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# Multi-Criteria Evaluation of eLearning Attributes using the Fuzzy TOPSIS Method*

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Various models of evaluating eLearning system success have been identified in the past and the need for *effective* evaluation of eLearning systems has been highlighted during the COVID-19 pandemic. The purpose of the present work is to elicit how both academic staff and students (the evaluators) view the performance of eLearning attributes when being taught using an eLearning system. The attributes are ranked using a multi-criteria evaluation algorithm called the Fuzzy Technique for Order Preference by Similarity to the Ideal Solution (Fuzzy TOPSIS). Here, using linguistic-response expert questionnaires, a set of eLearning system attributes and a set of eLearning system criteria are evaluated. The Fuzzy TOPSIS algorithm yields weightings for each of the attributes which can then be ranked to arrive at the optimal solution in terms of how well they contributed to the success of the current eLearning system. IT service quality is found to rank highest, followed by technical system quality, information quality and finally the consideration of different learning styles. Large agreement is seen between academic staff and student evaluators, with minor disagreement between students of two different disciplines. As regards practical implications, it is shown from the rankings that the eLearning system must be re-organized and consideration of different learning styles must be improved. The Fuzzy TOPSIS method has been found to be a reliable and economic evaluation approach of eLearning systems, since it does not require large numbers of evaluators and provides a ranking of attributes which translate directly into priorities for improvement.

**Keywords:** eLearning; eLearning system; TOPSIS; multi-criteria evaluation; fuzzy numbers

## 1. Introduction

This section provides the background related to eLearning attributes, the impact of the COVID-19 pandemic on eLearning systems, and approaches to evaluation of eLearning systems.

### *1.1 Attributes of eLearning systems*

In 2003, an updated Information Systems Success Model (ISSM) was proposed [1], which includes the seven attributes:

- information quality;
- system quality;
- service quality;
- intention to use;
- use;
- user satisfaction; and,
- net benefits.

However, the authors emphasized that the relationship between intention to use, use, user satisfaction and net benefits are not necessarily representing causal relationships and that these relationships may be complex. Since eLearning systems are information systems, the ISSM has been utilized numerous times for the purpose of evaluating eLearning system success. A systematic review was carried out and found, based on 92 primary studies from 2010 to 2020, that 20 studies integrated the ISSM with the Technology Acceptance Model (TAM) [2]. The TAM was originally developed to indirectly measure individuals' usage behaviors [3].

A structural equation analysis was carried out to analyze an *enterprise* systems success measurement model and found four distinct dimensions of the system:

- individual impact;
- organizational impact;
- system quality; and,
- information quality [4].

As before, the considered system was *not* an eLearning system, but the identified dimensions of the considered enterprise system are also relevant and important for a successful eLearning system. The high importance of system *quality* for an eLearning system has been confirmed, by identifying the attributes system design, system delivery, and system outcome, as the primary factors for overall success of an eLearning system [5]. Similarly, some work showed the high impact of system *characteristics* on eLearning [6].

An integrated success model with six dimensions, namely,

- learners;
- instructors;
- courses;

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- technology;
- design; and,
- environment, was developed [7].

This study found based on a survey that the critical factors for learners' satisfaction were related to the learners themselves, instructor, course, usefulness, ease of use, and the variety of assessment approaches. However, learner satisfaction is arguably only one criterion when evaluating eLearning system success, albeit an important one. Another empirical investigation into students' evaluation of eLearning systems within a higher education context was conducted [8]. It led to the Hexagonal eLearning Assessment Model (HELAM), which incorporates the following six dimensions:

- system quality;
- service quality;
- content quality;
- learner perspective;
- instructor attitudes; and,
- supportive issues.

Also related to eLearning system success in universities, the Measuring eLearning Systems Success model (MELSS Model) was developed [9]. It was found that the four important attributes are:

- technical system quality;
- user satisfaction;
- educational system quality; and,
- service quality.

More recently, an extensive literature review related to the evaluation of eLearning systems has been conducted which also considered the above findings [10]. It resulted in a multidimensional conceptual model, the Evaluating eLearning System Success (EESS) model, which includes a comprehensive range of success factors. Seven independent constructs were identified:

- technical system quality;
- information quality;
- service quality;
- educational system quality;
- support system quality;
- learner quality; and,
- instructor quality.

The EESS model will be used as a basis for the evaluation of the eLearning system of this study, which will be explained in more detail in the Methodology section.

