Visual Attention based Evaluation for Multiple-choice Tests in E-learning Applications

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Abstract—**Multiple-choice (MC) question is an important form of test to assess the students' academic achievement, especially in the e-learning applications. However, the classical evaluation metrics on MC questions (such as the correctness ratio) only consider the correctness of the final selection but ignore the solving progress of the testee. In the existing literature, the eye-tracking based visual attention was studied to infer the testee's cognitive progress towards a specific MC question. However, there is little work on the visual attention based evaluation of one complete MC test. In this paper, we measure the eye movement data of a group of students in an online test, which consists of forty more MC questions. We divide the screen area into five AOIs (area of interests), including one for the question and four for the candidate options. The fixation duration as well as the gaze sequence on these AOIs are recorded and studied. In the case study on the most difficult question, we observe the great differences among the eye movement of the testees in different academic levels. A new metric, namely Visual-Attention-assisted Score (VAS), is proposed to assess the student's performance with the bias of his fixations on the correct options. Experiment results show that, this metric can reflect the difference of gaze movement of testees, and thus it is helpful for the teachers to infer the real level of the students' academic achievement.**

I. Introduction

With the rapid development of information technology and Internet, online test has become a major form of assessment method in e-learning applications, in which the multiple-choice (MC) questions are preferred. By comparing the testee's answer with the correct answer, the system can provide the academic assessment on the specified topics. However, it is hard to treat such kind of evaluation result as the full description of the students' achievement on the mentioned topic. Since it only provides the final results and is lack of details of the solving processing, the obtained score can not precisely represent the real level of the students' academic achievement. For example, whether the selected answer is a result with careful consideration, or just a random choice. Although this problem can be partial solved by designing MC questions with better discrimination, there is still a need to infer and understand the testee's real performance.

The eye tracking technology was originally used in the study of basic cognitive processes and reading or other information processing by psychologists. The "eye-mind" hypothesis was proposed by Just and Carpenter [1], which suggests that eye movements provide a dynamic trace of where attention is being directed. That is, the current "visual attention" position somehow indicates that the tester is interested in the information. Although there are studies showing inconsistent results, it is widely agreed that during a complex information processing task such as reading, eye movements and attention are linked [2]. Supported by eye-tracking technologies and neurocognitive studies, there have been more applications in information processing such as reading comprehension [3] and visual searching [4]. Recently, some researchers have adopted this technique to explore learning processes in complex learning contexts such as multimedia learning, and science problem solving strategies [5]–[9].

In mathematics problem solving, Hegarty et al. [7] found that key information such as numbers and variable names to solving problems were fixated longer and were critical to the construction of the solution. Tsai et al. [8] began to study the students' visual attention in solving science MC question. They find that successful problem solvers focused more on relevant factors while unsuccessful problem solvers experienced difficulties in decoding the problem. Based on Tsai's work, Nahumi [9] studied the relationships between answers and tester's performance with regard to time spent watching the available options and gaze wavering between the most plausible choices. It is notable that, all of these existing work research took one single specific MC question designed carefully as the study objective. Their focus is to find the characteristics or similarities among students during their problem solving process in answering a single MC question. However, there is little work on the visual attention based evaluation of the whole online test.

In this paper, we focus on this issue and conduct a measurement-based study. We adopt the eye tracking based method to investigate the performance of one student class (consisted of 45 students) in a serial of multiple-choice tests (total 6 tests and 41 questions) of a short-term course. We divide the screen area into five AOIs (area of interests), including one for the question and four for the candidate options. The fixation duration as well as the gaze sequence on these AOIs are recorded and studied. A new metric, namely Visual-Attention-assisted Score (VAS), is proposed to assess the student's performance with the bias of his fixations on the correct options. Experiment results show that, this metric can reflect the difference of gaze movement of testees.

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The organization of this paper is as follows. Section II describes the basic measurement methods adopted in this paper. Section III reports the preliminary results of the online test. In Section IV, we conduct a case study on the eye movement data of the most difficult question in this test. The VAS metric is then proposed in Section V as well as the re-study on the test results. Finally, Section VI concludes the whole paper.

