QUALITY AND FEATURE OF MULTIPLE-CHOICE QUESTIONS IN EDUCATION

Bing Jia, Dan He, Zhemin Zhu
Beihua University, China
E-mail: jia.bing@foxmail.com, 15337614@qq.com, zhuzm485@nenu.edu.cn

Abstract

The quality of multiple-choice questions (MCQs) as well as the student’s solve behavior in MCQs are educational concerns. MCQs cover wide educational content and can be immediately and accurately scored. However, many studies have found some flawed items in this exam type, thereby possibly resulting in misleading insights into students’ performance and affecting important decisions. This research sought to determine the characteristics of MCQs and factors that may affect the quality of MCQs by using item response theory (IRT) to evaluate data. For this, four samples of different sizes from US and China in secondary and higher education were chosen. Item difficulty and discrimination were determined using item response theory statistical item analysis models. Results were as follows. First, only a few guessing behaviors are included in MCQ exams because all data fit the two-parameter logistic model better than the three-parameter logistic model. Second, the quality of MCQs depended more on the degree of training of examiners and less on middle or higher education levels. Lastly, MCQs must be evaluated to ensure that high-quality items can be used as bases of inference in middle and higher education.

Keywords: higher education, item evaluation, item response theory, multiple-choice test, secondary education

Introduction

In education exams, multiple-choice questions (MCQs) are commonly used in secondary and higher education because they can be easily and accurately scored and save significant manpower and time. Although some studies suggest that MCQs only focus on what students remember and do not assess the extent to which they understand, analyze, and apply course-related information (Walsh & Seldomridge, 2006), MCQs remain among the most common types of assessment questions extensively used in standardized tests (Bailey et al., 2012; DiBattista & Kurzawa, 2011; Zhu et al., 2018). On the one hand, MCQs can immediately cover instructional contents and be scored easily (Brown & Abdulnabi, 2017; DiBattista & Kurzawa, 2011; Nedeau-Cayo et al., 2013). On the other hand, MCQs provide students with a method based on their experiences. Examiners encourage examinees to guess whenever they can eliminate a wrong choice, which is a better strategy than completely blind guessing (Frary, 1988, p. 76). When the guessing process is not random, the success of the guessing process will be based on the examinees’ abilities (San Martín et al., 2006; van der Maas et al., 2011; Zhu et al., 2018). Hence, the chosen options in response to MCQs provide information of the examinees’ experiences. Only a few teachers have formal education on the rules of MCQ writing or MCQ assessment (Brown & Abdulnabi, 2017). Thus, when the quality of MCQs is not good owing to the lack of teacher training, test results may mislead the assessment of examinee achievement (Brady, 2005; Brown & Abdulnabi, 2017; Downing, 2005; Masters et al., 2001; Stagnaro-Green & Downing, 2006; Tarrant et al., 2006). Therefore, MCQ quality should be evaluated in the field of education.

This research was based on exam data from China and the US to obtain a general conclusion. Although several studies had shown a gap between the two countries in the teacher
and student levels (Stevenson et al., 1990; Stevenson & Stigler, 1994), MCQs had been widely used in China and the US. However, China has more students and smaller proportion of teachers and students compared with the US. Therefore, MCQs could compensate for the heavy work pressure. Moreover, examinations in China and the US may provide different information. This research used item response theory (IRT) and selected four exams in the two countries to evaluate the quality of MCQs. First, this research briefly reviewed the methods of assessing MCQ quality. Second, the IRT models that were used to assess MCQs in this research are introduced. Third, four MCQ exam data sets were assessed by using IRT models.

**Assessment of MCQ Quality**

Three methods are used to assess the quality of MCQs. The first is a conventional method based on process control. This method has four steps in writing MCQ items, namely, (1) defining content, (2) choosing style and format, (3) writing items, and (4) writing options (Halada & Rodriguez, 2013); and applies five items to assess item quality: (1) questions are clearly stated, (2) questions are free of errors, (3) distractors are feasible, (4) accompanying explanations are good, and (5) specified answer is correct (Purchase et al., 2010). However, these criteria are more about prevention than evaluation.

The second method is based on classical test theory (CTT). CTT indicates that the sum of examinees’ true scores based on theoretical ability and unobserved random error is equal to the scores of individual examinees in the test (observed score = true score + error). Thus, the examinees’ actual levels of ability are assessed by the number of correctly answered items (de Ayala, 2009; Schaughency et al., 2012). Difficulty and discrimination are the most common CTT indicators of one MCQ item. The difficulty (p) of each item can be signed by the proportion of candidates who answered an item correctly. Items p > .80 or p < .20, which means too easy or too difficult, respectively, will be rejected from the test because they fail to provide sufficient useful information on the examinees’ abilities (Brown & Abdulnabi, 2017). Discrimination (r) of each item can be signed using the Pearson product-moment correlation coefficient between the scores on the items and on the total test. Discrimination is a parameter that distinguishes between higher and lower ability examinees (Fan, 1998). Items that do not have a significantly positive value (r > .20) should be rejected (Ebel & Frisbie, 1991). However, CTT has two major limitations. (1) The observed score depends on the item sample and (2) the item statistical parameters depend on the examinee sample (Fan, 1998). These two limitations are summarized as circular dependency. Accordingly, estimating results in CTT depends heavily on samples because if the test is difficult, then students will obtain low scores. Hence, examinees will appear to be low achievers even if they have high levels of ability and vice versa (Hambleton et al., 1993). Similarly, the parameters of MCQs depend on the abilities of the sampled examinees, and changes in their abilities will affect the item parameters (Brown & Abdulnabi, 2017). When the class of examinees is changed, the same items will be assigned with different difficulty and discrimination values. From a statistical point of view, the reason for change is that CTT depends on the ability of the examinees and not on the distribution of student population abilities.

