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Fuzzy Evaluations Mappings to Model Opinions: Assessing Academic Quality in Technology Enhanced Learning Environments

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Abstract

The aim of this paper is to develop a quality assurance model to measure academic quality in technology enhanced higher education courses and programmes. It evaluates the academic quality of an artificial intelligence based active learning pedagogy in a course in which students co-create their own understanding of econometrics in a digitalised learning environment using Interactive Learning Documents (ILDs). ILDs are dynamic interactive documents developed in Jupyter notebook using Python programming language designed to facilitate interactive learning of data analysis, modelling and visualisation. The paper introduces fuzzy evaluation mappings and fuzzy sets to model expert and student opinions to derive a measure of overall quality within a multistage analytic hierarchical process. The model produces a distribution of academic quality. An in-class experiment with Newcastle University postgraduate students reveals that the quality of this technology enhanced learning model characterized as good, very good, and extremely good is a distribution represented by an overall quality evaluation vector with mean 0.14, median 0.11, std. 0.15, var. 0.024, kurtosis -0.88, skew 0.72, 60^{th} percentile 0.32, and 70^{th} percentile 0.21.

Keywords: Jupyter Notebooks, Econometrics, Fuzzy Comprehensive Evaluation Method, Fuzzy Sets, Artificial Intelligence

1 Introduction

The Office for Students' (OfS) regulatory framework for higher education in England recently changed the conditions of registration that relate to academic quality and standards[1]. These revised conditions set the new bar for higher education institutions to meet the demand of the regulator. Further to the benchmarks set out by OfS, UK higher education institutions compete for teaching rankings measured by the yearly National Student Survey (NSS) and the Postgraduate Taught Experience Survey (PTES). The outcomes of these surveys in addition to accreditation certifications are critical indicators of teaching quality for students who partially base their university choice decisions on these rankings. In order to support higher education institutions in competing for academic quality, this paper proposes a new quality assurance model for technology enhanced courses/programs taking pedagogical and technological variables into account [7].

To further meet the conditions of the rapid digital transformation of the education sector [10] this paper sets out to develop a quality assurance model for technology enhanced courses/programmes that can be used by higher education institutions to ensure consistency in academic quality across courses and programs. The novelty of the model is that it takes into account both; (i) the student learning experience and education expert opinions, and (ii) the effectiveness of learning with technology. The model utilizes fuzzy evaluation mappings [1] and fuzzy sets to interpret student and expert opinions in the

[1] https://www.officeforstudents.org.uk/advice-and-guidance/regulation/registration-with-the-ofs-a-guide/conditions-of-registration/

derivation of a measure of academic quality in a hierarchical structure [2]. The output of the model is a distribution representing overall academic quality.

The organization of the paper is a follows: Section two utilises fuzzy evaluation mappings and fuzzy sets in the development of the quality assurance model. Section three discusses the in-class experiment. Section four provides the results of the experiment. Section five is a conclusion followed by an appendix.

2 The Quality Assurance Model

Let there be n evaluation factors represented by a set

$$U = \{u_1, u_2, ..., u_n\}, \tag{1}$$

where u_i is the i^{th} evaluation factor in $u \in U$ and $u = (u_1, u_2, ..., u_n)$ a vector. There are m levels of appraisal grades represented by a set

$$V = \{v_1, v_2, ..., v_m\}, \tag{2}$$

where v_k is the k^{th} appraisal grade in $v \in V$ on a Likert scale and $v = (v_1, v_2, ..., v_m)$ is a vector. v_1 represents ”extremely disagree” and gradually increasing in incremental steps to v_m representing ”extremely disagree”. A mapping $U \to V$ is a fuzzy evaluation mapping if for each evaluation factor $u_i \in U$ there is a mapping

$$\mu_{\Pi_i} : U \to [0, 1] \tag{3}$$

where Π_i is a fuzzy set associated with evaluation factor $u_i \in U$. Alternatively, for every $u_i \in U$ the mapping $\Pi_i : U \to [0, 1]$ yields a row vector $\pi_i = (\pi_{i1}, \pi_{i2}, ..., \pi_{im})$, where π_{ik} represents the fuzzy membership degree of appraisal factor i to grade k. The general fuzzy appraisal matrix $[\pi_{ik}]$ for all evaluation factors $i = 1, ..., n$ and appraisal grades $k = 1, ..., m$ is denoted by

$$\Pi_{(n \times m)} = \begin{bmatrix} \pi_{11} & \pi_{12} & \cdots & \pi_{1m} \\ \pi_{21} & \pi_{22} & \cdots & \pi_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{n1} & \pi_{n2} & \cdots & \pi_{nm} \end{bmatrix}. \tag{4}$$

