Received: 31 September 2023; Revised: 23 November 2023; Accepted: 7 December 2023; Published: 20 December 2023

Intelligent Tutoring System: New Criteria and Evaluation to Measure Students' Degree of Mastery

Siti Khatijah Nor Abdul Rahim[1*], Amir Hamzah Jaafar[2], Geetha Baskaran[3]

[1]*School of Computing Sciences, College of Computing, Informatics and Mathematics, Universiti Teknologi MARA (UiTM), Shah Alam, Selangor, Malaysia; sitik781@uitm.edu.my*
[2]*E-Content (M) Sdn. Bhd., Jln Perdana, Cyber 12, 63000 Cyberjaya, Selangor, Malaysia; amirhamzah@e-content.com.my*
[3]*Procurement Services, University of Sydney, Forest Lodge, NSW 2037, Australia; geetha.baskaran@sydney.edu.au*

**corresponding author*

Abstract

Intelligent Tutoring System (ITS) is computer software designed to simulate or imitate a human tutor's behavior and guidance. By having the capability to interpret complex students' responses and to estimate the students' degree of mastery, ITS adeptly tailor their tutoring behavior. Despite its intelligent capability, there remains a need for improvement in the ITS concerning performance measurement, predictive accuracy, and adept handling of uncertainty in student interactions. Motivated by these considerations and the recognition that ITS can further enhance their effectiveness in guiding students toward a comprehensive understanding of specific topics, this study introduces a novel mechanism within the student module. The primary objective is to present innovative criteria and approaches for measuring a student's degree of mastery through meticulous data pre-processing. The study involved pre-processing data files to extract more meaningful information, aligning with its overarching aim. Several criteria analyzed during assessments, following pre-processing, were utilized as inputs for an evaluation function designed to evaluate students' performance, specifically their degree of mastery. The results obtained demonstrated the efficiency of this proposed approach in accurately measuring students' degree of mastery. This development carries meaningful implications, allowing ITS to serve as personalized tutors designed to match each student's capabilities, ultimately enhancing the learning experience.

Keywords: intelligent tutoring system, mastery level, pre-processing, evaluation criteria, evaluation function.

INTRODUCTION

Intelligent Tutoring System (ITS) is computer software designed to simulate or imitate a human tutor's behavior and guidance (Koedinger & Tanner, 2013; Ferster, 2022; Cuéllar-Rojas et al., 2022; Wang et al., 2023). ITS is designed to include techniques from the Artificial Intelligence (AI) discipline to provide tutors who know what to teach, whom to teach, and how to teach. ITS can be thought of as efforts made to produce computer systems with intelligent behavior, which if performed by humans can be described as 'good teaching' (Chanthiran et al., 2022; Nwana, 1990). With the aim to provide customized and immediate feedback or instructions to the learners (Psotka et al., 1988), it aids learners or students, in which it is designed to provide individual help to students in achieving good understanding during the learning process. ITS can be seen as personalized tutoring systems that arouse students' learning enthusiasm (Saidong et al., 2013).

One of the important features of ITS is the capability to interpret complex students' responses and to estimate the students' degree of mastery, and as a result, it manages to adjust the behavior of the tutoring accordingly. This capability helps ITS to function as personalized tutors. With this in mind, and realizing the fact that ITS can be further improved to provide better tutoring, it is believed that there is a call to further improve the module in interpreting students' responses and estimating the students' mastery level, thus the focus of this study. It should be stated here clearly that the focus of this paper is not to discuss the overall functions of the proposed Intelligent Tutoring System (ITS), but rather to discuss the 'engine' of the measuring function in evaluating students' mastery level for a particular topic. This study proposes to utilize a data pre-processing technique on the data captured by students' behaviors and responses while using the system. It is believed through pre-processing, richer information can be generated that will be able to measure the mastery level of each student, which can improve the capability and effectiveness of ITS.

LITERATURE REVIEW

This section presents the background of the study which covers the important aspects of this research according to the literature.

Intelligent Tutoring System: History and Challenges

Intelligent Tutoring System (ITS) is not new ideas or innovations in teaching. Nearly 50 years ago, in the late 1970s, scientists started to adopt AI technology in designing computer-based instructions (Yaratan, 2003, Karpouzis, 2023; Kurni et al., 2023; Sudin et al., 2022). 'Computer-Aided Instruction' (CAI) was the term used to refer to the use of computers in education. Since then, research in the domain of educational software incorporating AI has been known as 'ICAI', an acronym for 'Intelligent Computer-Aided Instruction', in which the term evolved from CAI. Later the term ITS was used interchangeably with ICAI for quite some time before the acronym ITS seemed to replace or diminish the term ICAI (Nwana, 1990; Yaratan, 2003).
In the early stage of building intelligent computer systems, there were quite a lot of issues with regard to cost and time. It was reported that in the past days, the cost of ICAI development was pretty high and it was common to require a million-dollar machine just to interact with one student, and usually the response time of the machine was not fast. The time needed to develop this educational software was also pretty high and it was mentioned that approximately 200 hours were needed to construct one hour's worth of conventional CAI, and the time will increase greatly in constructing the ICAI. Besides these issues, there was another obstacle, where it was realized that there was no established paradigm for aiding students to attain knowledge. Early ICAIs have trouble interacting intelligently with students due to not having a clear understanding of the impacts of the interactions on learning. However,

