Holistic effectiveness of e-learning systems using fuzzy Importance-Performance Analysis (IPA) in uncertainty

Ray Wang, David W.S. Tai, Jau-Shyong Chen & Kuo-Lung Yang

Hungkuang University,
Taichung, Taiwan

ABSTRACT: This study proposes a novel approach to fuzzy importance-performance analysis (FIPA) to modify conventional importance-performance analysis (IPA) for determining critical attributes in e-learning system measurements. There is an abundance of literature pertaining to the e-learning framework, but there is a shortage of literature on how to implement properly the framework in uncertainty with variance and interactive relationships. This study also considers the nature of fuzziness in human perception and avoids the erroneous assumptions of conventional IPA, proposing a hybrid approach, using the fuzzy theory to represent customer perception based on linguistic assessment aspects in uncertainty. The FIPA is a multi-criteria evaluation concept that highlights the status of importance and satisfaction. The four dependence aspects and twenty-one interactive criteria were evaluated from a sample of 189 respondents from a university of technology in Taiwan. The results and concluding remarks are discussed.

INTRODUCTION

Along with the rapid development of information technology and the popularisation of the Internet, e-learning has already become a trend, which conforms to trends and individualised learning needs [1][2]. However, there is no final conclusion regarding the learning achievements, as of yet [3-6]. This includes the sceptical teaching achievements of e-learning and the criticisms of the development and enforcement of teaching activities [7-9]. Therefore, many learners considered that establishing a set of digital teaching evaluation criteria could ensure the quality and effects of digital teaching [10-12]. However, there are no consistent discussions on the connotations of Taiwan's present digital teaching evaluation criteria, and there are no confirmed standards included in the dimensions and detailed items of the related evaluation criteria.

The quality assessment of digital teaching materials is a multiple-strategic problem. During estimation, all the detailed items must be considered thoroughly. This study uses the modified combination of fuzziness and importance-performance analysis to form Fuzzy Importance-Performance Analysis (FIPA) to solve this problem correctly. FIPA is mainly used in estimation criteria to solve problems. The objectives of FIPA are to systemise the complexities of the problems and to differentiate the differences in importance and actual performance of the various standards of the criteria, clearly defining their degree of importance and customer satisfaction, therefore, helping strategists to select the most appropriate solving cases by scheduling the priorities of available resources.

This study attempts to develop an e-learning performance assessment framework, namely Fuzzy Importance-Performance Analysis (FIPA) that is sufficiently general in the IPA concept. To date, few studies have adopted such a rigorous methodology. Therefore, this study proposes a mechanism, fuzzy set theory and importance performance analysis. Hence, the following sections present the proposed novel approach.

LITERATURE REVIEW

Determining Criteria

The evaluation criterion for the quality of digital teaching materials mainly uses references from the e-Learning Quality Certification Center [11]. Chen pointed out that the evaluation structure includes the contents of the teaching materials, guide and follow-up, teaching design and teaching media [13]. The connotations of the contents include: 1) contents of the teaching materials: the digital teaching materials must provide accurate contents and show appropriate organisation and clarity so that learners can obtain the expected knowledge and skills [14]; 2) guide and follow-up: through good learning guides and follow-ups, learners can easily grasp their learning progress, as well as help them in the organisation and understanding of the learning contents [15]; this includes the controlling of the mechanism of the learning progress, guidance, and follow-up of the learning process; 3) teaching design: the digital teaching materials must provide correct learning objectives, show appropriate teaching, use appropriate applications of the learning strategies so as to promote understanding, and must have good interactive learning, appropriate assessment and feedback mechanisms [16][17]; 4) teaching media: the teaching media convey the learning contents and its easy application of the learning interface, effective application of teaching media, as well as high quality teaching media, provide learners with learning motivations, and maintain their learning interests so as to promote the understanding of the learning contents, and obtain twice the results with half the effort [18].

Setting Quantitative Data

The quantitative (crisp) numbers of criteria have varying values that cannot be compared. The crisp value number must be normalised. The crisp number is normalised to achieve criteria values that are unit-free and comparable among all criteria. The normalised crisp values of W_{ij} are calculated as expressed in the following equation:

$$W_{ij}^{crisp} = \frac{W_{ij}^{k} - \min W_{ij}^{k}}{\max W_{ij}^{k} - \min W_{ij}^{k}}, \qquad W_{ij}^{crisp} \in [0,1]; k = 1,2,...n$$

METHODOLOGY

To determine the Fuzzy Importance-Performance Analysis (FIPA), the multiple and frequent evaluation criteria are structured into multi-level hierarchies. Hence, the first phase is to define the decision objectives. After defining the decision objectives, it is required to generate and establish the evaluation objectives in the current scenario, which is similar to a chain of the determinants-aspects and criteria. As discussed in the previous section, four aspects of FIPA are to be considered. Moreover, the criteria cluster has to be dependent. This section introduces determining criteria and quantitative data, the fuzzy set theory, IPA method and FIPA approach followed by the proposed analytical procedures.