II. Data analysis framework

A. Preliminaries

The eye-movement trajectory study can reveal the individual's internal cognitive process. The typical measurement of eye movement include the fixation durations, the focused area in screen (i.e., LookZones), and the sequence patterns of their fixated LookZones. Prior eye-tracking studies have provided an adequate amount of evidences demonstrating that people tend to have longer fixations on more important or complex information [2], [10] and pay more attention to relevant information than irrelevant information [11]. In general, when there is no existing memory on the watched content, eye fixation location can reflects attention and eye fixation duration reflects processing difficulty and amount of attention (the longer the information is fixated, the more complex it is).

In our experiment, we develop some text-reading questions in Psychology, which do no require any paper work. The testees have no related knowledge background on the taught topics. Based on the aforementioned literature, we assume that, in our context and experiments, the fixation duration and the number of gaze can indicate the cognition and processing of the corresponding area information. When one student has difficulty in the knowledge point or he is not so sure about the selection, he will spend more time on that area.

In the context of multiple-choice test, the displayed content of each question include the question title, and the four candidate options. These areas in the screen are named as Areas of Interests (AoIs). AoI is the basic unit for us to conduct the study on eye movement data. With the statistics of AoI data, it is feasible to investigate the cognitive process of testees. For exmaple, Tsai [8] focused on the eye fixation duration data, and investigate the effects of the chosen and rejected options, and the relevant and irrelevant factors; Nugra [9] designed a geometric question with two similar options to analyze the weaving behavior during the answer process.

B. Test scenario

We used the Tobii EyeX eye movement device to detect eye movement during the trial. It is a non-wearable device produced by Tobii Technology. Tobii EyeX captures eye movement data through corneal reflex. It can track the eye movement in the range of 40 $\times$ 30cm at a distance of 65cm. The sampling frequency is 60Hz, the precision is 0.5$\sim$1 degree, and the delay is 15 +/- 5ms. It can be attached to the bottom of the computer monitor by the magnetic stripe, and thus does not affect the normal activities of testees.

We develop one online multiple-choice test system. After the student login the online test system, the webpage will present the question and four answers. As shown in the Fig.1, each answer was labeled with alphabet letters in front of its description, from "A" to "D". Considering the various length of each text answer, we transfer the text answers into figures, so as to fix their display size. The question area and four answer areas naturally divide the webpage into five Areas of Interest (AoIs). We name them "Q" (the question area) and "A", "B", "C" and "D" (the four answers area). The following analysis will be based on these five AOIs.

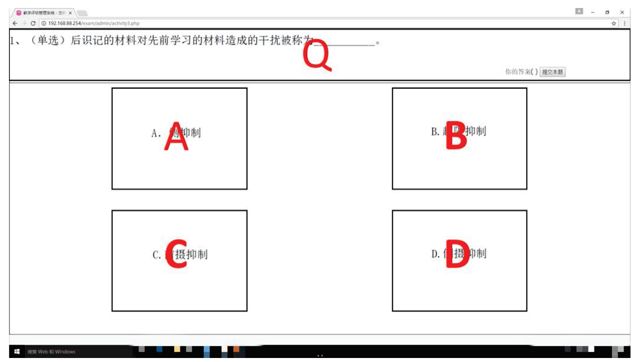

Fig. 1. The division of five AOIs in the screen

C. Process on raw eye movement data

When a student answers questions in the online test system, his selected answer is recorded by the testing system server. Meanwhile, the eye-movement data measured by the tracker (i.e.Tobii EyeX) is transmitted back to the server. The timestamps of these two data will be carefully synchronized. It is notable that, the raw data of eye movement is in the unit of every fixation point, rather than the pre-mentioned AoIs. Thus, it is necessary to conduct some data transformation processes before performing the gaze analysis.

When the Tobii EyeX tracker works, it reports the detected fixation data in a fixed frequency. Every fixation point has its corresponding time and coordinates. The obtained raw measurement data is the serial of $\{x_i, y_i, t_i\}$, where the point coordinates (x_i, y_i) represents the point in the screen (assuming that the origin point (0,0) locates in the upper left corner of the screen), t_i represents its occurred time, and i is the collected sequence index.

The fixation points (x_i, y_i) should be transferred to its corresponding AoI (denated as a_i). Along with the transformation, the duration of each fixation point can be calculated. The duration of one fixation of area is d_i, which is calculated by $d_i = t_{i+1} - t_i$. What's more, if any two consecutive fixation locates in the same AoI, these two records will be merged into one, and the resulted fixation duration is the sum of the original two. After these processes, we can obtain the AoI data in the serial of $\{a_j, t_j, d_j\}$, where a_j represents the id of the focused AoI, t_j represents the start time when the gaze moves to this AoI, d_j stands for the total fixation duration on this AoI and j is the sequence index after merging data.

