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# COMPUTERIZED ADAPTIVE TEST (CAT) OPTIMIZATION USING THE EFFICIENCY BALANCED INFORMATION (EBI) METHOD

**Aji Joko Budi Pramono**
Institut Agama Islam Negeri Ternate, East Java, Indonesia
Email:ajijoko@gmail.com[1]

**Abstract:**
This study aims to optimize Efficiency Balanced Information (EBI) for selecting items in the computer-based adaptive exam model (CAT), usually used in education. This optimization is used to reduce problems that often occur in CAT based on item response theory (TRB), namely the emergence of ability bias, large Mean Absolute Error (MAE), too many test lengths, and uncontrolled Standard Error Estimation (SEE). The success of the CAT-based exam is strongly influenced by the item selection method; therefore, an appropriate item selection strategy is needed. This study proposes selecting items using the EBI method to solve this problem. The simulation results show that the grain bias is slightly around zero, and CMAE is consistent in the allowable theta area. The average number of items presented is less than 20 when $-2<\theta<2$. The average test length increases to 25 seconds $|\theta| > 2$. The items presented show the different power parameters of questions (a) at the beginning of the test more than at the end of the test; therefore, this method can be the right solution for optimizing accuracy in selecting items

**Keywords:** *Computer Based Adaptive Test, Efficiency Balanced Information, Item Response Theory*

## INTRODUCTION

The Computer Adaptive Test (CAT) is an exam model using a computer to select and present items according to the examinees' abilities (Lord, 2012). CAT is a digital logic engine based on item response theory (TRB) as its working role model (Hambleton et al., 1991). Several items whose parameters are known are entered into a question bank. These items will be selected and presented according to the difficulty level of the questions to the examinee's ability. This adaptive CAT performance pattern means that if the test taker can complete the previous item questions, the system will present more difficult item questions or vice versa (Dunkel, 1998). According to Lord, adaptive means adjusting the ability level of each examinee, in contrast to the conventional paper-based exam model. which applies a classical assessment format based on all the abilities of examinees, including the exact time between exam participants and the same number of items for all (Bunderson et al., 1988). This conventional exam model has many weaknesses, namely in reliability and a sense of fairness among test takers, and is less effective if they have different levels of ability (Oud et al., 2019)

The computer is a machine to automate exam activities in conjunction with the exam. The development of the test model from a paper model to a computer-based exam model is known as Computerized Testing or Computerized-Based Testing/CBT (Naeem, 2019). This computer-based model is the first generation to use computers for testing (Gibbons et al., 1999). In the modern era, CAT is a concept developed in the second generation of testing methods for various testing problems, including examining medical health licenses in America (Maravić Čisar et al., 2016). Several countries that have developed the CAT model include the American Society for Clinical Pathology Board of Certification Exam, the National Council License Exam (NCLEX-RN Examination), the National Registry of Emergency Medical Technicians, and the North American Pharmacist License Check (Quiñones & Humphrey, 2007; Solberg, 2015)

CAT is proven to have many advantages, including the shorter test length compared to the CBT model exam (Postigo et al., 2020). The CAT estimation ability level is more accurate because each participant gets questions based on their ability, so the measurement error will be smaller (Rezaie & Golshan, 2015). Figure 1 is an illustration of the logic of the CAT model.

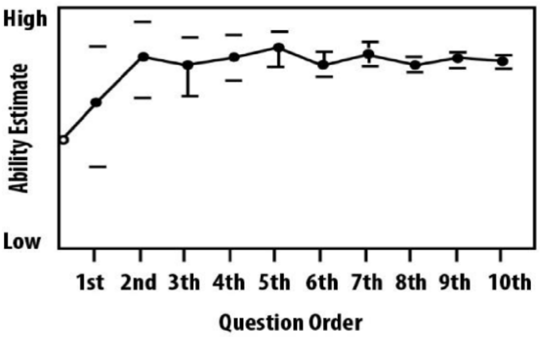


Figure 1. CAT capability estimation model

Figure 1 shows the pattern of test takers' ability levels to questions answered incorrectly at points 3, 6, and 8 and correct answers at points 2, 4, 5, and 7. The CAT compiling component requires an Algorithm, Question Bank, Item Selection Procedure questions, Ability Estimation, and termination rules (Falk & Feuerstahler, 2022). The development of other CATs required evaluating six components: item response model, item bank, initial item selection, the ability of the level estimation method, item selection procedures, and termination rules (Kingsbury & Zara, 1989). CAT needs to pay attention to the ability estimation model, especially the maximum estimation method, namely the Bayes method: Bayesian Owen Procedure Procedure, Expected Posterior (EAP) and Maximum Posterior Estimation (MAP) (Bock & Aitkin, 1981; Bock & Mislevy, 1982; Owen, 1975 )

