Early Detection of Metacognition Disparity Using a Fuzzy-Logic Based Model

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***Abstract*—This research to practice work-in-progress discusses how engineering educators continue to look for methods to improve students' success by improving the learning process. Numerous studies have shown that students' metacognition provides a reliable indicator of students' learning effectiveness. Moreover, results have shown a direct proportionality between improved students' metacognition and improved academic achievement. Therefore, efforts have been reported in the literature aiming at measuring metacognition and employing the results to improve outcomes of the educational experience. However, methods to measure metacognitive abilities and the process to employ relevant interventions aiming at improving the learning process, are still lengthy and cumbersome. This study was initiated to explore building a predictive model that could help expedite the process of identifying students with metacognitive disparities and the corresponding proper interventions needed to improve their learning at early stages of an educational course. The study is divided into two phases where the first phase, reported in this paper, includes exploring metacognition measurement and characterization methods to develop a model that can identify metacognition levels ordinally which can also be used to show changes in metacognition. The second phase includes expanding the first model to identify a targeted intervention with optimized details in order to improve students' level of learning and performance. For this purpose, concepts of fuzzy set theory were utilized to build the models. The first model produced a Metacognition Fuzzy Indicator (MFI) which identified students' metacognition levels based on performance assessment data collected early in the semester. A combination of direct and indirect assessment methods of students' attainment of course learning outcomes in four engineering courses were collected, -before and after interventions, and employed to build and test the model. Results of utilizing the model have shown consistent agreement between MFIs and students' performance improvement after implementing a variety of interventions in all tested courses. A second model was developed as an expansion of the existing model to start the second phase of this study and provide details of the recommended interventions per student by producing an Intervention Fuzzy Indicator (IFE). Future work will include providing results aiming at optimizing time and effort invested by the instructors to improve students' learning while increasing students' motivation and success through increased personalized educational interventions.**

Keywords— Metacognition Measurement, Fuzzy-logic modeling of Metacognition, Predictive Intervention Model

I. Introduction

Students' success is directly proportional to continuous improvement of the educational process. Educators usually assess students' attainment of course learning outcomes (CLOs) multiple times during a course to decide on the need and level of adjustment required to achieve maximum effectiveness of students' learning. These adjustments include introducing interventions that will improve students' learning. The effectiveness of these interventions relies on their design and implementation which requires reliable assessment and monitoring of students' learning.

According to the literature, students' metacognition is considered a reliable indicator of students' learning effectiveness [1]. Therefore, numerous efforts have been aiming at measuring metacognition and capitalizing on this knowledge to improve outcomes of the educational experience. Results of these efforts have shown that improved academic achievements are directly proportional to improved students' metacognitive abilities [2]. However, methods to effectively measure and employ metacognitive abilities in a continuous improvement loop to optimize the selection and implementation of interventions targeting an improved learning process are still lacking. This study was initiated to develop a method that could help expedite the process of identifying students with metacognitive disparities and the corresponding proper interventions needed to improve their learning. The following parts include a summary of the background, followed by a description of the goal of the study and the research methodology. A description of the work and results is provided next, followed by the discussion, conclusion, and future plans.

II. Background

Metacognition is the capability to think about thinking which produces better learning outcomes [3]. Higher metacognition levels represent a survival tool for students, especially for unsupervised learning and for their careers after graduation [4]. Students often show metacognitive illusion by selecting non-effective learning strategies such as the "cease-to-study" strategy because they thought that the studying they have already done is enough to achieve mastery of the topic [5]. Because of the direct proportionality between metacognition and students' improved learning, many researchers tried to characterize and measure metacognition [3]. However, several challenges were reported by instructors as they tried to find a way to measure students' metacognition levels appropriately. Consequently, similar challenges were found as educators tried to select proper interventions to alter the students' metacognition levels positively and effectively. In addition, instructors may need to change their teaching strategies during the semester to enhance the students' academic performance. However, selecting and implementing interventions is usually based on experience and could be improved significantly with an efficient tool to measure the students' metacognition level and redirect interventions appropriately and efficiently [4, 5].