It is notable that there are many fixations completed instantaneous. When the fixation duration d_j is smaller than the set length τ (typically $100 \sim 500ms$ [12]), it is considered to be a meaningless or invalid fixation on that AoI. So, we filter out the AoI which fixation duration is less than τ. Finally, we obtain the valid fixation sequence of AoI: $\{a_k, t_k, d_k\}$, $(k = 1, 2, \ldots, K)$, where K stands for the count of the finally obtained valid gaze data. The following analysis will all performed on this fixation sequence of AoI.

D. Calculation of AoI-fixation metrics

1) Fixation duration on the specific AoI: It stands for the total fixation duration of one single specific AoI. The fixation duration of the AoI a_k is denoted as D_a, which is defined by:

$$D_a = \sum_{k=0}^{K} d_k|_{a_k \equiv a} \tag{1}$$

where $a \in \{0, 1, 2, 3, 4\}$ stands for different AoIs.

2) Fixation count on the specific AoI: It stands for the total number of valid fixations locating in one AoI. The fixation count of the AoI a_k is denoted as C_a, which is defined by:

$$C_a = count(a_k)|_{a_k \equiv a} \tag{2}$$

where $a \in \{0, 1, 2, 3, 4\}$ stands for different AoIs.

3) Proportion of fixation duration and count: The real value of fixation duration and fixation count is significantly different from people to people. There is no standard for the two metrics. For the convenience of comparison, we introduce the relative metric to describe the duration and count of valid AoI-fixations.

For one AoI a, its proportion fixation duration is

$$p_a = D_a / \sum_{k=0}^{4} D_k \tag{3}$$

and the proportion fixation count is

$$q_a = C_a / \sum_{k=0}^{4} C_k \tag{4}$$

III. Overview Results of Online Test

A. Participants and procedure

We have 21 male and 24 female testees, volunteered to take part in the test. They are undergraduate students, aged from 18 to 22. All of them had normal or corrected to normal vision. We divided the 45 testees into 3 groups randomly, each group has 15 testees. One teacher from Central China Uniform University was invited to give a serial of lectures in fundamental Psychology. In the end, every testee completed 41 multiple-choice single-answer questions about psychology.

In the process of online test, the system will show the MC questions one by one to testees. The testees can click the option part just once to choose their answers. There is no time limitation for the students to answer the questions. As soon as they submit their selections, their choice will be stored in the database. And they will not have the chance to modify their selections. Online test system can record and store the time when a tester starts to answer one question and the time when he submits the selection. These data will be analyzed together with the eye movement data collected by Tobii EyeX.

B. Results of all the students

The correctness ratio of a question is a ratio of the number of students who were right to the total number of people participating in the test. The correctness ratio reflects the difficulty of the test questions, the higher the correctness ratio is, the more simple the problem is. For MC questions, there are only two states of the students' answer: right and wrong, represented by 1 and 0 respectively. Since the result depend on the final selection of the testee, we name this kind of criteria as Final Selection Scoring (FSS) in this paper.

We assume every question has 1 score, then the average score s of every students in this test can be calculated. Similarly, we calculate the average correctness ratio of each question. The corresponding results are plotted in Fig.2 and Fig.3. From the correctness ratio, we can identify the difficulty of questions and the knowledge mastery of students.