CAT requires psychometric considerations, including the availability of calibrated question banks. The algorithm for selecting item items requires an estimation of the examinee's ability (θ) and item difficulty (Marastuti et al., 2020). The availability of quality question items in the question bank determines the accuracy in determining the ability of examinees. Three aspects contribute to the quality of the question bank, namely: the size of the question bank, the parameters of the item items, and the structure of the content (Hussain et al., 2022)

The size of the question bank is influenced by the length of the test and the number of test takers. CAT developers are always based on item response theory that individual abilities are denoted by (θ), and the items' difficulty levels denoted by b are on the same dimension (Sudaryono, 2011). The relationship between item difficulty level and examinees' estimated ability can be discussed through item response theory (TRB). At the same time, there are 3 TRB models, namely one-parameter logistics (1P), 2P, and 3P. TRB is used in the development of CAT to calculate ability estimates, probability of answering information function values and Standard Error Measurement (SEM). The equation that is often used is as follows: $(\theta)Q_i(\theta), I_i(\theta)$

$$\theta = b_i + \frac{1}{Da_i} \ln \left(0{,}5\left(1 + \sqrt{(1 + 8c_i)}\right)\right) \quad (1)$$

$$P_i(\theta) = c_i + \frac{(1-c_i)e^{Da_i(\theta-b_i)}}{1+e^{Da_i(\theta-bi)}} \cdot \quad (2)$$

$$Q_i(\theta) = 1 - P_i(\theta) \quad (3)$$

$$I_i(\theta) = \frac{[P_i']^2}{P_i Q_i} \quad \text{.......... (4)}$$

$$SEM = \frac{1}{\sqrt{I(\theta)}} \quad \text{.......... (5)}$$

Several methods are used to select the next item in the CAT, including Maximized Fisher Information, A-Stratification, Global Information, Interval Information, Likelihood Weighted Information, Gradual Maximum Information Ratio and EBI (Chrysafiadi et al., 2020; Gawliczek et al., 2021; Han, 2018a). Based on the TRB, the items with the highest information value on the ability of a particular participant will be automatically selected to be presented to the test takers. The item information function is written as in equation 6 below.

$$I_{i(\theta)} = \frac{[P_i'(\theta)]^2}{[P_i(\theta)][Q_i(\theta)]}$$

..........
(6)

I_(i(θ)) represents the item number, and P' (θ) is the first derivative of P(θ) in θ(International Test Commission, 2005; Li et al., 2021). Equation (6) shows that the information value only depends on the item parameters (for example, a, b, and c for the IRT-3P model) and ability level (θ). In the implementation of multiple choice questions, if built through the TRB 3PL parameter model, then the selection of item items uses the Maximum Information Method, which will select the ith item that maximizes the function as in Equation 7

$$I_i(\hat{\theta}_j) = \frac{2{,}89 a_i^2 (1-c_i)}{[c_i + \exp(1{,}702 a_i(\hat{\theta}_j - b_i)][1+\exp(-1{,}702 a_i(\hat{\theta}_j - b_i)]^2}$$

..........
(7)

Ii, bi , and cI, are features that describe the level of difficulty of the items, information value and apparent factors. The weakness of this method is that it needs to be more accurate in estimating the participant's ability level at the beginning of the test and less optimal in exploiting the question bank. To increase the effectiveness and accuracy of the CAT, we need a modern item selection method as a selection strategy for the adaptive test algorithm. To overcome the weaknesses of the CAT model by using the highest information value. Therefore, we adopted the EBI method to maximize the selection of items with the parameter of differential power.