We employ triangular and Gaussian distribution functions μ in the construction of the mapping Π characterizing the fuzzy measure values π_{ik} for $i = 1, 2, ..., n$ and $k = 1, 2, ..., m$ [3, 4]. Where appropriate we combine the two distribution functions in the construction of fuzzy measure values sets. The construction of Π follows from survey and expert data. A focus group with experts provides the data points $v_{i1}, v_{i2}, ..., v_{im}$ of a distribution function μ for each evaluation factor $i = 1, ..., m$ in the factor set U and appraisal intervals $(v_{i1}, v_{i2}), (v_{i2}, v_{i3}), ..., (v_{i(m-1)}, v_{im})$. Then for all $\bar{v}_i \in [v_{i1}, ...v_{im}]$ the triangular distribution is given by

$$\mu_i(\bar{v}) = \begin{cases} p_k(\bar{v} - v_k) + 1, & \text{when } \bar{v} \in [v_k - \frac{1}{p_k}, v_k] \\ p_k(v_k - \bar{v}) + 1, & \text{when } \bar{v} \in [v_k, v_k + \frac{1}{p_k}] \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

where each $\bar{v}$ is some value provided by the subjects via survey data. Similarly, for the Gaussian distribution. A focus group with experts provides the data points $v_{i1}, v_{i2}, ..., v_{im}; \sigma_{i1}, \sigma_{i2}, ..., \sigma_{im}$, and $\sigma_k$where v_k represents the centre of the Gaussian distribution

$$\mu_i(\bar{v}) = e^{-\left(\frac{v-v_k}{\sigma_k}\right)^2}, \sigma_k > 0, \tag{6}$$

for all $\bar{v}_i \in [v_{i1}, ...v_{im}]$. From equations (5) and (6) we collect the values $\mu_i(\bar{v}_i)$ to obtain Π_i.

$$\Pi_i = \left\{ \mu_i(v_1), \mu_i(v_2), ..., \mu_i(v_m) \right\}. \tag{7}$$

In order to obtain a comprehensive overall quality evaluation vector $Q_{(1\times m)} = (q_1, q_2, ..., q_m)$ we construct a weight vector $W_{(n\times 1)}$ by the AHP method [8, 2] assigning relative weight w_i to evaluation factor $u_i \in U$ for every $i = 1, 2, ..., n$. The AHP method requires experts to make pair-wise comparisons between evaluation factors $E_1, E_2, ..., E_n$ and assigning numerical values a_{ij} for $i, j = 1, 2, ..., n$ to them. This yields a square matrix of relative weights $W_1, W_2, ..., W_n$ with the following properties: (i) $e_{ij} \approx \frac{W_i}{W_j}$, for $i, j = 1, 2, ..., n$, (ii) $e_{ii} = 1$, for all $i = 1, 2, ..., n$ (iii) if $e_{ij} = \alpha$ for $\alpha \neq 0$, then $e_{ji} = \frac{1}{\alpha}$, for $i = 1, 2, ..., n$, and (iv) if E_i is more important than E_j then $e_{ij} \cong (W_i/W_j) > 1$. These properties yield a positive definite and reciprocal matrix with 1's on the main diagonal. The advantage of this property is that experts only need to provide data for the upper/lower triangle of the matrix when trading off preferences, that is they report $L = n(n-1)/2$ data points. The properties now suggest a relationship

$$EW = nW, \tag{8}$$

which enables the computation of W using Saaty's method [2]. The overall quality evaluation vector Q is obtained by weighting the appraisal matrix. Hence,