The third method is based on IRT. In 1911, Binet selected items for the Binet–Simon Intelligence Scale (Baker & Kim, 2004). The proportion of correct responses at each age (ability level) in the scale was obtained and presented in tabular form. Terman (1916) plotted the proportion of correct responses as a function of age and fitted a smooth line to these points. Given that the smooth line is S-shaped, the function is called item characteristic curve (ICC). IRT can be regarded as a series of statistical models used to fit ICC. These models that are based on the dual properties of items and the examinees’ performance can be used to estimate their abilities (Hambleton & Jones, 1993). The item parameter estimation in IRT models is
based on the distribution of examinees. Thus, item parameters (e.g., difficulties, discrimination, and guessing) may be different in the different examinee teams (Borsboom, 2005; Embretson & Reise, 2000; Hambleton et al., 1993). However, the parameters of one item for different examinee teams can be linked by linear invariance of the item parameters. Discrimination parameter ($a$) and difficulty parameter ($b$) can be used to assess the quality of MCQs in IRT. The difficulty parameter is the point that equals examinees’ abilities, in which the probability of answering items correctly is 50% (Embretson & Reise, 2000) and often has a range of $-4b/4$. An item that is too difficult or too easy may lead the answers of the examinees to be correct or wrong. Consequently, the parameters of the IRT models may not be estimated.

In the $b$ region, ICC is nearly linear with a slope of $a/\sqrt{2\pi}$ (Lord & Novick, 1968). Thus, an approximate interpretation of the discrimination parameter indicates the slope of ICC at the point on an ability scale corresponding to the difficulty. In IRT, answering additional questions correctly does not increase the examinees’ abilities. In IRT, people’s scores increase based more on the number of difficult questions the examinees answered than the number of questions the examinees answered correctly (Brown & Abdulnabi, 2017). The other difference with CTT is that the items, regardless of large or small discrimination, are significant in IRT, particularly in computer adaptive testing. However, items that have negative discrimination value remain undesirable. Negative discrimination value means that high-ability examinees will not easily obtain the correct answers, but low-ability examinees may easily determine the correct one. In addition, different models of IRT can be used to judge the behavior of examinees. CTT barely has such a function, which is the advantage of IRT.

**Assessment of MCQs in Education**

Assessment of MCQs is an important and necessary undertaking. MCQs are commonly used in secondary and higher education. In secondary education, MCQs can extensively cover instructional content. MCQs are the most common item types for some subjects, such as mathematics and physics. Hence, MCQs’ quality must be guaranteed. In higher education, large-scale exams are administered for different majors or colleges. Teachers would have to exert effort to correct the papers. Therefore, teachers choose MCQs as the item types for the entire exam.

Assessment of MCQs in education follows two steps. The first step is designing MCQs. The design of the MCQ items must comply with guidelines for writing MCQs. Many guidelines are available (Brady, 2005; Burton, 2005; Downing & Yudkowski, 2009; Haladyna, 2004; 2013). Research has claimed that teachers who trained in MCQ item writing can produce high-quality MCQs (Jozefowicz et al., 2002), and low-quality written MCQs may negatively impact examinees’ performances or achievements (Clifton & Schriner, 2010; Downing, 2005; Tarrant et al., 2006). However, only a few academics have formal training in the principles of MCQ item writing (Brown & Abdulnabi, 2017). This lack of formal training causes the low quality of certain proportions of MCQs in exams (Downing, 2005; Ellsworth et al., 1990; Hansen & Dexter, 1997; Masters et al., 2001; Tarrant et al., 2006). Therefore, the second step, which is based on statistical method, is crucial.

The second step involves assessing the statistical properties of items by using a statistical method to exclude low-quality items. In general, teachers want to rule out items that are too difficult or simple, with worse discrimination, or easy to guess. In CTT, the discrimination parameter should be above +.20 (Ding & Beichner, 2009; Su et al., 2009; Thorndike, 2005). However, IRT is used as the assessment tool in the current research owing to the comparative disadvantages of CTT.
Models in IRT

The most popular model in IRT models is the two-parameter logistic (2PL) model (Birnbaum, 1968). The 2PL model can be used to calculate the probability of a correct item response with the item parameters and examinees' abilities. The probability of a correct response can be signed by $\Phi_{ij}$ and has the following form:

$$\Phi_{ij} = \frac{1}{1 + \exp(-a_i(\theta_j - b_i))},$$

(1)

where $a_i$ is the item discrimination parameter, $b_i$ is the item difficulty parameter with $i=1,\ldots, I$ is the indexing items, $j=1,\ldots, J$ is indexing examinee subscript. When $a_i$ equals 1, the 2PL model evolves to the one-parameter logistic (1PL) model. 1PL model has difficulty parameters only.

