A-Learning: A Computerized Adaptive Learning Expert System

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Abstract: Computer Adaptive Testing (CAT) methods have been widely used by test centres to assess examinees quickly. These methods change question difficulty in response to the performance of the examinee. This work presents a modified framework, which we call Computer Adaptive Learning (CAL). CAL uses the CAT principles to improve exam-training efficiency rather than assessment efficiency. We applied the proposed method to a learning platform and conducted a comparative experiment using 50 participants to investigate the effectiveness of CAL. We evaluated the system in terms of knowledge gain, learning efficiency, and engagement by comparing it to another adaptive method in which the game mechanics and UI adapt to the user's emotional state. Results confirm that the proposed CAL algorithm exposes the learner to questions more efficiently and improves the learning gain when compared to traditional systems in which difficulty increases sequentially. Engagement, however, did not differ across systems.

1 INTRODUCTION

Nowadays, there have been rising concerns over the decline in the number of people pursuing pedagogical degrees, shifting to careers in computer science and technology. Meanwhile, the number of enrollments in schools, especially in developing countries, has been seeing a pronounced increase. This has been making it increasingly difficult for teachers to provide individualised focus on the students' different learning needs and styles. In their book *Poor Economics* (Banerjee and Duflo, 2011), economists Abhijit Banerjee and Esther Duflo report the benefits of using computer-assisted learning programs. These programs allowed the students to learn at their own pace and helped them achieve higher scores on their tests (Banerjee et al., 2007). Today, AI has significantly enhanced these programs by fully customising the learning content. AI-powered intelligent tutoring systems (Giannandrea and Sansoni, 2013) are now able to assess the student's initial level in terms of both skill (Eggen, 2012) and knowledge (Doignon and Falmagne, 2012), make use of data gathered about the student as well as data collected from a multitude of other students, and adapt the instructional content with the purpose of optimizing the learning process. These platforms have gained widespread attention especially during the COVID-19 crisis situation.

A variety of other adaptivity techniques have previously been used in e-learning platforms and serious games to aid the learning process. A growing body of research in the field of Affective Computing (AC) focused on reducing the learner's cognitive burden by adapting features in an e-learning system to the emotional state of the learner (Solovey et al., 2011; Funk et al., 2015; ElKomy et al., 2017). A study by (Salah et al., 2018) in which the game mechanics and UI adapted to the learner's affective state showed a significant improvement in the learning gain and engagement level of students.

Meanwhile, systems that adapt the instructional content for the learner have been criticized for not enabling the student with the skills needed for long-term independent learning. Nevertheless, during critical times before an exam item-based exam training systems can help students identify practice questions that most suit their level of mastery of a subject and that quickly address gaps in their knowledge and understanding of a topic. This, in turn, saves them a lot of valuable time. One research study (Linssen, 2011) proposed an adaptive difficulty technique in the context of a serious game, however in such games the adaptivity feature would usually be confined to the scenario and mechanics of the game which prevents ICT-agnostic educators from building adaptive programs with their own educational content. Therefore, in this research study our aim was to incorporate item-based adaptive difficulty in a generic serious game

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which allowed ICT-agnostic educators to furnish the platform with their own question pools. The aim of the adaptivity feature is to render questions which suit and challenge the student's ability for the purpose of exam-training efficiency. Moreover, addressing the lack of empirical research of AI systems in education (Zawacki-Richter et al., 2019; Pedro et al., 2019), we wanted to investigate the effectiveness and engagement of this adaptivity feature when compared to that in which the game mechanics and UI adapted to the learner's emotional state according to the methods described in (Salah et al., 2018).

A well established methodology in the fields of Psychometrics and Education, which features an item-based adaptive difficulty mechanism is Computerized Adaptive Testing (CAT). The main goal of a CAT is to reduce the number of questions that an examinee has to answer in order to reach a reliable estimation of their ability. In effect, it has been proven that adaptivity implemented in CATs improves testing efficiency and reduces the test's length by up to 50-60% (Lord, 1980a; Freedle and Durán, 1987; Eggen, 2012).

Previous work shed some light on the potential of using the CAT models for the purpose of learning efficiency rather than assessment efficiency (Eggen, 2012; Wauters et al., 2010; Park et al., 2019; Pliakos et al., 2019; Pandarova et al., 2019). The keypoint which distinguishes the efficiency in the CAT's adaptivity is that questions are calibrated according to extra parameters other than their level of difficulty, such as how discriminating a question is between students of different ability levels (see Section 3.2.1). These parameters provide further insight into the ability level of the student and improves efficiency even further. However, there are several problems underlying the use of such methods generically and democratically in learning environments, namely that they require a large number of students to create a calibrated question pool dataset. Hence, in our work we address these problems and propose our own modified framework named Computer Adaptive Learning (CAL). The design focus of this framework is to be more suited for educators to create their own small-scale CAL programs.