### *1.2 COVID-19 Pandemic and eLearning Systems*

Following the forced adoption of eLearning during the COVID-19 pandemic, numerous studies investigated particular aspects of eLearning success in specific local and institutional contexts. Only a few of these studies can be mentioned here to reflect the wide range of different contexts that were investigated: Students' opinion on "Emergency Remote Teaching" versus face-to-face classes was analyzed in Spain [11]. The factors of learning management systems that affect sustainable education in Africa have been investigated [12]. ELearning systems success in Sri Lanka has been evaluated utilizing the previously mentioned Effective eLearning System Success (EESS) model [13].

A focus on assessing digital divides in higher education during the COVID-19 pandemic, using an extended model of the EESS model, has been reported [14]. First, the model's constructs were modified to learner quality, support system quality, and feature use. The last construct, feature use, was added as a separate construct since the adoption of eLearning systems became mandatory during the COVID-19 pandemic. However, the authors state that feature use is not necessarily an indicator of success and that it might be influenced by learning objectives, subject, or teaching methodology. Secondly, stress level was added as a separate dimension of the construct learner quality, since the COVID-19 pandemic has led to an increased level of stress [15]. Thirdly, the construct support system quality was expanded by adding the dimension, socio-emotional support.

Studies motivated by new challenges for universities during the COVID-19 pandemic led also to improvement of existing eLearning systems. Problems of traditional eLearning systems and the following digital technologies to improve an eLearning system have been analyzed: cloud computing, adaptive design, big data, 3D printing, wearable technologies and gamification [16]. These solutions are strongly related to the eLearning attribute "system quality", one of the common constructs of eLearning system models as shown before. Another issue of eLearning system quality, namely, face morphing attacks (i.e., attacks on face recognition in eLearning systems) has been dealt with [17].

The increase in utilizing eLearning systems triggered by the COVID-19 pandemic and the need for effective eLearning systems has been noted. Based on a comprehensive review of literature, it was found that additional research is needed to collect more insights from the *instructors'* perspective, because instructors are involved in using and managing eLearning systems. The study concluded that conducting more studies utilizing instructors is a promising direction for future research [18]. The present study is contributing to filling this gap.

### *1.3 Continual Improvement of eLearning Systems*

Findings related to the evaluation and continual improvement of eLearning systems have been published previously, and the following approaches were identified.

The Information System Impact Measurement Model [19] was used as a conceptual framework to measure the impact of an eLearning system [20]. Similarly, the same model has been used and it was recommended to monitor the impact of the eLearning system by using the model at least once every two years to facilitate continual improvement [21]. Student and academic staff feedback was used to continually improve an eLearning system [22]. A questionnaire survey was also used to collect student feedback on their experience with the eLearning system [23]. Replication of surveys over time allows to identify performance changes of the system and potential for improvement. Constructs and dimensions of eLearning system success models can be utilized as a framework for questionnaire surveys. However, the findings might be difficult to use for decision makers in that they do not easily translate to a ranking of necessary improvement actions.

With the aim to support the selection of eLearning products (for example, a learning management system), a decision framework incorporating quality function deployment, fuzzy linear regression, and optimization has been applied [24]. Similar to the present work, the Analytic Hierarchy Process (AHP) approach, and a Multi-Criteria Decision Making (MCDM) method, were used to select a suitable learning management system (LMS) for an organization [25]. Fuzzy logic has also been applied to improve and automate teaching and learning tasks [26].

Another strand of approaches, which provide improvement, are studies that analyzed how to identify issues, which subsequently could be fixed. The usage of root cause analysis to achieve eLearning system improvement based on institutional qualitative investigations has been described [27]. Utilizing data generated by the eLearning system itself, such as Moodle log data, has been used to evaluate and improve the eLearning system [28].

Based on this background related to existing eLearning system success models, the need to consider the instructors' perspective more, and the existing approaches to eLearning system improvement, the following sections describe the purpose, methodology and results of the study presented here.

## 2. Purpose and Aim

The threefold purpose of this study is to:

(1) test the Fuzzy TOPSIS approach for evaluating eLearning system attributes to provide priorities for continual improvement to decision makers;
(2) compare the evaluation of academic staff with the evaluation of students; and,
(3) evaluate an eLearning system at an institution that did not utilize eLearning before the COVID-19 pandemic.

The first purpose is grounded in the limitation of existing approaches to evaluation in that these merely allow the evaluation of improvement of individual constructs and dimensions of the eLearning system over time. For example, a repeated questionnaire survey simply allows the identification of differences when comparing with the original survey. However, usually decision makers need to decide which aspect of improvement to prioritize over other aspects. In some circumstances, such as a sudden lockdown caused by a pandemic, this decision needs to be done within a very short period. As we are dealing with the human subjectivity of the evaluator, Fuzzy TOPSIS is preferred to TOPSIS for this multi-criteria evaluation. A brief description of the Fuzzy TOPSIS method is given in the following Methodology section.