In an exam, the 2PL model can provide the item information by discrimination and difficulty parameters. However, the 2PL model does not include the guessing component. Given that the guessing process widely occurs in MCQs, many new models based on the 2PL model have been introduced by adding a guessing process $p(g)$. The most popular one is the three-parameter logistic (3PL) model. The 3PL structure is an item response function with $\Phi_{ij}$ and a guessing component (San Martín et al., 2006).

The structure is as follows:

$$P(\theta) = p(g) + (1-p(g))p(r).$$

(2)

In the 3PL model guessing function, is a constant based on an item, and the guessing function is reduced to a guessing parameter, such that, when $p(r)=\Phi_j$.

Although the 3PL model is popular in IRT in the past 20 years, studies have found that the parameter recovery accuracy for a 3PL model depends on the extent of guessing presented in the data (Han, 2012; Holland, 1990; Pelton, 2002; San Martin et al., 2006). Thus, San Martin et al. (2006) suggested that the 3PL model can only be used when the sample size is extremely large. Birnbaum (1968) conjectured that low-ability examinees may select correct responses by chance. Accordingly, the guessing parameter should be the same as the chance level $1/m$, where $m$ is the number of response options in MCQs. Thereafter, the guessing function is reduced to a constant $p(g)=1/m$, and this model is called 3PL with fixed lower asymptote (designated 3PL with FLA) when $p(r)=\Phi_j$. The function is as follows:

$$P(\theta) = \frac{1}{m} + \left(1 - \frac{1}{m}\right)\Phi_j.$$

(3)

This model contains g-process and has more accuracy parameter recovery than the 3PL model.

MCQ Assessment by IRT

Assessment under IRT should continue to be considered with CTT. Lord and Novick (1968) found a contact of discrimination between CTT and IRT when the abilities of the examinees followed a normal distribution. The discrimination in IRT is slightly larger than in CTT (discrimination in IRT and CTT are .258 and .436 and .25 and .4, respectively). In CTT, the discrimination parameter should be above +.15 (Kejoe, 1995), +.20 (Ding & Beichner, 2009; Su et al., 2009; Thorndike, 2010), and +.25 (Considine et al., 2005). When discrimination is .3, ICC will lose the S-shape and behave similarly as a straight line. Therefore, the discrimination parameter in IRT in the current research is divided into three intervals, namely, $-\infty < a_i \leq$
PROBLEMS OF EDUCATION IN THE 21ST CENTURY
Vol. 78, No. 4, 2020

0, – ∞ < a_i ≤ .3, and .3 < a_i < +∞ which correspond to unacceptable, recommend delete, and acceptable, respectively.

When the difficulty of one item is extremely low or extremely high, its discriminatory parameter tends to suffer (DiBattista & Kurzawa, 2011). MCQs that are extremely difficult (difficulty per parameter <.30) or extremely easy (difficulty per parameter >.90) will have difficulty in discriminating high and low achievers in CTT (Ebel & Frisbie, 1991). No research has been conducted on the contact of difficulty between CTT and IRT. This lack of research may be caused by the essential difference of difficulty between the two theories. The former is concerned with how many people determine the correct answer, while the latter is concerned with the examinees’ abilities. In general, the values of examinees’ abilities are from −3 to +3. This research divides the difficulty in IRT into two intervals, −2.4 < b_i ≤ 1.2 and otherwise, which correspond to unacceptable and acceptable, respectively (For the −3 to +3 interval, −2.4 and 1.2 correspond to 90% and 30%, respectively).

If the evaluation criteria for model selection (AIC and BIC) chose a guessing model, then items with a guessing parameter of >.25 are unacceptable when MCQs have four options (Brown & Abdulnabi, 2017). However, several studies have been convinced that guessing uses ability (San Martin et al. 2006; Zhu et al., 2018). The current research did not evaluate the quality of questions by guessing parameters. When a guessing model is selected by AIC or BIC, the examinees can be considered guessing in the exam. This method can be used to determine whether examinees were guessing in MCQs.

Model Size

Sample sizes should be considered because of the complexity of the IRT models (Hambleton & Jones, 1993). Research has suggested that the 1PL model will estimate accurately with N < 100 (Boone et al., 2014), and others are the opposite (Houts et al., 2016). IRT is more dependent on simple sizes (i.e., item and examinee sizes) than CTT (Akour & AL-Omari, 2013). Different estimation methods (e.g., MCMC, MLE, MH, and EM) have different requirements for sample size. Empirically, when the examinee sample is over 100 and the item size is above 50, 1PL, 2PL, and 3PL with FLA models will estimate accurately. However, the examinee samples should be above 500 for the 3PL model. Thus, the 3PL model may not converge estimates when the data are small.

Real Data

For exploring the normal nature of the MCQ exam, four samples of different sizes from US and China in secondary and higher education were chosen. All the data sets were analyzed using IRT methods to choose the best fitting model. And then, item parameters were estimated to assess the quality of MCQs.