$$Q = W \cdot \Pi, \tag{9}$$

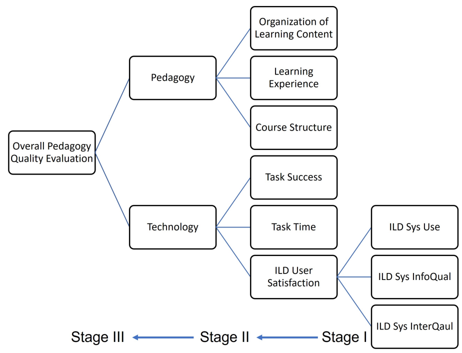


Figure 1: Methodology

Figure 1 outlines the overall methodology of the multi-stage evaluation process. Our goal is to provide a measure for the overall quality of our human-machine based interactive learning pedagogy denoted by Q_{Eval} (stage III). This evaluation vector is obtained by a staggered weighted average of "Pedagogy" and "Technology" evaluations denoted by

$$Q_{Eval} = W_{Eval} \cdot \Pi_{Eval}. \tag{10}$$

To construct "Π_{Eval}" two further stages in the hierarchy process need to be evaluated. At stage II, we separately measure the overall effectiveness of our ILD based pedagogy Q_{ped} and the effectiveness of our learning and teaching technology Q_{tech}. This requires calculating

$$Q_{ped} = W_{ped} \circ \Pi_{ped} \tag{11}$$
$$Q_{tech} = W_{tech} \circ \Pi_{tech}., \tag{12}$$

where Q_{ped} is a weighted average of Organization of Learning Content, Learning Experience, and Course Structure. Q_{tech} is a weighted average of Overall Task Success, Overall Task Time Feeling, and Satisfaction. The satisfaction vector is calculated at stage III by

$$Q_{sat} = W_{sat} \circ \Pi_{sat} \tag{13}$$

as a weighted average of ILD Use, ILD Sys InfoQual, and (iii) ILD Sys InterQual.

3 Experiment

An in-class experiment with a randomly selected pool of 33 postgraduate students enrolled in an Introductory Econometrics course delivered at Newcastle

University in the UK was conducted. The students were enrolled in Business School programs with strong quantitative orientation such as Financial Economics, International Economics and Finance, and Accounting and Finance. The program entry requirements were a 2:1 honours degree, or international equivalent, in any subject. Students also needed to demonstrate a good basic level of numeracy equivalent to UK GCSE or above prior to program enrolment. English language entry requirement were IELTS 6.5 overall (with a minimum of 6.0 in all sub-skills). The experiment cohort consisted of 52% male and 48% female. Students reported low (35%), average (45%), and advanced (20%) self-evaluated entry level mathematical skills.

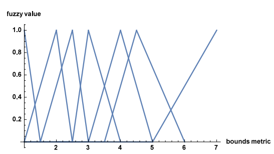
We developed interactive learning documents in Jupyter notebooks using mark down and LaTex syntax. Computer simulations and data modelling were coded in Python programming language. The ILDs included a variety of active learning elements such as dynamic plotting, pre-coded computer simulations and dynamic visualizations, data modelling, self-guided quizzes, video lecture material, and multiple-choice questions with answers. We used the Python packages Bokeh, Plotly , Matplotlib and iPython and the Faraway dataset to develop these learning activities. To further support students in their personalized learning, we developed a web-based chatbot which was integrated into the Jupyter notebooks-based ILDs. Students could interact with this digital learning companion around the clock. The chatbot was trained to provide learning content and to inform students about the course.

A product usability survey consisting of 19 technology related question was conducted [9]. This survey provided data to measure ILD product usability. The ILD product usability variable was constructed from three factors (i) ILD System Use, (ii) ILD Sys InfoQual, and (iii) ILD Sys InfoInter. A pedagogy effectiveness survey consisting of 14 questions was conducted. Three factors including (i) Organization of Learning Content, (ii) Learning Experience, and (iii) Course Structure defined the variable Pedagogy.

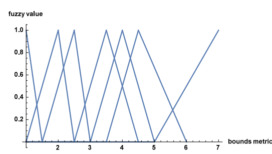
Expert data was collected from 5 experienced educators who agreed about the ranking of survey factors after a 30 minutes group discussion. The exercise consisted of individual preference ranking and agreeing as a group about the final representation of preferences (reference social preference). These data were collected in matrices E forming the basis of relative factor weights in the construction of the variables "User Satisfaction, Pedagogy, Technology, and Overall Quality of Pedagogy". Moreover, the same group of experts also agreed about the assumptions on evaluation mappings and provided bounds for each. That process took place over a 50 minutes group discussion.

