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A FRAMEWORK FOR A HEURISTIC APPROACH TO EVALUATING AND ASSESSING ADAPTIVE HYPERMEDIA LEARNING SYSTEMS

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ABSTRACT

This article provides a holistic view of e-Learning as a by-product of Adaptive Hypermedia Learning Systems (i.e. AHLS). It aims at proposing a generic framework for evaluating and assessing AHLS. While many of the existing assessment and evaluation instruments yield useful findings (1), most of them seem to be revolving around one key problem – with so many variables that can potentially be considered of impact to the quality of these instruments, how do we re-adapt the assessment and evaluation instruments to produce results that are relevant to our learners' ethnographic background[1], pedagogical paradigm[2], and the actual AHLS. It was also found that many authors choose to disregard (i.e. consciously or otherwise) some variables (2). This practice needs to be discouraged as it not only results in constraining findings but also distorts analysis of the flaws (and strengths) in current AHLS deployments. The proposed framework is designed on a premise that considers a number of studies namely; the E-VAL project models - considering factors from ethnographic, pedagogical, and applicable AHLS; and the Learning Object Review Instrument (LORI) – considering the nine dimensions of quality (3).

Key Words: Adaptive hypermedia learning system (i.e. AHLS), Ethnographic research methods, Pedagogical paradigm, Heuristic approach, e-Learning assessment, Evaluation framework

INTRODUCTION

This paper is aimed at proposing a heuristic framework tailored with the sole intent of improving existing evaluation and assessment methodologies used in determining the level of effectiveness of Adaptive Hypermedia Learning Systems (AHLS). AHLS or also known as Adaptive Educational Hypermedia Systems (AEHS) are reusable learning resources specifically designed to customize educational contents to an individual learner's preferences (1).

In order to better model the proposed framework, the author adopts a learner-centric (4) approach geared at viewing e-learning ventures as by-products of AHLS. In light of this, care has been taken to generalize the proposed framework and present it in a universal format in order to ease adaptability to e-Learning Assessment or Evaluation studies.

[1]designed to explore cultural phenomena(22)
[2]aligned to a particular subject area e.g. English, physics, computers (21)

BACKGROUND TO THE STUDY

AHLS are designed with the single intent of providing an educational content tailored to an individual learner (5). This is done by employing a 'user model' built on the basis of parameters derived from human factors (1).

These human factors play an important role in the conception and development of AHLS thereby ensuring that their educational context range from gender differences (6) through prior knowledge to cognitive styles (7). Therefore the approach in AHLS is that just as people differ in many aspects, so do ways in which they learn (8). The argument raised is that of individual learners in need of personalized learning styles.

Adaptive Hypermedia Learning Systems (AHLS) are specifically designed to provide this personalized service. AHLS closes this functional gap in Learning Management Systems (LMS) by providing a deployment approach that tailors a given learning experience (i.e. content and class activities) to an individual learner's needs (9).

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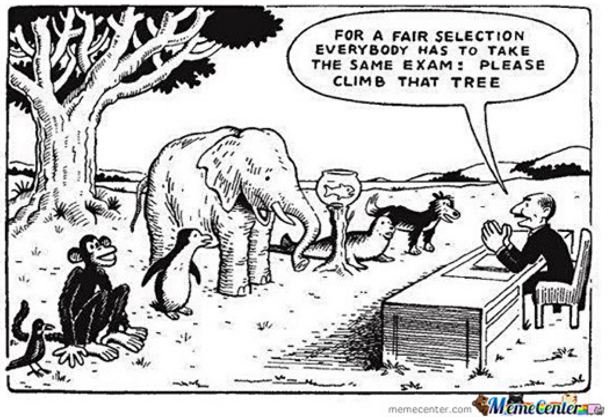


Figure 1: Need for AHLS - Given the array of learning types, how can anyone expect a design incorporating only one type of learning to work for everyone?(image source: memecenter.com)