Data Sets

The data sets comprised one from secondary education and one data set from higher education in the US (MEU and HEU, respectively); and one data set from middle education and one data set of higher education from China (MEC and HEC, respectively). All multiple-choice items contained four alternatives.
Table 1
Attributes of four data and writing teacher

| Exam | Attributes of Data | Attributes of Writing Teacher |
|------|-------------------|-------------------------------|
|      | Examinee Size     | Item Size                     | Train          | Company                  |
| MEU  | 2000              | 65                            | Trained        | University Teacher      |
| MEC  | 734               | 12                            | Not Trained    | University Teacher      |
| HEU  | 96                | 65                            | Not Trained    | Middle School Teacher   |
| HEC  | 1008              | 50                            | Being Trained  | Middle School Teacher   |

The MEU data contained 2,000 examinees. It was a state mathematics assessment that contained 65 MCQs. The data were used in an early research (Zhu et al., 2018). The HEU data were taken from 96 first-year student students and from a science freshman course in 2017 (spring). The exam consisted of 65 MCQs. The MEC data were from a mathematics simulated examination for a college entrance examination, which contained 12 MCQs. Different areas of China's college entrance examination use different exams in mathematics, but only 12 MCQs are included in each mathematics exam. In general, their difficulty parameters were increasing. HEC, which contained 50 MCQs, was from the final examination of Principles of Pedagogy. All registered students in the university need to take this exam. Therefore, a total of 1008 examinees from 11 majors (i.e., Biology, English, Physics, Mathematics, Chinese, Music, Art, History, Dance, Sports and Chinese Language and Literature) provided the data. The four MCQs were written by different teachers. MEU was written by the teacher who had passed MCQ writing training, and HEC was written by the teacher who participated in the training. HEU and MEC were written by teachers who were not trained in MCQ item writing. MEU and MEC were written by a university teacher, while HEU and HEC were written by middle school teachers.

Data Analysis

The data sets were analyzed using IRT. Four evaluation criteria for model selection were used in the real data: log likelihood (LL), −2LL, Akaike information criterion (AIC), and Bayesian information criterion (BIC). These are the most popular evaluation criteria in IRT. LL expresses the probability of a given set of observations for different values of statistical parameters. −2LL means −2 multiplied by LL. Given a set of competitive models for designated data, AIC estimates the quality of each model relative to the fitting between data and models. BIC is similar to AIC but adds a penalty term for the number of parameters. The model with the largest LL (lowest -2LL, lowest AIC, lowest BIC) value which means the best fitting model should be preferred. All exams were analyzed using the 1PL, 2PL, 3PL, and 3PL with FLA models, except for the science exam, because the number of examinees were below 100.

Research Results

Results of MEU

The MEU data came from 2000 examinees and had 65 MCQs that presented 4 options. The results of the MEU data are as follows.
Table 2
Goodness of Fit for MEU

| Criterion | 1PL     | 2PL     | 3PL     | 3PL with FLA |
|-----------|---------|---------|---------|--------------|
| LL*       | -67511  | -66697  | -66582  | -66926       |
| -2LL      | 135022  | 133394  | 133164  | 133850       |
| AIC       | 135152  | 133654  | 133554  | 134110       |
| BIC       | 135516  | 134382  | 134646  | 134838       |

*LL = Log Likelihood

Table 2 summarizes the fitting of the four models for the MEU data according to the LL, AIC, and BIC values. Although the goodness of fit of the 3PL model was better than the other models by \(-2\text{LL}\) and AIC, the fitting of the 2PL model was better than that of the other models by BIC. Given that BIC is more advanced than AIC, 2PL had the best fitting to the data. Table 3 shows the parameters.
## Table 3

*Item parameter by the 3PL model in MEU*

| Item | Discrimination | Difficulty | Item | Discrimination | Difficulty |
|------|----------------|------------|------|----------------|------------|
| 1    | 2.1132         | -.6976     | 34   | .9820          | .4315      |
| 2    | 1.8535         | -.8335     | 35   | 1.7461         | -1.6727    |
| 3    | 1.6916         | -.1999     | 36   | 1.5949         | -.5518     |
| 4    | 1.3193         | .3296      | 37   | 1.2554         | -.5831     |
| 5    | 1.6350         | -.7062     | 38   | 1.7614         | -2.562     |
| 6    | 1.0479         | -.4203     | 39   | .7282          | -1.0174    |
| 7    | .9722          | .2679      | 40   | .9490          | -1.1574    |
| 8    | 1.6024         | -1.2724    | 41   | 1.4250         | -2.407     |
| 9    | 2.022          | -1.1362    | 42   | .7850          | -1.1540    |
| 10   | 1.2668         | .2788      | 43   | 1.5006         | -1.2734    |
| 11   | 1.4010         | -.2582     | 44   | 1.2423         | .5989      |
| 12   | 1.2856         | .7626      | 45   | 1.8518         | -1.3875    |
| 13   | 1.3650         | -.1249     | 46   | 1.3387         | -.5634     |
| 14   | 1.4639         | -.7244     | 47   | .9081          | -.1467     |
| 15   | 1.2111         | -.5657     | 48   | 1.2582         | -1.8985    |
| 16   | 1.7974         | -1.6913    | 49   | 1.4789         | -1.7205    |
| 17   | 1.600          | -.8429     | 50   | 1.1996         | -.8432     |
| 18   | 1.3297         | -.4830     | 51   | 1.3667         | .1572      |
| 19   | 1.5312         | -.5796     | 52   | 1.0683         | .6201      |
| 20   | 1.3853         | -1.1751    | 53   | .3278          | -1.4600    |
| 21   | 1.0074         | -.3351     | 54   | 1.0363         | -.6617     |
| 22   | 2.3669         | -.9952     | 55   | 1.5048         | -1.5392    |
| 23   | 2.0074         | -.1253     | 56   | .6290          | -1.3656    |
| 24   | 1.7307         | -1.0988    | 57   | .9458          | -1.5654    |
| 25   | 1.3027         | -1.5379    | 58   | 1.6192         | -.5214     |
| 26   | 1.1391         | -.2850     | 59   | 1.1100         | .5149      |
| 27   | 2.1303         | -.8613     | 60   | .8932          | -.2721     |
| 28   | 1.2974         | -1.5938    | 61   | 1.1553         | -.2585     |
| 29   | 1.2892         | -.7045     | 62   | 1.4740         | -1.3182    |
| 30   | 1.6441         | -.2325     | 63   | 1.2890         | -.8158     |
| 31   | .8098          | -.3194     | 64   | 1.2960         | .4233      |
| 32   | .7927          | -.6782     | 65   | .9902          | -1.1348    |
| 33   | .8030          | -.1241     |      |                |            |

