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Analysis of Emerging Barriers for e-Learning Models: An Empirical Study

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Abstract:

The diffusion of the e-learning model during the last decade has contributed to solve many problems concerned with education at the workplace. Technological progress has significantly contributed to eliminating most limitations of the traditional education model, through improved access, diffusion of information, and the adaptation to individual needs. However, e-learning is an instrument, which does not ensure the automatic achievement of intended goals. Some studies have demonstrated that the mere conversion of course materials into an e-learning course may reduce motivation and thus, the level of effective learning.

In addition, appropriate design of course materials for e-learning programs might not be sufficient to achieve optimal results. In order to maximize the benefits of implementing an e-learning program, it is if fact necessary to take into account organizational issues, such as the existence of incentives, the distribution of time for learning at the workplace, or the management system being used, for example. This paper analyzes some organizational features, which are linked to learning in organizations and might help to better explain success of an e-learning program. In particular, we attempt to assess the impact of both incentives and the assignment of a specific period of time for education to personal satisfaction and the level of learning. To this end, we proposed a specific survey to users of e-learning courses at a consulting company, which includes questions about satisfaction, self-assessed learning and monetary or long-term (career) incentives, among others. The impact of different organizational characteristics on satisfaction and learning has been then estimated by a bivariate ordered probit model, which allows for considering both the nature of dependent variables and the possible correlation between equations.

The analysis sheds light on key practical organizational features, which should be taken into account in order to improving results of e-learning programs
The main goal of this analysis has been to provide evidences to support policies aimed to increase effectiveness of e-learning models. We have based on the e-learning experience of a consulting company, evaluating the effectiveness of this new model in terms of two variables: learning perceived and level of satisfaction of participants.

In order to analyze the determinants of both learning and satisfaction, we collected data from participants of e-learning programs. We found out that self-assessed satisfaction and perceived learning are likely to be affected by the same set of variables. On considering these relationships, and the nature of available data, both a simultaneous bivariate ordered probit model and a simultaneous bivariate probit model have been used in order to assess the impact of different factors on both satisfaction and perceived learning.

JEL Classification: A2
Key words: training and workforce, e-learning, human resources strategy.

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1. Introduction

The application of latest advancement in Information Technology to business education has contributed to fulfill most wishes of education managers. The demand for continuing education programs with top specialists, the costs of mobility, the fragmentation of learning time due to inopportune meetings, among other difficulties, seem to have came upon a solution with the so called e-learning model (Box, 1999; Kirby, 1999;Bose, 2003).

Technological improvement and the design of high-capacity networks for sharing data have allowed for solving most of the limitations of the traditional learning methodology, by facilitating both access to information and the adaptation of programs to individual needs. However, earlier applications of e-learning have shown that those technological tools do not automatically guarantee high levels of learning (Snyder et al., 2000; Ettinger et al., 2006, Fernández Díez de Lastra, R., 2001). Moreover, Ettinger et al. (2006) demonstrate that the mere act of uploading materials of traditional courses to a software platform may reduce motivation and, thus, learning outcomes. Discussion about these problems has generated a second wave of development of e-learning models (Servage, 2005). Due to the different approach to learning under the new model, it has been argued that e-learning needs a different pedagogical system (Roy, 2006). As a consequence, a number of firms, focused on the management of educational contents for e-learning, have born during the last decade. Those firms offer teams of experts in pedagogy, scriptwriters and technicians, who work for creating personalized educational paths and taking advantage of all possibilities of software platforms for enhancing learning. In addition, the development of e-learning educational materials has actually generated an increasing demand for standard rules to facilitate the compatibility of contents and software platforms (Singh and reed, 2002; Orbea, 2008).

Disposing of both advanced technological instruments and adapted learning programs however, does not guarantee the optimal management of e-learning within firms (Ettinger et al., 2006; Galagan, 2002; Netteland et al., 2007). In fact, it is necessary to consider where, when and how learning programs take place, to identify the possible difficulties, and how the firm should manage learning through a software platform (Zhand and Jasimuddin, 2008; Rahmandad et al., 2009). Learning by using the new training model requires self-motivation and self-management, and it demands both cultural and organizational changes (Redmon and Salopek, 2000; Tynjäla and Häkkinen, 2005; McPherson et al., 2005; Ettinger et al., 2005; Davis and Wong, 2007). Hence, organizations must strategically define what the main objective of e-learning is, and what they should do in order to achieve their goals.