The outline of the work can be listed as follows:

1. We describe our CAL framework building upon a pre-extisting CAT model [3].
2. We apply the CAL system to a platform with an editor which the educator can use to install and calibrate their own question pool [4].
3. We build two versions of a serious games platform rendering questions to the user: one with the CAL adaptivity feature, and another one with a different selection algorithm that increases the difficulty sequentially, and in which the game mechanics and UI adapt to the user's emotional state [5.2].
4. Using a between subject study we compare both versions to answer the following research questions [5.3]:
   - **(RQ1)** Is there a significant difference between the two versions on the learning gain of students?
   - **(RQ2)** Would the CAL's adaptive selection method expose students to questions more efficiently than the system in which the difficulty increases sequentially?
   - **(RQ3)** Is there a significant difference between the two adaptivity methods of the two versions on the engagement level of students?
5. We provide empirical evidence that the proposed CAL system has significant influence on the learning experience [6] and discuss the results.

2 BACKGROUND

2.1 Related Work

A lot of recent research studies proposed different adaptive algorithms that keep track of the learner's real-time ability change and render questions specific to their current ability. One research study concerned with the cold start problem (Park et al., 2019) explored supplementing the Elo Rating System (ERS) with explanatory Item Response Theory (IRT) to make the system more efficient and to reduce ability estimation issues. Other studies (Pliakos et al., 2019; Pandarova et al., 2019) proposed using a hybrid approach of IRT combined with machine learning. The main investigative feature within these studies was to improve the ability estimation accuracy. However, these models rely on large question pool datasets which would be burdensome for an educator to generate.

Another study explored item selection methods traditionally developed for computer adaptive tests (CATs) and proposed an alternative selection procedure based on Kullback-Leibner information (Eggen, 2012). One of the strength points of this study is that it draws the distinction between efficiency in testing and efficiency in training, where the proposed selection algorithm is constantly monitoring the student's *growth* in ability, and selecting items that feed this growth rather than items that test their ability. Simulation studies comparing the different selection algorithms showed that the differences between the CAT's Fisher information method and the KL information method for item selection were small.

Nevertheless, this study alongside others (Wauters et al., 2010) brings our attention to the potential use of CAT models in adaptive training systems.

3 METHODS

3.1 The Problem with Large Numbers

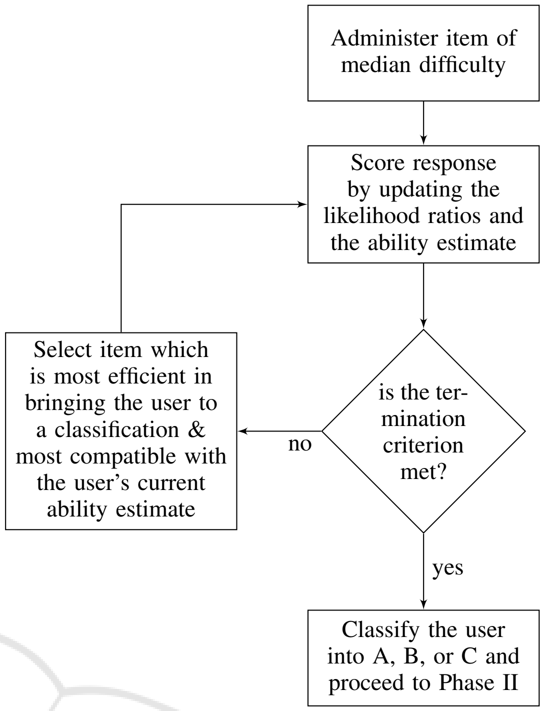
Most CAT models are built on item response theory (IRT), a powerful psychometrics paradigm invented by Fredrick Lord through the years 1968 - 1980 (Birnbaum et al., 1968; Lord, 1980b). The problem with IRT however, is that a large number of examinees (500-1000 in the 3PL-IRT model (Yoes, 1995)) are needed to take the paper-based test in the calibration phase in order to accurately estimate item parameters.

While this large number of examinees required doesn't pose a real problem for professional testing agencies, it comes as a real roadblock for small scale instructional programs that want to incorporate CATs. For these kinds of programs, as (T. Frick, 1992) puts it, *"the IRT approach to adaptive testing can be likened to the use of a cannon to kill a mosquito."*.

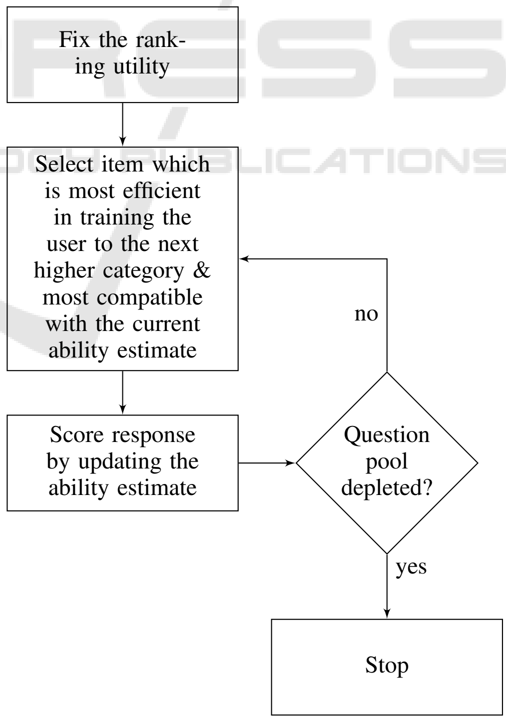
So instead, Frick proposed a discrete model, termed EXSPRT(Frick, 1992). It views CATs as an Expert system (Luk, 1991) with production rules, an inference engine and an intelligent item selection algorithm. We decided to use this model in our approach as it doesn't need as many calibration students (a minimum of 50) which makes it much less burdensome for educators using the system.