The item parameters of MEU by the 2PL model include difficulty and discrimination parameters. The difficulty parameters are from $-1.89853$ to $.7626612$, and 10 difficulty parameters are positive. The discrimination parameters are from $.3278112$ to $2.36695$, and all the values are positive. The discrimination parameters of $-\infty < a_i \leq 0$, $0 < a_i \leq .3$, $.3 < a_i \leq +\infty$ correspond to 0, 0, and 65 items, respectively. Table 4 shows the acceptability in MEU.
Table 4
Acceptability in MEU

| Discrimination | Difficulty |
|----------------|------------|
| Value          |            |
| \(-\infty < a_i \leq 0\) | 0 < a_i \leq 0.3 | 0.3 < a_i \leq +\infty | \(-2.4 < b_i \leq 1.2\) | \(b_i \leq -2.4\) or \(b_i \leq 1.2\) |
| Advice         | Unacceptable | Recommend | Delete | Acceptable | Acceptable | Unacceptable |
| Number         | 0 | 0 | 65 | 65 | 0 |

Table 4 illustrates that the quality of this exam is perfect, and all items should be accepted. This rating can be related to the skills of examiners. The MEU exam is an evaluation test, which has been designed by teachers who have passed the MCQ design training.

Results of MEC

MEC data were obtained from 734 examinees and contained 12 MCQs that had 4 options. The result of the MEC data is as follows.

Table 5
Goodness of Fit for MEC

| Criterion  | 1PL   | 2PL   | 3PL   | 3PL with FLA |
|------------|-------|-------|-------|-------------|
| LL*        | -2498 | -2477 | -2477 | -2484       |
| -2LL       | 4996  | 4954  | 4954  | 4968        |
| AIC        | 5020  | 5002  | 5026  | 5016        |
| BIC        | 5075  | 5112  | 5191  | 5126        |

*aLL = Log Likelihood

Table 5 summarizes the fitting of the four models for the MEC data according to LL, AIC, and BIC values. The fitting of the 2PL model was better than that of the other models by BIC, AIC, and -2LL. Hence, 2PL had the best fit to the data. Table 6 presents the parameters. Item 4 has unacceptable discrimination and difficulty parameters.

Table 6
Item parameter by 3PL model in MEU

| Item | Discrimination | Difficulty | Item | Discrimination | Difficulty |
|------|----------------|------------|------|----------------|------------|
| 1    | 1.3236         | -4.1386    | 7    | 1.9850         | -2.2485    |
| 2    | .9038          | -4.9618    | 8    | 2.2702         | -1.8790    |
| 3    | .1759          | -18.4270   | 9    | 1.3433         | -1.7954    |
| 4    | -1.6114        | 28.0032    | 10   | .9451          | -2.1729    |
| 5    | .8311          | -2.3700    | 11   | .8603          | -1.3057    |
| 6    | 1.0681         | -2.9202    | 12   | .9548          | -5.241     |
The item parameters of MEU by 2PL model in Table 6 include difficulty and discrimination parameters. The difficulty parameters are from $-18.42705$ to $28.0032$, and one difficulty parameter is positive. The discrimination parameters are from $-1.614428$ to $2.270278$, and one value is negative. The discrimination parameters, $-\infty < a_i \leq 0, 0 < a_i \leq 0.3, 0.3 < a_i \leq +\infty$ correspond to 1, 1, and 10 items, respectively. Seven difficulty parameters of the items were acceptable. Only one item (item 4, shading) had unacceptable discrimination and difficulty. Acceptability in MEC is shown in Table 7, and the ICCs are shown in Figure 1.