This study proposes a new method for selecting new items using the EBI criteria as a technique to optimize the value of information and selection of items by considering the items' differential power. This approach will select a substantial EBI score for the test taker. This method is expected to produce a presentation of items with a stable value of differential power at the beginning of the exam and at a difficulty level that does not have extreme spikes. The measurement of this method is by looking at changes in item bias conditions, Mean absolute error (MAE), Average Test Length, Item Exposure questions, and SEE. The contributions of this research are:

1) We propose an EBI-based CAT algorithm as a solution for CAT implementation by adopting a response theory model.
2) We describe the CAT theoretical model as the basis for developing the EBI model to achieve the integration of adaptive test functionality.
3) We present the results of EBI simulation and analysis in CAT for Conditional Bias, Mean Absolute Error (MAE), Average Test Length, Exposure Items and Standard Error of Estimation (SEE).

This study uses a simulation study to describe the design of the CAT algorithm. The software used in this study is SimulCAT (Han, 2018b). The item selection method uses Maximum Fisher Information (MFI) to measure participants' initial abilities and item parameters. In contrast, EBI is used to improve CAT optimization by utilizing the different power of the items. CAT optimization research compares the three item selection procedures, namely Maximum Fisher Information Procedure (MFI), The A-Stratified Multistage Computer Adaptive Testing (CAT), and The Refined Stratification Procedure (USTR) using the random selection method. This study implements USTR to reduce the error variance for STR under various conditions. USTR improves the use of item items while achieving comparable accuracy in ability estimation (Deng et al., 2010).

Tuckman explained that the CAT test is prepared by a team of experts or professional organizers (Tisocco & Liporace, 2021). This CAT has been applied as an excellent test for a relatively long time and can be applied to several schools with a large area. CAT can be combined with the Learning management system (LMS) as an integrated system to support several teacher and student activities during the learning process (Popova, 2019). Teachers use LMS to develop web-based learning processes, build communication with students, and monitor and assess student progress, while students use LMS for learning, communication, and collaboration. The adaptive system is very relevant to use in completing the evaluation model in the LMS model; the effectiveness and efficiency of this model are outstanding. One of the well-known LMS systems is Moodle which was developed initially as a series of modular object-oriented dynamic development environments based on social constructivism theory (LAN et al., 2017). Basic Moodle consists of site management, user management, curriculum management, work modules, forum modules, chat modules, resource modules, and test modules. Moodle's interface is straightforward and user-friendly to meet teaching needs with perfect compatibility. Moodle supports international resource standards such as IMS and SCORM and has good security performance. One of the modules in Moodle is CAT. CAT needs to control the presentation of the items to avoid repeating the items so that they can increase efficiency. The question bank in CAT contains items with a calibrated difficulty level, presenting the exam process according to discriminant values (LAN et al., 2017).

## RESEARCH METHODS

An essential component in developing CAT is a well-structured algorithm. Figure 2 is an algorithm model proposed in the development of CAT by selecting items using the EBI method.

