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A PRELIMINARY LEARNER ASSESSMENT FRAMEWORK ON E-LEARNING

Wenty Dwi Yuniarti[1,3], Sri Hartati[2,*] and Sigit Priyanta[2]

[1]Doctoral Program, Department of Computer Science and Electronics
[2]Department of Computer Science and Electronics
Faculty of Mathematics and Computer Sciences
Universitas Gadjah Mada
North Sekip, Bulak Sumur, Yogyakarta 55281, Indonesia
seagatejogja@ugm.ac.id
*Corresponding author: shartati@ugm.ac.id

[3]Department of Information Technology
Faculty of Science and Technology
Universitas Islam Negeri Walisongo Semarang
Jl. Prof. Dr. Hamka, Ngaliyan, Semarang 50185, Indonesia
wenty@walisongo.ac.id

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Abstract. *Online learning can guide learners to achieve their abilities if done well based on some principles. One of them is applying an assessment that motivates learning and informs the level of achievement of learning outcomes. Therefore, assessment is an essential element in online learning scenarios. It is undeniable that assessment problems in face-to-face learning have the potential to occur in online learning, such as product-oriented assessments only; haing not accommodated aspects of learning comprehensively; not yet accurate and objective, and lack of follow-up. This study proposes integrated performance analysis with decision support and recommendations in the assessment process to overcome these problems. The proposal is in the form of a model with four parts: learning outcome-based learning design; performance analysis with process mining; determining the level of ability using the Fuzzy Analytical Network Process (FANP) and 2-Tuple Fuzzy Linguistic, as well as knowledge-based recommendations. This model was introduced as an assessment model that can be applied to e-Learning in Indonesia.*
Keywords: Assessment, e-Learning, Fuzzy analytical network process, 2-Tuple Fuzzy Linguistic

1. **Introduction.** Online learning has consequences for separating physical interaction spaces and concerns about learner involvement and guarantees for learning achievement [1,2]. According to the National Higher Education Standard (SN Dikti), online learning can guide learners according to Learning Outcomes (LO) if appropriately implemented based on some principles [2]. One of these principles is the use of assessments that can motivate and inform learners' abilities. It is undeniable that assessment problems in face-to-face learning have the potential to occur in online learning. The issues include only product-oriented assessment, not process-oriented; assessment results cannot be used as feedback; assessment raises dissatisfaction because it is not transparent and not comprehensive [3]. Therefore, the assessments on e-Learning require an effort to run better [4].

According to [2], assessment is a tool to test the level of achievement of learning outcomes and plays a role in conditioning learners to be involved in learning. Assessment

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is also defined as all the means used to assess individual or group performance [5]. Previous study [4] has suggested some techniques and frameworks conduct the assessment in e-Learning. Data mining techniques are widely used, especially for assessment with a predictive approach [6-9]. Trends in the availability of data logs in information systems, including in e-Learning, encourage data logs for a more comprehensive assessment [10]. Several studies use data logs or combine data logs with learner profile data for performance prediction and assessment [1,6,11-13]. Data logs also detect learning problems that impact performance and learning outcomes, such as lack of involvement, procrastination, failure to complete tasks, and resignation [14-17]. In addition to the process, teachers also need a straightforward interpretation of the assessment results and follow-up. Some studies have applied fuzzy logic and decision support to presenting assessment results [3,18,19] and have developed an adaptive e-Learning with recommendations [20-23].

Although several techniques on assessment architectures have been developed, a comprehensive non-predictive assessment model is needed to support good online learning. This study proposes an assessment model to answer the following research questions: a) how to design a good assessment model based on learning outcomes, b) how to utilize a combination of performance analysis and assessment scores to make the assessment more comprehensive, c) how to manage various assessment data so that the determination of the ability level can be carried out accurately and fairly, and d) how to provide recommendations. This paper describes the proposed model with the organization: analysis of studies on assessment in e-Learning; proposed model and discussion, and conclusions.

2. Literature Review.

The study of literature on learning assessment in e-Learning and the need for a comprehensive assessment model is described as follows.

2.1. Student assessment on e-Learning.

According to [5], all interactions with users that generate data used for assessment are called assessment items. In the Learning Management System (LMS) of e-Learning, assessment items are obtained from the available assessment modules. A comprehensive assessment requires assessment items from some instruments. The work of [24] used analytic e-rubric as an alternative electronic assessment instrument. In addition to the assessment module and e-Learning rubric, according to [10], the availability of data logs in the LMS can be mined, taking knowledge from various perspectives to benefit from a more comprehensive assessment and evaluation.