Table 7

| Discrimination | Difficulty |
|----------------|------------|
| $-\infty < a_i \leq 0$ | $0 < a_i \leq 0.3$ |
| $0.3 < a_i \leq +\infty$ | $-2.4 < b_i \leq 1.2$ |

Advice |
|---|
| Unacceptable |
| Recommend Delete |
| Acceptable |
| Acceptable |
| 4+1* |

*4+1 means their 4 difficulty parameters of items small than -2.4, and 1 difficulty parameters larger than 1.2

Figure 1

ICCs of 2PL model in MEU

Negative discrimination for one item means that examinees with high abilities may not easily answer this item correctly, whereas examinees with low abilities may easily reply with the correct answer. This result is against the original intention of the exam. Figure 1 shows that the discrimination parameter of item 4 is negative. Thus, this item should be rejected. The discrimination of item 3 is $0.1759142$, and the S-shape shown in Figure 1 is nearly lost. Hence, the recommendation is to delete the item owing to low discrimination. This action will not bring a significant increase in the probability of answering correctly when the significant change in the ability exists. This exam was written by a middle school teacher who was not trained in MCQ item writing. This background may be the reason for the low-quality test questions. The first four items were simple. Overall, the difficulty of the test gradually increased, which was consistent with the original intention of the MCQ design.

Results of HEU

The HEU data came from 96 examinees and used 65 MCQs that had 4 options. The results of the HEU data is as follows.
Table 8

Goodness of Fit for the HEU

| Criterion | 1PL | 2PL | 3PL | 3PL with FLA |
|-----------|-----|-----|-----|--------------|
| LL*       | -3095 | -2946 | -2952 |              |
| -2LL      | 6190 | 5892 | Non-convergence | 5904 |
| AIC       | 6320 | 6152 |              | 6164 |
| BIC       | 6487 | 6485 |              | 6497 |

*LL=Log Likelihood

Table 8 summarizes the fitting of the four models for the HEU data according to the LL, AIC, and BIC values. The fitting of the 2PL model was better than that of the other models by BIC, AIC, and $-2LL$. Hence, 2PL had the best fit to the data. Table 9 shows the parameters. Items 8, 15, 23, 24, 32, and 65 have bad discrimination and difficulty parameters.
Table 9
*Item parameter by 2PL model in HEU*

| Item | Discrimination | Difficulty | Item | Discrimination | Difficulty |
|------|----------------|------------|------|----------------|------------|
| 1    | .5325          | -3.4995    | 34   | 1.2987         | -.4140     |
| 2    | .3689          | -3.5522    | 35   | .9570          | -1.8847    |
| 3    | 1.7733         | -1.7545    | 36   | .5510          | -3.307     |
| 4    | 1.2311         | -.7041     | 37   | .3245          | -1.2012    |
| 5    | 1.0981         | -2.0392    | 38   | .3920          | -4.8675    |
| 6    | .9033          | -2.8422    | 39   | .3082          | -1.6966    |
| 7    | .6651          | -4.0879    | 40   | 1.4462         | -1.1166    |
| 8    | .1855          | -7.2503    | 41   | .5298          | .3312      |
| 9    | -.3739         | -.2132     | 42   | 1.3359         | -1.507     |
| 10   | .9818          | -2.4201    | 43   | 1.7783         | -1.4215    |
| 11   | 1.2173         | -1.9038    | 44   | .7474          | -2.8634    |
| 12   | 1.5659         | -1.6429    | 45   | .7637          | .1760      |
| 13   | 1.2349         | -1.0009    | 46   | .7958          | -2.4814    |
| 14   | .2825          | -2.132     | 47   | .8398          | -1.4324    |
| 15   | -.3252         | -.6347     | 48   | -.4064         | -1.4231    |
| 16   | .4889          | -2.8691    | 49   | 1.4073         | -1.8194    |
| 17   | .6150          | .1407      | 50   | .2269          | -4.4155    |
| 18   | 1.2151         | .1039      | 51   | 1.1072         | -1.4926    |
| 19   | 2.3433         | -1.5597    | 52   | 1.2687         | -1.7880    |
| 20   | .7637          | -1.5410    | 53   | 1.4141         | -3.569     |
| 21   | 2.9663         | -1.7229    | 54   | 1.1807         | -6.233     |
| 22   | .1867          | -.9029     | 55   | 1.7712         | -4.076     |
| 23   | -.1175         | 11.3908    | 56   | 2.2198         | -1.9118    |
| 24   | .4200          | 3.1461     | 57   | 1.8666         | -2.1910    |
| 25   | -.4173         | -2.116     | 58   | 1.3369         | -2.3793    |
| 26   | 1.1451         | -3.1916    | 59   | 2.0738         | -1.9696    |
| 27   | .8500          | .3326      | 60   | 1.0608         | -1.5356    |
| 28   | .3131          | .9587      | 61   | .9791          | -1.4132    |
| 29   | 2.1511         | -1.1229    | 62   | 1.5173         | -4.290     |
| 30   | 1.7528         | -.5243     | 63   | 1.2799         | -5.064     |
| 31   | .4444          | -6.2792    | 64   | .8829          | -3.466     |
| 32   | .0085          | -81.2328   | 65   | -.1481         | 6.0183     |
| 33   | .6749          | -2.8436    |      |                |            |

The item parameters of HEU in the 2PL model included difficulty and discrimination parameters. The discrimination parameters ranged from -.420011 to 2.966365, and seven values were negative. The discrimination parameters, $-\infty < a_i \leq 0$, $0 < a_i \leq 0.3$, $0.3 < a_i \leq +\infty$, correspond to 7, 3, and 55 items, respectively. The difficulty parameters ranged from $-81.23288$ to $11.39088$, 10 difficulty parameters were positive, and 3 were above 1.2. Hence, 45 difficulty parameters of the items were acceptable. Table 10 shows the parameter acceptability.
Table 10

Acceptability in HEU

| Discrimination | Difficulty |
|----------------|------------|
| Value          |            |
| $-\infty < a_i \leq 0$ | $0 < a_i \leq 0.3$ | $0.3 < a_i \leq +\infty$ | $-2.4 < b_i \leq 1.2$ |

| Advice          | Number | Unacceptable | Recommend Delete | Acceptable | Acceptable | Unacceptable |
|-----------------|--------|--------------|-----------------|------------|------------|--------------|
| Number          | 7      | 3            | 55              | 45         | 17+3*      |

*17+3 means their 17 difficulty parameters of items smaller than -2.4, and 3 difficulty parameters larger than 1.2.