Since the two main users of an eLearning system, academic staff and students, approach usage of the eLearning system from different perspectives, an evaluation with the aim of continual improvement needs to consider both of these perspectives. This warrants the second purpose of this study, the comparison of evaluations of academic staff with the evaluations of students.

Finally, adopting improvement steps from institutions that developed an eLearning system before the COVID-19 pandemic are inconclusive since they adjusted already existing eLearning systems. In contrast, an institution that did not utilize eLearning before the COVID-19 pandemic and had to develop and implement an eLearning system within a very short period is more likely to identify different priorities of improvement actions. This explains the third purpose of this study, the evaluation of an eLearning system at an institution that did not utilize eLearning before the COVID-19 pandemic.

## 3. Methodology

After describing the purpose and aim of this study, this section explains the eLearning system used here, involved evaluators, the evaluation approach, and the Fuzzy TOPSIS method of combining the evidence.

### *3.1 Analyzed eLearning System*

The eLearning system considered here consisted of the learning management system (LMS) Moodle to provide learning material and to deliver assessments, MS Teams for verbal and written online interaction between students and academic staff, MS Outlook for written online interaction (emails), and the Respondus LockDown browser and Monitor (Respondus®Inc. https://web.respondus.com/he/lockdownbrowser/2000) as the online assessment surveillance system. The eLearning system was introduced at a private university in Kuwait during a short period of time in March 2020, when a total lockdown was implemented to fight the COVID-19 pandemic. In general, the digital infrastructure of educational institutions in Kuwait was not ready for the sudden implementation of online learning [29] and virtual learning environments did not exist in Kuwait prior to the pandemic [30]. However, students in higher education were found to be ready for eLearning during the pandemic in terms of a positive perception of innovation, optimism, usefulness, and ease of use, although they were also found to feel insecure and uncomfortable [31].

### 3.2 Evaluators of eLearning System

Evaluators involved in this study were academic staff of the civil engineering department, namely two laboratory instructors (LAB), seven instructors (IN), and four professors (PROF), in addition to three civil engineering students and three mechanical engineering students. Although all evaluators had experienced the introduction and implementation of the eLearning system in March 2020, they were asked to evaluate the eLearning system as applied in spring 2021, since it was then that the eLearning system had a much higher level of maturity (i.e., no system changes were introduced during the semester).

### 3.3 Evaluation Approach

For the evaluation of the eLearning system a model consisting of five criteria (C1 to C5) and four attributes (A1 to A4) has been developed based on the literature presented in the introduction section. Two questions posing alternative answers, consider all seven constructs of the Evaluating eLearning System Success (EESS) model [32]. To collect data, a questionnaire consisting of the two questions was composed. Following the questionnaire introduction, the first question, i.e. "What is the weight (importance) of the following items?", measured the criteria of the eLearning system using linguistic responses on a seven-point response scale from very high to very low, as explained in the sub section Fuzzy TOPSIS method:

C1: Easy to use.
C2: High Learning Effectiveness.
C3: Consistent with organizational requirements.
C4: Consistent with Learner personality.
C5: Consistent with Instructor personality.

The second question, i.e. "For each of these criteria, please evaluate the following attributes of the eLearning system, based on your experience during Spring 2021", evaluated the following four attributes of the eLearning system, using linguistic responses on a six-point response scale, from very good to very poor, as shown in the sub section Fuzzy TOPSIS method:

A1: Technical System Quality.
A2: Information Quality.
A3: IT Service Quality.
A4: Considers different Learning Styles.

The analysis of the collected data used a mixed study approach, namely, the Fuzzy TOPSIS method as a primary approach, and descriptive statistics based on mean values derived from the linguistic responses as a secondary approach. The choice of the Fuzzy TOPSIS approach was made because the logic was understandable and seemed appropriate due to the subjective nature of evaluation, even expert evaluation. Also, the algorithm is such that each stage allows for following the results for the attributes for each of the criteria. Finally, the algorithm considers the priority weightings [33]. The Fuzzy TOPSIS method is explained in detail in the following sub section.

### 3.4 Fuzzy TOPSIS Method

Traditional TOPSIS uses an index of similarity (or closeness) to the ideal solution and the longest distance from the negative-ideal solution [34]. This version of TOPSIS compares the alternatives by using the weights identified for all the criteria, normalizes the scores, and then calculates the distance to the ideal and negative-ideal solutions. The similarities calculated with respect to the ideal solution can then be used to rank the attributes.

However, the original weightings identified by evaluators are often problematic, in that, uncertainty and subjectivity may come into the evaluation process. Hence there is a need for an extension to TOPSIS which can convert linguistic survey responses into fuzzy numbers. These can then be used to elicit ranking of the attributes while accounting for uncertainties.