PROBLEM STATEMENT

A review of the existing literature has been conducted leading to the conclusion that most instruments developed for the Evaluation and Assessment of AHLS are justified through ethnographic research methods (i.e. handing questionnaires to participants) (2)(10). While many of these tools bore useful findings, most seem to revolve around one key question how do we re-adapt the assessment and evaluation instruments to produce results that are relevant to our learners' ever changing ethnographic background, pedagogical paradigm, and the actual adaptive hypermedia learning system. The usual practice of disregarding some variables(11) is one to be discouraged as it not only results in constraining findings but also distorts analysis of the flaws (and strengths) in current e-Learning venture.

MOTIVATION

In addition to bringing a number of benefits such as low cost, ease of access, and user convenience; the primary concern of e-learning ventures is to *improve existing learning processes* and *provide means for an easy integration of new teaching strategies*(10).

One key challenge faced by many researchers in this regard is to come up with the *right approach* of evaluating and assessing the entire e-learning venture. Another major problem is to *decide on the inclusion of variables*(12) that may potentially have an impact in the study design (2) and determine what constitutes dependent, independent, and irrelevant variables in the study(13).

Depending on the scale of the study, this inherent problem, may bias the conclusions and prevent the study from accurately gauging the significance of the selected variables or missing them altogether (2).

To derive the pool of variables of interest, a review of numerous studies including the E-VAL project and the LORI project was conducted. To avoid discarding important variables, cluster analysis (14) was used to rather converge them into homogeneous groups.

The proposed framework is therefore presented as a heuristic approach for an assessment and evaluation methodology; offering a framework that is both generic and adaptable to e-learning systems as by-products of AHLS.

CONCEPTUAL FRAMEWORK

In order to establish a baseline to the study, the proposed framework will be referred to as the e-Val Framework in which '**e**' stands for e-Learning and '**Val**' for the valuation process that one goes through to determine the actual benefits of an e-Learning venture. The following diagram is used to demonstrate how the e-Val Framework would work in a given e-Learning scenario.

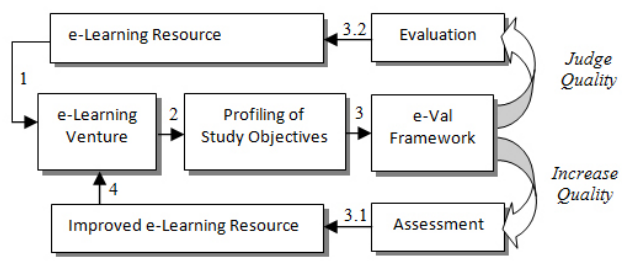


Figure 2: Demonstration of how the e-Val Framework functions

It is therefore hoped that the e-Val Framework may provide both a means for conducting an assessment aimed at increasing the level of quality and/or performing an evaluation with the intent of judging the level of quality of the e-Learning venture (15).

THE E-VAL FRAMEWORK: A TOOL FOR PARAMETRIC DEDUCTIONS

Derived e-Learning Ventures Characteristics and Factors

The related studies reviewed revealed the list of generic factors presented in table 1 and that of characteristics presented in table 2 below.

Table 1: Factors used to describe a Generic e-Learning Venture

1	Technological appropriateness	TA
2	Learning Environment appropriateness	EM
3	Learning context suitability	CG
4	Learner's aptitude	LA
5	Pedagogical alignment	PFLX
6	Quality alignment	QMO

