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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, 60th percentile 0.32, and 70th 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

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 as follows: Section two utilizes fuzzy eval-
uation 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 ap-
pendix.

2 The Quality Assurance Model

Let there be \( n \) evaluation factors represented by a set
\[
U = \{u_1, u_2, \ldots, u_n\},
\]
where \( u_i \) is the \( i^{th} \) evaluation factor in \( u \in U \) and \( u = (u_1, u_2, \ldots, u_n) \) a vector. There are \( m \) levels of appraisal grades represented by a set
\[
V = \{v_1, v_2, \ldots, v_m\},
\]
where \( v_k \) is the \( k^{th} \) appraisal grade in \( v \in V \) on a Likert scale and \( v = (v_1, v_2, \ldots, v_m) \) 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
\[
\mu_{\Pi_i} : U \to [0, 1]
\]
where \( \Pi_i \) 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 \( \pi_i = (\pi_{i1}, \pi_{i2}, \ldots, \pi_{im}) \), where \( \pi_{ik} \) represents the fuzzy membership degree of appraisal
factor \( i \) to grade \( k \). The general fuzzy appraisal matrix \( [\pi_{ik}] \) for all evaluation
factors \( i = 1, \ldots, n \) and appraisal grades \( k = 1, \ldots, m \) is denoted by
\[
\Pi_{(n \times m)} = \begin{bmatrix}
\pi_{11} & \pi_{12} & \cdots & \pi_{1m} \\
\pi_{21} & \pi_{22} & \cdots & \pi_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
\pi_{n1} & \pi_{n2} & \cdots & \pi_{nm}
\end{bmatrix}.
\]

We employ triangular and Gaussian distribution functions \( \mu \) in the construc-
tion of the mapping \( \Pi \) characterizing the fuzzy measure values \( \pi_{ik} \) for \( i = 1, 2, \ldots, n \) and \( k = 1, 2, \ldots, m \) [3, 4]. Where appropriate we combine the two
distribution functions in the construction of fuzzy measure values sets. The
construction of $\Pi$ 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 $\mu$ 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

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

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

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

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 $\Pi_i$.

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

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 $e_{ij} \geq (W_i/W_j) > 1$. 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

$$
EW = nW,
$$

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,

$$
Q = W \cdot \Pi,
$$
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

$$Q_{Eval} = W_{Eval} \cdot \Pi_{Eval}. \hspace{1cm} (10)$$

To construct “$\Pi_{Eval}$” 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

$$Q_{ped} = W_{ped} \circ \Pi_{ped} \hspace{1cm} (11)$$

$$Q_{tech} = W_{tech} \circ \Pi_{tech}. \hspace{1cm} (12)$$

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

$$Q_{sat} = W_{sat} \circ \Pi_{sat} \hspace{1cm} (13)$$

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 $\Pi_{sat}$ 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

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

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

$$E_{sat} = \begin{bmatrix}
1 & 1.1 & 0.9 \\
0.91 & 1 & 0.8 \\
1.11 & 1.25 & 1
\end{bmatrix}. \quad (15)$$

which, using the average of normalized columns yields

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

From this matrix we obtain the weight vector

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

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

$$\text{satisfaction} = W_{sat} \cdot \Pi_{sat} \quad (18)$$

which is a vector $[0.0093366, 0.00549294, 0.02169, 0.106635, 0.294025, 0.334395, 0.228426]$. 
We now construct the appraisal matrix $\Pi_{tech}$ 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.

$$\Pi_{tech} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.1295 & 0.2505 & 0.5563 & 0.0637 \\ 0.0082 & 0.0665 & 0.0403 & 0.4123 & 0.2993 & 0.0775 & 0.0959 \\ 0.0084 & 0.0055 & 0.021 & 0.1074 & 0.2906 & 0.3400 & 0.2257 \end{bmatrix}$$ \hspace{1cm} (19)

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

$$E_{tech} = \begin{bmatrix} 1 & 3/4 & 4/5 \\ 4/3 & 1 & 2/3 \\ 5/4 & 3/2 & 1 \end{bmatrix}$$ \hspace{1cm} (20)

which, using the average of normalized columns yields

$$E_{tech,\text{norm}} = \begin{bmatrix} 0.28 & 0.23 & 0.32 \\ 0.37 & 0.31 & 0.27 \\ 0.35 & 0.46 & 0.41 \end{bmatrix}.$$ \hspace{1cm} (21)