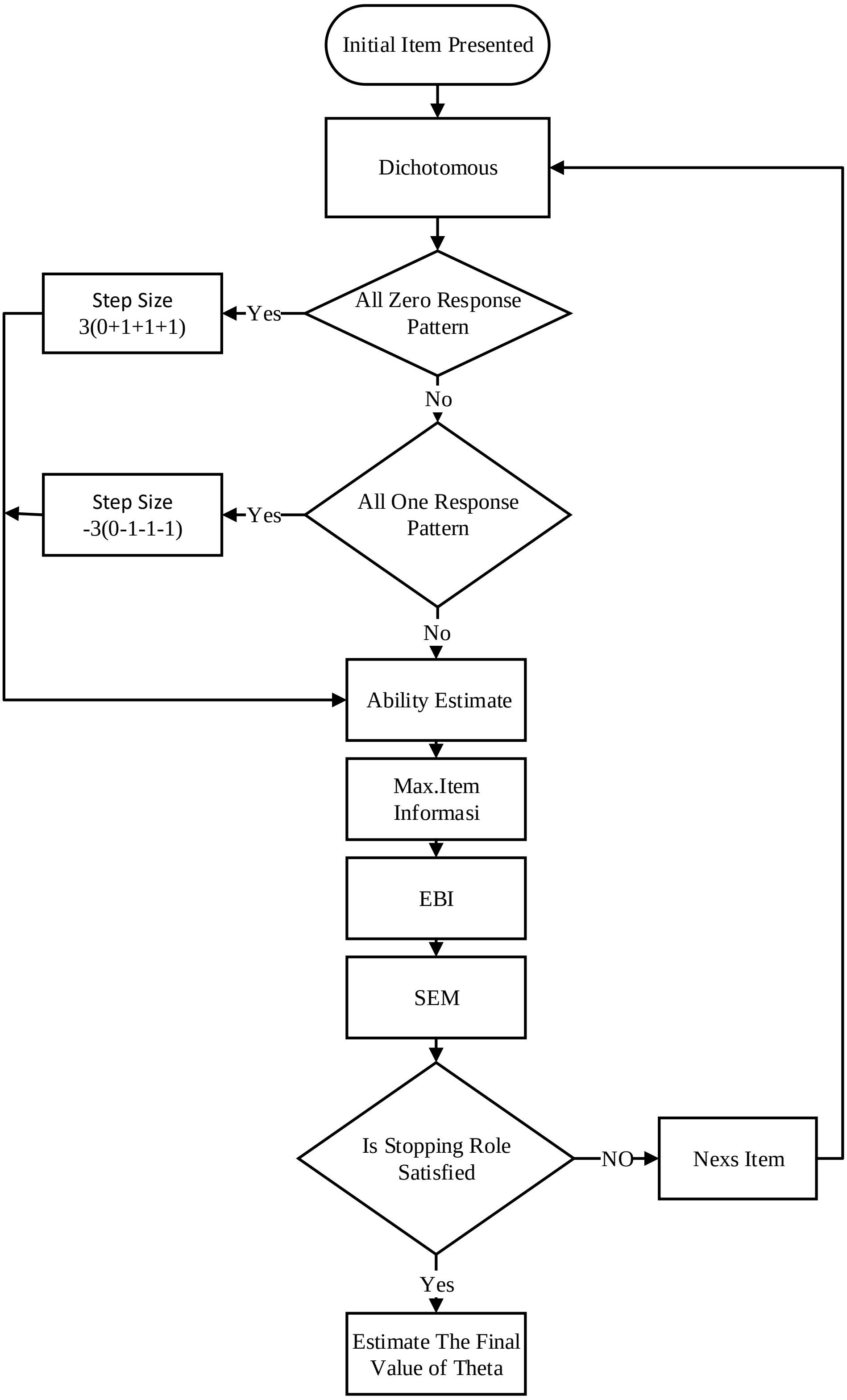


Figure 2. The proposed CAT algorithm

The first process runs the CAT algorithm, which estimates the test takers' initial abilities; if there is no information about the test takers' initial abilities, they are given items with a moderate level of ability. After getting the student's response, the system will assess the correct or incorrect answer to decide whether the SEM criterion score is met, whether the test is stopped and vice versa. After getting the items, they will be returned to the test takers. The following process calculates the estimated initial ability using the Maximum Likelihood Estimation (MLE) model. The primary function of the MLE is to find the value of θ, which maximizes the probability function L(θ), which in practice is done using the Newton-Raphson procedure. The weakness of applying the MLE method is the inability of the likelihood function to find the maximum solution when the test taker answers all the items correctly or incorrectly. So need the help of the Step-Size method. After the estimated ability of the participants is calculated, the computer will select the next item. The method used to select the following item is the EBI method.

Using EBI in this CAT algorithm, we propose to select items with different power values as a reference for presenting the items; if the differential power is low, then they will be presented at the initial test, and the level of difficulty will be selected at the end of the test. If a low difficulty level appears at the start of the trial, the test length will not be maximized. For this purpose, it is necessary to know the components of EBI, one of the essential components in EBI is Expected Item Efficiency (EIE) to realize potential information between theta values. If an item I produces an MFI value, the expected efficiency after item j is calculated by equation 7 as follows :

$$\theta_i^*[\hat{\theta}_j]$$

$$EIE = \frac{I_i[\hat{\theta}_j]}{I_i[\theta_i']}$$

........................................................................................................................................................