In our CAL framework, we build upon Frick's EXSPRT model and extend it to classify the user into A, B, or C grade categories, using the sequential probability ratio test (SPRT) (Spray, 1993) to serve for the termination criterion. The main goal of the selection algorithm is to select questions that are both compatible with the user's mastery level as well as challenging and time efficient.

Accordingly, our CAL is divided into two phases which render questions to the user (figure 1), Phase I is a CAT expert system, which aims to classify the user (as an examinee) as an A, B or C student, and Phase II benefits from the user's test result in Phase I, along with the items' information, pre-attained through calibration, to further elect questions for the user (as a trainee) that most challenge their current estimated ability level.



(a) Phase I: A CAT Expert System.



(b) Phase II: From CAT to CAL.

Figure 1: Flow Chart of the CAL System.

3.2 Phase I: An Extended CAT Expert System

The system is divided in this phase into 3 engines:

1. **Calibration Engine:** Empirically calibrates the question pool according to 3 item parameters: difficulty, discrimination, and utility. These parameters are derived from a set of probability rules that make up the "knowledge base" of the expert system.
2. **Inference Engine:** Uses the Bayesian method for scoring (Frick, 1989; Schmitt, 1969) and the sequential probability ratio test (SPRT) (Kingsbury and Weiss, 1983; Reckase, 1983; Wald, 1947) for termination.
3. **Intelligent Selection Engine:** Continuously selects questions that quicken classifying the user into a master or non-master (or an A, B, or C student).

3.2.1 Calibration Engine

In order to calibrate the item pool, the paper-based-test must first be given to a representative sample of examinees, whom we will name "calibration students". The procedure is as follows:

1. Design a pool of MCQs of varying difficulties, which covers a single instructional topic.
2. Give the paper-based-test to a representative sample of calibration students with varying competencies (ideally half are masters and half are non-masters).
3. Choose a mastery cut-off score (eg. 85%).
4. Divide the calibration students into masters and non-masters based on their test scores.
5. For each item in the question pool, calculate the probabilities of correct and incorrect responses as follows:

$$P(C_i) = (\#r_i + 1)/(\#r_i + \#w_i + 2) \tag{1}$$
$$P(\neg C_i) = 1 - P(C_i) \tag{2}$$
$$P(C_i \mid M) = (\#T_{im} + 1)/(\#T_{im} + \#W_{im} + 2) \tag{3}$$
$$P(\neg C_i \mid M) = 1 - P(C_i \mid M) \tag{4}$$
$$P(C_i \mid N) = (\#T_{in} + 1)/(\#T_{in} + \#W_{in} + 2) \tag{5}$$
$$P(\neg C_i \mid N) = 1 - P(C_i \mid N) \tag{6}$$

Such that, for an item i: P(C_i), P(¬ C_i), P(C_i | M), P(C_i | N) is the correct answer probability, the incorrect answer probability, the probability of a correct answer by a master and the probability of a correct answer by a non-master respectively.

This process and calculations is automated in our implementation of the Editor which will be discussed in 4.

Subsequently, 3 parameters can be calculated for each question in the question pool:

- **Discrimination:** Item discrimination is how discriminating the item is between masters and non-masters. It is calculated as follows:

$$D_i = P(C_i \mid M) - P(C_i \mid N) \tag{7}$$

  A highly discriminating item is one of the "golden items" that only the master students were capable of answering correctly and which subsequently contributed to their high scores. This plays the biggest role in test efficiency.

- **Difficulty and Item/Examinee Incompatibility Index:** Not only do we want to render items of high discrimination but we also want to render items whose difficulty is compatible with the examinee's current ability level estimate. An item's difficulty is the probability that this item is answered incorrectly P($\neg C_i$). The examinee's ability estimate $E(\theta_j)$ is calculated to be comparable to the items' difficulties. The incompatibility index I_{ij} is then the incompatibility between each item difficulty and the examinee's ability estimate.

$$E(\theta_j) = (\#r_j + 1)/(\#r_j + \#w_j + 2) \tag{8}$$
$$I_{ij} = abs\{(1 - P(C_i)) - E(\theta_j)\} \tag{9}$$

- **Utility:** Finally, an item's utility parameter is established, which is the ratio between discrimination and incompatibility index.

$$U_{ij} = D_i/(I_{ij} + 0.0000001) \tag{10}$$

Extension to A,B, or C grade categories:

In order to extend the model to choose between 3 discrete alternatives instead of 2, the students in the estimation sample would be divided into A, B, and C students using 2 cut-off scores (A cut-off and B cut-off) and the probabilities of correct and incorrect responses are incremented to accommodate A, B, and C categories.