The rest of the paper is organized as follows. Section 2 describes the main objective and the methodology used in the analysis. Section 3 presents data, descriptive statistics, and the model that will be estimated. Section 4 discussed main results, and the last section summarizes conclusions.

2. Main goal and methodology

The aim of this paper is to assess the impact of different organizational factors on the success of e-learning programs, in terms of both self-reported satisfaction and the level of learning. Hence, this study adds to the analysis of the efficacy of e-learning models from an organizational perspective by providing some useful insights, which may help to improve decision-making related to employee's continuing education and satisfaction.

To this end, the case of EVERIS, one of the first firms that introduced e-learning as the standard methodology for its employees, has been studied. From a methodological point of view, the analysis can be divided into two parts. Firstly, both directors and users of e-learning programs at EVERIS have been surveyed. The survey included questions about personal satisfaction, level of learning, and relevant organizational factors such as the existence of incentives, the preference for e-learning compared to the traditional system, and users' capacity to use the technological platform (variables are fully described in the next section).

In order to assess the impact of the explicative variables on satisfaction and learning, we estimated a bivariate ordered probit model, which is specified by seemingly unrelated equations. The main reason for using this methodology is the potential existence of an indirect relationship between satisfaction and learning, which might cause biased results when two different ordered probit models are considered, one for satisfaction and the other for the level of learning. There is a growing empirical literature which makes use of bivariate probit models. Greene and Hanser (2009) cite more than 20 different papers applying this methodology from 1997 to 2007, though first applications are due to Calhoun (1989, 1991, and 1994).

More recently, Dawson and Dobson (2010), for instance, use bivariate probit models in order to assess the impact of social pressure and nationality of referees on the probability of awarding yellow and red card to European football players of home teams. The methodology used here is the same used in these papers and, explicitly, we have followed Sajaia (2008) for its implementation in Stata©.

3. Development of the analysis

3.1. Previous overview

As starting point of the framework, we analyzed both strategic and organizational factors that have driven a firm such as EVERIS to choose an e-learning model. To this end, we discussed the reasons for the implementation of e-learning with directors of EVERIS, who helped them to a better understanding of the relevant variables.

As a multinational consulting firm, EVERIS offers solutions for business strategy, development and maintenance of technological appliances. The growth of the number of employees (from 3300 persons in 2004 to 7400 in 2009), as well as the increased volume of projects and its differentiation, justified in 2006 the strategic decision of adopting e-learning for continuing education at EVERIS. On evaluating this choice, the board of directors analyzed the need for aligning with new tendencies of professional education, and they also underlined both the possibility of offering a larger number of courses, and the opportunity for cost-reduction.

In particular, two main goals emerged as reasons for the change toward an e-learning model: enlarging the offer of educational programs, and innovating through alternative models of learning. Provided that one value of EVERIS is the building of a learning software platform for continuing education for its employees, these goals were perfectly aligned with their business strategy.

In order to carry out the implementation, departments of Marketing, People and Human Resources worked together and, under the direction of their Corporate University, they evaluated open-source applications for collaborative learning. The adoption of e-learning was thus an internal process of the organization, and it took about six months.

Employees at EVERIS are characterized by higher qualified and technical skills than other professionals, which allowed the firm for not investing in their capacity to use the learning platform. It should be noted that this is one of the main investment limitations in other organizations.

The management of the e-learning model in this firm involves the development of a supply of courses, which reflect the professional needs of employees and makes use, to this end, of specific personal mapping for professional development. Each personal map consists of mandatory courses, recommended programs, and other optional courses depending on both personal preferences and job skills. This educational system aims to achieve the goal of 40 hours of education per employee and year, by investing about 10 millions of euros yearly.
Nowadays, the learning model of this company takes the form of "blended-learning", combining lectures and online courses available at EVERCAMPUS.

Though the firm did not design an explicit incentive scheme, the monetary value of grades achieved by EVERCAMPUS is published and communicated to employees, thus underlining their direct value in terms of employability or market value of professionals.