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nowadays these issues have been resolved and therefore research and developments of ITS are continuing to evolve rapidly (Anderson et al., 1985; Cuéllar-Rojas et al., 2022; Wang et al., 2023, X. Huang et al., 2023). Nowadays, ITS is still proven to be very effective and research in this area still progressing rapidly including the development of ITS for teaching specific subjects, discussions on some issues including its barriers, challenges, and identification of future enhancements (Nye, 2015; Kulik & Fletcher, 2016; Aleven et al., 2015; Mahdi et al., 2016; Bhagat et al., 2018, Chango et al., 2021; Cuéllar-Rojas et al., 2022; Wang et al., 2023, X. Huang et al., 2023, Zhang et al., 2023).

Mastery Learning

English Oxford Living Dictionary defines "mastery" as comprehensive knowledge or skill in a particular subject or activity. According to Cambridge Dictionary, if someone has a "mastery" of something, they are extremely skilled at it. In the context of this study, mastery is the competencies or the comprehensiveness of a student on a particular topic. In 1968, Benjamin Bloom was the first to propose the Mastery Learning concept (Bloom, 1968). Mastery learning initially known as "Learning for Mastery" is an educational philosophy and instructional strategy that states that a student must achieve a level of mastery in a prerequisite knowledge before proceeding to learn the next level of knowledge. If a student does not achieve mastery on a given assessment of a particular knowledge, that student will be given additional support in learning and reviewing the knowledge and he/she will be assessed again. The process will continue in a cycle until the student achieves mastery, and can move forward to learn the next stage (Bloom, 1968; VanLehn, 2006; Yilmaz et al., 2022; Khazanchi et al., 2022).

Mastery learning requires that the tutoring system have a mechanism to evaluate the student's degree of mastery in a particular knowledge (Ferster, 2022; VanLehn, 2006), The focus of instruction in the Mastery Learning principle is the time required for different students to learn the same knowledge or material and accomplish the same level of mastery. This is very different from the classic teaching model, in which all students are given almost the same amount of time to learn the same knowledge or materials, and it focuses more on differences in the students' abilities (VanLehn, 2006; Bloom, 1968). The mastery level of topics in a particular subject is highly dependent on the ability to absorb knowledge during class or time invested during independent learning to study a particular topic. Many ITS have utilized well-established technologies that are proven to be effective for skill mastery in numerous domains (Y. Huang et al., 2023).

Features and Advantages of Intelligent Tutoring System

Intelligent Tutoring System (ITS) can be considered very significant and important in the teaching and learning process. Among the importance of ITS in teaching and learning is the capacity to offer students individualized education that takes into account their particular learning preferences and styles (Lin et al., 2023), significantly more successful in encouraging learning than other computer-based teaching methods which proves notable increase in student overall performance (Kochmar et al., 2022) and create learning environments that adjust to individuals' different skills and traits (Fang et al., 2022).

Intelligent Tutoring System (ITS) is capable of interpreting complex student's responses and estimating the student's degree of mastery as it executes (Koedinger & Tanner, 2013). Some ITS analyzed online learning behavior based on certain data or variables, for example, total time spent online, the total number of contents or pages viewed online, etc (Šarić-Grgić et al., 2023). ITS can assist students in learning various subjects by posing questions, analyzing responses, and offering personalized feedback and instructions. A unique profile for each student will be built to evaluate the student's performance, thus ITS can adjust their tutoring behavior accordingly. The goal of ITS is not really to identify which response is incorrect but to identify specifically in which part of the response the student did not answer correctly. For this purpose, ITS can monitor each step of responses and thus can determine precisely where and why the wrong responses are made. ITS will continue posing problems or questions to students that test a concept until the system detects the student has mastered the concept well (Koedinger & Tanner, 2013).

ITS can work with a large number of students, either individually or simultaneously, and regardless of the number of students, the system can function as a personalized tutor that can provide individualized instructions (Koedinger & Tanner, 2013; Anderson et al., 1985; Ma et al., 2014; Kochmar et al., 2022). The beauty of ITS is that they can track the student's particular approach during the learning and assessment session. In the normal practice of teaching, whenever a student does not understand the lesson being taught by the tutor, an explanation will be given again by the tutor. Researchers using ITS however have discovered that a better and more effective approach for students to learn is to let them explain what they understand to the intelligent tutor, and in response to that, the tutor can assess each step of the explanation, provide tips or hints, and give the students space and time to learn or work out a particular topic. Since ITS is a computer system (not human), it can reduce the uneasy or inferiority complex feelings of students admitting to a human that they do not understand certain knowledge. As it is impossible for learning institutions to provide a human tutor for each student, ITS is a very useful replacement to offer personalized assistance to students during learning or assessments that are adjusted to their learning speed and requirements (Koedinger & Tanner, 2013).