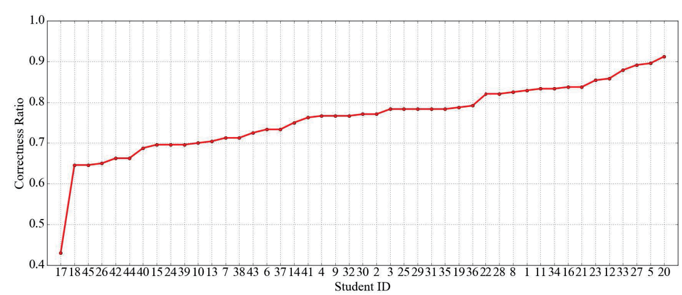

Fig. 2. Correctness ratio of the students

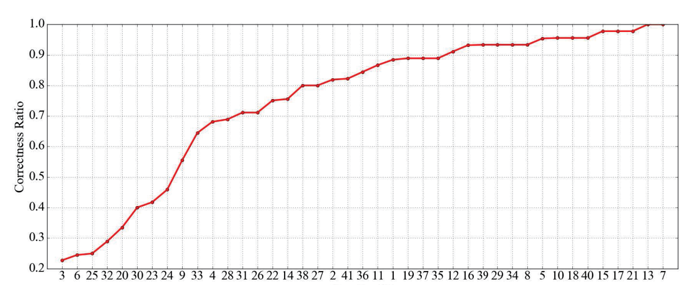

Fig. 3. Correctness ratio of the questions

In Fig.2, student No.17 has the lowest correct ratio which is far away from the other students. So we will not take him into our account in the following analysis. The correct ratio of that 44 students are ranging from 64.58% to 91.25% (with the mean of 76.91%, and the standard deviation of 0.071). As shown in the Fig.3, the correct ratio of these 41 questions are ranging from 22.70% to 100.00%. From the point view of the correct ratio, question No.3 is the most difficult question, question No.7 and No.13 are the most easy questions in this test.

C. Observation on individual students

The individual performance in answering the difficult questions is always interested by the teachers. In this subsection, we investigate the score results of the most difficult question No.3. For the convenience of analysis, we divide the testees into three groups according to the value of his correctness ratio: Group H (higher than average), Group V (average), and Group L (lower than average). The students in Group H are with the ID of $\{23, 12, 33, 27, 5, 20\}$, while those in Group L are $\{18, 45, 26, 42, 44, 40, 15, 24, 39\}$.

In Group H, 50% of the members (the ID of $\{20, 27, 12\}$) failed in question No.3. While, as to Group L, 77.78% of the members (the ID of $\{18, 26, 42, 44, 40, 24, 39\}$) failed. It is interesting that, the student with the highest score in this test (student No.20) also failed in question No.3; but the student with the lowest score (student No.45) provided correct answer for question No.3.

We are interested in the visual attention observations of these two students, whether the best student (No.20) really didn't know the answer? whether the worst student (No.45) wan by luck? This motivated us to perform detailed analysis in the next section.

IV. Visual attention analysis: A case study

The order in which the testee visit each AOIs reflects his thinking process. For example, when he reads the question content, he possibly wants to understand the question; when he reads the option areas, he aims at finding the most appropriate answer. In this way, we can infer the cognitive process through the sequence of AOIs.

One of the special phenomena of eye movement in MC question is the weaving behavior [9], in which the testee moves his gaze focus between two similar options. When the student is hesitant between two options, he will read back and forth between the two selections. So in the collected fixation sequence, there will be two successive AoIs appear repeatedly, such as "ABABAB...". Motivated by this observation, we explore the statistics of two successive AoI fixations, rather than study the whole sequence.

For a sequence $\{a_1, a_2, \cdots, a_k, a_{k+1}, \cdots, a_K\}$, we can divide the original fixation sequence into the successive AoI pair of $\{a_k, a_{k+1}\}$, such as {AB, AC, ... }. We then count the number of appearance of each pair in the fixation sequence, and further calculate the corresponding proportion over the total. The resulted statistics are provided in the following table, Table I, in which the detailed fixation sequence of four testees on the question No.3 are listed.

In order to comparing the different gaze behaviors, we list the results of two more students rather than the pre-mentioned No.20 (best) and No.45 (worst). We select the student No.33 in Group H (who provides correct answer in question No.3) and student No.44 in Group L (who provide wrong answer in question No.3) as the comparision candidates.

We focus on the Group H firstly. As shown in Table I, as for student No.20, the total account of thinking modes with the correct answer "B" is 73.1%. It is much higher than the other modes which means that he paid more attention on the right answer. The "BD" mode of thinking accounted for 42.3%, indicating that student No.20 most possibly hesitated between the "B" and "D" selections. Therefore, we infer that student No.20 has a good knowledge background on the question No.3. As for student No.33, the total account of thinking modes with the correct answer "B" is 60.6%. It is higher than the modes unrelated to "B". We can infer that he must grasp about the knowledge of question No.33 very well, which enables him to show confidence in eye movement.