Several items (i.e., 15, 23, 24, and 65) had unacceptable discrimination and difficulty parameters. Figure 2 shows that ICC of the items was decreasing, and all four items were extremely difficult.

Figure 2

ICCs of 2PL model in HEU

The discrimination parameters of items 15, 23, and 24 were negative, and the discrimination parameters of items 8, 22, and 32 were considerably small. The probability of a correct item response will become a straight line. A total of 20 items had difficulty parameters that were considerably large or small. A total of 4 items must be deleted, 19 items should be deleted, and 1 item is recommended to be deleted. This result accounted for 36.9% of the total items. Hence, the examination quality of the science freshman course was not ideal. The teacher who wrote this exam was not trained in MCQ writing.

Result of HEC

HEC is the final examination of Principles of Pedagogy administered in the provincial universities of China. The data came from 1008 examinees and the 50 MCQs had 4 options. Table 11 shows the result of the goodness of fit.
Table 11
Goodness of Fit for the HEC

| Criterion | 1PL | 2PL | 3PL | 3PL with FLA |
|-----------|-----|-----|-----|-------------|
| LL        | -23363 | -23288 | -23273 | -23553 |
| -2LL      | 46726 | 46576 | 46546 | 47105 |
| AIC       | 46826 | 46776 | 46846 | 47506 |
| BIC       | 47072 | 47268 | 47583 | 47797 |

*LL=Log Likelihood

Table 11 summarizes the fitting of the four models for the HEC data according to the LL, AIC, and BIC values. The fitting of the 2PL model was better than that of the other models by BIC, AIC, and −2LL. Hence, 2PL had the best fit to the data. Table 12 shows the parameters.

Table 12
Item parameter by 2PL model in HEC

| Item | Discrimination | Difficulty | Item | Discrimination | Difficulty |
|------|----------------|------------|------|----------------|------------|
| 1    | .6455          | -2.4457    | 26   | .6347          | -9.127     |
| 2    | 1.2045         | -1.6687    | 27   | .7673          | -2.7523    |
| 3    | 1.1753         | -2.1569    | 28   | 1.1248         | -1.4340    |
| 4    | .8745          | -1.9263    | 29   | .9641          | -2.0333    |
| 5    | .9850          | -1.7998    | 30   | 1.1592         | -2.1377    |
| 6    | .5271          | -2.6933    | 31   | 1.1554         | -1.2114    |
| 7    | .9292          | -1.7485    | 32   | .7915          | -1.2184    |
| 8    | .9584          | -1.4585    | 33   | 1.0578         | -1.8038    |
| 9    | .9954          | -1.6352    | 34   | 1.0022         | -1.7915    |
| 10   | 1.0638         | -1.5479    | 35   | .7843          | -1.7383    |
| 11   | .7309          | -1.8956    | 36   | 1.1337         | -1.2625    |
| 12   | .7263          | -1.6809    | 37   | .8840          | -1.8274    |
| 13   | .7071          | -2.1333    | 38   | .8183          | -1.4568    |
| 14   | .8385          | -1.3122    | 39   | .6962          | -2.4359    |
| 15   | 1.2246         | -1.5387    | 40   | 1.1790         | -1.7167    |
| 16   | .7317          | -2.5494    | 41   | 1.2298         | -1.2589    |
| 17   | .8780          | -1.8374    | 42   | 1.2594         | -1.3773    |
| 18   | .8611          | -1.8749    | 43   | 1.2097         | -1.0256    |
| 19   | .7361          | -2.5030    | 44   | 1.3262         | -1.4568    |
| 20   | 1.1752         | -1.6403    | 45   | .8642          | -1.1404    |
| 21   | .8700          | -1.0667    | 46   | .7598          | -2.1071    |
| 22   | 1.1631         | -1.6598    | 47   | .9691          | -1.7370    |
| 23   | .8539          | -2.0611    | 48   | .8393          | -1.7279    |
| 24   | .4740          | -1.4296    | 49   | 1.1735         | -1.6492    |
| 25   | .9604          | -1.4494    | 50   | .8920          | -1.6899    |
The item parameters of HEC by 2PL model included difficulty and discrimination parameters. The discrimination parameters ranged from .4740901 to 1.326276, and no value was negative. All discrimination parameters were in \( .3 < a_i \leq +\infty \). The difficulty parameters ranged from \(-2.752367\) to \(-9127278\), and not one difficulty parameter was positive. Table 13 shows the parameter acceptability.