More importantly however, there will be three discrimination parameters, and subsequently three utility parameters instead of one, each discriminating between 2 of the 3 classification alternatives ($D_i\{AB\}$), ($D_i\{BC\}$) and ($D_i\{AC\}$). And thus utilities $U_{ij}\{AB\}$, $U_{ij}\{BC\}$, and $U_{ij}\{AC\}$.

3.2.2 Inference Engine

After calibration is completed, the items are now ready for the inference and selection engines. Here is where the adaptivity function takes place. The CAT continuously infers information about the user's ability from their responses and accordingly selects questions for the user from the calibrated question pool. The selected question always aims to classify the user faster into one of the category levels and to match the user's estimated ability in real-time.

(i) The Scoring method in the CAT Expert System follows a Bayesian process, where a likelihood ratio (LR) is computed each time the user answers a question:

$$LR = \frac{P_{om}\prod_{i=1}^{n} P(C_i \mid M)^s[1-P(C_i \mid M)]^f}{P_{on}\prod_{i=1}^{n} P(C_i \mid N)^s[1-P(C_i \mid N)]^f} \tag{11}$$

For a numerical example of this Bayesian reasoning process, refer to (Frick, 1989).

(ii) The sequential probability ratio test (SPRT) then determines the termination criterion by defining the following 3 rules:

- *Rule S1:* if $LR \geq M_{th.}$, then stop and choose master.
- *Rule S2:* if $LR \leq N_{th.}$, then stop and choose non-master.
- *Rule S3:* if $N_{th.} < LR < M_{th.}$, then select another item, update the LR, and apply the three rules again.

Where, $M_{th.}$ is the mastery threshold and $N_{th.}$ is the non-mastery threshold, whose values are calculated based on error rates established a-priori (Wald, 1947).

Extension to A,B, or C grade categories:
To extend the scoring method, 3 likelihood ratios are computed instead of 1. Each compares between 2 of the 3 classification alternatives.

$$LR1 = \frac{Prob(Examinee\ level\ is\ B)}{Prob(Examinee\ level\ is\ C)}$$

$$LR2 = \frac{Prob(Examinee\ level\ is\ A)}{Prob(Examinee\ level\ is\ B)}$$

$$LR3 = \frac{Prob(Examinee\ level\ is\ A)}{Prob(Examinee\ level\ is\ C)}$$

Then, for the termination criterion we define an upper bound (UB) and a lower bound (LB) for each likelihood ratio. For a user to be classified, for example as a B student then LR1 must exceed its upper bound UB1 *and* LR2 must be lower than the lower bound LB2. This follows from Spray's extension of the SPRT (Spray, 1993).

- *Rule S1:* If $(LR1 \leq LB1)$ **and** $(LR3 \leq LB3)$, then terminate and choose C student.
- *Rule S2:* If $(LR1 \geq UB1)$ **and** $(LR2 \leq LB2)$, then terminate and choose B student.
- *Rule S3:* If $(LR2 \geq UB2)$ **and** $(LR3 \geq UB3)$, then terminate and choose A student.
- *Rule S4:* Otherwise, select another question, update the likelihood ratios and apply the 4 rules again.

Where, LB1 and UB1 are the lower and upper bounds for LR1 respectively, LB2 and UB2 for LR2 *..etc*

In short, the CAT uses the likelihood ratios to continuously compare the alternatives of the user's classification, and terminates when it has achieved enough confidence that the user is more likely to be categorized into one of the grade level categories as opposed to all others.

3.2.3 Selection Engine

Selection in Frick's EXSPRT model is based on maximum information search and select (MISS), in which the user's achievement estimate E(j) is saved and continuously re-calculated each time they make a correct or incorrect answer, as per equation 8, the item incompatibility index (Iij) is also continuously re-calculated using equation 9. The selection algorithm then picks the next selected item to be that of the greatest current utility as per equation 10, which means that;
"It will be the remaining one which is *most discriminating* between masters and non-masters, and *least incompatible* with the examinee's current ability level estimate".

In the extended model however, selection becomes a bit more challenging as there is no longer one utility parameter but 3.

The selection engine uses the information provided by the inference engine and calculates 3 distance equations:

$$dA = (UB2 - LR2) + (UB2 - LR3). \tag{12}$$

$$dB = (UB1 - LR1) + (LR2 - LB2). \tag{13}$$

$$dC = (LR1 - LB1) + (LR3 - LB3). \tag{14}$$

The minimum of the 3 distances is used to determine which classification the user is closest to, each time they make a correct or incorrect answer. Based on this current information, it selects one of the 3 utility parameters for ranking the items that quickens bringing the user closer to their most likely classification.

3.3 Phase II: From CAT to CAL

With the ongoing adaptive difficulty feature at hand, the CAT system works reasonably well on its own in training the user. However, two important questions remain; what to do after the CAT test finishes and how to benefit from its result. Accordingly, our proposed technique serves as a continuation to the CAT test in phase I. The approach was to use the test result along with the information about the items to promote questions that most efficiently challenge the user's established ability. This is achieved by looking at the item utility parameters from a different perspective.