(7)

The efficiency of the items from equation 3 has the estimated theta interval value which is defined as the SEE which is determined at intervals of ± 2 e or 2 SEE of the estimation ability after the second item is conditioned to be identical to the item selection approach. The information is maximized θ ̂_j ± 2ε and will follow the equation 8 as follows.

$$\int_{\theta=\hat{\theta}_L}^{\hat{\theta}_R} I_i[\theta]\, d\theta \qquad (8)$$

Then the Efficiency equation of the problem becomes.

$$IE_i[\hat{\theta}_j] = \int_{\hat{\theta}_j-2\varepsilon_j}^{\hat{\theta}_j+2\varepsilon_j} \frac{I_i[\theta]}{I_i[\theta_i^*]}\, d\theta \qquad (9)$$

To improve the item selection method, it is necessary to pay attention to the test's information about the estimated ability during the presentation selection procedure. The item information is also evaluated within the range, which is identical to the interval information criterion proposed by Veerkamp namely θ ̂_j+2_εj, by combining the item efficiency domain and the test information domain , by the equation

$$EBI_i[\hat{\theta}_j] = \int_{\hat{\theta}_j-2\varepsilon_j}^{\hat{\theta}_j+2\varepsilon_j} \frac{I_i[\theta]}{I_i[\theta_i^*]}\, d\theta + \int_{\hat{\theta}_j-2\varepsilon_j}^{\hat{\theta}_j+2\varepsilon_j} I_i[\theta] d\theta \qquad (10)$$

Item efficiency and item information are evaluated in equal-width intervals, but it is important to understand that the span width acts like the weight of the differential between two elements (item efficiency vs. test information) in the equation. Furthermore, if equation 10 is derived, it will produce the EBI method with equation 11 as follows: θ ̂_j+2_εj

$$EBI_i[\hat{\theta}_j] = \left(\frac{1}{I_i[\theta_i^*]}\right) \int_{\hat{\theta}_j-2\varepsilon_j}^{\hat{\theta}_j+2\varepsilon_j} I_i[\theta] d\theta \qquad (11)$$

Where the equations like bi when using the 1PL or 2PL model are the same. But when using the 3PL model and if c iθ_i^(* ) = 0, the estimated ability θi can be calculated using Birnbaum's solution as in equation 12.

$$\theta_i^* = b_i + \frac{1}{Da_i} ln\left(\frac{1+\sqrt{1+8c_i}}{2}\right) \qquad (12)$$

Level With this procedure, the estimated ability level of the examinee is adjusted to the difficulty of the items and is set at ± 2e or 2 Estimated Standard Error (SEE). With this criterion, items with lower item power (a) can be selected at the beginning of the test. In contrast, those with higher items will be selected later.

This research used SimulCAT Software. to estimate the maximum likelihood (MLE) score. We used SimulCAT to use the data and generate new values. Table 1 illustrates the scores for conducting this experiment.

Table 1. SimulCAT Dataset

| Simulates | Method |
|---|---|
| Item pool | 300 items based on 2-parameter logistics |
| Examines Characteristics | 200 |
| Item Characteristics | Par. (A) min. 0.5; max 1.5<br>Par. (b) min -3; max 3<br>Par. (c) min 0; max 0 |
| Item selection criterion | EBI |
| Score estimation | LHE<br>Initial score randomly was chosen between -0.5 and 0.5<br>Limit the estimated jump by 1 for the first five items |
| Variable-length | SEE; 0.3 Items maximum of 50 |
| Output | Save item use |

The data table above contains the parameters of the item items, including the level of difficulty (b), the difference in power (a), and the guess factor (c), the level of different power of the items, while the computational process of the CAT algorithm is as shown in Figure 3.