METHODOLOGY

Motivated by the insights gained from the background study on the importance of assessing the degree of mastery of students in the underlying knowledge, this study is proposing an Intelligent Tutoring System (ITS) that can measure the degree of mastery through data pre-processing. Recall that by knowing the student's degree of mastery, the intelligent tutor can provide personalized assistance according to the student's mastery, thus learning can be done more effectively.

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The pre-processing will be done on certain data files, for example, data files consisting of students' responses and behavior during assessments, answers recorded for assessments, duration of time taken to answer assessments, duration recorded for all students in a particular assessment, and duration for independent study. Data will be captured through ITS interfaces specially designed for this study to improve interactions between humans and computers and provide learners with more effective learning experiences (Ahuja et al., 2022).

Data Pre-Processing

Data pre-processing can be defined as processing done on raw data prior to another processing stage. Pre-processing the original raw data shall transform the data into a more organized format and usually is easier and more effective to process later. The other advantage of data pre-processing is that it can extract hidden information that is implicit in data and generate richer information that is more meaningful and can be utilized more intelligently. Data pre-processing has found extensive applications across various domains, including data mining (Wasilewska & Menasalvas, 2023), scheduling (Benedikt et al., 2020), image processing (Vimal et al., 2020), as well as in specialized fields such as semiconductor manufacturing and aerospace (Deane et al., 2020), to name a few. Data pre-processing includes data cleaning, data integration, data transformation, data reduction, and data discretization. Through data pre-processing, the dimensionality of data can be reduced, facilitating faster execution of subsequent tasks. Realizing that ITS should be capable of interpreting and analyzing student responses, a unique profile creation becomes essential for evaluating student performance. Therefore, a pre-processing method will be employed to generate more meaningful data, which can be further utilized to measure the student's degree of mastery.

Criteria to Measure the Degree of Mastery

Several criteria will be employed to measure a student's degree of mastery in a particular topic. The criteria include:

1. Level or category of question during assessment (According to Bloom's Taxonomy)
2. Time spent on reading/independent study for a particular topic (If Any) – future work will determine whether the study is happening
3. Confidence level of student during assessment
    a) Number of "Not Sure" marking
    b) Number of "No Idea At All" marking
    c) Number of answered questions
    d) Number of unanswered questions
4. Number of correct answers or weightage of answers in the assessment
5. Average time spent on answering assessments for a particular topic

Information from the Criteria as Inputs to Evaluation Function

The mastery level of each student will be assessed using the criteria outlined in the previous section. These criteria, analyzed during assessments through pre-processing, will serve as inputs to an evaluation function for evaluating student performance, specifically the mastery level. The explanations for each criterion are as follows:

1. Level or category of question during assessment (according to Bloom's Taxonomy)
   a) The keyword used in the question can be leveraged to determine the difficulty level of the question
   b) Example: If the question uses the term "define", as in "Define Artificial Intelligence."
      i. *The assumption is that the question falls under the "Knowledge/ Remember" level.*
      ii. *Once the level is identified, this information can be used to determine the student's mastery level.*
      iii. *An additional assumption is made that the higher the level of the question a student can answer, the higher their mastery level in a particular topic or subject*

2. Time spent on reading/independent study for a particular topic
   a) The duration dedicated to independent study can serve as an indicator of the degree of mastery in a particular topic
   b) A significant amount of time spent in independent learning on a particular topic might indicate that the student has attained substantial knowledge.
      i. *Longer periods spent during independent study may indicate a higher degree of mastery of the underlying knowledge.*
      ii. *Conversely, shorter time durations during independent study may suggest a lower degree of mastery of the underlying knowledge.*

   Note that we acknowledge the possibility that an extended study duration might indicate a student is at a beginner level in the subject, while a shorter study duration could suggest a higher mastery level. However, it is crucial to emphasize that our research scope is limited to topics the student has never learned before. Therefore, our assumptions, as outlined in points i and ii above, remain applicable within this specific context.

3. Confidence level of the student during assessment (i.e. when answering questions during assessments given)
   a) In the ITS proposed in this study, the interfaces are designed to assist students both during tutoring/learning, and assessments.
   b) Specific features are incorporated to aid students in managing their answering process during assessments.
   c) The ITS provides two buttons allowing students to "mark" questions during assessments based on their certainty towards each answer.