During a CAT, after each user's response, the remaining items are sorted according to one of the 3 item utilities $U_{ij}\{AB\}$, $U_{ij}\{BC\}$, and $U_{ij}\{AC\}$, depending on the classification to which the user is currently closest to. Hence, the sorting utility is different each time they make an answer.

Alternatively, in Phase II the sorting utility is fixed based on the CAT's final classification result to be one of another set of 3 item utilities $\{U_{ij}\{AB\}, U_{ij}\{BC\}, U_{ij}\{A\}\}$ for the remainder of the session. Where $U_{ij}\{A\}$ is a 4th item utility parameter which is calculated according to the following equation:

$$U_{ij}\{A\} = P(\neg C_i \mid A)/I_{ij} \tag{15}$$

The following algorithm follows after the user has been classified by the CAT:

- If the user is a C student, fix the ranking utility to be $U_{ij}\{CB\}$.
- If the user is a B student, fix the ranking utility to be $U_{ij}\{AB\}$.
- If the user is an A student, fix the ranking utility to be $U_{ij}\{A\}$.

By intuition, we consider the following comparison: On the one hand, from an assessment perspective, ranking items according to their $U_{ij}\{AB\}$ means sorting them according to how useful they are in discriminating between A and B level categories to speed up the classification process. On the other hand, from a training perspective, ranking items according to $U_{ij}\{AB\}$ promotes the items whose likelihood of an A student responding correctly is higher than the likelihood of a B student responding correctly. And thus could be viewed as sorting the items according to how beneficial they are in efficiently training a B student to become an A student.

The same goes for $U_{ij}\{AB\}$. Moreover, if the user is identified as an A student, then we do not have a higher level to transition them to and so we target the questions that A students answer incorrectly, by fixing the ranking utility to be $U_{ij}\{A\}$.

Summing up, the CAT in phase I aims to efficiently classify the user (examinee) into an A, B, or C student, and after it has terminated, phase II starts in which we continue to update the user (trainee)'s achievement estimate every time they make an answer, as well as, the incompatibility index for each item to maintain compatibility between the next selected item's difficulty and the user's ongoing achievement -ie. real-time adaptivity doesn't stop.

Furthermore, item selection is fulfilled by using the CAT's result to fix the ranking parameter to be the item utility that would efficiently transition the user into the next higher level.

Hence, training could continue until all the questions have been rendered or until the user decides to stop and restart the test.

4 SYSTEM APPLICATION

We applied the CAL system to a platform of serious games designed to render MCQs to the user. The platform was augmented with an "Editor" to be used by educators to supply the platform with different pools of MCQs and set up their own adaptive training system, making the system generic and democratic.

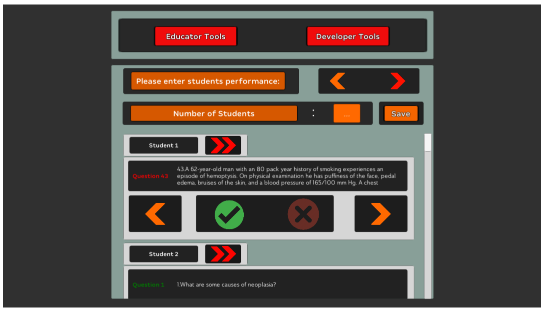
4.1 Editor

To create their own CAL system, the educator should follow steps 1 and 2 listed in 3.2.1. Then, the educator uses the editor to supply the platform with the collected information and set up a fully functioning CAL system of their own question pool.

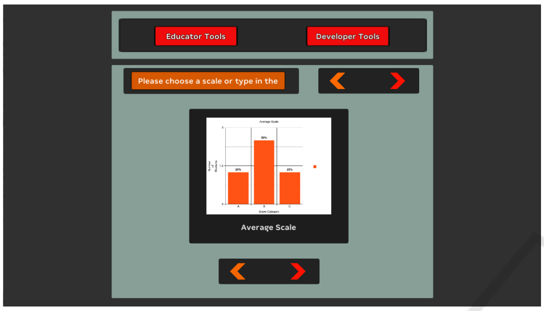
This is achieved in 3 stages: The first stage is where the educator types the MCQs and their respective answer choices, and saves them for calibration. In the second stage, the educator supplies the students' responses from the paper-based tests to each of the questions as in figure 2. This is needed to calculate the probability equations 1 through 6. First the educator states the number of students that took part in the paper-based tests, and then a list is created. For each student, the educator should supply the response, whether correct or incorrect, to each question in the registered question pool, and using arrow keys they could navigate through the questions.

A critical factor that determines how the CAL will perform is choosing the A cut-off and the B cut-off. If the test was well designed and the students were carefully selected, ideally the students would be distributed evenly among the 3 grade categories, however this is not always the case. Therefore, the third and final stage is designed to give the educator statistics about the student distribution based on a chosen cut-off score.

The following distribution scales are produced that distribute the students in the estimation sample



(a) Stage 2



(b) Stage 3

Figure 2: The Editor.

into the 3 level categories according to their result scores. By clicking one of the scales, the educator can view the A and B cut-off scores that would be needed to achieve that specific distribution. These scales are:

- The uniform scale, where the number of students is uniformly distributed among the 3 level categories.
- The average scale, where most of the students are categorized as B-level (average) students.
- The excellence scale, in which the higher the level, the fewer the students that qualify for it.
- The extremity scale, in which there are more students around the two extreme level-categories A and C than there are in the middle level-category B.
- The underdog scale, in which there more students are classified as high achievers.