Fuzzy Set Theory

To determine the qualitative measures, fuzzy set theory can express and handle vague or imprecise judgments mathematically. In the fuzzy set theory, each number between 0 and 1 indicates a partial truth, whereas crisp sets correspond to binary logic (0, 1). In particular, to tackle the ambiguities involved in the process of linguistic estimation, it is beneficial to convert these linguistic terms into TFNs. This study builds on some important definitions and notations of fuzzy set theory from Chen [19].

Definition 1: A TFN $\tilde{N}$ can be defined as a triplet (*l*, *m*, *u*), and the membership function $\mu_{\tilde{N}}(x)$ is defined as:

$$\mu_{\tilde{N}}(x) \begin{cases} 0, & x \prec l \\ (x - l)/(m - l), & l \leq x \leq m \\ (u - x)/(u - m), & m \leq x \leq u \\ 0, & x \succ u \end{cases}$$

Where *l*, *m*, and *u* are real numbers and $l \leq m \leq u$, see Figure 1.

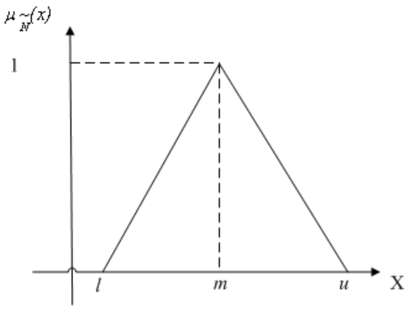

Figure 1: A triangular fuzzy number $\tilde{N}$.

Definition 2: Let $\tilde{N}_1 = (l_1, m_1, u_1)$ and $\tilde{N}_2 = (l_2, m_2, u_2)$ be two TFNs. The multiplication of $\tilde{N}_1$ and $\tilde{N}_2$ denoted by $\tilde{N}_1 \otimes \tilde{N}_2$.

Two positive TFNs, $\tilde{N}_1 \otimes \tilde{N}_2$ approximates a TFN as follows:

$$\tilde{N}_1 \otimes \tilde{N}_2 \cong (l_1 \otimes l_2, m_1 \otimes m_2, u_1 \otimes u_2).$$

The criteria consist of four aspects and thirty-four measures, the criteria are determined from extensive literature and expert teams. The triangular fuzzy membership functions (Table 1) can accommodate the qualitative data while the evaluators process the evaluation as linguistic information. This proposed framework allows experts to identify options using linguistic expressions. The unique point of this study was involved in qualitative measures in linguistic terms presented by TFNs and defuzzified into a crisp value for analysing the cause and effect model. The following tables present the application of TFNs for Fuzzy importance-performance analysis.

Table 1: Linguistic Scales [20].

Linguistic variable	triangular fuzzy numbers (TFNs)
very poor	(0, 0, 0.3)
poor	(0.2, 0.3, 0.4)
fair	(0.35, 0.5, 0.65)
good	(0.6, 0.7, 0.8)
very good	(0.75, 1.0, 1.0)

This study applies the conversion of the fuzzy data into crisp scores, developed by Opricovic and Tzeng [21]. The main procedure is to determine the left and right scores via fuzzy minimum and maximum. The total score is determined as a weighted average according to the membership functions.

$\tilde{X}$ is assumed to be an arbitrary convex and bounded fuzzy number. The assessed values of qualitative criteria metrics for FIPA, $\tilde{X} = ({}_L x_{ij}, {}_m x_{ij}, {}_R x_{ij})$, *i*=1,2,3,4 and *j*=1,2,3…,7 in this study. $\tilde{X} = ({}_L x_{ij}, {}_m x_{ij}, {}_R x_{ij})$ represents TFNs, and x_{ij} are presented in the left, middle, and right positions; ${}_L x^k{}_{ij}, {}_m x^k{}_{ij}, {}_R x^k{}_{ij}$, represent overall average ratings of aspect *ith*, criteria *jth* over *kth* evaluators, and x^p_{ij}, p =1, 2,……*k*, represents the fuzzy numbers for each evaluator. The normalisations of TFNs are as follows $\begin{cases} z_L x^p{}_{ij} = ({}_L x^k{}_{ij} - \min_L x^k{}_{ij}) / \delta^{\max}_{\min} \\ z_m x^p{}_{ij} = ({}_m x^k{}_{ij} - \min_m x^k{}_{ij}) / \delta^{\max}_{\min} \\ z_R x^k{}_{ij} = ({}_R x^k{}_{ij} - \min_R x^k{}_{ij}) / \delta^{\max}_{\min} \end{cases}$; where $\delta^{\max}_{\min} = \max_R x^k{}_{ij} - \min_L x^k{}_{ij}$.

