquire some learning skills, like keeping, organizing and elaborating notes from lectures, learning how to keep in memory what they read in a book or a paper in a journal, learning how to write a report better and so on, in order to achieve higher grades, which is the ultimate purpose of their university education. In fact, student assessment based solely on examinations has been argued to function as a serious obstacle to obtaining deep personal understanding [12]-[14].

This situation is clearly depicted in this research: learning skills and educational performance are negatively and significantly related. Collaboration is positively and significantly related to skill development, but not to educational performance. Similarly, stress exists only for those students who try to develop learning skills, but still, on average the fortunate rest who are naturally more endowed may get the higher grades even if they have not tried so much as the less fortunate students. Such an educational system could be appropriately summarized as a "non-skill oriented education".

On the basis of these results, a reform program is under preparation recommending changes to the educational learning process and adjustments to Greece’s educational system to the demands of the digital labor market. This program, which will not be discussed here, will have a pilot application phase next semester.

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