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d) The buttons are labeled "ANSWERED, BUT NOT SURE", and "NO IDEA AT ALL," which students can click during the answering process (refer to Figure 1).
e) A summary of their answers in progress is displayed in the top section of the question.
f) Questions answered by the student but marked as "ANSWERED, BUT NOT SURE" are indicated with a yellow color, while unanswered questions marked as "NO IDEA AT ALL" are shown with a blue color indicator. Questions answered without any markings are indicated with a green color, and questions not answered at all are marked in red (refer to Figure 2).
g) The system can determine the degree of mastery of the student for assessed topics based on the color markers recorded during the assessment.
   i. *Answering straightaway indicates a high confidence level (time taken to answer is recorded, with less time indicating higher confidence),*
   ii. *Questions marked as "ANSWERED, BUT NOT SURE" signify a low confidence level and, consequently, a low degree of mastery.*
   iii. *Questions marked as "NO IDEA AT ALL" clearly indicate very low confidence and, thus, a very low degree of mastery.*
   iv. *Unanswered questions marked in red suggest the student does not know the answers, indicating a low degree of mastery.*
   v. *Despite the assumed high confidence levels when answering straightaway, the correctness of the answer (number of correct and incorrect responses) is considered when measuring the degree of mastery.*

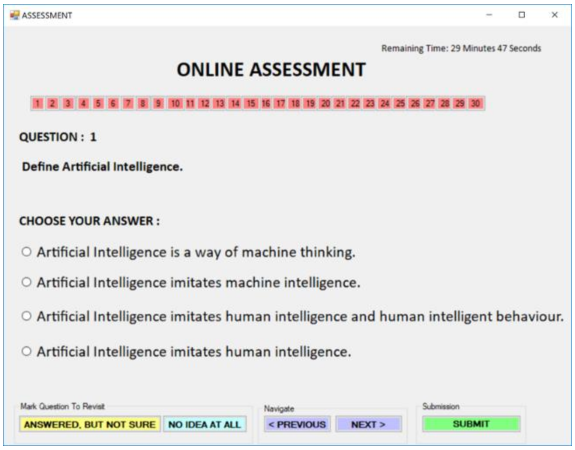

Figure 1: Interface designed to assist students during assessments in the proposed ITS

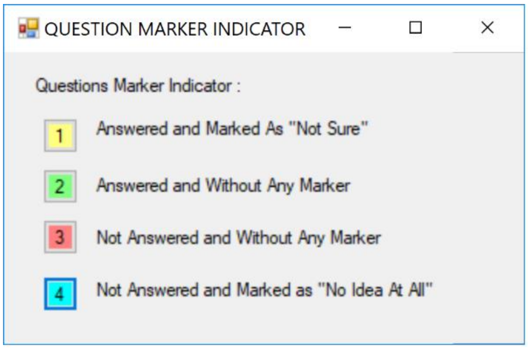

Figure 2: Interface showing the question marker indicator

4. Number of correct answers or weightage of answers in the assessment
   a) Each answer to a question is assigned a weightage. A weightage of 1 indicates a correct answer, while a weightage of 0 indicates an incorrect answer. Additionally, answers may have a weightage of 0.25, 0.50, or 0.75. The higher the weightage assigned based on the selected answer, the greater the assumption of the student having a higher degree of mastery in the underlying knowledge.
   b) This approach allows students to earn partial marks based on their demonstrated knowledge, even if their answer is not entirely correct. The assigned weightage serves as a matrix for measuring the student's degree of mastery. Examples of answers with weightages are given in Table 1.

Table 1: Example of answers with its weightage

Choice of Answer Listed	Weightage
Artificial Intelligence imitates human intelligence.	0.75
Artificial Intelligence imitates human intelligence and human intelligent behavior.	1
Artificial Intelligence imitates machine intelligence.	0
Artificial Intelligence is a way of machine thinking.	0.25

5. Average time spent on answering assessments for a particular topic
   a) The time dedicated to answering questions during assessment can serve as an indicator of the degree of mastery in a specific topic.
      i. *Longer durations might indicate a lower degree of mastery of the underlying knowledge.*
      ii. *Conversely, shorter durations might suggest a higher degree of mastery of the underlying knowledge.*

It is important to note that the system proposed in the study is capable of automatically identifying the topic of the assessed questions based on the words used in the question through the pre-processing

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mechanism. For this purpose, important keywords for each topic in a particular subject are stored in the database. This functionality allows the system to measure the degree of mastery for each student. The comprehensive list of topics along with their corresponding keywords is presented in Table 2.