The educator then saves the chosen scores to finalize the 3 calibration stages and publish their fully adaptive MCQ game.

5 TESTING AND EXPERIMENTAL DESIGN

5.1 Calibration Phase

To test the system, we asked a college professor to provide us with an MCQ question pool that tests a pathology topic. We further instructed the educator to design and divide the question pool into 3 levels, the first level consists of 13 very easy questions, the second level consists of 13 questions of medium difficulty, and the third level consists of 20 very difficult questions.

5.2 Two Versions

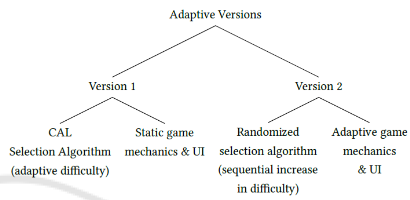


Figure 3.

Then, we created a games platform that rendered the questions to the student. We created two separate versions of the platform summarized in the above tree diagram, as part of a comparative study to evaluate different learning parameters.

The first version uses the calibrated question pool and operates the CAL system, while the game mechanics and user interface remain consistent throughout all the games. The second version applies the adaptivity feature proposed by (Salah et al., 2018) where the game mechanics and UI adapt to the user's emotional state. The emotions are reported in between games using the Self Assessment Manikin (SAM) described in (Salah et al., 2018) and the different game metrics are modified according to table 1.

Table 1: Mapping Emotion to Timer and Music.

Emotion / Metric	Timer	Music
Boredom	Decrease time limit	Play active music
Frustration	Increase time limit	Play relaxing music
Relaxed	Decrease time limit	No change

Table 2: Mapping Emotion to Theme Color and Scoring.

Emotion / Metric	Theme Color	Scoring Method
Boredom	Red	Increase penalty
Frustration	Increase time limit	Play relaxing music
Relaxed	Decrease time limit	No change

For the second version, we created another randomized selection algorithm to be able to compare it to the CAL system. It selects a total of 21 questions (less than half the question pool) from the 3 difficulty levels designed by the educator: 7 questions randomly selected from the easy difficulty level, followed by 7 questions randomly selected from the medium difficulty level, and finally 7 questions randomly selected from the high difficulty level.

In this way the randomized selection algorithm has no bias towards any one level, and operates in the conventional manner of increasing the difficulty sequentially (non-adaptive). It doesn't skip questions the way the CAL system does if the user is performing well, and it is indifferent to the user's skill level so it can render questions that are too easy or too difficult compared to the user's ability.

Finally, with all things considered, we aligned both systems to be as alike as possible wherever the adaptivity features are not concerned. The user repetitively plays the games back to back until they finish answering the 21 questions, after which, the session abruptly ends.

5.3 Design and Procedure

We invited 50 students that were currently enrolled in the Pathology course to take part in the experiment. The age range was from 20 to 22. They were randomly and evenly divided amongst the two versions of the game so that 25 played in each one, however they did not know which version they were assigned to, and they all participated in the following 3 tests:

- **Learning Gain:** This test consists of a paper-based pre-test and post-test taken before and after playing the game. The two tests were identical and consisted of the full set of 46 MCQs, which was used in the computer systems. The difference between the student's score on both tests comprised their learning gain.
- **Exposure Efficiency:** This test was designed to quantifiably compare the efficiency of the two selection algorithms. It evaluates how many questions the algorithm was able to successfully target and render out of all the questions that the student answered incorrectly in their pre-test, within the game's "21 Questions Period".

  This is achieved by first, marking the questions that the student answered incorrectly on the pre-test. Then, we log all the questions that are rendered to the user during the game in a text file. Finally, we match and mark the questions rendered to the user which they had answered incorrectly in the pre-test, and calculate the exposure efficiency:

  $$Exposure\ Efficiency = \frac{w_e}{w} \tag{16}$$

  Where,
  - w: number of questions answered incorrectly on the pre-test.
  - w_e: number of questions answered incorrectly on the pre-test and were rendered in the game.
- **Engagement Level:** This test is a standardized questionnaire (Pearce et al., 2005) used to test the engagement level of the student. The student is asked to rate agreement to different questions measuring their level of enjoyment and control throughout the experience. The mean of their ratings is finally calculated.

An independent t-test was used to analyze the results of the comparative tests with a significance threshold of p =< 0.05.

The CAL selection algorithm in *version 1* is compared to the randomized selection algorithm in *version 2* in terms of learning gain, and exposure efficiency, where the learning gain describes what information the student actually remembers. Whereas, exposure efficiency describes the selection algorithm's efficiency in exposing the user to questions they hadn't already known.

The engagement of the CAL's adaptive difficulty in *version 1* is compared against that of the emotional adaptivity feature in *version 2*.