Then we discuss the two cases in Group L. As for student No.44, who is also wrong in this question, the total account of thinking modes with the correct answer "B" is 33.0%. It is much lower than that unrelated to "B". We infer that he is not interested in the right answer. As for student No.45, we can find he is quite confident about the option "B", with as large as 74.4% of fixation related to "B".

Through the analysis on the 4 students' AoI sequences, we can observe the different gaze movement modes in different testees. The disadvantages of FSS scoring criteria (i.e. correct for 1 and wrong for 0) are also illustrated. For example, the student No.20 really knows a lot about the correct option, even more than the student that achieves the correct answer (i.e., No.33). These observations motivate us to develop a new scoring criterion, which takes the visual attention data into account.

V. Visual attention assisted Scoring

A. Motivation

Motivated by the observation results in the preceding section, we aim to propose a kind of scoring criterion for MC questions. The basic idea is to take the measured visual attention as the correction component to the existing FSS criteria. The new criteria should provide better discrimination for the knowledge awareness of the testees.

B. Measurement of visual attention

First of all, we need to develop a kind of quantitative metric to represent the degree of visual attention on the specific AoI. As reported by the existing literature, watching more time or

TABLE I
STATISTICS OF CONSECUTIVE FIXATION SEQUENCE OF FOUR STUDENTS ON QESTION NO.3

Stu. ID	Group	Average score	Score in Ques.3	Related to B(%)	Unrelated to B(%)	A-B (%)	B-C (%)	B-D (%)	C-D (%)	A-D (%)	A-C (%)
20	H	0.92	0	73.1	26.9	30.8	0.0	42.3	7.7	3.8	15.4
33	H	0.88	1	60.6	39.4	21.2	15.2	24.2	6.1	6.1	27.3
44	L	0.64	0	33.3	66.7	5.6	11.1	16.7	33.3	11.1	22.2
45	L	0.62	1	74.4	25.6	4.7	14.0	55.8	7.0	4.7	14.0

frequency means more visual attention. Thus, we propose a simple linear formula to combine the measurement of fixation duration and fixation count together. We define the attention (P_a) of one AoI area (a) in the following formula:

$$P_a = \theta_t \cdot p_a + (1 - \theta_t) \cdot q_a \quad (5)$$

where θ_t is a adjustable parameter, $0 \leq \theta_t \leq 1$. When θ_t is greater than 0.5, that means the gazing duration has more weight in the calculation of visual attention, otherwise, less weight in calculation.

C. Differentiated scoring based on rank of visual attention

According to the relationship between the AoI of correct answer (denoted as a^*) and the AoI with top one visual attention (denoted as a^1), we can infer the real knowledge awareness of the testee. For example, when $a^* = a^1$, the testee completely grasp about the related knowledge. When $a^* \neq a^1$ and the testee makes wrong choice, we can infer that he really doesn't understand the point and needs improvement. When $a^* \neq a^1$ but the testee makes correct choice, the situation is a bit complex. One possible case is that, the testee does the MC question via some skill (such as the exclusion method), and he does not need to read the correct option. Another possible case is, the testee is hesitate in several options but he choose the correct answer with his luck.

Following this kind of reasoning, we could classify the student's cognition into 8 levels by the combination of the correctness of his final answer and his visual attention represented by the top one AoI. We calculate the visual attention of each option according to (5), and then find the AoI with the top one visual attention. Based on the relationship of attention ranking K and the selection score s, we propose a kind of Visual-Attention-assisted Scoring criterion (VAS), which is described in Table II.

TABLE II
VISUAL-ATTENTION-ASSISTED SCORING CRITERION

No.	FSS score s	Attention rank K	Awareness of knowledge	VAS score
1	1	1	Fully	α_1
2	1	2	Partial	α_2
3	1	3	A little	α_3
4	1	4	A little	α_4
5	0	1	Partial	β_1
6	0	2	Partial	β_2
7	0	3	Not at all	β_3
8	0	4	Not at all	β_4

Where $\alpha_1, \alpha_2, \cdots, \beta_4$ are adjustable parameters, and they are all ranging from 0 to 1. The closer of VAS to 1, the more awareness of knowledge is inffered from his visual attention. After obtaining the VAS of every testee on every question, it is easy to calculate the average score of each testee and each question.