Table 2: List of topics and keywords

Topic	Keywords
Introduction to Artificial Intelligence	Neumann, Artificial, Rational, Machine, Human, Von, John, Pitts, Wallter, Mcculloch, Warren, Turing, Alan, Intelligence, Intelligent
Knowledge Representation	Rule-Based, Expert, System, Inference, Human, Conventional, Development, Chain, Rules, Forward, Backward, Chaining
Reasoning with Uncertainty	Probability, Theory, Uncertainty, Bayesian, Reasoning, Factors, Certainty, Factors
State Space And Heuristic Search	Breadth-First, Problem-Solving, Uninformed, Breadth-First, Informed, Strategies, Tree, Heuristic, Best-First, Depth-First, Greedy, Best-First, A*, Local, Hill-Climbing
Knowledge Representation Scheme	Neural, Function, Inferences, Linguistic, Logic, Fitness, Hedges, Classical, Mutation, Artificial, Biological, Crossover, Chromosomes, Back-Propagation, Boolean, Perceptron, Networks, Genetic, Algorithms, Fuzzy, Expert, Systems
Agents	Actuators, Environment, Rationality, Measure, Structure, Software, Rational, Omniscient, Task, Agent

The information obtained from the aforementioned criteria through pre-processing, as discussed in this section, will serve as valuable input for the evaluation function designed to measure the student's degree of mastery.

Evaluation Function to Measure the Degree of Mastery

The degree of mastery of a student on the underlying knowledge is reflected in the student from various aspects of the learning process. The ultimate indicator lies in the student's capability to apply acquired knowledge to answer questions, either objective or subjective. Calculating a student's degree of mastery involves considering multiple aspects related to the learning process, encompassing study time, question types, confidence levels, and answer correctness. In the question-answering process, students encounter a diverse set of questions from various topics, each varying in difficulty. The final evaluation of students' performance involves awarding marks for correct answers. However, the system meticulously records and evaluates each question separately, contributing to the degree of mastery in a particular area or topic. Each question is affiliated with a related topic and difficulty level, directly corresponding to Bloom's Taxonomy.

The system continuously tracks a student's performance based on the topics covered. The materials provided for study pertain to specific topics or a combination of topics. Upon completion of the courseware for a particular topic, the system calculates the effort invested in determining the degree of mastery for that topic. However, the degree of mastery gained through study has a limit, regulated by the time spent on independent study. Further study efforts beyond this limit do not contribute additional points to the degree of mastery attained independently.

This study proposes a breakdown for calculating the degree of mastery, where the time spent on independent study holds a weightage of 20%, the confidence level during assessment contributes 10%, the average time taken to answer questions holds a weightage of 20%, and the correctness of answers contributes 50%, as illustrated in Figure 3. The degree of mastery for a specific topic is thus expressed as:

Degree of Mastery (Topic) = Time of Independent Study + Confidence Level during Assessment + Average Time to Answer + Correctness of Answers

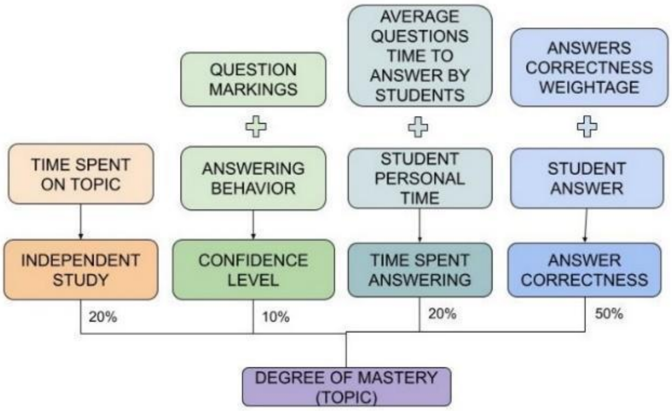

Figure 3: Components of the degree of mastery (topic)

The time taken to answer a question is contextualized with the question's historical time factor. Using a statistical function, if the time taken falls within the normal range, the weightage is between 0.25 to 0.75. Anything above the normal range (less time spent) will have a weightage between 0.75 to 1, while anything below the normal (more time spent) will have a weightage of 0.25 and below. The time spent studying a particular topic is directly linked to the knowledge obtained on that topic. The main assumption is that a longer duration spent on a topic indicates a higher degree of mastery, and conversely, a shorter duration suggests a lower degree of mastery.

The degree of mastery of a particular topic is reflected in a student's ability to consistently answer questions correctly throughout the entire assessment session. For an objective and continuous assessment, the percentage considers all answers given by a student on a particular topic. The formula calculates the total amount of correct questions answered divided by the total number of questions attempted on that topic. In cases where a question constitutes knowledge of more than one topic, the answer for that question will contribute to all relevant topics in degree of mastery calculations. The

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confidence level of a student is evaluated in comparison to other students attempting the same question. Each question has an average time taken to answer and a scoring ratio among students. Evaluation is based on individual performance relative to the overall or previous student performance.

RESULTS AND ANALYSIS

This section delves into the analysis of the results obtained from the proposed ITS under the student module, designed in this study to measure the student's mastery level through pre-processing. The following explanations are presented in a manner that includes captured screenshots of select interfaces, aiding readers in comprehending the measurement process for criteria such as the student's confidence level.

As previously mentioned, a utility allowing students to mark certain questions is integrated into the proposed ITS. The primary aim is to enable students to systematically manage the answering process during the assessment. Another crucial objective, central to this study, is to monitor and record students' responses during assessments, particularly focusing on tracking their confidence levels. This information serves as a vital input for an evaluation function designed to measure mastery level at a later stage. The interface presented in Figure 4 captures the initial stage of the assessment. showcasing questions numbered 1 to 30 as unanswered (indicated by the red buttons).