4 Analysis and Results

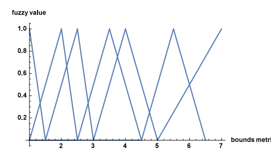
We construct the appraisal matrix Π_{sat} using fuzzy values for (i) ILD Use (6), (ii) ILD Sys InfoQual (7), and (iii) ILD Sys InterQual (Fuzzy Values ILD Sys InterQual) obtained using the metrics 2 yielding



(a) ILD System Use



(b) ILD Sys InfoQual



(c) ILD Sys InterQual

Figure 2: Satisfaction Metrics

$$\Pi_{sat} = \begin{bmatrix} 0.0000 & 0.0166 & 0.0250 & 0.1082 & 0.3288 & 0.3027 & 0.2187 \\ 0.0000 & 0.0000 & 0.0092 & 0.1212 & 0.2276 & 0.4452 & 0.1968 \\ 0.0252 & 0.0000 & 0.0288 & 0.0935 & 0.3165 & 0.2734 & 0.2626 \end{bmatrix}. \tag{14}$$

An expert ranking of ILD Use, ILD Sys InfoQual, and ILD Sys InterQual yields a matrix

$$E_{sat} = \begin{bmatrix} 1 & 1.1 & 0.9 \\ 0.91 & 1 & 0.8 \\ 1.11 & 1.25 & 1 \end{bmatrix} \tag{15}$$

which, using the average of normalized columns yields

$$E_{sat,norm} = \begin{bmatrix} 0.3311 & 0.3284 & 0.3333 \\ 0.3010 & 0.2985 & 0.2963 \\ 0.3679 & 0.3731 & 0.3704 \end{bmatrix}. \tag{16}$$

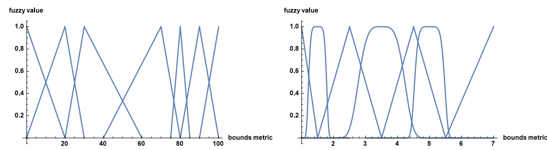
From this matrix we obtain the weight vector

$$W_{sat} = (0.3309, 0.2986, 0.3705). \tag{17}$$

Next, we construct the variable satisfaction using equations (14) and (17).

$$\text{satisfaction} = W_{sat} \cdot \Pi_{sat} \tag{18}$$

which is a vector [0.0093366, 0.00549294, 0.02169, 0.106635, 0.294025, 0.334395, 0.228426].



(a) Task Success (b) Task Time

Figure 3: Performance Metrics

We now construct the appraisal matrix Π_{tech} using fuzzy values for (i) Overall Task Success (Table 4), (ii) Overall Task Time Feeling (Table 5) illustrated in figure 3 and (iii) Satisfaction obtained from calculations above.

$$\Pi_{tech} = \begin{bmatrix} 0 & 0 & 0 & 0.1295 & 0.2505 & 0.5563 & 0.0637 \\ 0.0082 & 0.0665 & 0.0403 & 0.4123 & 0.2993 & 0.0775 & 0.0959 \\ 0.0084 & 0.0055 & 0.021 & 0.1074 & 0.2906 & 0.3400 & 0.2257 \end{bmatrix} \tag{19}$$

An expert ranking of Overall Task Success, Task Time, and Satisfaction yields a matrix

$$E_{tech} = \begin{bmatrix} 1 & 3/4 & 4/5 \\ 4/3 & 1 & 2/3 \\ 5/4 & 3/2 & 1 \end{bmatrix} \tag{20}$$

which, using the average of normalized columns yields

$$E_{tech,norm} = \begin{bmatrix} 0.28 & 0.23 & 0.32 \\ 0.37 & 0.31 & 0.27 \\ 0.35 & 0.46 & 0.41 \end{bmatrix}. \tag{21}$$

From this matrix we obtain the weight vector

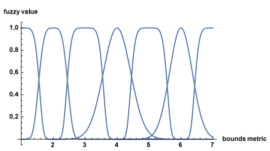
$$W_{tech} = (0.28, 0.32, 0.41). \tag{22}$$

Next, we construct the variable "Technology" using equations (19) and (22).