Table 2: Characteristics of a Generic e-Learning Venture

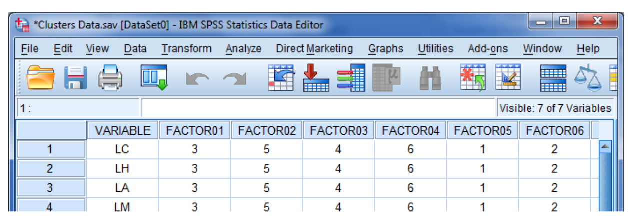
1	Learner's physical characteristics	LC
2	Learner's learning history	LH
3	Learner's attitude versus the entire learning experience	LA
4	Learner's motivation versus a given learning style	LM
5	Learner's familiarity with the technology	LF
6	The immediate (physical) learning environment's level of preference	EH
7	the organization or institution environment's level of preference	EO
8	The mobility (or BYOD) option's level of preference	EM
9	Social economic factors of a given learner	CSEF
10	Political context	CP
11	Cultural background of the learning venture	CC
12	Geographic location of the learning venture	CG
13	Learning environment hardware	THW
14	Learning environment software	TSW
15	Learning environment's level of connectivity	TC
16	Learning environment's level of accessibility	TA
17	Learning environment's mode of delivery	TD
18	The level and nature of the learner's support systems	PSUP
19	Course material accessibility issues	PACC
20	pedagogic methodology's ability to attain learning objectives	PMET
21	Level of adaptability of the course content or assessment style to learner's preference	PFLX
22	Learner's autonomy	PAUT
23	Selection and/or recruitment success level of learner after attaining learning objectives	PREC
24	Level of effectiveness of assessment and examination instruments	PAST
25	Accreditation and certification of learning programme	PACR
26	Content quality	QCT
27	Learning Objective Alignment	QLO
28	Learner's perceived level of motivation	QMO
29	Presentation design	QPD
30	Adaptive to user preferences	QAD
31	Accessibility to learning resources	QAC
32	Reusability of learning objectives	QRE

CLUSTER ANALYSIS: MEASURING HOMOGENEITY

Guiding Assumptions

Representativeness of the Sample

For the initial run of the model, our pilot study group consisted of 32 randomly selected[3] volunteers. The volunteers' ranking of each of the 32 key characteristics against factors was considered and an average measure was drawn for each of the characteristics for processing. To determine the factor-specific groups of homogeneous objects, the K-Means Cluster Algorithm (12) was used. We refer to these factor-specific groups as clusters.



	VARIABLE	FACTOR01	FACTOR02	FACTOR03	FACTOR04	FACTOR05	FACTOR06
1	LC	3	5	4	6	1	2
2	LH	3	5	4	6	1	2
3	LA	3	5	4	6	1	2
4	LM	3	5	4	6	1	2

Figure 3: SPSS v21 Data view of Ranked Variables per Factor

As illustrated in figure 3, each of the coded characteristics was ranked on a factor-specific scale (i.e. counts not recurring within characteristics). To tie the characteristics to factors, a Likert scale of 1 to 6 was used and the collected data was processed using SPSS.

Reduced Impact of Multicollinearity

Multicollinearity occurs when two or more predictor variables in a multiple regression model are highly correlated; allowing

[3]Using deliberate sampling technique

one variable to linearly predict the other(s) with a non-trivial degree of accuracy (18). Multicollinearity is an important assumption for researchers who wish to introduce new variables within the identified characteristics or introduce new characteristics altogether to improve the model factors.

As a recommendation to future studies; to avoid any effect (19) due to Multicollinearity on the predictor variables one should:

- Reduce the variables to equal numbers in each set of correlated measures, or
- Use a distance measure that compensates for the correlation, such as Mahalanobis(12) distance

Deriving Clusters

In order to ensure that the identified characteristics (i.e. LC, LH, LA, etc…) in table 2 are properly classified according to identified generic factors in table 1, cluster analysis techniques are employed to guarantee that the resulting factor-based grouping (18) of the characteristics exhibit high internal (within cluster) homogeneity and high external (between cluster) heterogeneity (19).

Table 3: Distances between final cluster (C#) centers

C#	1	2	3	4	5	6
1		7.49	2.83	7.88	8.25	2.45
2	7.48		8.00	2.45	4.25	6.93
3	2.83	8.00		8.37	7.62	2.83
4	7.88	2.45	8.37		3.47	7.88
5	8.25	4.25	7.62	3.47		7.88
6	2.45	6.93	2.83	7.88	7.88	

With reference to the results in table 3, the centroids[4](20) for each of the clusters could be identified.