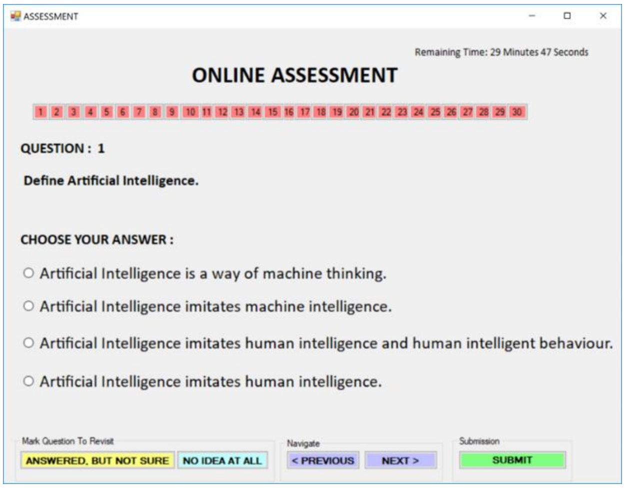

Figure 4: Interface screenshot at the beginning of assessment taken by Student A

Notably, the lower section of the interface provides buttons such as "ANSWERED, BUT NOT SURE", and "NO IDEA AT ALL", enabling students to mark questions based on their confidence level. While this utility may seem inconspicuous at first glance, it plays a crucial role in helping students manage the answering process systematically. This functionality proves particularly valuable as it allows students using the tutoring system to swiftly assess the status of all questions during assessments. This feature becomes a time-saving asset, preventing students from revisiting all questions to identify the ones answered or unanswered. The utility's significance becomes apparent when students wish to re-evaluate questions they are uncertain about or questions they answered but are not entirely sure of. The system employs distinct color codes to provide a clear indicator for each scenario. In Figure 5, the interface reflects the state after Student A has answered Question 1. Notably, the button labeled '1', corresponding to Question 1, is now highlighted in yellow, signaling that Student A has marked it as "ANSWERED, BUT NOT SURE."

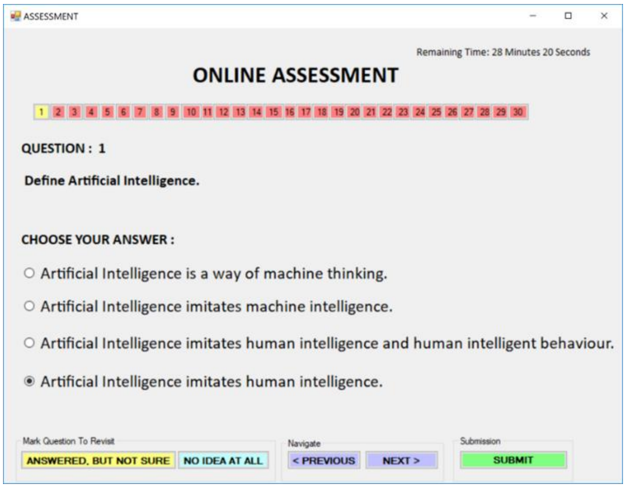

Figure 5: Interface screenshot after Student A answers Question 1

As the assessment progresses, Figure 6 illustrates that the student has answered Question 2 without applying any marker. The absence of a marker is interpreted by the system as indicating a high level of confidence in the answer. It is important to note that high confidence does not guarantee the accuracy of the response. The system assesses the correctness of the answers only after the student submits them at the end of the assessment session.

Received: 31 September 2023; Revised: 23 November 2023; Accepted: 7 December 2023; Published: 20 December 2023

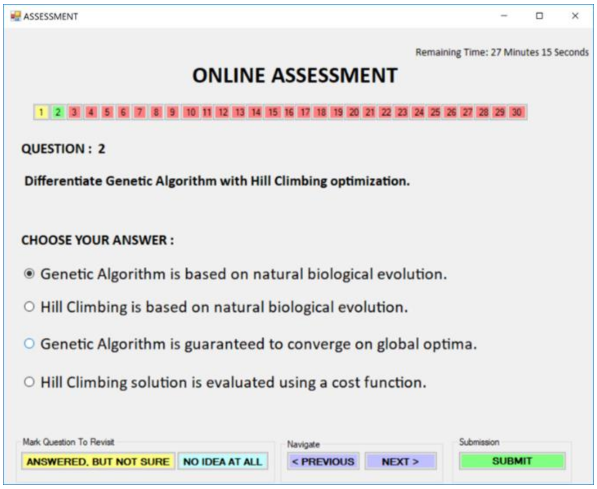

Figure 6: Interface screenshot after Student A answers Question 2

For illustrative purposes, an additional screenshot was captured during the assessment, as shown in Figure 7, depicting the moment when the student was reviewing Question 7. In this snapshot, Student A has applied two markers using a blue color code, designating that he or she has marked Question 4 and Question 7 as "NO IDEA AT ALL". This color code signifies a lack of confidence and indicates that the student perceives these questions as challenging or beyond his or her knowledge. The system interprets these markers as an indication of insufficient knowledge and a low confidence level on the assessed topic. This valuable information is recorded and will play a pivotal role in the subsequent evaluation function used to measure the student's mastery level.