Normally, without the use of fuzzy logic, evaluations made by human beings have to be binary, i.e., good-bad, yes-no, or on-off. However, this black-white description in real life can be separated by many shades of gray, which should be taken into account for evaluations. This uncertainty, or vagueness may be accounted for using fuzzy logic [35].

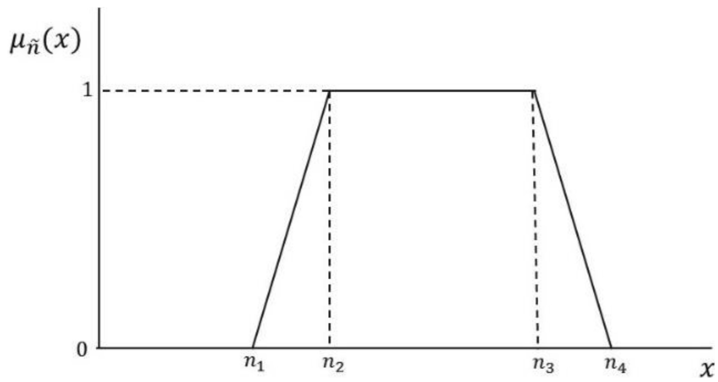


**Fig. 1.** Trapezoidal fuzzy number.

Fuzzy sets may be expressed as membership functions where the membership function is defined as a number in the range 0 to 1 and denote as, $\mu A(x)$. This means that if an element $x$ is a member of the set $A$ then the membership function $\mu A(x) = 1$ and if not, $\mu A(x) = 0$. The membership function can vary from a high to a low degree and it is continuous. There are many ways of defining the membership function, for example, using triangular or trapezoidal [36] formulations. The membership function used here is the trapezoidal fuzzy number (Fig. 1) defined as

$$\mu_{\tilde{n}}(x) = \begin{cases} 0, & x < n_1 \\ \dfrac{x - n_1}{n_2 - n_1}, & n_1 \le x \le n_2 \\ 1, & n_2 \le x \le n_3 \\ \dfrac{x - n_4}{n_3 - n_4}, & n_3 \le x \le n_4 \\ 0, & x > n_4 \end{cases} \quad (1)$$

It should be noted that in the following a fuzzy number will be identified by a tilde. For fuzzy trapezoidal numbers the following elementary operations can be defined [37], with some used for matrix multiplication during this work:

$$(\tilde{m} \oplus \tilde{n}) = (m_1 + n_1, m_2 + n_2, m_3 + n_3, m_4 + n_4)$$

$$(\tilde{m} \ominus \tilde{n}) = (m_1 - n_1, m_2 - n_2, m_3 - n_3, m_4 - n_4)$$

$$(\tilde{m} \otimes \tilde{n}) = (m_1 \times n_1, m_2 \times n_2, m_3 \times n_3, m_4 \times n_4)$$

$$(\tilde{m} \otimes r) = (m_1 \times r, m_2 \times r, m_3 \times r, m_4 \times r) \quad (2)$$

$$(\tilde{m} \oslash \tilde{n}) = (m_1/n_4, m_2/n_3, m_3/n_2, m_4/n_1)$$

$$(-\tilde{m}) = (-\tilde{m}_1, -\tilde{m}_2, -\tilde{m}_3, -\tilde{m}_4)$$

$$(1/\tilde{m}) = (1/\tilde{m}_4, 1/\tilde{m}_3, 1/\tilde{m}_2, 1/\tilde{m}_1)$$

An equivalent method for the traditional TOPSIS analysis when finding the distance of the positive and negative ideals needs to be developed for fuzzy numbers. The method used here is the vertex method for the trapezoidal fuzzy numbers $\tilde{m} = (m_1, m_2, m_3, m_4)$ and $\tilde{n} = (n_1, n_2, n_3, n_4)$ defined as [38]

$$d(\tilde{m}, \tilde{n}) = \frac{1}{2}\sqrt{(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2 + (m_4 - n_4)^2} \quad (3)$$

As a starting point for Fuzzy TOPSIS, evaluators need to provide raw data in the form of evaluations of the attributes in relation to the evaluation criteria. This can be done using a numerical scale or by a linguistic expression as, for example, detailed in Tables 1 and 2.