3.2. Model description

The main objective of this paper is to assess the impact of different key organizational factors on the levels of both satisfaction and learning related to the e-learning model. At this point, firstly, it should be observed that this study makes use of categorical dependent variables, which constraint the possibility of specification of the model. It is assumed here that the same set of variables might have an effect on both satisfaction and learning, as in

$$SAL_i = f(x_i), \quad [1]$$

$$SAS_i = g(x_i). \quad [2]$$

SAL (Self-Assessed Learning) represents the level of learning and SAS (Self-Assessed Satisfaction) the level of satisfaction. Neither the level of learning nor the level of satisfaction are directly observable from answers to survey questions; hence, following Greene and Hensher (2008), we assume that latent variables SAL_i^* and SAS_i^* depend on

$$SAL_i^* = x_1^{'}\beta_1 + \varepsilon_{Ai}, \qquad [3]$$
$$SAS_i^* = x_1^{'}\beta_2 + \varepsilon_{Si}, \qquad [4]$$

where β_1 and β_2 are vectors of unknown parameters, ε_A and ε_S are error terms, and x1 is the vector of explicative variables. Explicative variables are, by assumption, exogenous; that is, E[$x_1^{'}\ \varepsilon_{Ai}$]=0, E[$x_1^{'}\ \varepsilon_{Si}$]=0. Provided that the specification proposed by [3] and [4], which represent seemingly unrelated equations, does not imply any identification problem, we can use the same set of explicative variables. In fact, there are not any theoretical reasons to exclude some variable from one particular equation. We can observe in our database the values of the categorical variables SAL_i and SAS_i such that

$$SAL_i = \begin{cases} 1 \text{ si } SAL_i^* \le c_{A1} \\ 2 \text{ si } c_{A1} < SAL_i^* \le c_{A2} \\ 3 \text{ si } c_{A2} < SAL_i^* \le c_{A3} \\ 4 \text{ si } c_{A3} < SAL_i^* \le c_{A4} \\ 5 \text{ si } c_{A4} < SAL_i^* \end{cases} ; \quad SAS_i = \begin{cases} 1 \text{ si } SAS_i^* \le c_{S1} \\ 2 \text{ si } c_{S1} < SAS_i^* \le c_{S2} \\ 3 \text{ si } c_{S2} < SAS_i^* \le c_{S3} \\ 4 \text{ si } c_{S3} < SAS_i^* \le c_{S4} \\ 5 \text{ si } c_{S4} < SAS_i^* \end{cases}, \qquad [5]$$

where $c_{j1} < c_{j1} < c_{j1} < c_{j1} < c_{j1},\ j = SAL, SAS$. The probability of being SAL_i =k and SAS_i =1 is

$$\Pr(SAL_i = k, SAS_i = l) = \Pr(c_{Ak-1} < SAL_i^* \le c_{Ak}, c_{Sl-1} < SAS_i^* \le c_{Sl})$$
$$= \Pr(SAL_i^* \le c_{Ak}, SAS_i^* \le c_{Sl}) - \Pr(SAL_i^* \le c_{Ak-1}, SAS_i^* \le c_{Sl})$$
$$- \Pr(SAL_i^* \le c_{Ak}, SAS_i^* \le c_{Sl-1}) + \Pr(SAL_i^* \le c_{Ak-1}, SAS_i^* \le c_{Sl-1}). \qquad [6]$$

When error terms are distributed as normal bivariant with correlation ρ, their contribution to the likelihood function can be expressed as

$$\Pr(SAL_i = k, SAS_i = l) = \Phi(c_{Ak} - x_{1i}^{'}\beta_1, c_{Sl} - x_{1i}^{'}\beta_2, \rho)$$
$$-\Phi(c_{Ak-1} - x_{1i}^{'}\beta_1, c_{Sl} - x_{1i}^{'}\beta_2, \rho) - \Phi(c_{Ak} - x_{1i}^{'}\beta_1, c_{Sl-1} - x_{1i}^{'}\beta_2, \rho)$$
$$+\Phi(c_{Ak-1} - x_{1i}^{'}\beta_1, c_{Sl-1} - x_{1i}^{'}\beta_2, \rho). \qquad [7]$$

The logarithmic likelihood function for observation I is, thus,

$$\ln L_i = \sum_{k=1}^{5} \sum_{l=1}^{5} I(SAL_i = k, SAS_i = l) \ln \Pr(SAL_i = k, SAS_i = l). \quad [8]$$