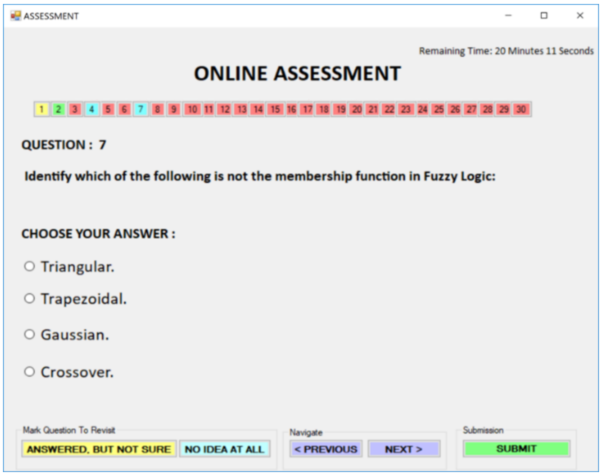

Figure 7: Interface screenshot when Student A reviewed Question 7

Next, an example of how the system analyzes the student's responses, based on the screenshots of the interfaces above for Questions 1 through Question 4, is given in Table 3.

Table 3: Detailed assessment data extracted from student responses to Questions 1 through 4

Question	Topic Assessed	Answered (NO MARKER)	Answered (NOT SURE)	Not Answered (NO MARKER)	Not Answered (NO IDEA AT ALL)	Sum of Responses	Confidence Level Calculated for Each Question
Penalty		0	0.5	0.75	1		
Question 1	Topic 1	1	1	0	2	4	0.375
Question 2	Topic 1	1	0	0	0	1	1
Question 3	Topic 1	0	0	1	1	2	0.125
Question 4	Topic 1	0	0	1	1	2	0.125

According to Table 3, when a student answers a question without applying any marker, there is no penalty imposed in determining the student's mastery level. However, answering a question while marking it as "NOT SURE" incurs a penalty of 0.5. If a student opts not to answer a question and refrains from applying any marker, a penalty of 0.75 is assigned. In the case where a student neither answers a question nor puts any marker but designates it as "No IDEA AT ALL", the largest penalty of 1 is imposed.

To understand the rationale behind these penalty values, let's consider the distinctions between 0.75 and 1. The system interprets a student not answering a question without a marker as possibly not having viewed the question yet, considering it less serious. On the other hand, if a student has seen a particular question but marks it as "NO IDEA AT ALL", it indicates a lack of knowledge on that topic, and thus, a more substantial penalty is applied. This differentiation reflects the severity of the student's response, justifying the varying penalty values.

Recognizing the potential for a student to assign different markers to the same question, i.e., changing markers for the same question multiple times, the system has taken this likelihood into account and formulated a method to determine the confidence level. For instance, referring to Table 3, Question 1 has received one marking for "ANSWERED, BUT NOT SURE" after the initial answer and two markings for "NO IDEA AT ALL". Assuming the final submission was made without any marker, the value '1' is assigned under this criterion, resulting in a cumulative total of 4. The confidence level for Question 1 is then calculated using the proposed formula:

[1 – [(Total answered * 0) + (Total answered and not sure * 0.5) + (Total not answered * 0.75) + (Total not answered and no idea at all * 1)]] / sum of responses
= [1 - [(1 * 0) + (1 * 0.5) + (0 * 0.75) + (2 * 1)]] / 4
= [1 – (0 + 0.5 + 0 + 2)] /4
= [1 – 2.5] / 4
= 0.375

Received: 31 September 2023; Revised: 23 November 2023; Accepted: 7 December 2023; Published: 20 December 2023

Given that all four questions (Question 1 to Question 4) belong to Topic 1, the confidence level for Topic 1 can be calculated by finding the average of the confidence levels for each question, as illustrated below:

$$\text{Confidence level for Topic 1} = (0.375 + 1 + 0.125 + 0.125) / 4 = 0.40625$$

Recall that the time taken by the student to answer a particular question is also an important factor in determining the mastery level. Consequently, the time taken by the student to answer each question is meticulously recorded. The recorded times for Student A's responses to Question 1 through Question 4 are detailed in Table 4. Additionally, Table 4 includes information on the average time taken by all students.