A fuzzy multi-criteria evaluation problem with $m$ alternatives $\{A_1, A_2, \ldots, A_m\}$ and $n$ criteria $\{C_1, C_2, \ldots, C_n\}$ can be expressed by the evaluation matrix [39]

$$\widetilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \quad (4)$$

**Table 1.** Linguistic expressions to prioritize each of the criteria

| **Linguistic expression** | **Trapezoidal Fuzzy Number** | **Abbreviation** |
|---|---|---|
| Very High | (0.8 0.9 1.0 1.0) | VH |
| High | (0.7 0.8 0.8 0.9) | H |
| Medium High | (0.5 0.6 0.7 0.8) | MH |
| Middle | (0.4 0.5 0.5 0.6) | M |
| Medium Low | (0.2 0.3 04 0.5) | ML |
| Low | (0.0 0.2 0.2 0.3) | L |
| Very Low | (0.0 0.0 0.1 0.2) | VL |

**Table 2**. Linguistic variables for evaluations

| **Linguistic expression** | **Trapezoidal Fuzzy Number** | **Abbreviation** |
|---|---|---|
| Very Good | (8 9 10 10) | VG |
| Good | (6 7 8 9) | G |
| Fair | (4 5 6 7} | F |
| Medium Poor | (2 3 4 5) | MP |
| Poor | (1 1 2 3) | P |
| Very Poor | (0 0 0 1) | VP |

and the fuzzy weight vector

$$\widetilde{W} = [\widetilde{w}_1 \ \widetilde{w}_2 \ \cdots \ \widetilde{w}_n]$$

If there are $L$ evaluators, then the evaluations made by the evaluators can be given in the form

$$\tilde{x} = (a_{ijl}, b_{ijl}, c_{ijl}, d_{ijl}), \tilde{w} = (w_{ij1}, w_{ij2}, w_{ij3}, w_{ij4}), \quad (5)$$
$$\text{where } (i = 1,2,\dots,m; j = 1,2,\dots,n))$$

The criteria values given by the evaluators are expressed as $\tilde{x} = (a_{ij}, b_{ij}, c_{ij}, d_{ij})$ with

$$a_{ij} = \min_l\{a_{ijl}\}, \quad b_{ij} = \frac{1}{L}\sum_{l=1}^{L} b_{ijl},$$
$$c_{ij} = \frac{1}{L}\sum_{l=1}^{L} c_{ijl}, \quad d_{ij} = \max_l\{d_{ijl}\} \quad (6)$$

The weights for the evaluation criteria are expressed as $\tilde{w} = (w_{j1}, w_{j2}, w_{j3}, w_{j4})$ with

$$w_{j1} = \min_l\{w_{jl1}\}, \quad w_{j2} = \frac{1}{L}\sum_{l=1}^{L} w_{jl2},$$
$$w_{j3} = \frac{1}{L}\sum_{l=1}^{L} w_{jl3}, \quad w_{j4} = \max_l\{w_{jl4}\} \quad (7)$$

The normalized fuzzy evaluation matrix, $\tilde{R} = [\tilde{r}_{ij}]$ is now computed as

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*} \ \frac{b_{ij}}{c_j^*} \ \frac{c_{ij}}{c_j^*} \ \frac{d_{ij}}{c_j^*}\right) \text{ and } c_j^* = \max_i\{c_{ij}\} \text{ (benefit criteria)}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{d_{ij}} \ \frac{a_j^-}{c_{ij}} \ \frac{a_j^-}{b_{ij}} \ \frac{a_j^-}{a_{ij}}\right) \text{ and } a_j^- = \min_i\{a_{ij}\} \text{ (cost criteria)} \quad (8)$$

Next the weighted normalized fuzzy evaluations matrix is calculated as $\tilde{V} = (\tilde{v}_{ij})$ where $\tilde{v}_{ij} = \tilde{r}_{ij} \times w_j$.

**Table 3.** Example for linguistic response evaluation (weights) of eLearning criteria: academic staff

| Evaluator | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| IN01 | VH | L | ML | VL | M |
| IN02 | H | VH | H | H | H |
| IN03 | MH | MH | MH | M | MH |
| IN04 | H | ML | MH | H | L |
| IN05 | VH | VL | M | L | H |
| IN06 | M | H | H | H | MH |
| IN07 | MH | MH | MH | M | L |
| LAB01 | MH | M | M | MH | MH |
| LAB02 | M | M | ML | M | M |
| PROF01 | H | VH | H | M | MH |
| PROF02 | VH | VH | VH | VH | VH |
| PROF03 | VH | VL | MH | VL | MH |
| PROF04 | M | ML | MH | L | L |

This is followed by calculations for the Fuzzy Positive Ideal Solution (FPIS, $A^*$ and the Fuzzy Negative Ideal Solution (FNIS, $A^-$ which are defined as

$$A^* = (v_1^*, v_2^*, \dots. v_n^*), \quad A^- = (v_1^-, v_2^-, \dots. v_n^-) \quad (9)$$

and with $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$

$$\tilde{v}_j^* = \max_i\{v_{ij4}\}, \quad \tilde{v}_j^- = \min_i\{v_{ij1}\} \quad (10)$$

and taking $d$ as the distance between two fuzzy numbers together with the vertex method the distances for FPIS and FNIS can be calculated as

$$d_i^* = \sum_{j=1}^{n} d(\tilde{v}_{ij}, v_j^*), i = 1,2,\dots,m$$
$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, v_j^-), i = 1,2,\dots,m \quad (11)$$

Once these distances are known, the closeness coefficient $CC_i$ for each alternative $A_i$ is calculated as

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \quad (12)$$

Using the closeness coefficient, the alternatives can be ranked, with the highest closeness coefficient representing the best alternative. Results are presented and discussed in the following section.