2.2. Techniques, approaches, and assessment frameworks in e-Learning.

The work of [4] suggests several techniques, approaches, and frameworks to assess learners on e-Learning, such as gamification, data mining, Internet of Things, and fuzzy logic. Utilizing data mining for assessment is quite a lot, such as [8] comparing the C4.5 and Naïve Bayes algorithms, [9] using random forests and artificial neural networks, and [11] using fuzzy association rule mining. However, most of the use of these data mining techniques [8,9,11] is for assessment with a predictive approach which is less suitable for non-predictive assessments.

Improving the ability of information systems, including e-Learning, to record and store behavioural data, called data logs [10], makes assessment analysis more comprehensive. Data logs are used to detect potential problems that impact performance and learning outcomes in e-Learning, such as detecting the risk of failure to complete assignments using random forest, generalized linear model, gradient boosting machine, neural networks [14]; evaluating procrastination behaviour and its relationship with performance using association rules [15]; predicting withdrawal using deep learning [13]; presenting a dropout prediction based on time series forest classification [17], and identifying low learner engagement and its impact on performance using decision tree, J48, JRIP classifier, gradient-boosted classifier, and Naïve Bayes classifier [16]. Unfortunately, studies related to student involvement, procrastination, resignation and the risk of failure to complete assignments were used to detect potential problems, not for a comprehensive assessment. Data logs are also used for performance analysis using the process mining technique. Previously, [25] used a factor analysis model with a questionnaire to perform a performance analysis in the company. Logs data can be an alternative source of data to replace questionnaires [19]. Another use of process mining is to assess the self-regulated learning skill of the learners using the Inductive Miner [1] and to predict academic performance based on profile data and the conformance checking result using Heuristic Miner [6]. Both studies use process mining for assessment with a predictive approach.

There is a need for accurate, and fair assessment results. The work of [18] uses fuzzy logic to present the assessment results on e-Learning from quiz scores and attendance so that it is less comprehensive. The work of [3] uses fuzzy multi-criteria decision making to determine the level of ability accompanied by the unification of numerical and linguistic assessment data. This study provides an objective approach. Unfortunately, it is implemented in face-to-face learning, not in e-Learning. Another research is [19], which presents performance assessment using process mining, multiple-criteria decision analysis, and analytical hierarchy process weighting. This study is implemented in companies with one performance output. Further analysis is needed regarding the compatibility of its implementation in e-Learning for several learners.

A good assessment should be able to provide recommendations for improvement of learning and follow-up. Several studies have developed e-Learning architecture with recommendations [20-23]. Unfortunately, the implementation of these architectures is only part of the learner assessment process in e-Learning. There has been no alignment process with the learning design, nor has any recommendation to become a good and comprehensive assessment model. The shortages of previous studies can be overcome by a comprehensive assessment model, which combines various assessment data in e-Learning comprehensively, and is equipped with decision support and recommendation.

3. **Proposed Model and Discussion.** The proposed model consists of four parts: learning design, performance analysis, determining the level of ability, and recommendations. Figure 1 presents a schematic of the proposed model. The discussion of the four parts of this model is the answer to the research question. The development of the model begins with preparing a learning design, called the semester learning plan or RPS, which becomes the basis for performance analysis, determining the level of ability and providing recommendations.

3.1. **Learning design.** The learning design forms activities to formulate CLO (Course Learning Outcomes), LLO (Lesson Learning Outcomes), and LLO indicators. The learning design part in Figure 1 shows the relationship between CLO, LLO, and LLO indicators [2]. The learning design is arranged with the following stages.

1) Formulate CLO to achieve learners' abilities.
2) Formulate LLO based on CLO. LLO shows the final ability at each learning stage and contributes cumulatively to CLO.
3) Determine indicators of achievement of LLO. Develop materials, learning activities, assignments, techniques and assessment instruments for each LLO.

The learning assessment design in Table 1 is based on the learning design part in Figure 1. The course has several CLO and LLO. Each LLO is related to one or more CLOs. Each LLO has some learning achievement indicators and is implemented as a learning stage with a particular duration, tasks, technique, and assessment instrument [2,26].