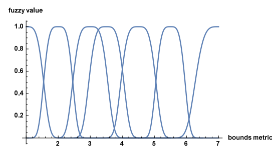
$$\text{Technology} = W_{tech} \cdot \Pi_{tech} \tag{23}$$

which is a vector [0.00556072, 0.0218947, 0.0198141, 0.205756, 0.279929, 0.333191, 0.133336].

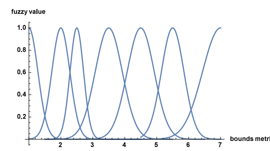
We now construct the appraisal matrix Π_{ped} using fuzzy values for (i) Organization of Learning Content (Table 1), (ii) Learning Experience (Table 2),



(a) Org. of Learning



(b) Learning Experience



(c) Course Structure

Figure 4: Pedagogy Metrics

and (iii) Course Structure (Table 3) with metrics provided by figure 4 yielding a matrix

$$\Pi_{ped} = \begin{bmatrix} 0 & 0 & 0 & 0.0284 & 0.3435 & 0.4139 & 0.2142 \\ 0 & 0 & 0 & 0.0618 & 0.2063 & 0.5110 & 0.2208 \\ 0 & 0 & 0 & 0.0434 & 0.2795 & 0.4334 & 0.2436 \end{bmatrix} \tag{24}$$

An expert ranking of Organization of Learning Content, Learning Experience, and Course Structure yields a matrix

$$E_{ped} = \begin{bmatrix} 1 & 3/2 & 2/3 \\ 2/3 & 1 & 3/5 \\ 3/2 & 5/3 & 1 \end{bmatrix} \tag{25}$$

which, using the average of normalized columns yields

$$E_{ped,norm} = \begin{bmatrix} 0.32 & 0.36 & 0.29 \\ 0.21 & 0.24 & 0.26 \\ 0.47 & 0.40 & 0.44 \end{bmatrix}. \tag{26}$$

From this matrix we obtain the weight vector

$$W_{ped} = (0.32, 0.24, 0.44) \tag{27}$$

.

Next, we construct the variable "Pedagogy" using equations (24) and (27).

$$\text{Pedagogy} = W_{ped} \cdot \Pi_{ped} \tag{28}$$

which is a vector [0, 0, 0, 0.0439307, 0.27882, 0.450119, 0.227063].

We now construct the overall appraisal matrix Π_{Qeval} using fuzzy values for (i) Technology and (ii) Pedagogy obtained from calculations above.

$$\Pi_{Qeval} = \begin{bmatrix} 0.006068 & 0.023535 & 0.021506 & 0.21223 & 0.285062 & 0.319964 & 0.141061 \\ 0 & 0 & 0 & 0.042416 & 0.284972 & 0.44468 & 0.227544 \end{bmatrix} \tag{29}$$

An expert ranking of Technology and Pedagogy yields a matrix

$$E_{Qeval} = \begin{bmatrix} 1 & 5/8 \\ 8/5 & 1 \end{bmatrix} \tag{30}$$

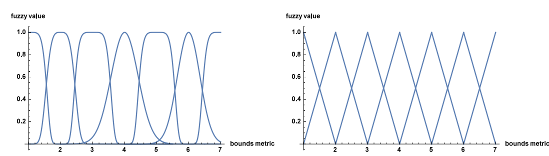
which, using the average of normalized columns yields

$$E_{Qeval,norm} = \begin{bmatrix} 0.38 & 0.38 \\ 0.62 & 0.62 \end{bmatrix}. \tag{31}$$

From this matrix we obtain the weight vector

$$W_{Qeval} = (0.38, 0.62). \tag{32}$$

Next, we construct the variable "Technology" using equations (29) and (32) with metrics provided in figure 5