## 4. Results and Discussion

This section presents examples of collected data, the rankings of the attributes obtained by the Fuzzy TOPSIS approach and mean values of the eLearning attributes, as well as discussions of the findings.

Linguistic response evaluations of the weight of each criterion C1 to C5 (easy to use; high learning effectiveness; consistent with organizational requirements; consistent with learner personality; consistent with instructor personality) are shown exemplary for the academic staff evaluators in Table 3. The academic staff evaluators were made up of Professors (PROF), Laboratory Instructors (LAB) and Instructors (IN). Similarly, an evaluation by students was carried out. As given in Table 1, the ratings ranged from very low (VL) to very high (VH), with each of the evaluators indicating their perceived relative importance of the five criteria. The results reflect how different the evaluators perceived the importance of these criteria – even within the same position category. For example, Prof02 assigned a very high importance to all five criteria, whereas Prof04 assigned a medium importance to criteria 1, medium high importance to criteria 3, medium low importance to criteria 2 and low importance to criteria 4 and 5. The difference of perceived importance might be related to individual experiences with the eLearning system, or different expectations regarding the performance of an eLearning system.

As an example, the linguistic response evaluation of criteria C1 (Easy to use) given by the academic staff evaluators is shown in Table 4. Ranging from very poor (VP) to very good (VG) in line with Table 2, the evaluators evaluated the performance of attributes A1 to A4 (Technical System Quality; Information Quality; IT Service Quality; Considers different Learning Styles). This procedure was carried out in a similar fashion for the criteria C2 to C5. The student evaluators provided similar evaluations. The shown evaluations reflect a general positive perception of criteria C1 regarding all four attributes in that most evaluations are "fair", "good" or "very good". This means at first glance, the technical system was easy to use, the information presented through the eLearning system was easy to access, the IT Service was easy to utilize, and the consideration of different learning styles was easy to assess. However, results of the Fuzzy TOPSIS methodology given further below allow a more differentiated interpretation.

The Fuzzy TOPSIS approach does not require the calculation of mean values for the considered criteria. However, to give further insights for the study presented here, the linguistic responses have been converted to crisp numbers which allowed the calculation of the mean values shown in Table 5. For the three position groups, professors, instructors, and laboratory instructors, and the four attributes A1 to A4, mean values have been calculated for the criteria C1 to C5 (M – C1 to M – C5), as well as for the average of C1 to C5 (M – C-all).

The values in Table 5 prove that the evaluation of eLearning attributes cannot be done reliably without stating specific criteria to evaluate against. For example, the highest mean value of the average of all criteria (M – C-all) is 4.40 for the professors. However, this covers a large range from 4.00 for criteria C4 to 5.00 for criteria C1. Similarly, large ranges can be seen for the other attributes and the other two positions of the academic staff evaluators. Therefore, evaluations of eLearning attributes on a response scale without defining specific criteria, cannot be considered as a reliable method of evaluation. Consequently, these results are not interpreted here; instead, the performance of the four attributes will be interpreted based on the Fuzzy TOPSIS results presented further below.

In a next step, the mean values of the average of all criteria have been ranked (from largest to lowest), for the three positions, professors, instructors, and laboratory instructors. The rankings are shown in Table 6, and can be seen that all positions

**Table 4.** Example for eLearning attributes linguistic response evaluation (performance): criteria 1 – academic staff

| Criteria | Attr. | IN 01 | IN 02 | IN 03 | IN 04 | IN 05 | IN 06 | IN 07 | LAB 01 | LAB 02 | PROF 01 | PROF 02 | PROF 03 | PROF 04 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| C1 | A1 | F | G | G | VG | VG | VG | F | F | F | F | F | F | G |
| | A2 | F | F | G | VG | F | VG | F | F | F | MP | G | G | F |
| | A3 | F | G | G | G | F | VG | G | G | F | MP | G | VG | VG |
| | A4 | MP | VG | F | G | G | VG | P | MP | MP | P | F | G | P |