From this matrix we obtain the weight vector

$$W_{tech} = (0.28, 0.32, 0.41).$$ \hspace{1cm} (22)

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

$$\text{Technology} = W_{tech} \cdot \Pi_{tech}$$ \hspace{1cm} (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 $\Pi_{ped}$ using fuzzy values for (i) Organization of Learning Content (Table 1), (ii) Learning Experience (Table 2),
and (iii) Course Structure (Table 3) with metrics provided by figure 4 yielding a matrix

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

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

\[
E_{ped} = \begin{bmatrix}
1 & 3/2 & 2/3 \\
2/3 & 1 & 3/5 \\
3/2 & 5/3 & 1 \\
\end{bmatrix}
\]  \(25\)

which, using the average of normalized columns yields

\[
E_{ped, norm} = \begin{bmatrix}
0.32 & 0.36 & 0.29 \\
0.21 & 0.24 & 0.26 \\
0.47 & 0.40 & 0.44 \\
\end{bmatrix}.
\]  \(26\)

From this matrix we obtain the weight vector

\[
W_{ped} = (0.32, 0.24, 0.44)
\]  \(27\)

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

\[
\text{Pedagogy} = W_{ped} \cdot \Pi_{ped}
\]  \(28\)

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

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

\[
\Pi_{Qeval} = \begin{bmatrix}
0.006068 & 0.023533 & 0.021506 & 0.21223 & 0.285062 & 0.319964 & 0.141061 \\
0 & 0 & 0 & 0.042416 & 0.284972 & 0.44468 & 0.227544 \\
\end{bmatrix}
\]  \(29\)
An expert ranking of Technology and Pedagogy yields a matrix

\[
E_{Qeval} = \begin{bmatrix}
1 & 5/8 \\
8/5 & 1
\end{bmatrix}
\]  \hspace{1cm} (30)

which, using the average of normalized columns yields

\[
E_{Qeval,norm} = \begin{bmatrix}
0.38 & 0.38 \\
0.62 & 0.62
\end{bmatrix}.
\]  \hspace{1cm} (31)

From this matrix we obtain the weight vector

\[
W_{Qeval} = (0.38, 0.62).
\]  \hspace{1cm} (32)

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

\[
Q_{eval} = W_{Qeval} \cdot \Pi_{Qeval}
\]  \hspace{1cm} (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, dian 0.04, std. 0.17, var. 0.03, kurtosis -0.88, skew 0.72, 60\textsuperscript{th} percentile -0.49, skew 0.92, 60\textsuperscript{th} percentile 0.35, and 70\textsuperscript{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\textsuperscript{th} percentile 0.35, and 70\textsuperscript{th} percentile 0.24.

(c) Technology Vector with mean 0.14, 0.14, median 0.11, std. 0.14, var. 0.02, std. 0.13. kurtosis -2.03, skew 0.23, 60\textsuperscript{th} kurtosis -2.10, skew 0.36, 60\textsuperscript{th} percentile percentile 0.20, and 70\textsuperscript{th} percentile 0.28. 0.31, and 70\textsuperscript{th} percentile 0.24.

(d) ILD User Satisfaction Vector: mean

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

<table>
<thead>
<tr>
<th>Subject</th>
<th>Extremely poor</th>
<th>Very Poor</th>
<th>Poor</th>
<th>Neutral</th>
<th>Satisfied</th>
<th>Very Satisfied</th>
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Table 1: Fuzzy Values Organization of Learning Content

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<th>Poor</th>
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Table 2: Fuzzy Values Learning Experience
Fuzzy evaluations mappings to model opinions

### Course Structure

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Table 3: Fuzzy Values Course Structure

### Overall Task Success

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Table 4: Fuzzy Values Overall Task Success

### Overall Task Time Feeling

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Table 5: Fuzzy Values Overall Task Time Feeling
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Table 6: Fuzzy Values ILD Sys Use

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Table 7: Fuzzy Values ILD Sys InfoQual

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Table 8: Fuzzy Values ILD Sys InterQual
References


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