The left (*ls*) and right (*rs*) normalised values are computed as $\begin{cases} zls^p_{ij} = z_m x^k{}_{ij} / (1 + {}_m x^k{}_{ij} - {}_L x^k{}_{ij}) \\ zrs^p_{ij} = z_R x^k{}_{ij} / (1 + {}_R x^k{}_{ij} - {}_m x^k{}_{ij}) \end{cases}$.

The total normalised crisp value is computed as $y^k_{ij} = \left[zls^p_{ij}\left(1 - zls^p_{ij}\right) + zrs^k_{ij}\ zrs^k_{ij}\right] / \left[1 - zls^p_{ij} + zrs^p_{ij}\right]$.

The crisp values are computed as $w^k_{ij} = \min_L x^k{}_{ij} + y^k_{ij}\delta^{\max}_{\min}$.

To integrate the different opinions of evaluators, this study adopts the synthetic value notation to aggregate the subjective judgment for *k* evaluators, given by $\tilde{w} = \frac{1}{k}(\tilde{w}^1_{ij} + \tilde{w}^2_{ij} + \tilde{w}^3_{ij} + ... + \tilde{w}^k_{ij})$.

Importance-Performance Analysis

An importance-performance analysis (IPA) draws implications for managing e-learning effectiveness criteria. IPA identifies the relative importance of the attributes associated with an e-learning system, while at the same time indicates the degree of performance. The results are plotted graphically on a two-dimensional grid, in which the importance of the criteria is displayed on the vertical axis while the satisfaction level is displayed on the horizontal axis. The resulting four quadrants are labelled as: *Concentrate here*, *Keep up the good work*, *Low priority* and *Possible overkill* (Figure 2).

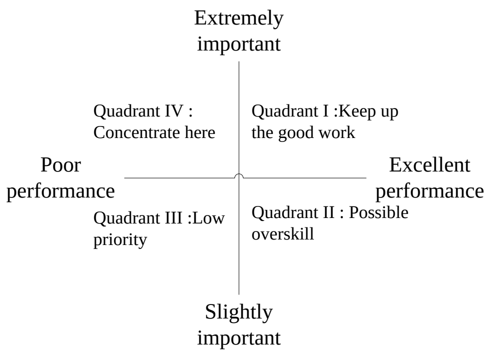

Figure 2: Importance-performance analysis evaluation grid.

Fuzzy Importance-Performance Analysis

IPA has been applied as an effective means of evaluating a firm's competitive position in the market, identifying improvement opportunities and guiding strategic planning efforts [22][23]. IPA, first introduced by Martilla and James [24], identifies which product or service attributes a firm should focus on to enhance customer satisfaction [25]. Recently, Matzler, Bailom, Hinterhuber, Renzl and Pichler [26] noted that between the single attribute variables, a rather strong multicollinearity is to be expected. Therefore, they determined the potential influence of multicollinearity on regression coefficient estimation. Consequently, they declared multiple regression analysis as an inappropriate tool for deriving reliable impact measures when multicollinearity exists within independent variables. As suggested by Hair, Anderson, Tatham and Black, partial correlation analysis is more suitable than regression analysis for quantifying the influence of independent variables on dependent variables when multicollinearity exists within independent variables [27]. Therefore, Matzler, Bailom, Hinterhuber, Renzl and Pichler used dichotomised partial correlation analysis with dummy variables to identify the three factor category of each single attribute [26].

Generally, surveys examining respondents' perceptions of satisfaction or service quality have used questionnaires in which respondents indicate their feelings with reference to selected linguistic terms. But human judgments of events may vary significantly according to the subjective perceptions or personality of individuals, even when the same linguistic term is used [28]. Thus, when using fuzzy numbers to represent specific linguistic terms, researchers must consider the differences among the survey respondents. Data were collected via the random stratified sampling of technological university students from northern, central and southern Taiwan. A total of 189 effective samples were statistically retrieved and used as the basis for analysing and understanding the importance and satisfaction of the various evaluation criteria of digital teaching.

