A Design of Adaptive User Interface to Cater the Learners' Diversity in Online Learning for Blended-Learning

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Abstract: Blended learning is a method that involved face-to-face and guided non-face-to-face stages of teaching and learning practices. Face-to-face teaching and learning is a common practice long before computers and internet technology come into existence. On the other hand, guided non-face-to-face teaching and learning is a practice that employed and used the computer and internet technology to deliver teaching and stimulate the learning process of students without seeing in formal meeting between students and lecturers. However, as long as the guided non-face-to-face is concern, the diversity of the students or learners need to be put into consideration. Everyone has different ways in cognitive learning style. Each learner possesses a unique way in acquiring, memorising, manipulating and understanding knowledge and information. Therefore, this paper describes the design of intelligent adaptive user interface for tutorial package to cater the diversity of learners in online learning practices. A mamdani-style of fuzzy logic inference approach is employed to design the adaptivity of the user interface for user model.

Keywords: Interactive Application, Intelligent Tutorial Package, User Model

1. Introduction

Recent studies show that blended-learning technology produces significant results for students as well as for the teachers. As for the students, blended-learning improves the cognitive process and provides better learning environment which is flexible as well as offering students autonomy and self-pacing in learning according to their interest and needs. Whilst, for the teachers, there is more time to do what they do the best such as the use of rich resources in classroom thus provides interesting lessons (Lungu, 2013). Furthermore, the blended-learning enhanced student-teacher perception of learning. The given tasks and activities in blended-learning environment also have increased collaborative interaction between students and students as well as students and instructors (Karimi, Ahmad, & Badariah, 2013).

1.2 Blended-Learning

Review of literature uncovered various definitions of blended learning. Blended-learning is categorised into four concepts which are (1) combination of web-based technology such as live virtual classroom, self-paced instruction, collaborative learning, streaming video, audio and text to accomplish an educational goal; (2) combination of pedagogical approaches such as constructivism, behaviourism and cognitivism to produce an optimal learning outcome with or without instructional technology; (3) combination of instructional technology such as videotape, CD-ROM, web-based training and film with face-to-face instructed training; and (4) combination of instructional technology with actual job task in order to create a harmonious effect of learning and working (Driscoll, 2002).

Blended-learning as a thoughtful integration of classroom face-to-face (synchronous) learning experiences with online distance learning experiences (asynchronous) and activities beyond the classroom (Garrison & Kanuka, 2004; Lungu, 2013). Blended-learning model is developed to enhance lecture delivery in a large, diverse introductory psychology unit, introducing the use of an online, personalised learning system for lecture preparation and using lecture time to extend students' understanding (McKenzie et al., 2013). In essence blended learning is a mechanism that bridges the old and the new by impacting policy and strategic initiatives in higher education at virtually level (Moskal, Dziuban, & Hartman, 2013).

1.3 User Diversity and Preferences

Blended-learning does not only focus on face-to-face learning activities but also emphasis on the online learning activities that employ the computing and web-based technology. However, everyone has different ways or approaches of cognitive learning style. Users have different needs as the learning process is always unique and commonly according the interest, preferences, knowledge, skills and needs of the learners. Hence, no single interface will satisfy all users or learners. There is a shortage in blended learning designs that can be unintentionally followed by instructors. It is a considerable complexity in blended-learning implementation with the challenge of virtually limitless design possibilities and applicability to so many context (Garrison & Kanuka, 2004).

Therefore, an intelligent user interface in online learning environment must be designed to facilitate and personalise learners as well as to auto-adjust the learning context just like a teacher's capability in personalising his or her students in face-to-face learning process. Personalisation mechanisms often employ behaviour monitoring and machine learning techniques to aid the user in the creation and management of a preference set that is used to drive the adaptation of environments and resources in line with individual users' needs (Gallacher & Papadopoulou, 2013).

1.4 Behavioural Approach and Adaptivity

Behaviourists believe that environment shapes students' behaviour. They are concerned with is the changes of students' behaviour which occurred as a result of learning. Behaviourist theory emerges in the form of operant conditioning using reinforcement.