D. Re-visit the question No.3

We adopt VAS to re-study the score result of the pre-mentioned most difficult question No.3. According to the formula 5, the degree of attention of the subjects to each option area is calculated. We adopt following parameter settings: $\theta_t = 0.5$, $\alpha_1 = 1$, $\alpha_2 = 0.8$, $\alpha_3 = \alpha_4 = 0.6$, $\beta_1 = 0.4$, $\beta_2 = 0.2$, $\beta_3 = \beta_4 = 0$. Fig. 4 shows the result of VAS and FSS of question No.3.

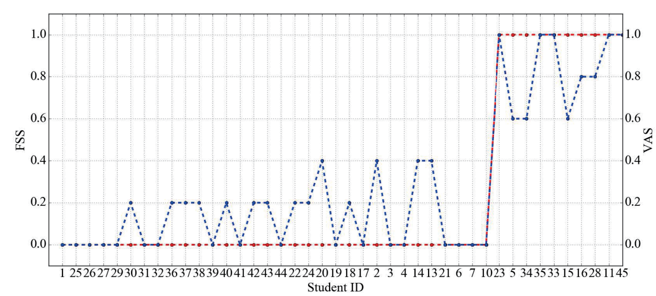

Fig. 4. Students' performance in question No.3: FSS vs. VAS

As shown in the figure, the value of VAS score is not only 0 or 1 but ranged in $[0, 1]$, which provides more details about the performances of the testee. Based on this VAS result, it is easy for a teacher to identify the students who are indeed partially know about the point, and who are totally unaware of the point.

E. Re-visit the student performance in the test

Following the similar method, we can produce the average VAS of each testee. The results are plotted in Fig. 5, together with those of FSS criteria. The curve with blue points corresponds to the result of VAS, while that with red points stand for FSS.

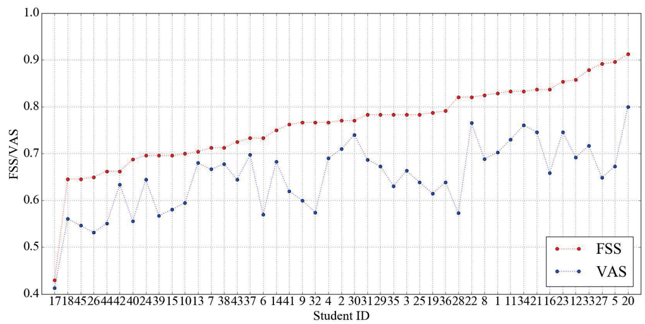

Fig. 5. Students' average performance in this test : FSS vs. VAS

We observe that the two curves show a certain correlation, which imply that VAS does not change the basic trend of FSS. Due to the negative correction of VAS on the absolute score 1, the average VAS curve is lower than that of FSS. However, the VAS curve discover some interested results. For example, some students (such as No.28) have much less VAS than the normal, which indicates they are not as good at the knowledge as the previous criterion. On the other hand, some students (such as No.13) have relative high VAS in the neighborhood, which means that they have great potential to get promotion.

In order to demonstrate the different view of VAS, we count the number of students in different VAS score and compare with that in final selection score in Table III.

TABLE III
THE DISTRIBUTION OF STUDENT'S SCORE

Score value	VAS		FSS	
	# stu.	proportion(%)	# stu.	proportion(%)
1	5	11.11	10	22.22
0.8	2	4.44	0	0
0.6	3	6.67	0	0
0.4	4	8.89	0	0
0.2	10	22.22	0	0
0	21	46.67	35	77.78

Based on the FSS, 77.78% students score 0 while the others score 1. However, based on our VAS criteria, these student can be sorted into different levels of knowledge. 4 students are found to provide wrong answer but still know something relevant to the correct option. That is different from the score 0, which means they know nothing about the question. In summary, the VAS criteria can help teachers identify the students who really has difficulty in solving problem.

VI. CONCLUSION

Multiple-choice (MC) question is an important form of test to assess the students' academic achievement, especially in the e-learning applications. However, the classical evaluation metrics on MC questions (such as the correctness ratio) only consider the correctness of the final selection but ignore the solving progress of the testee. In the existing literature, the eye-tracking based visual attention was studied to infer the testee's cognitive progress towards a specific MC question. However, there is little work on the visual attention based evaluation of one complete MC test.

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