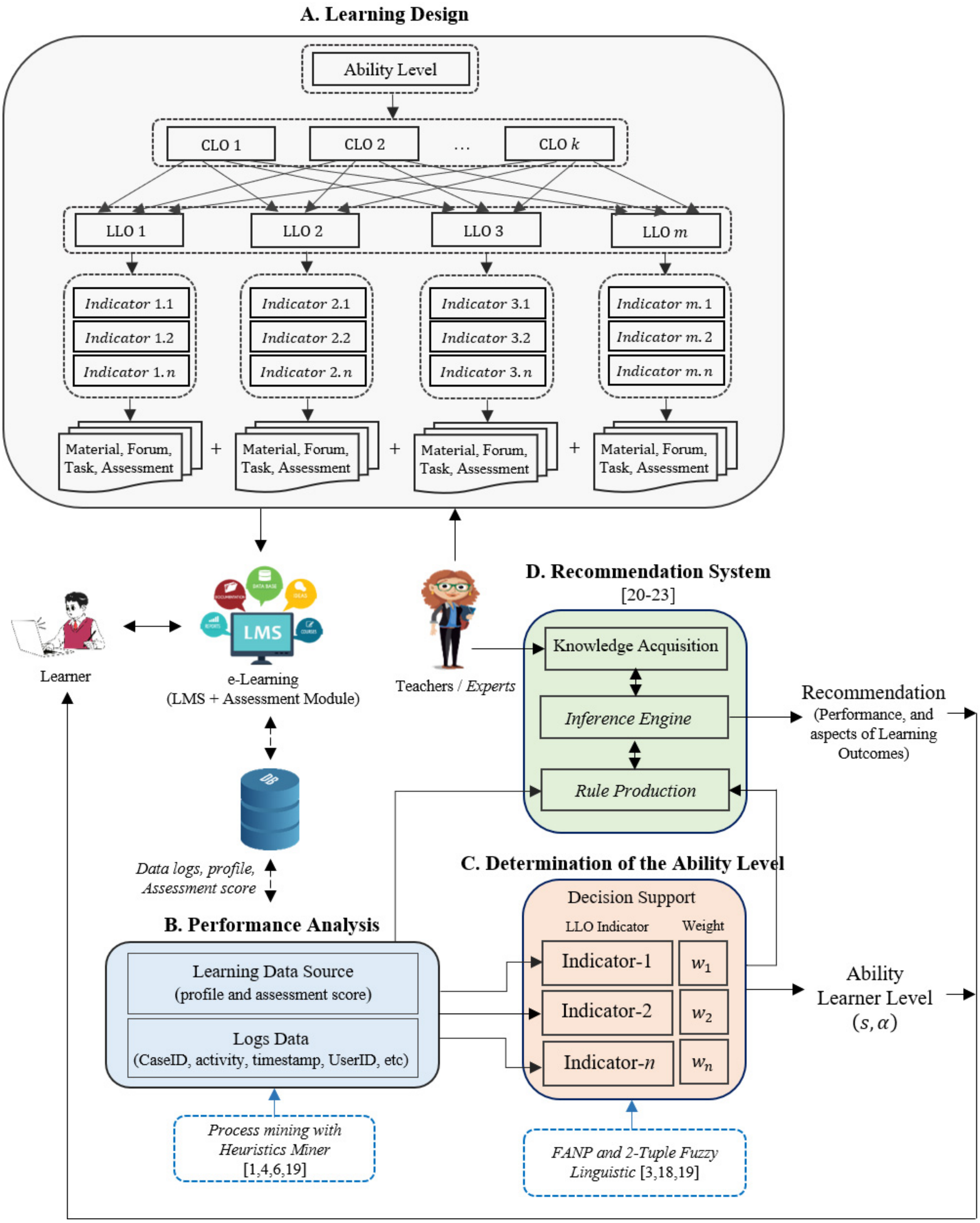

FIGURE 1. The proposed model

3.2. **Performance analysis.** Moodle LMS logs data become the datasets in this performance analysis. Figure 2 presents a performance analysis scheme with the following stages.

1) Preparation, including interviews, data extraction, and preprocessing. Interviews gather information from teachers or experts about learning activities according to RPS. Each LLO is implemented in a sequence of activities: material (A), question and answer forum (B), tasks or assignments (C), and assessment (D). Data extraction includes

Table 1. Learning assessment design

Week	CLO	LLO	LLO indicators	Assessment technique	Assessment instrument
1	CLO 1	LLO 1	Indicator 1.1 Indicator 1.2	Task 1	Instrument 1
2, 3	CLO 1 CLO 2	LLO 2	Indicator 2.1 Indicator 2.2 Indicator 2.3	Task 2	Instrument 2
n	...	...	...	...	...