According to the father of behaviourism, Skinner (1953), conditioning is a process of substituting stimulus. A neutral stimulus acquires the power to provoke or produce a response which was originally stimulated by the other stimulus. The changes occur when the neutral stimulus is followed or reinforced by the effective stimulus. He identified two types of conditioning processes which are (1) respondent and operant, and (2) primary reinforces (satisfy primary needs) and secondary reinforces (provide satisfaction). Reinforces can either be positive or negative. It is believed that the presence of reinforcement can increase a behaviour while the absence of reinforcement can weaken it (Skinner, 1953).

Skinner (1953) states that, in educational environment, the process of reinforcement based on the operant conditioning can be as follows;

- Diagnose student's behaviour.
- Establish a sequence of reinforceable steps, or remove reinforcement that is producing negative behaviour to move the learner to the desired behaviour.
- Wait for the desired response and reinforce it.

The traditional user interface does not react dynamically with the users in the sense that they are unable to adapt themselves to the user in real-time as the user's behaviour changed. Consequently, learners feel bored as the interface does not satisfy their personal view, level and preferences. Thus, it leads to the frustration in which decline the number of learners who are not willing to participate or not in favour in online learning.

In contrast to the traditional static user interface, an intelligent adaptive interface come into existence and stills an active area of research. Adaptive user interface is differ from adapted (customized) or adaptable (customizable) interface because adaptive interface may change dynamically and automatically at real interaction time without user's intervention (Martins, 1996). Adaptive means an ability to alter the aspects of its own structure, functionality and interface in order to accommodate or facilitate the diverse needs of individuals or groups of user and changing needs of users over time (Viano, Parodi, Alty & Khalil, 2000). An important distinction between adaptive and adaptable is that adaptive able to modify the interface, while adaptable needs the users to deliberately choose the adaptation (Rothrock, Koubek & Fuchs, 2002).

In this paper, we defined behavioural as the process of learners learn and explore the topic and content of the given online tutorial. The behaviour or respond of the learners will be captured and recorded by the intelligent mechanism of the user interface. The recorded or captured respond of the user or learner will be used by the intelligent interface to learn, thus predict and infer to the learner's preferences as well as adapt to the level of the learners accordingly.

2. Methodology

Designing and developing an intelligent user interface of tutorial package requires some computational intelligent mechanism that is able to adapt according to the specific user level and model. The online learning material must be able to recognise and uniquely identify the identity of each individual. Therefore a proper database logical design, the inference engine as well as the user model must be designed. Figure 1 depicts the proposed framework of adaptive user interface for online tutorial package.