(a) Pedagogy (b) Technology

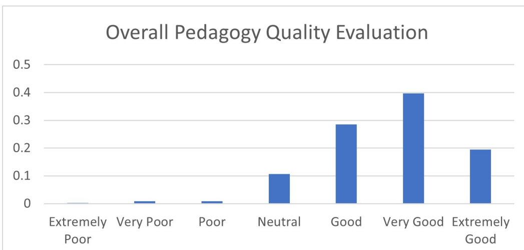
Figure 5: Overall Metrics

$$\text{Qeval} = W_{Qeval} \cdot \Pi_{Qeval} \tag{33}$$

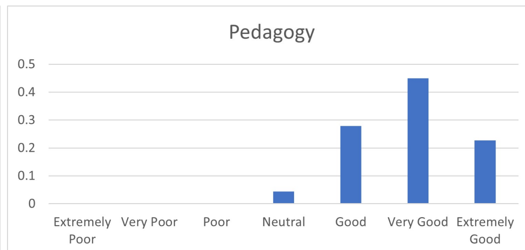
which is a vector [0.00230584, 0.0089433, 0.00817228, 0.106945, 0.285006, 0.397288, 0.19468].

5 Conclusion

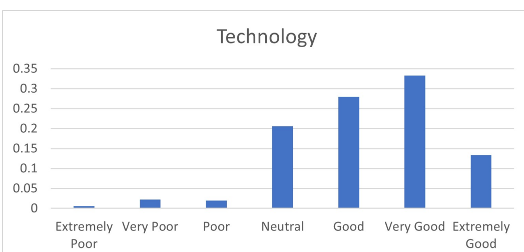
We consider a model in which students and experts independently provide opinions about academic quality in technology enhanced learning environments. In order to effectively measure opinions, we utilise fuzzy evaluation mappings and fuzzy sets. A measure of overall quality is obtained by considering these mappings within a technology enhanced hierarchical process. The model is particularly useful for measuring academic quality in artificial intelligence-based learning and teaching settings since it takes technological effectiveness into account in its overall measure of academic quality.



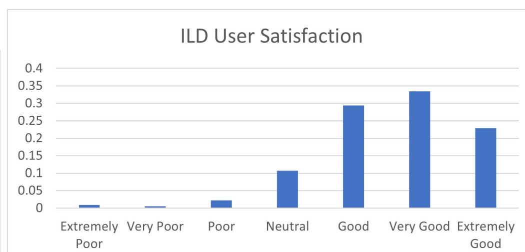
(a) Overall Quality Vector with mean 0.14, median 0.11, std. 0.15, var. 0.024, kurtosis -0.88, skew 0.72, 60^{th} percentile 0.32, and 70^{th} percentile 0.21.



(b) Pedagogy Vector with mean 0.14, median 0.04, std. 0.17, var. 0.03, kurtosis -0.49, skew 0.92, 60^{th} percentile 0.35, and 70^{th} percentile 0.24.



(c) Technology Vector with mean 0.14, std. 0.13. kurtosis -2.03, skew 0.23, 60^{th} percentile 0.20, and 70^{th} percentile 0.28.



(d) ILD User Satisfaction Vector: mean 0.14, median 0.11, std. 0.14, var. 0.02, kurtosis -2.10, skew 0.36, 60^{th} percentile 0.31, and 70^{th} percentile 0.24.

Figure 6: Quality Evaluation Vectors

The current model employs average preferences of a small cohort of experts representing the sector's views about pedagogical aspects. An empirical approach to measuring "expert preferences" based on a large sector sample of expert opinions would improve the robustness of our results and help establishing the precise categorical bounds of the evaluation mappings and the shape of the fuzzy sets. This is an avenue for future research.

6 Appendix

Organization of Learning Content							
Subject	Extremely poor	Very Poor	Poor	Neutral	Satisfied	Very Satisfied	Extremely Satisfied
1	0	0	0	0.062	1	0.018	0
2	0	0	0	0	0.151	0.645	0
3	0	0	0	0.29	0.971	0	0
...	...	...	...	...	...	...	...
32	0	0	0	0	0	0.169	0.971
33	0	0	0	0	0.151	0.645	0
Sum	0	0	0	0.966	11.674	14.065	7.279
Normalized Sum	0	0	0	0.0284	0.3435	0.4139	0.2142

Table 1: Fuzzy Values Organization of Learning Content

Learning Experience							
Subject	Extremely poor	Very Poor	Poor	Neutral	Satisfied	Very Satisfied	Extremely Satisfied
1	0	0	0	0	0	0.988	0
2	0	0	0	0	0.217	0.821	0
3	0	0	0	0	1	0	0
...	...	...	...	...	...	...	...
32	0	0	0	0	0	0	0.617
33	0	0	0	0	0	0.988	0
Sum	0	0	0	1.851	6.185	15.317	6.619
Normalized Sum	0	0	0	0.0618	0.2063	0.5110	0.2208