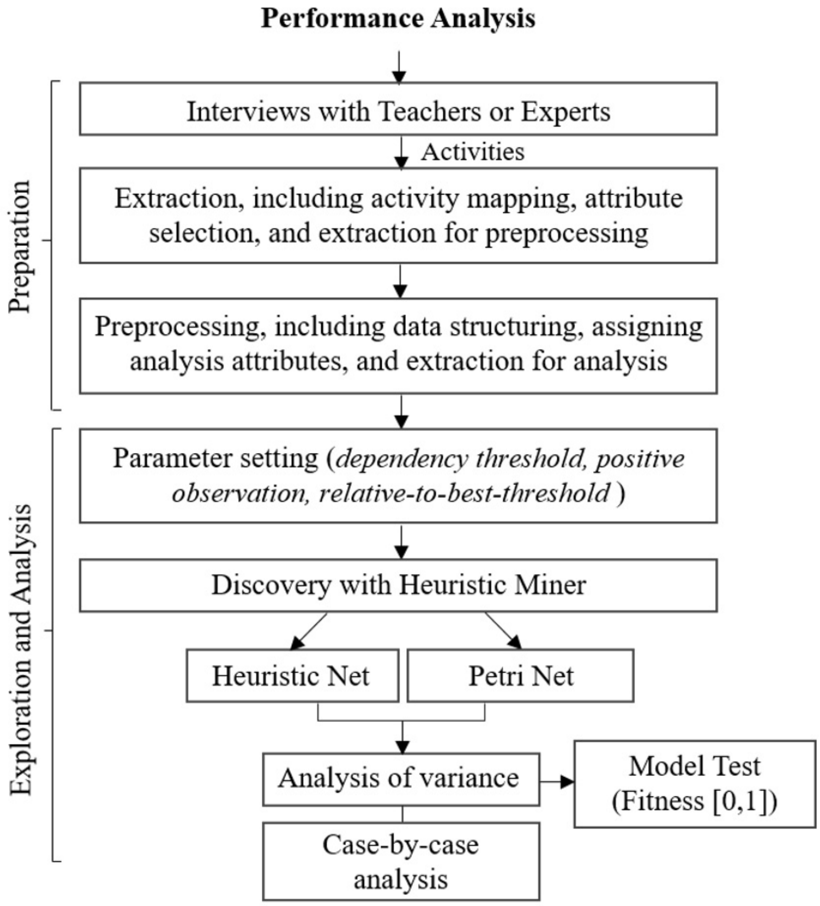

Figure 2. Performance analysis scheme

activity mapping, attribute selection, and data extraction for preprocessing. Preprocessing is preparing data structures with appropriate attributes for analysis needs.

2) Exploration. The result of preprocessing is in the form of datasets that will be mined using the heuristics miner algorithm by starting with the determination of the dependency threshold, positive observation, and relative-to-best-threshold parameters. The data logs look for multiset traces using Equation (1), where T is a set of activities $(A, B, C, D, \ldots)$, the activity flow is a trace, $W \subseteq T$ where W is a repeating multiset trace, and n is n loop for the same trace or sequence of activities.

$$W = \{(A, B, C, D)^n, (A, B, D)^n\} \tag{1}$$

The next step is to calculate causal independencies using the dependency graph according to Equation (2) [1,27], where $A >_w B$ is the sequence of activities that follow directly.

$$A \Rightarrow_w B = \frac{|A >_w B| - |B >_w A|}{|A >_w B| + |B >_w A| + 1} \tag{2}$$

The heuristic miner algorithm produces a Heuristic net and a Petri net that will show several variants of the learning process. In each variant, a fitness dimension test is carried out using Equation (3) to ensure the suitability of the learner's learning process with the standard learning design.

$$f = \frac{1}{2}\left(1 - \frac{\sum_{n=1}^{k} nimi}{\sum_{n=1}^{k} nici}\right) + \frac{1}{2}\left(1 - \frac{\sum_{n=1}^{k} niri}{\sum_{n=1}^{k} nipi}\right) \tag{3}$$

where k is the number of different traces; ni is the number of process instances of trace i; mi is the number of tokens missing from trace i; ri is the number of tokens remaining from trace i, and pi is the number of tokens produced from trace i.

3) Analysis, including discovery analysis and case-by-case analysis [27]. Discovery analysis is used to see the deviation between the actual learning process and the standard learning process. Case-by-case analysis (in-depth analysis) is used to analyze the involvement of learners in learning activities and the timelines of carrying out tasks.