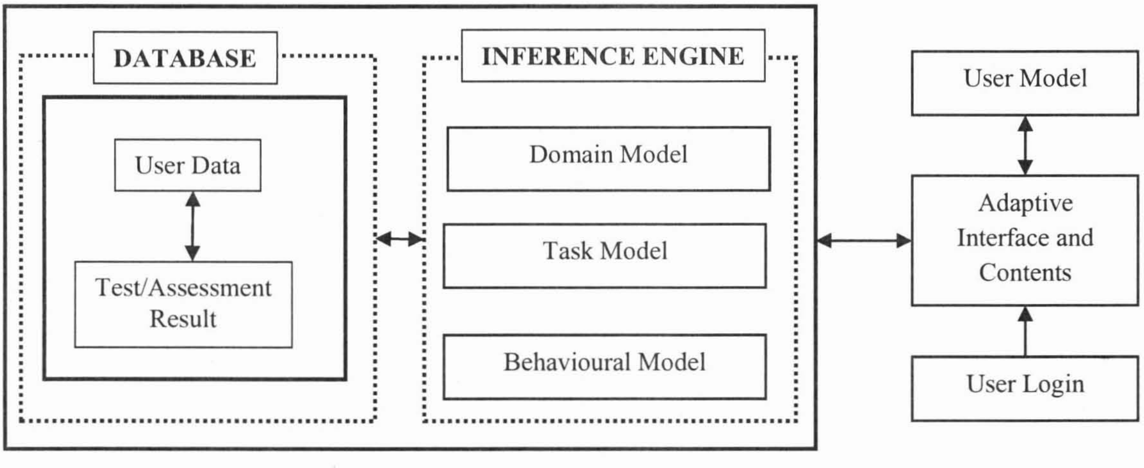

Fig. 1 Proposed Framework of Adaptive User Interface for Online Tutorial Package

2.2 Entity / Table Description of Database Logical Design

The design of this online tutorial puts emphasis on the adaptive capability of its user interface thus accommodates the suitable interface and content according to the learners' level. Therefore, a user profile needs to be collected, stored in the database and will later be used to infer and adapt to the diversity of the learners or users who are engaged and used the online tutorial. The database consists of three entities or tables along together with its data field or attribute as shown in Table 1.

Table 1. Entity Name and its Attributes

Entity / Table Name	Attributes / Data Field
UserData	***loginID (PK)***, *password, name, attempt, firstDate, lastDate, totalTime, sectionComplete, currentSection*
TestResult	***testControlNumer (PK)***, *loginID (FK), testDate, testTime, topic, score*
TestResultDetail	*testControlNumber (FK), question, score, userResponse*

2.3 Inference Engine Elements - Domain Model, Task Model and Behavioural Model

Domain model contains the information of the course/subject domain of the tutorial package. On the other hand, task model and behavioural model are working memories that stored rules and facts. Task model and behavioural model work together with domain model to process and infer the users' or learners' behaviour. The data that is processed by the task model and behavioural model is later stored in short term or working memory.

In essence, the inference engine is a place or working memory that stores inference rules and fact to build up adaptive strategy. Inference rules are the combination of variables, facts and data that are processed by the task model and behavioural model to infer the learners and users' behaviour. Once the inference rules are executed and matched to the value of the variables, the inference engine will be fired and achieved goal will be executed. As the case of inferring process of the adaptive strategy, the inference engines evaluate the behaviour of the learners and determined the cognitive level and preferences of the learners/users.

2.4 Constructing Linguistics Values using Mamdani Style Fuzzy Logic

Fuzzy logic is a form of many-valued logic that uses approximation or vague rather than fixed or exact value. Fuzzy logic is not logic that is fuzzy, but logic that is used to describe fuzziness. Fuzzy logic is the theory of fuzzy sets, sets that standardise vagueness or ambiguousness. Fuzzy logic is based on the idea that all things admit of degrees (Negnevistsky, 2011).

Constructing any inference rules must be thoroughly defined and designed. Lack of definition of rules may sometimes cause the designed rules inappropriate, not suitable to the domain and hardly to be implemented. When dealt with modelling, among the best representation to be used is linguistics variable because some value cannot be represented in a simple mathematical or numerical values.

Most of the people do not think in terms of traditional IF-THEN rules or precise number. Humans tend to categorise things precisely using rules for making decision that may have shades of meaning. As for example, students' mark can be low, average and high. Fuzzy logic is a rule-based technique that represents such impression by creating rules that use approximate value. It describes a particular phenomenon or process linguistically and then represents that description in simple number or flexible rules.

Using fuzzy logic approach, the section level, score, session time and user model can be described according to their linguistics values. The following are the representation of linguistics value of section level, score, session time and user model.

2.4.1 Linguistics Value for Section Level Variable

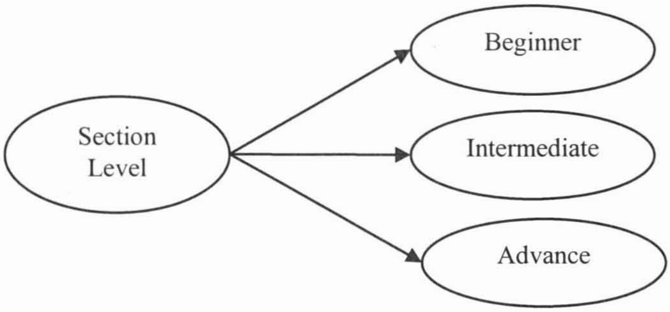

Fig. 2 Linguistics Values for Section Level Variable

Fig. 2 depicts the linguistics value of section level variable which are beginner, intermediate, and advance. The assumption is made by the taking into consideration level of topic for any particular course/subject which are categorise into three level which are beginner, intermediate and advance. This linguistics value is used to monitor the current section/topic of the learners.