Interventions to improve students' learning include a wide spectrum of evidence-based techniques and activities which can be selected and implemented by the instructor to improve students' learning. [8]. Examples of interventions include flipping the classroom to focus on problem solving, step-by-step problem solving, adding a reflection element to technical work, assigning extra reading, re-design of assessment tools, assigning group work, and PBL, to name a few [9]. These interventions are usually introduced by instructors to the entire class based on experience in interpreting results of assessment instruments such as exams. However, the effectiveness of these interventions has a greater potential if they are designed to be targeted and personalized, and if they are implemented as part of a continuous improvement loop where their effect is monitored efficiently through a direct indicator such as metacognition levels of the students.

Fuzzy logic is a computational method that imitates human reasoning and cognition. Fuzzy logic has been used widely in applications that involve imprecise data and when the relation between the model's input parameters is unclear [10]. Fuzzy set models have an advantage over probabilistic processing in that Fuzzy models require little data with minimal defined relationships [11]. Also, Most mathematical modeling tools are dichotomous making them difficult to use in measuring students' metacognition levels. In general, fuzzy models are more humanlike models to capture expert knowledge which seems most suitable in the evaluation of the student's metacognition level [12].

This work proposes two models to measure a students' metacognition levels and to provide a set of targeted and personalized interventions. The first model would provide the instructor with reliable measurements or ranking of students' metacognitive abilities as well as the change in these measurements. A fuzzy-logic-based model is selected to accomplish this task because it combines different inputs at different scales to produce standardized outputs. The second model is a predictive model that will provide the instructor with the details to select a targeted and personalized intervention that is optimized to improve learning effectiveness. Examples of these interventions include the type of metacognitive strategy and the level of emphasis needed in each intervention. These models will be tested in a continuous improvement strategy to optimize and automate their effectiveness. This work-in-progress paper reports details of the first phase which includes developing and testing the first model as well as developing the second model with early implementation of the continuous improvement strategy.

III. Methodology

A. *Research goal and questions*

The purpose of this work is to propose an innovative model based on fuzzy logic to measure students' metacognition from their performance assessment using regular assignments and tests. In the following phase, the proposed model will be expanded to improve the effectiveness of educational interventions aimed at improving students' learning. The following research questions were formulated:

1. How can students' metacognition levels be measured consistently and effectively?
2. How can the most effective interventions be identified based on metacognition levels to enhance the student's metacognitive level and academic performance?

B. *Participants*

The study involved 57 students from three different courses in the department of mechanical engineering at The University of Texas at Tyler (UT-Tyler). A mixed-methods approach was employed to collect both direct and indirect assessment data of students' attainment of CLOs in these courses, at different stages. IRB exemption status was granted for this study.

C. *Procedure*

Fig. 1 shows the strategy proposed to implement fuzzy logic in building a model that intakes student's performance direct and

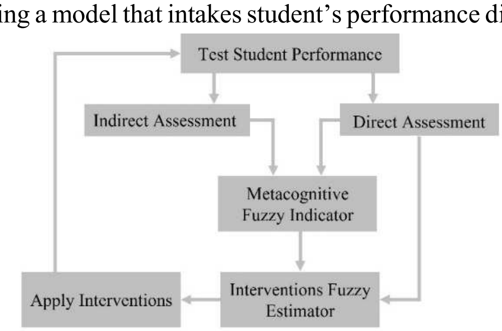

Fig. 1. Strategy for Metacognition measurement and utilization to identify proper intervention using Fuzzy Logic.

indirect assessment results and outputs a Metacognition Fuzzy Indicator (MFI) which indicates a corresponding level of metacognition. The MFI was created based on fuzzy set theory. The indirect assessment result represents the students' estimate of their ability to achieve a certain course learning outcome (CLO) and the direct assessment result is the students' exam result covering the same CLO.

IV. WORK AND RESULTS

A. Metacognition Measurement Model

Fig. 2 shows a graphical representation of the proposed MFI model. The fuzzification unit of this model reads all inputs (Indirect and direct) and processes them using a generalized bell-shaped function (1), where: a determines the width of the bell, b is a positive integer, and c sets the center point. This part of the model converts each input crisp value into a linguistic value on an ordinal scale (Poor, Fair, Good, and Excellent).