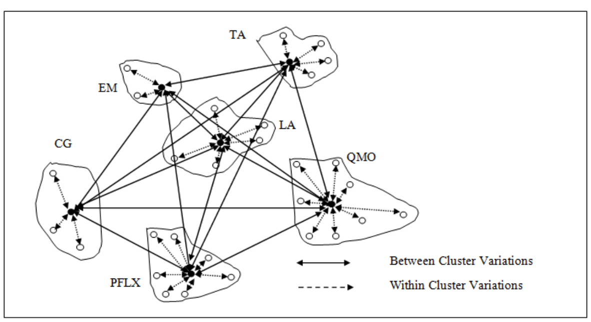


Figure 4: Cluster Diagram Showing Between and within Cluster Variations

Figure 4 illustrates these clusters, namely: LA – for learner's aptitude, EM – for learning environment, CG – for learning context suitability, TA – for technological appropriateness, PFLX - for pedagogical alignment, and QMO – for quality alignment.

[4]The point with an average ranking of minimum squared deviation across all the points falling in a given cluster

Defining the Identified Clusters

To facilitate adaptation to multiple studies, a common language by means of First Order Logic (FOL)(17)(16) to present the resultant clusters (i.e. the independent variables) will be adopted.

Cluster 01: Learner's Aptitude

Let L= *an individual learner's characteristics*.

Then, an individual learner may be defined as:

$$atupleL = \{\exists\ L_i \mid 1 \leq i \leq \infty\} \tag{1.1}$$

Therefore in relation to this study, an individual learner's level of aptitude can be defined as:

$$\therefore L = \exists I_i \in \{L_C, L_H, L_A, L_M, L_F\} \tag{1.2}$$

Therefore, the multiple regression model used to measure the effect of the regressors L_C, L_H, L_A, L_M, and L_F on the Learner's aptitude is:

$$L_i = \beta_0 + \beta_C L_C + \beta_H L_H + \beta_A L_A + \beta_M L_M + \beta_F L_F + \varepsilon_i \tag{1.3}$$

Cluster 02: Learning Context Suitability

Let C= *a learning context's characteristics*.

Then, a given learning context may be defined as:

$$atupleC = \{\exists\ C_i \mid 1 \leq i \leq \infty\} \tag{2.1}$$

Therefore, in relation to this study a given learning context's level of suitability can be defined as:

$$\therefore C = \exists\ C_i \in \{C_{SEF}, C_P, C_C, C_G\} \tag{2.2}$$

Therefore the multiple regression model used to measure the effect of the regressors C_{SEF}, C_P, C_C, and C_G on the Learning Context's suitability is:

$$C_i = \beta_0 + \beta_{SEF} C_{SEF} + \beta_P C_P + \beta_C C_C + \beta_G C_G + \varepsilon_i \tag{2.3}$$

Cluster 03: Technological Appropriateness

Let T = *a technology's characteristics*.

Then, a given technology may be defined as:

$$a\ tuple\ T = \{\exists\ T_i \mid 1 \leq i \leq \infty\} \tag{3.1}$$

Therefore in relation to this study, a given technological appropriateness' level can be defined as:

$$\therefore T = \exists\ T_i \in \{T_{HW}, T_{SW}, T_C, T_A, T_D\} \tag{3.2}$$

Therefore the multiple regression model used to measure the effect of the regressors T_{HW}, T_{SW}, T_C, T_A, and T_D on the Technological appropriateness is:

$$T_i = \beta_0 + \beta_{HW}T_{HW} + \beta_{SW}T_{SW} + \beta_C T_C + \beta_A T_A + \beta_D T_D + \varepsilon_i \quad (3.3)$$

Cluster 04: Pedagogical Alignment

Let *P = a pedagogy's characteristics*.