2.4.2 Linguistics Value for Session Time

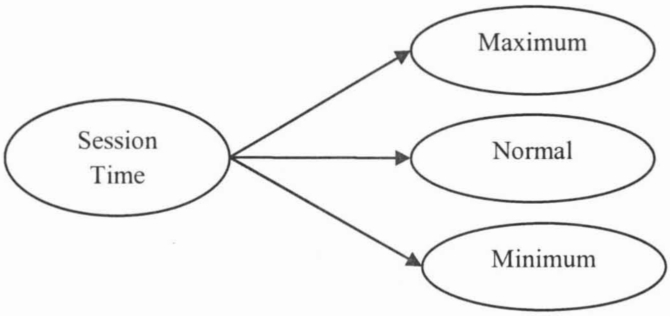

Fig. 4 Linguistics Values for Session Time Variable

Fig. 4 above shows the linguistics value for session time variable; maximum, normal, and minimum. The maximum value represents the idea that the learners are spending longer time than usual in navigating or studying the particular topic/content. On the other hand, minimum value of session times signifies that the learners are either not interested on the particular topic/content or the topic is easy to understand and comprehend. However, this value will be countered back with the value in score variable to infer the appropriate user model of the learners.

2.4.3 Linguistics Value for Score Variable

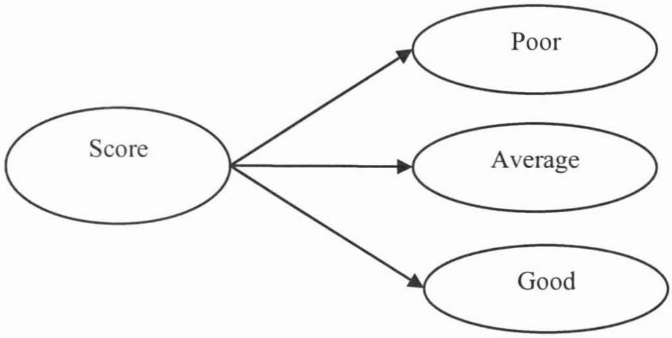

Fig. 3 Linguistics Values for Score Variable

Fig.3 above illustrates the linguistics value for score variable; poor, average and good. The value of the score variable is evaluated after the learners have taken quiz. The linguistics value for score model is taken from the Outcome-Based Education- Closing the Loop (OBE-CDL) report.

2.4.4 Linguistics Value for User Model

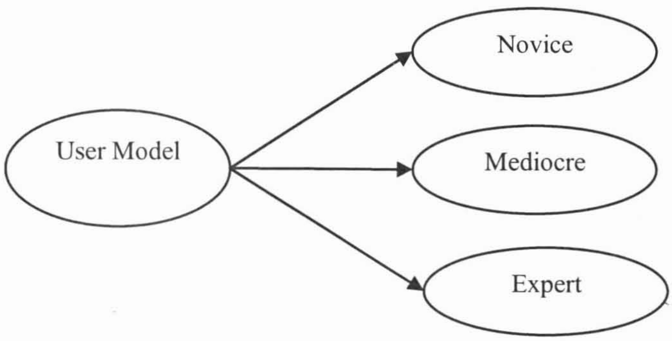

Fig. 5 Linguistics Values for User Model Variable

Fig. 5 depicts the linguistics value for user model variable which are novice, mediocre, and expert learners/users. User model is formed by combining the three variables gathered from (1) section level variable, (2) score variable, and (3) session time variable.

2.4.5 User Model Adaptivity Using Decision Tree Strategy

Fig. 6 illustrates the decision tree representation which combined three linguistics variables and its linguistic values. While Table 2 expresses the IF-THEN inference rules that derived from the decision tree strategy as shown in Fig. 6. Combination of three linguistics variable and three linguistics value had produced 27 user models. The formula for getting the total number of user model for adaptive user interface is calculated using the following simple mathematical formula in Eq. (1). Table 3 on the other hand shows the fuzzy inference rules that constructed based on the decision strategy in Table 2.