By adding [8] for each of the N observation we obtain

$$\ln \mathcal{L} = \sum_{i=1}^{N} \sum_{k=1}^{5} \sum_{l=1}^{5} I(SAL_i = k, SAS_i = l) \ln \Pr(SAL_i = k, SES_i = l) [9]$$

Using [9], we can estimate model [3]-[4] by the procedure described in Sajaia (2008).
It could be argued that model [3]-[4] takes the form of a seemingly unrelated specification, though both dependent variables might have a direct impact on each other. Hence, either equation [3] or [4], or both of them, should include as explicative variable the dependent variable used in the other equation. Though this might be true in principle, we have estimated the model with a simultaneous bivariate ordered probit specification, and tests carried out permit to exclude a direct effect of either satisfaction or learning on the other variable. Accordingly, the seemingly unrelated specification has been adopted here.

3.3. Data and descriptive statistics

Data have been collected by a survey to 84 employees of EVERIS, who have attended e-learning courses and voluntarily answered our online questionnaire. It should be noted that courses have, on average, a rate of drop out equal to 28% and thus, our sample may be consequently biased. In addition, given our objective we have decided to survey employees independently from the specific course they attended, and we focused on specific organizational measures such as incentives, time and space availability for learning, and the skills that permitted to use the learning platform in a profitable way. Table 1 presents the definitions of variables being analyzed, along with descriptive statistics.

Table 1. Variables and descriptive statistics.

Variable	Description	Mean (sd)
SAS	Self-assessed satisfaction; it takes discrete values from 1 (not at all satisfied) to 5 (very satisfied)	4,06 (0,848)
SAL	Self-assessed learning; it takes discrete values from 1 (very low) to 5 (very high)	3,454 (0,851)
TECNO	1 = learning technology is perceived as excellent; 0 = otherwise.	0,523 (0,502)
NOINC	1 = there are no incentives to learning (both real and perceived); 0 = otherwise.	0,666 (0,474)
TIME	1 = specific time for learning available; 0 = otherwise.	0,13 (0,339)
EASY	1 = if the use of the learning platform is perceived as very easy; 0 = otherwise.	0,19 (0,395)
MODEL	1 = if respondant prefers a traditional learning methodology; 0 = otherwise.	0,623 (0,487)
TECHSUP	1 = if respondant works in technical support dep. 0 = otherwise.	0,511 (0,502)

4. Results

We have estimated model [3]-[4] by both a bivariate ordered probit model and two separated ordered probit models for each dependent variable. Table 2 shows results of the bivariate model (column 1) and the two ordered probit models (columns 2 and 3). Firstly, regarding the interdependency between equations [3] and [4], it can be observed that the correlation between error terms is positive and significantly different from zero; moreover, on testing the null hypothesis of independency of the two equations, it is obtained that the hypothesis does not hold true. In other words, the two ordered probit models produce biased estimations, which may be adjusted by the bivariate model. On considering results of column 1, the first relevant result is the positive impact of incentives on both satisfaction and self-assessed level of learning. In particular, incentives (either monetary incentives or the possibility of advancements in the professional career) have a greater effect on satisfaction compared to learning. The ability to handle the technological platform (variable EASY) has similar relative results on learning and personal satisfaction. In the same way, a good assessment of the technological aspect of the platform (TECNO) generates an increase in the probability of both being satisfied, and awarding a positive evaluation to the level of learning.

On the other hand, assigning a specific amount of time to learning during working day has interesting consequences. In fact, having time for education boosts the level of learning, whereas its impact on satisfaction is not significant. This variable thus appears to be especially relevant to the goal of optimizing investments in education. On considering the professional group, being a computer technician has a significant impact on satisfaction. Possibly, due to their higher “sensibility” to technological aspects of the e-learning platform, computer technicians report a significantly lower level of satisfaction; however, there is not such effect on the level of learning. In other words, computer technicians report a lower level of satisfaction and the same level of learning.

Preference for an e-learning model compared to classic methodology, based on the meeting of trainer and trainee in a common space and time, is another interesting variable being analyzed. Estimations suggest that people preferring the classic methodology are both less satisfied with e-learning and report to have achieved a lower level of learning.

Table 2. Results of estimations.