Then, a given pedagogy may be defined as:

$$a\ tuple\ P = \{\exists\ P_i \mid 1 \le i \le \infty\} \quad (4.1)$$

Therefore in relation to this study, a given pedagogy's level of alignment can be defined as:

$$\therefore P = \exists\ P_i \in \{P_{SUP}, P_{ACC}, P_{MET}, P_{FLX}, P_{AUT}, P_{REC}, P_{AST}, P_{ACR}\} \quad (4.2)$$

Therefore the multiple regression model used to measure the effect of the regressors P_{SUP}, P_{ACC}, P_{MET}, P_{FLX}, P_{AUT}, P_{REC}, P_{AST}, and P_{ACR} on pedagogical alignment is:

$$P_i = \beta_0 + \beta_{SUP}P_{SUP} + \beta_{ACC}P_{ACC} + \beta_{MET}P_{MET} + \beta_{FLX}P_{FLX} + \beta_{AUT}P_{AUT} + \beta_{REC}P_{REC} + \beta_{AST}P_{AST} + \beta_{ACR}P_{ACR} + \varepsilon_i \quad (4.3)$$

Cluster 05: Quality Alignment

Let *Q = a quality's characteristics*.

Then, a given quality may be defined as:

$$a\ tuple\ Q = \{\exists\ Q_i \mid 1 \le i \le \infty \quad (5.1)$$

Therefore in relation to this study, a quality's level of alignment can be defined as:

$$\therefore Q = \exists\ Q_i \in \{Q_{CT}, Q_{LO}, Q_{FA}, Q_{MO}, Q_{PD}, Q_{AD}, Q_{AC}, Q_{RE}\} \quad (5.2)$$

Therefore the multiple regression model used to measure the effect of the regressors Q_{CT}, Q_{LO}, Q_{FA}, Q_{MO}, Q_{PD}, Q_{AD}, Q_{AC}, and Q_{RE} on quality alignment is:

$$Q_i = \beta_0 + \beta_{CT}Q_{CT} + \beta_{LO}Q_{LO} + \beta_{FA}Q_{FA} + \beta_{MO}Q_{MO} + \beta_{PD}Q_{PD} + \beta_{AD}Q_{AD} + \beta_{AC}Q_{AC} + \beta_{RE}Q_{RE} + \varepsilon_i \quad (5.3)$$

Cluster 06: Learning Environment's Appropriateness

Let *E= a learning environment's characteristics*.

Then, a given learning environment may be defined as:

$$tuple E = \{\exists\ E_i \mid 1 \le i \le \infty\} \quad (6.1)$$

Therefore, a given learning environment's level of appropriateness can be defined as:

$$E = \exists E_i \in \{E_H, E_O, E_M\} \quad (6.2)$$

Therefore the multiple regression model to measure the effect of the regressors E_H, E_O, and E_H on the Learning environment's appropriateness is:

$$E_i = \beta_0 + \beta_H E_H + \beta_O E_O + \beta_M E_M + \varepsilon_i \quad (6.3)$$

THREATS TO VALIDITY OF THE E-VAL FRAMEWORK REGRESSION MODELS

In order to avoid a biased estimator of the causal effect due to the identified regressors[5], one needs to ensure that the statistical inferences about causal effects are valid for the population being studied (i.e. Internal validity) and that they can be generalized from the population and setting studied to other populations and settings (i.e. external) (19). In this context the term "settings" refers to the legal, policy, physical environment and other related salient features.

MODEL VALIDITY

This section is used to demonstrate how the multiple regression models described in the e-Val Framework can be used to conduct assessment and/or evaluation in an actual study. For the sake of brevity, the regression model for learner's aptitude will be used.

Adapting the e-Val Framework entirely depends on how a given researcher presents his/her research objectives.