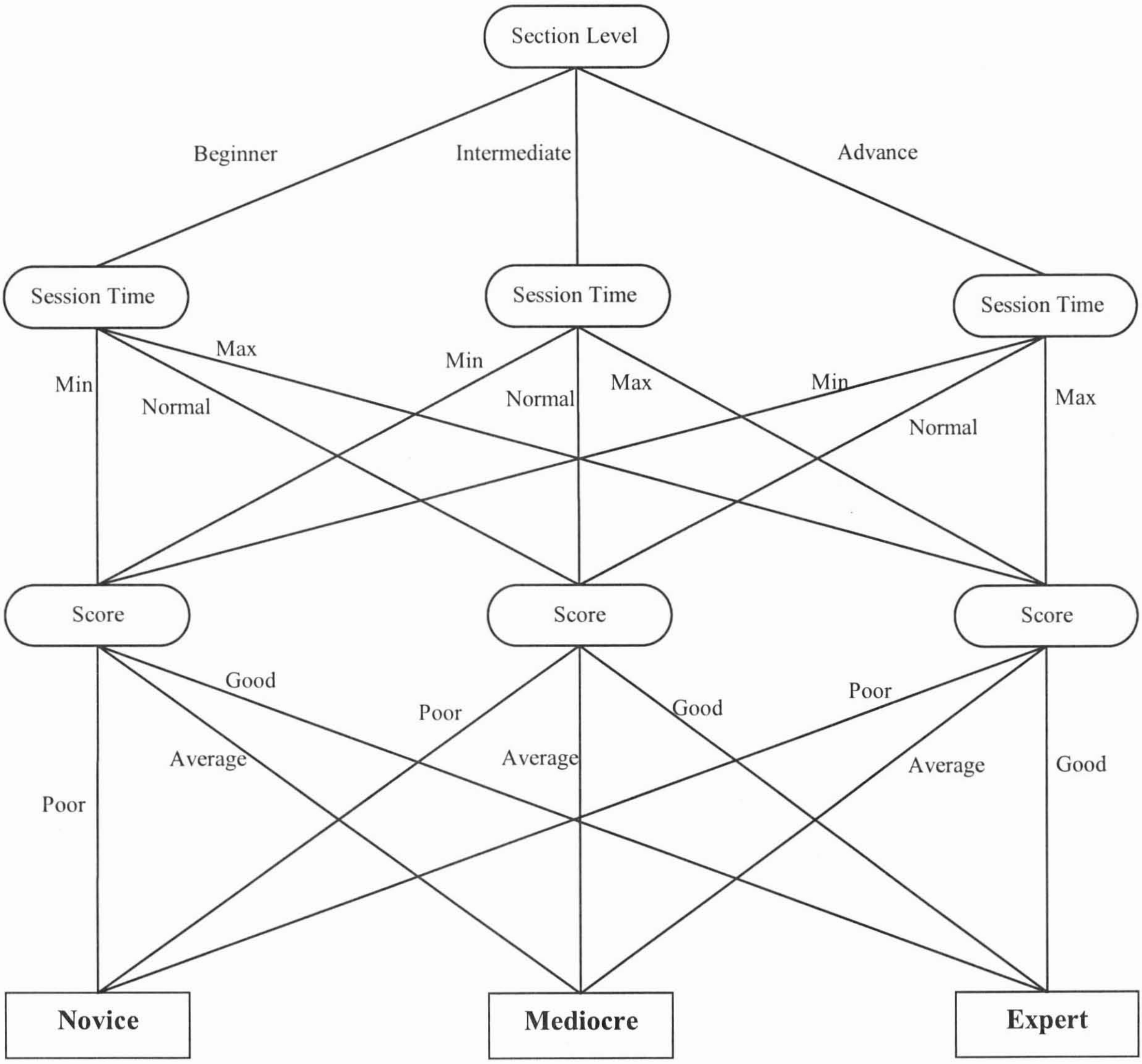

Fig. 6 Decision Tree for Adaptivity Strategy

$$\text{Total Number of User Model} = \text{Number of Linguistics Variable}^{\text{Number of Linguistic Value for each Linguistics Variable}} \quad (1)$$