6 RESULTS

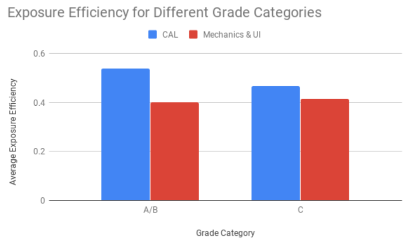
Table 3: Mean and Standard Deviation for the different tests.

	V1: CAL Adaptivity	V2: UI Adaptivity
Learning Gain	M=24.1 , SD=6.89	M=17.5 , SD=7.49
Exposure Efficiency	M=0.494 , SD=0.092	M=0.411 , SD=0.066
Engagement	M=2.17 , SD=0.451	M=2.05 , SD=0.565

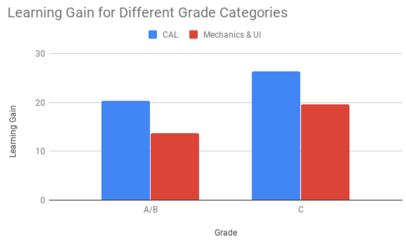
Table 4: Test Results and Significance

(RQ1) Learning Gain	CAL Group > UI Group mean diff=6.6 , p=0.002 95% CI, 2.51 - 10.69
(RQ2) Exposure Efficiency	CAL Group > UI Group mean diff=0.083 , p < .001 95% CI, 0.038 - 0.129
(RQ3) Engagement	No significant difference. mean diff=0.116 , p=0.455 95% CI, -0.195 - 0.427

The results (tables 3 & 4) showed that both the learning gain **(RQ1)** and the exposure efficiency **(RQ2)** for the group that used the CAL adaptive difficulty version of the platform were significantly higher than those for the group that was exposed to the version were the game mechanics and UI adapted to user's emotional state and where the questions' selection was random (p=0.002, p < .001 respectively). However, there was no significant difference between both



(a) Exposure efficiency for different grade categories.



(b) Learning gain for different grade categories.

Figure 4: Independent T-tests for different Grade Categories.

versions of the system on the engagement level of the students **(RQ3)**.

Furthermore, we divided the students from each of the sample groups to those who scored higher than the B cut-off on the pre-test and those who scored lower. We ran separate t-tests for these faceted grade categories.

Results from the A/B students showed that exposure efficiency resulting from the group that used the CAL version was significantly higher than that of the other group that used the Emotional adaptivity version ($p = 0.001$) with a mean difference of 0.152.

On the other hand, results from the C students showed that exposure efficiency resulting from the group that used the CAL version was not significantly higher than that of the other group that used the Emotional adaptivity version($p = 0.069$) with a mean difference of 0.044.

7 DISCUSSION

Our results showed that the proposed CAL system was successful in improving the learning gain of the students across all grade categories, as well as efficiently training them with questions that challenged their skill level.

Furthermore, amongst C students exposure efficiency was not significantly higher for the CAL algorithm when compared to that of the randomized selection algorithm [figure 4a]. This proves the point that the CAL's efficiency is most effective with A and B students as they are the ones who benefit from skipping questions, while C students would make a lot of mistakes and would thus benefit from any manner of exposure. Nevertheless, the significant difference between the two systems' learning gain results for C students [figure 4b] proves that exposure does not equal learning which reflects the benefit of the CAL's compatibility index when dealing with C students.

On the other hand, there was no significant difference in the engagement level between the two adaptivity features.

Among the limitations, the students playing the emotionally adaptive version of the game usually reported they were feeling ”excited”. According to the system's implementation ”excitement” is a desirable learning emotion, thus no noticeable changes were made in the game. Another limitation was that the session was fairly short with few switches between game scenes, so the user did not get a chance to experience all the changes that correspond to the different emotional reports. As a result, the emotional adaptivity feature might have been latent for several participants.

According to our study, the designed adaptive algorithm effectively improves students' learning, with only 50 students needed to calibrate the question pool dataset as opposed to 500 and 1000. This makes this system much less burdensome for ICT-agnostic educators who wish to create their own adaptive learning programs. Future work would be needed to test the usability of the Editor (4.1) for different educators.

8 CONCLUSION

In this paper, we designed an item-based computer adaptive learning/training system (CAL). It trains the learner by rendering items that most efficiently transitions them into a higher mastery category and whose difficulty is compatible with the learner's ability, estimated from their ongoing performance. The designed system also enables the educator to publish their own adaptive learning program and to reuse it with different question pools. A comparative experiment was conducted on 2 adaptive versions of a learning platform, *version 1*: operated the CAL adaptive difficulty system, and *version 2*: adapted the game mechanics and UI to the user's emotions while increasing the difficulty sequentially. Results showed that **(RQ1)** *version 1* significantly improves the learning gain of students when compared to *version 2*, **(RQ2)** *version 1* exposes students to questions more efficiently than *version 2*, however **(RQ3)** engagement was found not to differ between the two systems.

REFERENCES

Banerjee, A. V., Cole, S., Duflo, E., and Linden, L. (2007). Remedying education: Evidence from two randomized experiments in india. *The Quarterly Journal of Economics*, 122(3):1235–1264.