To demonstrate this, let us suppose that our aim is to run an experiment where:

An individual learner's characteristic is described using the following variables:

- L_C described in terms of age: L_{CA}, sex: L_{CS}, and visual impairment: L_{CV} of the respondent.
- L_H described in terms of experience rating: L_{HE}, level of attainment: L_{HL}, and enrolment Program duration: L_{HD}.
- L_A described in terms of attitude of learner towards learning experience: L_{AE}
- L_M described in terms of learner's motivation towards a given learning style: L_{MS}
- L_F described in terms of learner's familiarity with the technology: L_{FT}

Therefore for the tuple L:

[5]Independent variable also known as a "predictor variable", "explanatory variable", or an "input variable.

ð The parametric model is:

$$L_i = \beta_0 + \beta_C(L_{CA} + L_{CS} + L_{CV}) + \beta_H(L_{HE} + L_{HL} + L_{HD}) + \beta_A(L_{AE}) + \beta_M(L_{MS}) + \beta_F(L_{FT}) + \varepsilon_i$$

ð The fitted parametric model is:

$$\hat{L} = \hat{\beta}_0 + \hat{\beta}_C(L_{CA} + L_{CS} + L_{CV}) + \hat{\beta}_H(L_{HE} + L_{HL} + L_{HD}) + \hat{\beta}_A(L_{AE}) + \hat{\beta}_M(L_{MS}) + \hat{\beta}_F(L_{FT})$$

ð The fitted value for point '*i*' is:

$$\hat{L}_i = \hat{\beta}_0 + \hat{\beta}_{CA}L_{(CA)_i} + \hat{\beta}_{CS}L_{(CS)_i} + \hat{\beta}_{CV}L_{(CV)_i} + \hat{\beta}_{HE}L_{(HE)_i} + \hat{\beta}_{HL}L_{(HL)_i} + \hat{\beta}_{HD}L_{(HD)_i} + \hat{\beta}_{A}L_{(AE)_i} + \hat{\beta}_{M}L_{(MS)_i} + \hat{\beta}_{F}L_{(FT)_i}$$

To demonstrate the effect of the variables L_{CA}, L_{CS}, L_{CV}, L_{HE}, L_{HL}, L_{HD}, L_{AE}, L_{MS}, and L_{FT} on learners' level of aptitude in experiment *i*, the following simple set of test data will be used:

Table 4: Model Test Data

$\hat{L}_i$	L_{CA}	L_{CS}	L_{CV}	L_{HE}	L_{HL}	L_{HD}	L_{AE}	L_{MS}	L_{FT}
85.0	19	1	0	3	3	1.0	5	4	5
50.0	38	2	0	3	5	5.0	5	3	2
60.0	22	1	0	3	4	3.0	1	3	4
80.0	29	2	1	3	4	3.0	2	4	4
87.0	27	2	0	4	3	2.0	2	3	3
47.0	30	1	0	4	4	3.5	1	1	2
86.0	19	2	1	3	2	1.0	2	3	3
43.0	36	2	1	5	4	3.5	3	3	1
93.0	19	2	0	3	3	3.0	3	4	4
65.0	33	2	0	4	2	1.5	2	3	5
74.0	17	1	1	3	3	2.0	4	5	5
70.0	26	1	0	4	4	4.0	2	3	4
77.0	28	2	1	4	4	3.0	3	4	4
93.0	26	1	0	3	3	2.7	4	5	5
50.0	16	2	1	3	2	2.0	3	3	5

Table 5 : ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	3260.669	9	362.297	1.994	.232[b]
Residual	908.664	5	181.733		
Total	4169.333	14			

It can be deduced from table 6 that the F-ratio is not statistically significant. Hence the conclusion that the assumption of equal variances is tenable (i.e. there is homogeneity of variance).