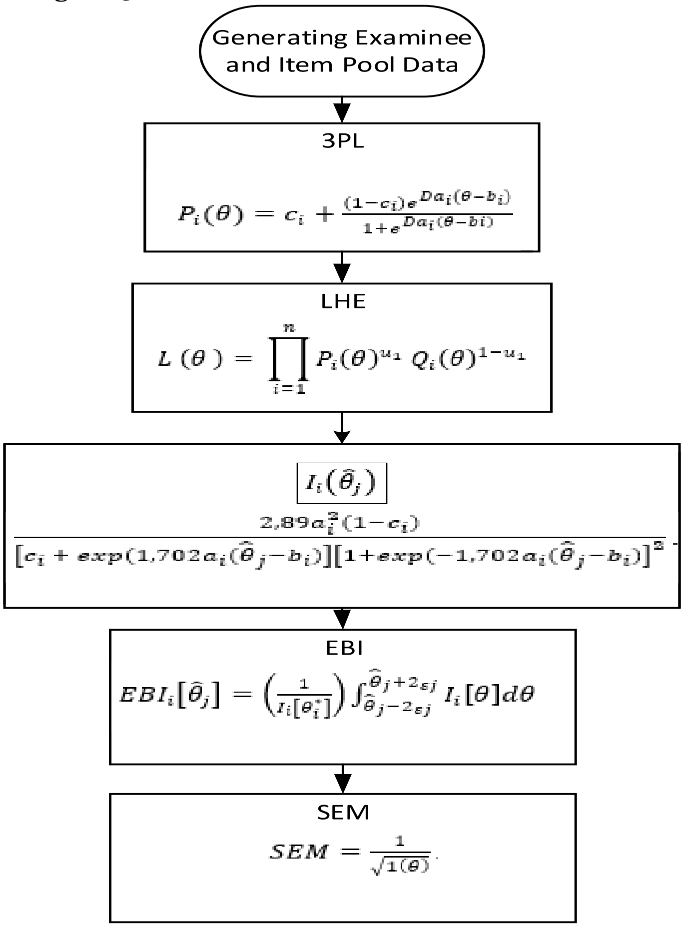


Figure 3. Computational Process CAT Simulation

This study uses MLE to estimate the ability of examinees and participant response patterns with the Step Size Method. The final process in this algorithm uses the EBI function criterion method with a termination value of 0.3. The SEM value with an achievement of 0.30 will be equivalent to a reliability of 0.91 in the classical model test.

**RESULTS AND DISCUSSION**

In this section, we present a complete graphical presentation of the simulation results. The first result is the value bias in the ability estimation domain. Systematic measurement error or so-called statistical bias theta calculates true theta according to equation 13 as follows.

$$Bias = \frac{\sum_{i=1}^{I}(\hat{\theta}_i - \theta_i)}{I} \quad (13)$$

The above formula defines the number of participants, is the initial theta θ ̂_i is the approximate result of thetaθ_i. If calculated in terms of theta capabilities from -3 to 3, the results are in graphical form in Figure 4 as follows

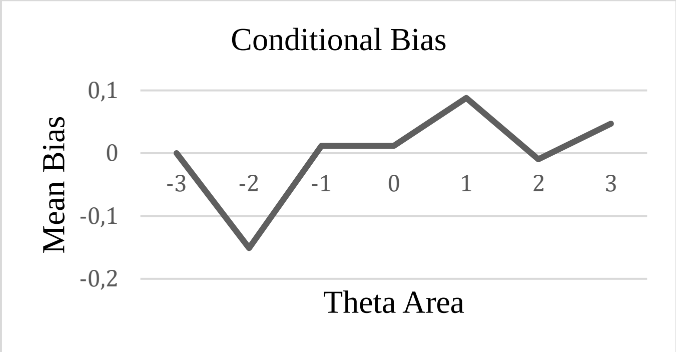


Figure 4. Average bias

Mean Absolute Error (MAE) is a useful statistic that summarizes the overall measurement error (both systematic and unsystematic inaccuracy MAE which can be calculated by equation 14 as follows.