RESULTS

Contributions

Along with the rapid development of new technologies in recent years, e-learning has increasingly gained worldwide popularity among governments and institutes of higher education. The government of Taiwan implemented a higher education e-learning program in 1996. The policies adopted in this program have since fostered an environment advantageous to the close cooperation of government, industry and academia. Under the prosperous and booming e-learning education markets, the Taiwan Government built up groups of e-learning designers and met the students' demand in related education processes. Therefore, a set of objective evaluation standards were established to face the needs and urgency of the vigorous development of e-learning mechanisms, so as to enhance competitiveness and fully satisfy the market and customer demands, and develop a closer relationship with suppliers and customers.

Implication and Strategic Advantages

Using simple visual analysis, the IPA evaluation grid reveals strengths and weaknesses of the criteria under consideration and, therefore, draws managerial implications for e-learning systems. The current competitive positions of the systems are identified (Figure 3).

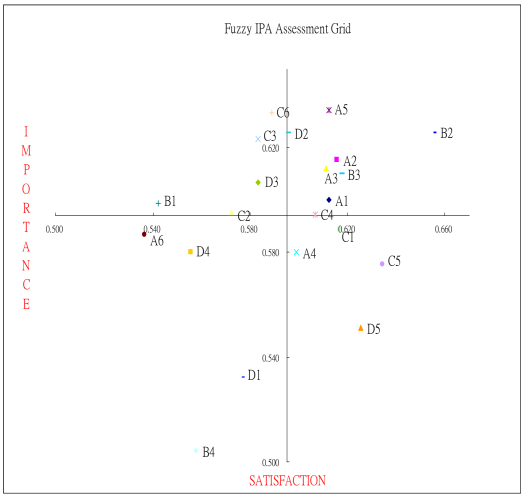

Figure 3: FIPA evaluation grid.

DISCUSSIONS AND CONCLUSIONS

The IPA evaluation is displayed in Figure 3. There were five criteria (B1, C2, C3, C6 and D3) loaded in the *Concentrate Here* quadrant. The above criteria showed that the importance given by the respondents was high; however, the actual performance was not as expected. This is an important point for related e-learning units to immediately work on improving. In addition, four criteria were located in the *Low Priority* quadrants which were A6, B4, D1 and D4. Although the eight criteria performed below the average level, they were considered not very important to e-learning performance. As the respondents were paying less attention to these criteria, the related units did not need to invest much to improve its performance in the areas. Four criteria were identified in the *Possible Overkill* quadrant. They were A4, C1, C5 and D5. Finally, the remaining eight criteria were in the *Keep up the Good Work* quadrant, indicating that the four criteria (A1, A2, A3, A5, B2, B3, C4 and D2) had performed particularly well in this area (Table 2).

Table 2: IPA evaluation quadrant.

Quadrant I keep up the good work	Quadrant II concentrate here	Quadrant III low priority	Quadrant IV possible over skill
A1. Accuracy of the contents of the teaching materials A2. Conforms to the level of the learners A3. Reasonable and definite structures A5. Appropriate quantity B2. Easy operations and applications B3. Simplified help functions C4. Consistency of the contents of the teaching materials and teaching objectives D2. Ability to promote the understanding of the learning contents	B1. Appropriate learning guide functions C2. Show effective pre-determined learning contents C3. Promote the linking of the learning contents an d expected knowledge C6. Interaction during the learning process D3. Ability to show the contents of the teaching materials appropriately	A6. Provide appropriate practice and assessment B4. Show complete and incomplete learning contents D1. Ability to promote learning motivations D4. Ability to accurately express the learning contents	A4. Possess deep and wide ranges C1. Clear and definite teaching objectives C5. Ability of the practicing process to give appropriate feedback D5. Good production quality

ACKNOWLEDGEMENTS

The authors would like to thank the National Science Council of the Republic of China for financially supporting this research under Contract No. NSC97-2511-S-241-013-MY3. We are also grateful to the reviewers and the editor for their constructive comments and assistance in revising and polishing this paper.