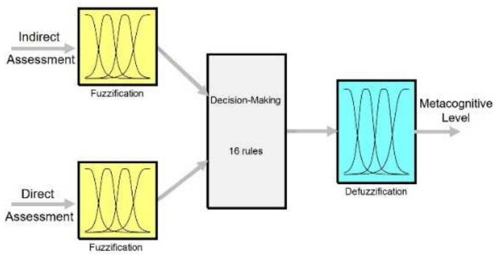

Fig. 2. Architecture of the Metacognition Fuzzy Indicator (MFI) Model

$$f(x,a,b,c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \quad (1)$$

The decision-making unit of the model reads input linguistic values and generates one linguistic value per applied rule. This process is based on expert knowledge and a set of 16 rules, Table I shows some of these rules.

TABLE I. METACOGNITION FUZZY INDICATOR RULES

Input Membership Functions		**Output Membership Function**
Indirect	***Direct***	***Metacognition Level***
Poor	Poor	Excellent
Poor	Excellent	Poor
Fair	Poor	Good
Fair	Excellent	Fair
Good	Poor	Fair
Good	Excellent	Good
Excellent	Poor	Poor
Excellent	Excellent	Excellent

Four output membership functions were chosen for optimal model sensitivity where each function represents a certain Metacognition level ordinally arranged. Two experts in fuzzy logic were consulted during the model design process. The experts helped in verifying the tools and methodology of quantifying the model linguistic variables. Finally, the defuzzification unit uses the center of gravity (CoG) rule to combine the output linguistic values from each rule and produce one crisp output value. The model output is the student's metacognition level from 1 to 5, here 1 represents poor and 5 represents Excellent metacognition level.

B. Intervention Selection Model

The structure of the Intervention Fuzzy Estimator (IFE) model is quite similar to the MFI with the direct assessment result and MFI as an input. The aim of these interventions is the enhance both the student's academic performance and metacognitive level. Therefore, the MFI and the direct assessment results are used in the IFE model. The model uses sets of 16 rules to find the proper intervention(s) out of 5 intervention levels aiming to improve learning effectiveness. Table II shows some of these rules. This is the beginning of the second phase of the work which is still in-progress.

TABLE II. INTERVENTION FUZZY ESTIMATOR RULES

Input Membership Functions		**Output Membership Function**
MFI	***Direct***	***Intervention***
Poor	Poor	Poor / A step-by-step solution
Poor	Excellent	Fair / Concept maps
Fair	Poor	Poor / A step-by-step solution
Fair	Excellent	Good / Advise themselves
Good	Poor	Fair / Concept maps
Good	Excellent	Very Good / Create positive energy
Excellent	Poor	Good / Advise themselves
Excellent	Excellent	Excellent / Feedback

While the model will indicate the most needed intervention for each student, it could also mean that the student may need all other interventions with less priority. Table III provides more details about each intervention ordered by priority based on need indicated by the IFE.

TABLE III. LIST OF INTERVENTIONS

Intervention	**IFE Range**	**Details**
A step-by-step solution	<1.5	Solve selected problems using the step-by-step method
Concept maps	<2.5 >1.5	Summaries of all formulas covered in one sheet
Advise themselves	<3.5 >2.5	students need to write to themselves some comments on what they did wrong when they studied and what they should do for the next exam
Create positive energy	<4.5 >3.5	Encouragement and motivation to study
Feedback	>4.5	Provide actionable, focused, and specific feedback after the test

The MFI model was tested on the entire range for all possible input values producing results as shown by Fig. 3. The MFI values increase when the difference between the direct and the indirect assessment values increases.

Following, the MFI model was used with sets of direct and indirect assessment data from three different engineering courses, assessing students' level of attainment of some CLOs of the course, at the beginning of the semester.

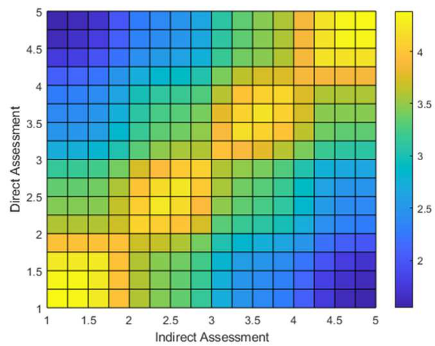

Fig. 3. MFI values for the entire range of inputs

A similar process was repeated using a new set of direct and indirect assessment data from the same courses, collected after different types of educational interventions were applied in the class exclusive of the MFI results, assessing students' attainment of a completely different set of CLOs. MFI results of processing the earlier and the later sets of data from the different courses is presented in Fig. 4.