Table 6: Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
(Constant)	66.29	51.04		1.29	.25
L_{CA}	-.77	.99	-.31	-.78	.47
L_{CS}	10.04	10.28	.29	.98	.38
L_{CV}	-20.05	9.30	-.59	-2.16	.09
L_{HE}	-1.52	8.39	-.06	-.18	.86
L_{HL}	4.64	9.82	.24	.47	.66
L_{HD}	-8.11	6.92	-.52	-1.17	.29
L_{AE}	-5.35	3.85	-.39	-1.39	.23
L_{MS}	17.78	6.46	1.02	2.75	.04
L_{FT}	-4.73	5.38	-.35	-.88	.42

$$\hat{L}_i = 66.29 - 0.77L_{(CA)_i} + 10.04L_{(CS)_i} - 20.05L_{(CV)_i} - 1.52L_{(HE)_i} + 4.64L_{(HL)_i} - 8.12L_{(HD)_i} - 5.35L_{(AE)_i} + 17.78L_{(MS)_i} - 4.73L_{(FT)_i}$$

Suppose our aim is to answer the following research questions:

QUESTION 1: Does the learner's attitude towards a given learning experience play any role in his/her level of aptitude?

In this case, the null and alternative hypothesis and the test statistics are the following:

STEP 01: HYPOTHESIS STATEMENT $H_0 : \beta_A = 0$; $H_1 : \beta_A \neq 0$

STEP 02: TEST STATISTICS

$$t = \hat{\beta}_A \Big/ se\left(\hat{\beta}_A\right) = -5.345 \big/ 3.850 \cong -1.387$$

STEP 03: DECISION

Since the *t*-value is relatively high, the researcher might decide to test it at a level of 1%. For $\alpha = 0.01$, we reject if $\left|t_{\hat{\beta}_A}\right| \geq t_{n-k}^{\alpha/2} \rightleftharpoons t_{15-10}^{0.01/2} \rightleftharpoons t_5^{0.005} = 4.0322$. Given that $|t|=1.387 < 4.03$, we fail to reject H_0 in favor of H_1.

STEP 04: CONCLUSION

Therefore, on the basis of the data provided, there is insufficient evidence to conclude that the learner's attitude towards a given learning experience has a significant effect on his/her level of aptitude for significance level of 1% and, thus of 5% and 10%.

QUESTION 2: Does the learner's visual impairment have a negative effect on his/her level of aptitude?

In this case, the null and alternative hypothesis and the test statistics are the following:

STEP 01: HYPOTHESIS STATEMENT $H_0: \beta_{CV} = 0$; $H_1: \beta_{CV} < 0$

STEP 02: TEST STATISTICS

$$t = \hat{\beta}_{CV} \Big/ se\left(\hat{\beta}_{CV}\right) = -20.049 \big/ 9.300 \cong -2.156$$

STEP 03: DECISION

Since the *t*-value is relatively high, the researcher might decide to test it with a level of 1%. For $\alpha = 0.01$, we reject if $t_{\hat{\beta}_{CV}} \leq -t^{\alpha}_{n-k} \rightleftharpoons -t^{0.01}_{15-10} \rightleftharpoons -t^{0.01}_{5} = -3.365$. Given that t = -2.156 > -3.365, we fail to reject H_0 in favour of H_1.

STEP 04: CONCLUSION

Therefore, on the basis of the data provided, there is insufficient evidence to conclude that the learner's visual impairment has a significantly negative effect on his/her level of aptitude for significance level of 1%.

CONCLUSION AND FUTURE WORK

This paper is a step in the right direction in the development of robust and generic research methodologies for measuring the effectiveness of e-learning ventures through evaluation and assessment.

Consented effort has been made to ensure that the proposed e-Val Framework is not only grounded on solid theoretical precepts but also presented in a format that is comprehensive, generic, and adaptable enough for an easy integration as a measuring tool to numerous studies.

A deliberate measure had been taken to enable researchers to have more flexibility in to use the e-Val Framework with the assumption that they would adapt it to their specific needs. Moreover, one might instead of sticking to a purely multiple regression approach adopt a multivariate approach by combining the individual regressor equations to derive a more unified measure of effectiveness centered on the user, e-learning resource, quality of learning style, etc…

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