Table 2: Fuzzy Values Learning Experience

Course Structure							
Subject	Extremely poor	Very Poor	Poor	Neutral	Satisfied	Very Satisfied	Extremely Satisfied
1	0	0	0	0	0.009	0.6976	0.105
2	0	0	0	0	0.009	0.6976	0.105
3	0	0	0	0.009	0.779	0.141	0
...	...	...	...	...	...	...	...
32	0	0	0	0	0	0.008	0.779
33	0	0	0	0	0.106	0.961	0.018
Sum	0	0	0	1.214	7.814	12.1184	6.812
Normalized Sum	0	0	0	0.0434	0.2795	0.4334	0.2436

Table 3: Fuzzy Values Course Structure

Overall Task Success							
Subject	Extremely poor	Very Poor	Poor	Neutral	Satisfied	Very Satisfied	Extremely Satisfied
1	0	0	0	0	0.888	0.056	0
2	0	0	0	0	0	0.611	0
3	0	0	0	0	0	0.889	0
...	...	...	...	...	...	...	...
32	0	0	0	0.889	0	0	0
33	0	0	0	0	0	0.556	0.444
Sum	0	0	0	3.3890	6.5540	14.5576	1.6660
Normalized Sum	0	0	0	0.1295	0.2505	0.5563	0.0637

Table 4: Fuzzy Values Overall Task Success

Overall Task Time Feeling							
Subject	Extremely Poor	Very Poor	Poor	Neutral	Satisfied	Very Satisfied	Extremely Satisfied
1	0	0	0	0.858	0.5	0	0
2	0	0	0	0.087	1	0.368	0
3	0	0	0	0.087	1	0.368	0
...	...	...	...	...	...	...	...
32	0	0	0	1	0	0	0
33	0	0	0	0	0	0.5	1
Sum	0.34	2.767	1.68	17.166	12.463	3.228	3.994
Normalized Sum	0.0082	0.0665	0.0403	0.4123	0.2993	0.0775	0.0959

Table 5: Fuzzy Values Overall Task Time Feeling

ILD Sys Use							
Subject	Extremely Poor	Very Poor	Poor	Neutral	Satisfied	Very Satisfied	Extremely Satisfied
1	0	0	0	0	0	0.584	0.063
2	0	0	0	0	0.875	0.625	0
3	0	0	0	0.375	0.625	0.125	0
...	...	...	...	...	...	...	...
32	0	0	0	0	0	0.167	0.375
33	0	0	0	0	0	0.084	0.438
Sum	0.000	0.500	0.750	3.250	9.875	9.090	6.567
Normalized Sum	0.0000	0.0166	0.0250	0.1082	0.3288	0.3027	0.2187

Table 6: Fuzzy Values ILD Sys Use

ILD Sys InfoQual							
Subject	Extremely Poor	Very Poor	Poor	Neutral	Satisfied	Very Satisfied	Extremely Satisfied
1	0	0	0	0	0.429	0.953	0
2	0	0	0	0	0.286	0.857	0
3	0	0	0	0.5	0	0	0
...	...	...	...	...	...	...	...
32	0	0	0	0	0	0.095	0.429
33	0	0	0	0	0	0	0.715
Sum	0	0	0.286	3.786	7.111	13.909	6.149
Normalized Sum	0.0000	0.0000	0.0092	0.1212	0.2276	0.4452	0.1968

Table 7: Fuzzy Values ILD Sys InfoQual

ILD Sys InterQual							
Subject	Extremely Poor	Very Poor	Poor	Neutral	Satisfied	Very Satisfied	Extremely Satisfied
1	0	0	0	0	1	1	0.25
2	0	0	0	0	0.75	0	0.125
3	0	0	0.5	0.25	0	0	0
...	...	...	...	...	...	...	...
32	0	0	0	0	0	0.5	0.5
33	0	0	0	0	0	0.75	0.375
Sum	0.875	0	1	3.25	11	9.5	9.125
Normalized Sum	0.0252	0.0000	0.0288	0.0935	0.3165	0.2734	0.2626

Table 8: Fuzzy Values ILD Sys InterQual

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