Total Number of User Model = 3^3

Total Number of User Model = 27

Table 2. Decision Strategy to Construct Inference Rules

Rules #	Section Level	Session Time	Score	User Model
R1	*Beginner*	*Minimum*	*Poor*	Beginner Student Type M1
R2	*Beginner*	*Minimum*	*Average*	Intermediate Student Type M1
R3	*Beginner*	*Minimum*	*Good*	Expert Student Type M1
R4	*Beginner*	*Normal*	*Poor*	Beginner Student Type M2
R5	*Beginner*	*Normal*	*Average*	Intermediate Student Type M2
R6	*Beginner*	*Normal*	*Good*	Expert Student Type M2
R7	*Beginner*	*Maximum*	*Poor*	Beginner Student Type M3
R8	*Beginner*	*Maximum*	*Average*	Intermediate Student Type M3
R9	*Beginner*	*Maximum*	*Good*	Expert Student Type M3
R10	*Intermediate*	*Minimum*	*Poor*	Beginner Student Type M4
R11	*Intermediate*	*Minimum*	*Average*	Intermediate Student Type M4

Rules #	Section Level	Session Time	Score	User Model
R12	*Intermediate*	*Minimum*	*Good*	Expert Student Type M4
R13	*Intermediate*	*Normal*	*Poor*	Beginner Student Type M5
R14	*Intermediate*	*Normal*	*Average*	Intermediate Student Type M5
R15	*Intermediate*	*Normal*	*Good*	Expert Student Type M5
R16	*Intermediate*	*Maximum*	*Poor*	Beginner Student Type M6
R17	*Intermediate*	*Maximum*	*Average*	Intermediate Student Type M6
R18	*Intermediate*	*Maximum*	*Good*	Expert Student Type M6
R19	*Advance*	*Minimum*	*Poor*	Beginner Student Type M7
R20	*Advance*	*Minimum*	*Average*	Intermediate Student Type M7
R21	*Advance*	*Minimum*	*Good*	Expert Student Type M7
R22	*Advance*	*Normal*	*Poor*	Beginner Student Type M8
R23	*Advance*	*Normal*	*Average*	Intermediate Student Type M8
R24	*Advance*	*Normal*	*Good*	Expert Student Type M8
R25	*Advance*	*Maximum*	*Poor*	Beginner Student Type M9
R26	*Advance*	*Maximum*	*Average*	Intermediate Student Type M9
R27	*Advance*	*Maximum*	*Good*	Expert Student Type M9

Table 3. IF-THEN Inference Rules

Rules #	IF-THEN Inference Rules	
R1	IF	*sectionLevel is beginner*
	AND	*sessionTime is minimum*
	AND	*score is poor*
	THEN	*userModel is beginnerStudentM1*
R2	IF	*SectionLevel is beginner*
	AND	*sessionTime is minimum*
	AND	*score is average*
	THEN	*userModel is intermediateStudentM2*
R3	IF	*sectionLevel is beginner*
	AND	*sessionTime is minimum*
	AND	*score is good*
	THEN	*userModel is advanceStudentM1*
R4	IF	*sectionLevel is beginner*
	AND	*sessionTime is normal*
	AND	*score is poor*
	THEN	*userModel is beginnerStudentM2*
R5	IF	*sectionLevel is beginner*
	AND	*sessionTime is normal*
	AND	*score is average*
	THEN	*userModel is intermediateStudentM2*
R6	IF	*sectionLevel is beginner*
	AND	*sessionTime is normal*
	AND	*score is good*
	THEN	*userModel is advanceStudentM2*
R7	IF	*sectionLevel is beginner*
	AND	*sessionTime is maximum*
	AND	*score is poor*
	THEN	*userModel is beginnerStudentM3*
R8	IF	*sectionLevel is beginner*
	AND	*sessionTime is maximum*
	AND	*score is average*
	THEN	*userModel is intermediaterStudentM3*
R9	IF	*sectionLevel is beginner*
	AND	*sessionTime is maximum*
	AND	*score is good*
	THEN	*userModel is advanceStudentM3*
R10	IF	*sectionLevel is intermediate*
	AND	*sessionTime is minimum*
	AND	*score is poor*
	THEN	*userModel is beginnerStudentM4*
R11	IF	*sectionLevel is intermediate*
	AND	*sessionTime is minimum*
	AND	*score is average*