Table 4: Student A's response times and average durations with standard deviation and points based on all students' averages

Question	Time Recorded To Answer	Average Time Taken By All Students To Answer	Standard Deviation	Point Obtained
Question 1	0.8	1.37	0.403051	0.596949
Question 2	1	1	0	1
Question 3	1.2	1.7	0.353553	0.646447
Question 4	0.9	1.5	0.424264	0.575736

By analyzing the time spent on answering each question and the average time taken by all students for the same question, a standard deviation of the time taken by a student for each question can be determined. This value serves to gauge how far a student's time spent deviates from the mean value for the group of students. The points obtained concerning the time spent are calculated as 1 minus the standard deviation value. Subsequently, the total points for the time factor are determined as follows:

$$\text{Total Point (Average Time To Answer)} = (0.596949 + 1 + 0.646447 + 0.575736) / 4 = 0.704783$$

Besides the above two criteria, the accuracy of answers plays an important role in assessing the student's mastery level. The selected answers by Student A are documented and presented in Table 5.

Table 5: Student A's responses – Correctness and weightage of answers to questions during assessment for pre-processing

Question	Correctness of Answer	Weightage of Answer
Question 1	Right	1
Question 2	Right	1
Question 3	Wrong	0.75
Question 4	Right	1

Student A has correctly answered 3 out of 4 questions. As Questions 1 to 4 belong to the same topic, the average correctness value for Topic 1 can be determined. Rather than a straightforward calculation of 3 out of 4 marks (as Question 3 does not contribute to any marks), this study takes a nuanced approach to the calculation. Acknowledging that some listed answers are not entirely wrong and can be partially accepted, the marks are calculated by finding the average weightage for each answer. Thus, based on Table 5, instead of assuming a wrong answer is equivalent to 0 marks and a correct answer is equivalent to 1 mark, the total marks obtained are suggested to be calculated by finding the average weightage for each answer. Consequently, the total marks obtained for Student A are as follows:

$$
\begin{aligned}
\text{Correctness of Answers} &= (1 + 1 + 0.75 + 1) /4 \\
&= 3.5 / 4 \\
&= 0.875
\end{aligned}
$$

For each student, the total time spent on independent study for each topic is meticulously recorded, a crucial factor in measuring the student's mastery level. As previously mentioned, the belief is that a longer duration spent on independent study correlates with a deeper understanding, contributing to a higher degree of mastery of the underlying knowledge. In the proposed module for evaluating mastery levels, the time spent studying is assessed against the suggested Student Learning Time (SLT). Taking Student A as an example, assuming a total study time of 175, and an SLT of 180, the accepted learning time is calculated below:

$$
\begin{aligned}
\text{Accepted Learning Time} &= (175 / 180) \\
&= 0.972
\end{aligned}
$$

To gauge the mastery level of a student, exemplified here by Student A, all the aforementioned values serve as inputs to an evaluation function employing the formula below. As previously outlined, the degree of mastery is calculated with the time of independent study accounting for 20%, the confidence level during assessment at 10%, the correctness of answers at 50%, and the average time taken to answer questions at 20%.

Degree of Mastery (Topic) = Time of Independent Study + Confidence Level During Assessment + Correctness of Answers + Average Time to Answer

$$
\begin{aligned}
&= (0.972 * 20) + (0.40625 * 10) + (0.875 * 50) + (0.704783 * 20) \\
&= 81.35
\end{aligned}
$$

The final value obtained through the evaluation function using all the input values for Student A is 81.35 out of 100 marks. This high value indicates a commendable degree of mastery, signifying that Student A possesses a strong understanding of the underlying knowledge of a particular topic. This information on the student's degree of mastery can prove invaluable for the ITS to act as a personalized tutor. For instance, in the case of a student with a notably low degree of mastery in a specific topic, the

Received: 31 September 2023; Revised: 23 November 2023; Accepted: 7 December 2023; Published: 20 December 2023

ITS can recommend an extended learning time for that particular area. Additionally, ITS can suggest a list of topics that demand more attention from the student due to weaknesses identified in those areas.

CONCLUSION AND FUTURE WORK

In conclusion, the utilization of data pre-processing in this study empowered the proposed ITS to interpret students' responses and behaviors, generating richer and more insightful information. This information, proven to be highly beneficial, served as a set of inputs for an evaluation function, allowing the measurement of the student's degree of mastery. The ITS stands to gain significantly from this mastery level information as it enables the adaptation of tutoring styles, essentially transforming into a personalized tutor. Given the impracticality of providing a human tutor for each student in educational institutions, the ITS emerges as a valuable substitute, offering tailored assistance aligned with individual learning speeds and requirements.

Future work aims to define a scoring scale that can be seamlessly incorporated into the ITS, enhancing the accuracy of measuring mastery degree. Additionally, there is a prospect for developing a prediction module to predict students' performance based on a set of assessment questions. This predictive capability allows the ITS to adapt personalized tutoring based on significant deviations between actual results and predictions, ultimately contributing to improved student performance.

ACKNOWLEDGEMENTS

The authors would like to thank Universiti Teknologi MARA for the research grant and financial support that facilitated the successful execution of this research project.

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