	(1)		(2)	(3)
	APREND	**SATIS**	**APREND**	**SATISF**
NOINC	-0,973**	-1,211**	-0,964**	-1,256**
	(-2,93)	(-3,27)	(-2,92)	(-3,35)
HERRAOK	0,934**	1,091**	0,921**	1,094**
	(2,58)	(2,54)	(2,55)	(2,55)
PREFMOD	-0,639**	-0,759**	-0,64**	-0,835**
	(-2,23)	(-2,23)	(-2,24)	(-2,61)
TECNOOK	0,939**	0,902**	0,948**	0,926**
	(3,16)	(2,92)	(3,17)	(2,98)
TIEMPOHAB	0,786*	0,168	0,787*	0,178
	(1,83)	(0,38)	(1,84)	(0,41)
INF	0,526	-0,865**	-0,522	-0,867**
	(-1,78)	(-2,67)	(-1,76)	(-2,68)
N	77		77	77
□	0,470 [0,127]			
Model stat	36,51**		43,58**	49,04**
LR test	9,99			

Note. Statistical z in brackets. ** = confidence level 95%; * = confidence level 90%.

Estimations carried out allows for predicting the effect of explicative variables on the probability of reporting at the same time both a high level of satisfaction (SAS = 5) and a high level of learning (SAL = 5), when incentive schemes are introduced. This is a relevant prediction, provided that it explains the impact of a (costly) organizational measure with potential benefits. Under this scenario, the model predicts that adopting an incentive scheme, when no incentives are initially implemented, causes an increase of about 121.5% in the probability of declaring both SAL = 5 and SAS = 5.

Explicitly, the probability of reporting a high level of satisfaction would grow about 112.6%, whereas the increase in the probability of reporting a high level of learning would be equal to 79.5%. In other words, incentive schemes affect the level of satisfaction most. Another interesting result is obtained when analyzing a scenario in which people are not assigned any amount of time for studying. In fact, the model predicts that when specific time for study is assigned to people, the probability of reporting a high level of learning increases of about 80%.

5. Conclusions

E-learning does not automatically imply learning. In fact, it might actually reduce the level of learning, motivation and satisfaction of users, when it consists of just uploading course materials initially designed for use with classic methods. As a consequence of this, a complete pedagogical system has been developing through recent years, which is aimed at establishing the educational process in the new technological environment. At the same time, companies are conscious that some organizational features may facilitate learning within the new model and thus, they can contribute to improve both its efficacy and efficiency.

This paper has considered the impact of a number of organizational features on satisfaction and learning of users. It is shown, firstly, that incentives schemes play a key role in augmenting the level of both satisfaction and learning. It should be noted, moreover, that by incentive we mean either monetary rewards, which are almost absent in our sample, or the expectation of advancements in the professional career within the firm. This circumstance may also help to better understand the greater impact of incentives on satisfaction respect to learning, which we found out in our analysis. In other words, the organizational value of learning programs for employees, independently from the level of learning, not only causes their greater acceptance, but it may also positively affect behaviors in such a way that favor learning. Efficacy of learning programs may thus improve by linking the human resources development policy with results obtained in e-learning courses.

Another interesting conclusion we obtained in the analysis is the importance of assigning a specific amount of time for attending e-learning courses. Explicitly, it is shown here that time available for learning has a positive and significant impact on learning, whereas it does not affect satisfaction. This implies a relevant question. In fact, one of the main advantages of e-learning is its temporal flexibility, which permit to working and studying during the same period of time. Model predictions about the positive effects of a fixed amount of time available for learning are thus in apparent contrast with flexibility. On the other hand, it seems logical that focusing on study during a certain amount of time, without disturbance or interruption due to working activity, facilitates concentration and therefore, learning. One possible solution we propose is to assign an amount of time to each student, who is then responsible to use it whenever he or she wants, thus obtaining some degree of flexibility together with reducing interruptions when studying.

On considering the limitations of our analysis, it should be noted that our sample includes all users of e-learning programs within a single firm. Firstly, this constraints the possible generalization of results, and further research is thus needed in order to confirm our conclusions. Moreover, we considered e-learning users independently from the program attended. In other words, an implicit hypothesis of this piece of research is that courses have homogeneous and comparable characteristics regarding their internal structure and therefore, users' opinion is assumed to be referred to the e-learning model rather than one particular program. This limitation suggests one step forward in the same line of research. It would be interesting, if data were available, to divide the sample and study the impact of organizational measures depending on both the type of course and the professional category of the student. In addition, comparing results with other firms that adopted the e-learning model would permit to analyze additional policies aimed at improving efficiency.

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