Banerjee, A. V. and Duflo, E. (2011). *Poor economics : a radical rethinking of the way to fight global poverty*, chapter 4 - Top of the Class, pages 188–196. PublicAffairs.

Birnbaum, A., Lord, F., and Novick, M. (1968). Statistical theories of mental test scores. *Some latent trait models and their use in inferring an examinee's ability. Addison-Wesley, Reading, MA*.

Doignon, J.-P. and Falmagne, J.-C. (2012). *Knowledge spaces*. Springer Science & Business Media.

Eggen, T. J. (2012). Computerized adaptive testing item selection in computerized adaptive learning systems. *Psychometrics in Practice at RCEC*, page 11.

ElKomy, M., Abdelrahman, Y., Funk, M., Dingler, T., Schmidt, A., and Abdennadher, S. (2017). Abbas: an adaptive bio-sensors based assistive system. In *Proceedings of the 2017 CHI conference extended abstracts on human factors in computing systems*, pages 2543–2550.

Freedle, R. O. and Durán, R. P. (1987). *Cognitive and linguistic analyses of test performance*, volume 22. Ablex Pub.

Frick, T. W. (1989). Bayesian adaptation during computer-based tests and computer-guided practice exercises. *Journal of Educational Computing Research*, 5(1):89–114.

Frick, T. W. (1992). Computerized adaptive mastery tests as expert systems. *Journal of Educational Computing Research*, 8(2):187–213.

Funk, M., Dingler, T., Cooper, J., and Schmidt, A. (2015). Stop helping me-i'm bored! why assembly assistance needs to be adaptive. In *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*, pages 1269–1273.

Giannandrea, L. and Sansoni, M. (2013). A literature review on intelligent tutoring systems and on student profiling. *Learning & Teaching with Media & Technology*, 287:287–294.

Kingsbury, G. G. and Weiss, D. J. (1983). A comparison of irt-based adaptive mastery testing and a sequential mastery testing procedure. In *New horizons in testing*, pages 257–283. Elsevier.

Linssen, J. (2011). Adaptive learning in an educational game–adapting game complexity to gameplay increases efficiency of learning. Master's thesis.

Lord, F. (1980a). Application of item response theory to practical testing problems. first. *Hilsdale, New Jersey, EUA: Lawrence Erlbaum Associates*.

Lord, F. M. (1980b). *Applications of item response theory to practical testing problems*. Routledge.

Luk, H. (1991). An empirical comparison of an expert systems approach and an irt approach to computer-based adaptive mastery testing.

Pandarova, I., Schmidt, T., Hartig, J., Boubekki, A., Jones, R. D., and Brefeld, U. (2019). Predicting the difficulty of exercise items for dynamic difficulty adaptation in adaptive language tutoring. *International Journal of Artificial Intelligence in Education*, 29(3):342–367.

Park, J. Y., Joo, S.-H., Cornillie, F., van der Maas, H. L., and Van den Noortgate, W. (2019). An explanatory item response theory method for alleviating the cold-start problem in adaptive learning environments. *Behavior research methods*, 51(2):895–909.

Pearce, J. M., Ainley, M., and Howard, S. (2005). The ebb and flow of online learning. *Computers in human behavior*, 21(5):745–771.

Pedro, F., Subosa, M., Rivas, A., and Valverde, P. (2019). Artificial intelligence in education: Challenges and opportunities for sustainable development.

Pliakos, K., Joo, S.-H., Park, J. Y., Cornillie, F., Vens, C., and Van den Noortgate, W. (2019). Integrating machine learning into item response theory for addressing the cold start problem in adaptive learning systems. *Computers & Education*, 137:91–103.

Reckase, M. D. (1983). A procedure for decision making using tailored testing. In *New horizons in testing*, pages 237–255. Elsevier.

Salah, J., Abdelrahman, Y., Dakrouni, A., and Abdennadher, S. (2018). Judged by the cover: Investigating the effect of adaptive game interface on the learning experience. In *Proceedings of the 17th International Conference on Mobile and Ubiquitous Multimedia*, pages 215–225. ACM.

Schmitt, S. A. (1969). *Measuring uncertainty: An elementary introduction to Bayesian statistics*. Addison-Wesley.

Solovey, E. T., Lalooses, F., Chauncey, K., Weaver, D., Parasi, M., Scheutz, M., Sassaroli, A., Fantini, S., Schermerhorn, P., Girouard, A., et al. (2011). Sensing cognitive multitasking for a brain-based adaptive user interface. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 383–392.

Spray, J. A. (1993). Multiple-category classification using a sequential probability ratio test.

Wald, A. (1947). Sequential analysis, john wiley & sons. *New York, NY*.

Wauters, K., Desmet, P., and Van Den Noortgate, W. (2010). Adaptive item-based learning environments based on the item response theory: Possibilities and challenges. *Journal of Computer Assisted Learning*, 26(6):549–562.

Yoes, M. (1995). An updated comparison of micro-computer based item parameter estimation procedures used with the 3-parameter irt model. *Saint Paul, MN: Assessment Systems Corporation*.

Zawacki-Richter, O., Marín, V. I., Bond, M., and Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education*, 16(1):1–27.