**Table 5**. eLearning attributes Means – academic staff

| | M – C1 | M – C2 | M – C3 | M – C4 | M – C5 | M – C-all |
|---|---|---|---|---|---|---|
| Prof. | | | | | | |
| A1 | 4.25 | 3.25 | 3.75 | 3.75 | 4.00 | 3.80 |
| A2 | 4.25 | 4.25 | 4.50 | 4.00 | 4.50 | 4.30 |
| A3 | 5.00 | 4.25 | 4.25 | 4.00 | 4.50 | 4.40 |
| A4 | 3.25 | 3.25 | 3.75 | 3.00 | 4.50 | 3.55 |
| Instr. | | | | | | |
| A1 | 5.14 | 5.14 | 4.57 | 3.57 | 5.14 | 4.71 |
| A2 | 4.71 | 4.86 | 4.86 | 3.57 | 5.00 | 4.60 |
| A3 | 4.86 | 4.86 | 4.86 | 4.57 | 5.14 | 4.86 |
| A4 | 4.43 | 4.43 | 4.43 | 3.71 | 4.86 | 4.37 |
| Lab. | | | | | | |
| A1 | 4.00 | 4.50 | 4.00 | 4.00 | 4.00 | 4.10 |
| A2 | 4.00 | 4.50 | 4.50 | 4.50 | 4.50 | 4.40 |
| A3 | 4.50 | 4.50 | 4.50 | 4.50 | 4.50 | 4.50 |
| A4 | 3.00 | 3.50 | 4.00 | 3.50 | 3.50 | 3.50 |

of the academic staff evaluators agree on the highest performance of IT Service Quality and the lowest performance of the Consideration of different Learning Styles.

However, the individual perceptions must be considered "fuzzy" since they are not only influenced by personal experience, but also by comments from students and colleagues. Therefore, interpretation of the results will be based on the Fuzzy TOPSIS rankings presented further below.

To test if the inclusion of "fuzziness" may have led to a ranking of attributes different from the previously presented ranking based on Mean values, both rankings are compared in Table 7. The two rankings are identical, which might be related to clearly distinct evaluations of the four attributes, as shown by the clear differences between the Mean values (Table 6). The high performance of IT Service Quality was also found by [40], based on a survey of academic staff and students of various institutions of higher education in the same country and using Mean values as the basis for the ranking.

On contrasting the highest rank of attribute performance with the lowest rank, attribute 4 (Considers different Learning Styles) is on the lowest rank. This is not surprising since the eLearning system had to be developed at the beginning of the COVID-19 pandemic, within a very short period, to minimize disruptions of the learning experience. However, academic staff need to pay attention to the question of how different learning styles can be considered better within the given eLearning system. The answer to this question is beyond the scope of the study presented here, but the finding suggests giving priority to attribute 4 when deciding on steps towards improvement of the eLearning system.

The results regarding attribute 1 (Technical System Quality) and attribute 2 (Information Quality) reflect that all evaluator groups see potential for improvement. However, instructors see Technical System Quality on rank 2, whereas professors and laboratory instructors see Technical System Quality on rank 3. Since laboratory instructors collaborated not only with instructors, but also with professors, they may have realized some limitations of the technical system, which may have "felt" less by the instructors of diploma courses. For example, the bachelor curriculum includes courses utilizing Project-Based Learning (PBL) which was more challenging to integrate in the technical system of the eLearning system than face-to-face traditional courses since hands-on activities related to project work could not be integrated in the eLearning system. Instructors of diploma courses did not face this challenge. Common feedback from all academic staff related to the technical quality of the eLearning system was related to students not precisely following the technical instructions. Furthermore, the number of technical instructions, to ensure compatibility of different integrated systems such as lockdown browser, the learning management system and MS Teams during live online assessments, was considered too numerous.

On the other hand, professors collaborated with laboratory instructors on several courses with the aim to improve the quality of laboratory teaching material. This may also have contributed to the higher ranking of Information Quality (both rank 2) compared with the instructors (rank 3).

Finally, the results of the student evaluations are presented and interpreted. A comparison of mechanical engineering students (Mech. Stud.) with civil engineering students (Civil Stud.) is

**Table 6.** eLearning Attributes - Ranking of Means of evaluations – academic staff

| | **Professors** | | **Instructors** | | **Lab.** | |
|---|---|---|---|---|---|---|
| | **M – all criteria** | **Rank – all criteria** | **M – all criteria** | **Rank – all criteria** | **M – all criteria** | **Rank – all criteria** |
| A1 | 3.80 | 3 | 4.71 | 2 | 4.10 | 3 |
| A2 | 4.30 | 2 | 4.60 | 3 | 4.40 | 2 |
| A3 | 4.40 | 1 | 4.86 | 1 | 4.50 | 1 |
| A4 | 3.55 | 4 | 4.37 | 4 | 3.50 | 4 |