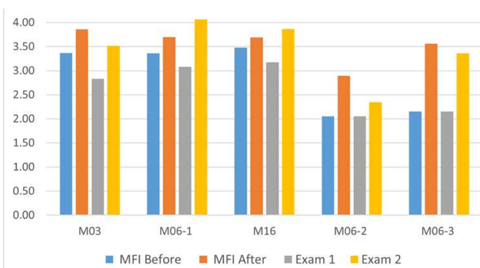

Fig. 4. Change in Average MFI vs. change in Average Exam results for each of the courses included in the study, all on a 5-point scale.

Direct assessment data (exams) used for each MFI run is also included in Fig. 4 for comparison. The courses used were Mechanics of Materials (M06-1, M06-2 and M06-3) from three different semesters, Mechanical Systems Design (M03), and Heat Transfer (M16). In addition, the IFE model was developed and tested using the same data at the beginning of the semester for the same courses used previously. Fig. 5 shows results from the IFE model tests over the entire range of input values.

The model generates low numbers when the student is in need for more interventions. These preliminary results seem to generally agree with the interventions already used by the instructors in the courses. However, more development, tests, and tuning are needed for this model which is part of the following phase of this work.

The proposed MFI model was based on fuzzy logic to accommodate data with very little characterized relations, and to consistently generate ordinal results. The model was built to input data from direct and indirect performance assessment in different engineering courses and produce an indicator of metacognition for each student. Fig. 3 shows MFI values over the entire range of inputs, where metacognition is indicated to be higher when the difference between the input data is lower.

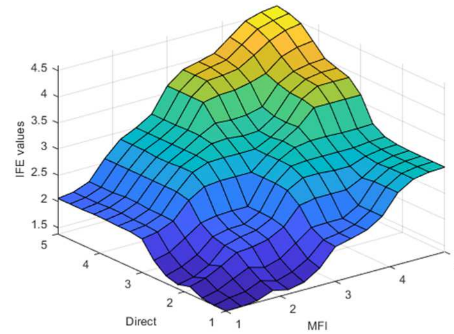

Fig. 5. IFE vlaues for the entire range of inputs

V. DISCUSSION

This is consistent with the definition of metacognition where students are able to estimate how much they know very closely (indirect assessment), verified by their exam scores (direct assessment). The bigger the difference between these two values, the higher the disparity in metacognition, and the lower the MFI value. This was the basic logic of the ranking in table I. To validate the MFI model results, a comparison between the change in average MFI produced per course vs. the change in the average of exam scores for the same class (direct assessment), after the implementation of different interventions, were presented in Fig. 4. This comparison shows an agreement of proportionality between the change in MFI and students' performance change.

Expanding on the previous findings, the IFE model was developed to intake the MFI output and the direct assessment values, as shown in Fig. 1, and output details of interventions needed per student. The direct assessment value was considered again because the aim is to use the IFE output of indicated set of interventions to improve both student metacognition and performance, as much as possible. Results of testing the model over the entire range of inputs are shown in Fig. 5 A lower value IFE indicates the need for more significant intervention, including any lower priority interventions on the list. This is also the base of logic used in the ranking in table II. This model is still under development and testing as part of a future phase of this work.

VI. CONCLUSION

A fuzzy-logic-based model was developed and tested to measure students' metacognition levels (MFI), and change in these levels, consistently, using traditional direct and indirect assessment data of students' performance. Capabilities of the model were expanded by developing a second model that uses the MFI combined with direct assessment data to indicate the level of intervention needed for improving students' performance and metacognition. Preliminary tests of the second model show results in the correct direction. However, more testing and improvement are needed to finalize this model as part of the following phase of this work. The outcomes of this research are expected to enhance instructors' ability to monitor and adjust students' success in learning through a continuous improvement cycle based on consistent and reliable performance measurement coupled with consistent estimation of proper targeted and personalized educational interventions.

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