Rules #	IF-THEN Inference Rules	
	THEN	*userModel is intermediateStudentM4*
R12	IF	*sectionLevel is intermediate*
	AND	*sessionTime is minimum*
	AND	*score is good*
	THEN	*userModel is advanceStudentM4*
R13	IF	*sectionLevel is intermediate*
	AND	*sessionTime is normal*
	AND	*score is poor*
	THEN	*userModel is beginnerStudentM5*
R14	IF	*sectionLevel is intermediate*
	AND	*sessionTime is normal*
	AND	*score is average*
	THEN	*userModel is intermediateStudentM5*
R15	IF	*sectionLevel is intermediate*
	AND	*sessionTime is normal*
	AND	*score is good*
	THEN	*userModel is advanceStudentM5*
R16	IF	*sectionLevel is intermediate*
	AND	*sessionTime is maximum*
	AND	*score is poor*
	THEN	*userModel is beginnerStudentM6*
R17	IF	*sectionLevel is intermediate*
	AND	*sessionTime is maximum*
	AND	*score is average*
	THEN	*userModel is intermediateStudentM6*
R18	IF	*sectionLevel is intermediate*
	AND	*sessionTime is maximum*
	AND	*score is good*
	THEN	*userModel is advanceStudentM6*
R19	IF	*sectionLevel is advance*
	AND	*sessionTime is minimum*
	AND	*score is poor*
	THEN	*userModel is beginnerStudentM7*
R20	IF	*sectionLevel is advance*
	AND	*sessionTime is minimum*
	AND	*score is average*
	THEN	*userModel is intermediateStudentM7*
R21	IF	*sectionLevel is advance*
	AND	*sessionTime is minimum*
	AND	*score is average*
	THEN	*userModel is advanceStudentM7*
R22	IF	*sectionLevel is advance*
	AND	*sessionTime is normal*
	AND	*score is poor*
	THEN	*userModel is beginnerStudentM8*
R23	IF	*sectionLevel is advance*
	AND	*sessionTime is normal*
	AND	*score is average*
	THEN	*userModel is intermediateStudentM8*
R24	IF	*sectionLevel is advance*
	AND	*sessionTime is normal*
	AND	*score is good*
	THEN	*userModel is expertStudentM8*
R25	IF	*sectionLevel is advance*
	AND	*sessionTime is maximum*
	AND	*score is poor*
	THEN	*userModel is beginnerStudentM9*
R26	IF	*sectionLevel is advance*
	AND	*sessionTime is maximum*
	AND	*score is average*
	THEN	*userModel is intermediateStudentM9*
R27	IF	*sectionLevel is advance*
	AND	*sessionTime is maximum*

Rules #		IF-THEN Inference Rules
	AND	*score is good*
	THEN	*userModel is expertStudentM9*

3. Conclusion

In conclusion, this paper describes the design of intelligent adaptive user interface of tutorial package for online learning environment to cater the diversity of the learners in blended-learning setting. The development of user models is based on the three predefined linguistics variable which are section level, session time as well as the score of the learners or users in which each of the linguistics variables produced another three linguistics value. The fuzzy logic mamdani-style is employed to derive the fuzzy linguistics value such as poor, average, good, maximum, normal, minimum, beginner, intermediate and advance. The derived linguistics values were used to design the IF-THEN inference rules which produced 27 different user models.

It is our hope that the design addressed in this paper has shed a light to the courseware developer as well as the information and communication technology practitioners in producing intelligent interface tutorial package to cater and accommodate the diversity of the learners in online learning environments, hence solve the problem in blended-learning, particularly the non-face-to-face guided practices.

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