REFERENCES

1. Delargy, K. and Leteney, F., Managing Competencies during Times of Change. *Knowledge Management Review*, 8, **1**, 12-15 (2005).
2. Hanna, M., Data mining in e-learning domain. *Campus-wide information systems*, 21, **1**, 29-34 (2004).
3. Selim, H.M., Critical success factors for e-learning acceptance: Confirmatory factor models. *Computers and Educ.*, 49, 396-413 (2007).
4. Sun, P-C., Tsai, R.J., Finger, G., Chen, Y-Y. and Yeh, D., What drives a successful e-learning? An empirical investigation of the critical factors influencing learner satisfaction. *Computers and Educ.*, 50, 1183-1202 (2008).
5. Tzeng, G-H., Chiang, C-H. and Li, C-W., Evaluating intertwined effects in elearning program: A novel hybrid MCDM model based on factor analysis and DEMATEL. *Expert Systems with Applications*, 32, 1028-1044 (2007).
6. Wang, Y-S., Wang, H-Y. and Shee, D.Y., Measuring e-learning systems success in an organizational context: Scale development and validation. *Computers in Human Behavior*, 23, 1792-1808 (2007).
7. Cuban, L., *Oversold and underused: Computers in the classroom.* Cambridge, MA: Harvard University Press (2001).
8. Fabos, B. and Young, M.D., Telecommunication in the classroom: Rhetoric versus reality. *Review of Educational Research*, 69, **3**, 217-259 (1999).
9. Harris, S., Innovative pedagogical practices using ICT in schools in England. *J. of Computer Assisted Learning*, 18, **4**, 449-458 (2002).
10. ASTD (2003), 15 July 2007, http://www.learningcircuits.org/Hglossary
11. e-Learning Quality Certification Center: e-learning materials V3.0 H (2007), 24 July 2007, http://www.elq.org.tw/contListv3.htm
12. Michigan Virtual University, Standards for quality online courses (2002), 30 December 2004, http://standards.mivu.org/standards
13. Chen, M.P., An evaluation of the ELNP e-learning quality assurance program: Perspectives of gap analysis and innovation adoption. *Educational Technol. & Society* (2009) (in press).

14. Siragusa, L., Dixon, K.C. and Dixon, R., Designing quality e-learning environments in higher education. *Proc. Ascilite Singapore 2007*, 923-935 (2007).
15. Jovanović, J., Gašević, D., Knight, C. And Richards, G., Ontologies for Effective Use of Context in e-Learning Settings. *Educational Technology & Society*, 10, **3**, 47-59 (2007).
16. Wasko, M.M. and Faraj, S., Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly*, 29, **1**, 35-57 (2005).
17. Zhang, G., Jin, Q. and Lin, M., A framework of social interaction support for ubiquitous learning. *Proc.The 19th Inter. Conf. on Advanced Information Networking and Applications* (AINA'05) (2005).
18. Chao, R-J. and Chen, Y-H., Evaluation of the criteria and effectiveness of distance e-learning with consistent fuzzy preference relations. *Expert Systems with Applications*, 36, 10657-10662 (2009).
19. Chen, S.M., Evaluating weapon systems using fuzzy arithmetic operations. *Fuzzy Sets and Systems*, 77, 265-276 (1996).
20. Tseng, M.L., Using linguistic preferences and grey relational analysis to evaluate the environmental knowledge management capacities. *Expert Systems with Applications* (2009) (in press).
21. Opricovic, S. and Tzeng, G.H., Defuzzification within a multi-criteria decision model. *Inter. J. of Uncertainty, Fuzziness and Knowledge-Based Systems*, 11, **5**, 635-652 (2003).
22. Hawes, J.M. and Rao, C.P., Using importance-performance analysis to develop health care marketing strategies. *J. of Health Care Marketing*, 5, 19-25 (1985).
23. Myers, J.H., *Measuring Customer Satisfaction: Hot Buttons and Other Measurement Issues.* American Marketing Association, Chicago, IL: USA (1999).
24. Martilla, J.A. and James, J.C., Importance-performance analysis. *J. of Marketing*, 41, **1**, 77-9 (1977).
25. Matzler, K., Fuchs, M. and Schubert, A.K., Employee satisfaction: does Kano's model apply? *Total Quality Management & Business Excellence*, 15, **9/10**, 1179-98 (2004).
26. Matzler, K., Bailom, F., Hinterhuber, H.H., Renzl, B. and Pichler, J., The asymmetric relationship between attribute-level performance and overall customer satisfaction: a reconsideration of the importance-performance analysis. *Industrial Marketing Management*, 33, 271-7 (2004).
27. Hair, J.F., Anderson, R.E., Tatham, R.L. and Black, W.C., *Multivariate Data Analysis*. (4th Edn), Prentice-Hall, Upper Saddle River, NJ: USA (1995).
28. Chiou, H.K., Tzeng, G.H. and Cheng, D.C., Evaluating sustainable fishing development strategies using fuzzy MCDM approach. *Omega*, 33, 223-34 (2005).