$$MAE = \frac{\sum_{i=1}^{I}|\hat{\theta}_i - \theta_i|}{I} \quad (14)$$

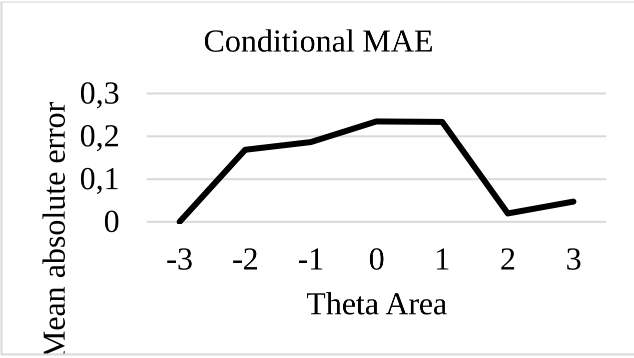


Figure 5. Conditional MAE

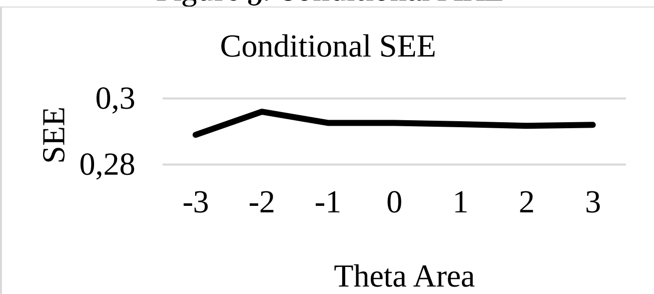


Figure 6. Conditional SEE

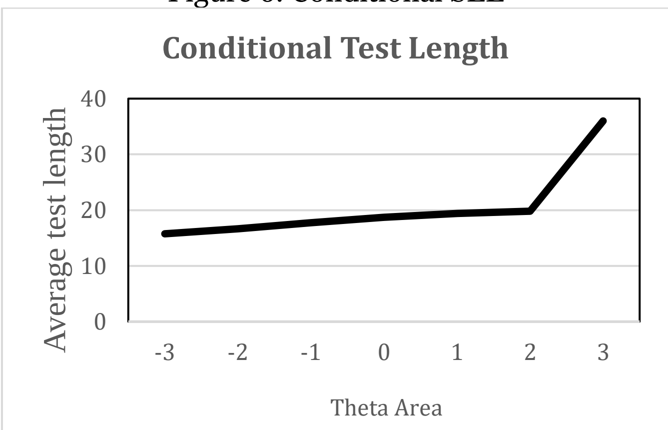

Figure 7. Average test length

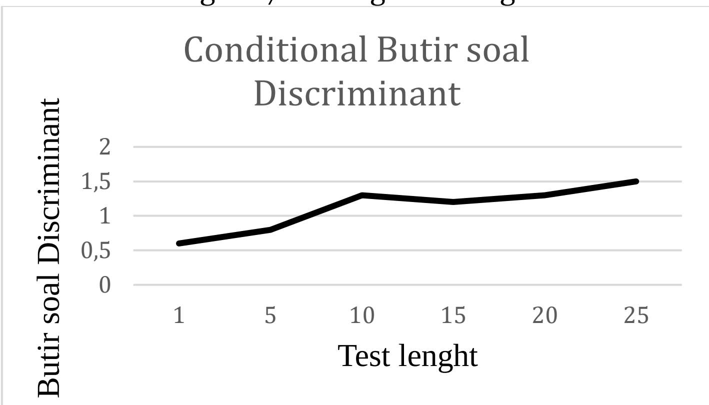


Figure 8. Item exposure based on b-value

Figure 5 illustrates the MAE condition with a minimum value (below 0.3). This figure shows that the MAE values appear to be consistent across the Theta area. The bias condition in Figure 5 shows that the systematic error is very little or even almost zero. The average number of items managed (when meeting the SEE criteria for 0.3) in Figure 6 is less than 20 seconds. Current test length | θ | > 2, on average, an increase of about 25. The maximum test length is 25 of 300 items with a maximum limit of 50 pieces. This shows that the grain bias presented is very small, namely a maximum of 50% of the maximum allowable portion. -2 <θ <2

Based on the experiment, we can prove the relationship between item exposure and different power parameter questions (a), that the CAT model can produce lower a scores on the initial test, and the final test can increase according to the level of difficulty of the items presented. This condition is a logical consequence of EBI if the different power values (a) are low, the items will be presented at the beginning. The more items that are selected at the end, the more difficult the level of difficulty of the items. The research results show that the EBI application can produce an accurate ability to estimate and guarantee the use of the question bank.

## CONCLUSION

CAT implementation requires a method of selecting items as a selection strategy in the adaptive test algorithm. Thus, we propose an EBI method for estimating the ability level of participants in the integral domain. This EBI method involves initial estimation, information value, and all items with parameters to set the item difference power of common questions at the initial level and increases at the end of the exam process; this has an impact on the length of the test because the difference in different power of questions is low, identical to the level item difficulty. The EBI method has resulted in a shorter number of presented items, around 20 to 25.

This simulation shows that EBI can be a prospective method of selecting items in developing modern CAT. Utilizing the proposed EBI can produce 1 item from several questions in integral domain intervals based on the examinees' ability. This method obtains more efficient scores, improves adaptive functionality testing, and improves consistency between CAT components and EBI backtracking. As further research, new studies are needed with many question banks aimed at improving the item search process.

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