3.3. **Determination of the ability level of learner.** Determination of the ability level consists of weighing the CLO, LLO, LLO indicators, and unification of numerical and linguistic assessment data.

3.3.1. *Determination of the weight of CLO, LLO and LLO indicators using Fuzzy Analytical Network Process (FANP).* FANP overcomes the limitations of ANP in dealing with uncertain situations such as preferences to CLO and LLO by experts [3]. Based on several studies [3,28], the network structure formation and weight calculation are as follows.

1) Construct the ANP model based on the learning design part in Figure 1.
2) Determine the fuzzy linguistics scale for pairwise comparison. The formulation of the fuzzy linguistic scale consists of a numerical scale, a linguistic scale, a fuzzy scale (l, m, u), and reciprocal.
3) Prepare a pairwise comparison matrix for each cluster for CLO, LLO and LLO indicators using the fuzzy linguistic scale specified in point 2. Furthermore, the pairwise comparison matrix will be the basis for calculating each weight for both CLO, local weights for LLO and LLO indicators.
4) Construct unweighted supermatrix, weighted supermatrix, and limit supermatrix. Finally, calculate the total weights.

3.3.2. *Unification of assessment data using 2-Tuple Fuzzy Linguistics.* Determination of the ability level of learners involves a collection of assessment data in numerical and linguistics forms. Table 2 shows an example of an assessment scheme with numerical and linguistic values.

TABLE 2. Assessment scheme with numerical and linguistic values

Alternative/ learner	LLO b_1				LLO b_2				LLO b_3				LLO b_n			
	t_1	t_2	...	t_h	t_1	t_2	...	t_h	t_1	t_2	...	t_h	t_1	t_2	...	t_h
a_1	x_{11}	s_{12}														
$\vdots$																
a_m																

In Table 2, $A = \{a_1, \ldots, a_m\}$ is the set of learners, $B = \{b_1, \ldots, b_n\}$ is the set of criteria representing LLO, $T = \{t_1, \ldots, t_h\}$ is the set of techniques different assessments, $x \in [0, 1]$ is the value of in numeric, and $s \in S = \{s_0, \ldots, s_g\}$ is the value of in linguistic. Unification is carried out with the following steps [3,29].

1) Preprocessing. Preprocessing consists of preparing competency weights from the FANP (Section 3.3.1), and converting the numerical assessment score to the interval $[0, 1]$.
2) Transformation. The preference value (from Table 2) is presented in decision matrix with numerical elements $x \in [0, 1]$ and linguistics $S_i = \{s_0, s_1, \ldots, s_g\}$. Furthermore, the decision matrix is converted into a 2-tuple decision matrix, through 2 types of transformation procedure, namely numerical transformation and linguistic transformation.
3) Aggregation. All judgements from the 2-tuple linguistic decision matrix were aggregated. The result of the aggregation is the level of learner ability which is represented in 2-tuple linguistic such as Equation (4), where $(s, \alpha)_i$ is the final value of the i, n is the number of learners, s is the linguistic term, and α is a numerical value that indicates the comparison ability with other learners and the potential for learners to achieve higher rankings.

$$(s, \alpha)_i,\ i = 1, \ldots, n;\ s \in S;\ \alpha \in [-0.5, 0.5] \tag{4}$$

For example, the final value of learner in the 2-tuple linguistic score is $(G, 0.47)$, where G is the linguistic term, and 0.47 is a numerical value. The description of this 2-tuple linguistic score is Good, having the potential of 47% to achieve higher ranks [3].

3.4. **Knowledge-based recommendation.** Figure 1 illustrates the recommendation section, which consists of facts about the learner's condition from the results of performance analysis and determination of ability level, acquisition of knowledge from teachers or experts, and inference engine. Knowledge representation uses the IF-THEN production rules to perform inference using the forward chaining method.

4. **Conclusions.** This model answers research questions related to assessment on e-Learning to support good online learning. First, the assessment is developed based on the learning design by considering the alignment of materials, activities, and tasks with learning outcomes. Second, the assessment is more comprehensive because it combines performance analysis and assessment scores. Third, the assessment is more accurate and fair because it presents the learner's ability based on the weighting and unification of the assessment data. Fourth, the assessment provides recommendations for follow-up. In the future, this model can be implemented in e-Learning at universities in Indonesia. Limitations still exist because the model is only implemented in the Moodle LMS based on learning design (RPS).

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