**Table 7.** Ranking of eLearning Attributes – Fuzzy TOPSIS versus Means – academic staff

| | **Professors** | | **Instructors** | | **Lab** | |
|---|---|---|---|---|---|---|
| | **Fuzzy TOPSIS Rank** | **Means Rank** | **Fuzzy TOPSIS Rank** | **Means Rank** | **Fuzzy TOPSIS Rank** | **Means Rank** |
| Technical System Quality | 3 | 3 | 2 | 2 | 3 | 3 |
| Information Quality | 2 | 2 | 3 | 3 | 2 | 2 |
| IT Service Quality | 1 | 1 | 1 | 1 | 1 | 1 |
| Considers different Learning Styles | 4 | 4 | 4 | 4 | 4 | 4 |

**Table 8.** Ranking of eLearning Attributes – Fuzzy TOPSIS versus Means – students

| | **Mech. Stud. Fuzzy TOPSIS** | **Mech Stud. Means** | **Civil Stud. Fuzzy TOPSIS** | **Civil Stud. Means** |
|---|---|---|---|---|
| Technical System Quality | 2 | 2 | 3 | 3 |
| Information Quality | 3 | 3 | 1 | 1 |
| IT Service Quality | 1 | 1 | 2 | 2 |
| Considers different Learning Styles | 4 | 4 | 4 | 4 |

provided in Table 8. For students of both disciplines, the ranking based on Fuzzy TOPSIS methodology is identical with the ranking based on Mean values. Furthermore, all student evaluators agree on the lowest rank of attribute 4 (Considers different Learning Styles). This is in line with the previously identified rank of the academic staff evaluators (Table 7). However, a difference can be seen regarding the highest rank. Mechanical engineering student evaluators agree with the academic staff evaluators in that attribute 3 (IT Service Quality) is seen on rank 1, whereas the civil engineering student evaluators see this attribute only on rank 2, and attribute 2 (Information quality) on rank 1.

Although the ranking presented here does not help in identifying the underlying reasons, the result confirms the importance of including evaluators from different disciplines. The applied eLearning System was the same across the different disciplines, but in civil engineering the quality of included information was perceived higher than the IT Service Quality. Since the approach of the IT department was the same towards all disciplines, this can only be explained by a considerable high quality of included information. In fact, communication with the Head of Department – Civil Engineering confirmed that the included information was reviewed and optimized during the development of the eLearning system and much effort had been invested in the development of high-quality online laboratory sessions. The latter confirms the previous evaluation of the lab instructors (Table 7). However, the low ranking of attribute 4 (Considers different Learning Styles) shows that students agree with the academic staff that this attribute can be improved. Also, in line with the interpretation of academic staff evaluations, the ranking of attribute 1 (Technical System Quality) suggests potential for improvement of the technical aspects of the eLearning System. In addition to the reasons mentioned by academic staff and reported in the previous section, a re-occurring feedback of students was related to unreliable internet connections, which was also reported from other countries such as Jordan [41] and confirms that concerns related to the digital divide [42] must be taken seriously.

The following conclusions can be drawn from the presented results.

## 5. Conclusion

Fuzzy TOPSIS method was applied to evaluate the eLearning system attributes IT service quality, technical system quality, information quality and consideration of different learning styles at an institution of higher education that developed and implemented eLearning during the COVID-19 pandemic.

Findings provided evidence that eLearning attributes cannot be evaluated reliably without stating the specific criteria to evaluate against. IT Service Quality was found to rank highest, whereas the Consideration of Different Learning Styles ranked lowest. As an important practical implication, the eLearning system should be enhanced to cover different learning styles better.

The attributes technical system quality and information quality were ranked second and third, hence, reflecting potential for improvement. Academic staff confirmed that students faced difficulties in following the technical instructions of the eLearning system and with the number of technical instructions, resulting from the integration of MS Teams, Moodle, Respondus LockDown browser and Monitor (Respondus®Inc.) and MS Outlook.

Large agreement was found between student evaluators and academic staff evaluators. However, mechanical engineering students agreed with academic staff regarding the highest rank of IT service quality, whereas civil engineering student evaluators see this attribute only on rank 2 and information quality on rank 1. The extraordinary high quality of incorporated civil engineering learning material was identified as the underlying reason. As a practical implication, evaluators from different disciplines and from academic staff and student body need to be included in the evaluation, although all worked with the same eLearning system.

In summary, the Fuzzy TOPSIS method has been found to be a reliable and economic evaluation approach of eLearning systems since it does not require large sample sizes of evaluators and provides a ranking of attributes which translate directly into priorities of improvement actions.

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