**Table 13**

*Acceptability in HEU*

| Discrimination | Difficulty |
|----------------|------------|
| \(-\infty < a_i \leq 0\) | \(-\infty < b_i \leq 0\) |
| \(0 < a_i \leq 0.3\) | \(0.3 < a_i \leq +\infty\) |
| \(0 < b_i \leq 1.2\) | \(-2.4 < b_i \leq 1.2\) |

| Advice | Value | Number | Description |
|--------|-------|--------|-------------|
| Unacceptable | \(-\infty < a_i \leq 0\) | 0 | |
| Recommend Delete | \(0 < a_i \leq 0.3\) | 44 | |
| Acceptable | \(0.3 < a_i \leq +\infty\) | 50 | |
| Acceptable | \(-2.4 < b_i \leq 1.2\) | 6+0* | |
| Unacceptable | \(-\infty < b_i \leq 0\) | 0 | |

Note: *6+0* means their 6 difficulty parameters of items small than -2.4, and no difficulty parameters larger than 1.2

Table 13 illustrates that all discrimination of the items was acceptable. The 44 difficulty parameters of the items acceptable indicated 67% of the total. Only 6 difficulty parameters of the items were below \(-2.4\), and the smallest one was \(-2.752367\). All the discriminate parameters were acceptable. No items had bad different and difficulty parameters together. Hence, the exam quality was very good. This exam was written by an Education teacher, who is undergoing training in MCQ writing.

**Discussion**

This research showed that whether the examinees choose the guessing method was not related to the question or exam type. One of the disadvantages of MCQs is that students who do not know the correct answer may arrive at the correct one by guessing. However, this research showed that examinees may not choose to guess in an MCQ exam. This result is consistent with that in a previous research (Brown & Abdulnabi, 2017). A logical approach is to analyze items using a statistical model capable of detecting the effects of chance performance (Brown & Abdulnabi, 2017). The 2PL model, which has no guessing parameter, consistently has the best fit for MEU, MEC, HEU, and HEC. This result may be attributed to the four exams being general, and not competitive. The basic purpose of the four exams is to test whether the students have learned specific knowledge. Hence, the scope of knowledge in the exam is clear to the examinees. Thus, they may have prepared for the exam well, so that no guessing is needed for them.

Training teachers in MCQ writing was necessary because of the unideal quality of MEC and HEU. The other two data sets were better. On the one hand, the result showed that propositional techniques between higher and secondary education did not necessarily have differences. On the other hand, propositional techniques between China and the US were not necessarily different. The writer of MEU is a professional proposition technician, thereby explaining the perfect quality of the exam. The HEC writer is an education teacher. Although she is not a professional proposition technician, she receives good education training and is being trained when she was writing the exam. Her background could explain why the quality of HEC is good. Flawed MCQ items may result in misleading insights into student performances and contaminate important decisions. Hence, proposition teachers must receive the relevant propositional technical training. Unfortunately, the majority of Chinese and American teachers are untrained.
The low-quality examination found by research and analysis had shown the need to evaluate the quality of test questions before the examination. At this point, schools in China and the US should evaluate the quality of their exams. Moreover, the quality evaluation of mid-term examination questions could effectively improve the quality of the final examination (Brown & Abdulnabi, 2017). Subsequently, the effect of the evaluation of students’ level could be improved. In China, schools seldom conduct quality evaluation of test questions, except for the national examination, based on statistical methods. The current research showed that the evaluation of test questions based on proposition rules was not reliable. Tarrant et al. (2006) evaluated 2,770 MCQs used over five years (from 2001 to 2005) and concluded that nearly half (46%) of the items were bad because of violation of item-writing guidelines. The quality of HEU showed that the items of the exam should be assessed as well.

In the whole world, MCQs are commonly used in secondary and higher education. Compared to the previous research, in this research the data of middle and higher education examinations from different countries were analyzed to give a more general description of MCQs. There are some low quality MCQs in both China and the US exams. The proposition teachers who are trained by MCQ writing can write high quality items whatever they are in middle school or higher school. So, the items of the education exam should be assessed, and proposition teachers should receive the relevant proposition technical training in statistics. In particular, the MCQs quality analysis method based on IRT should be one of the main contents of training.

The quality of MCQs was assessed by IRT. Four different models were used to fit exam data: 1PL 2PL 3PL 3PL with FLA. Four evaluation criteria for model selection were used in the real data: LL, −2LL, AIC, BIC. The feature of the most fitting model was used to interpret MCQs exams. All the data consistently has the best fit to 2PL model, which has no guessing parameter. That means teachers do not need to worry about students may guess in MCQs. Oppositely, in most MCQs exams, students resolve the items with their abilities. The limitation of this research is the use of simple models.

**Conclusions**

The research results showed the quality of MCQs was not ideal in some exams. It is necessary to eliminate the low-quality MCQs before the test. The effective way to improve MCQ quality is to train teachers in MCQ writing. Proposition teachers must receive the relevant proposition technical training. This can improve the accuracy of student assessment. The research results also showed the examinees could choose the correct answers without choosing a guessing method, even if they had a chance to guess. The future research about student's response pattern can be carried out by other researchers related to the results of this study. Complex IRT models can be used to analyze and explore the answer patterns of students under different examinations.

**Acknowledgements**

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was partially supported by the National Education Science of China (Grants CHA190269). Special thanks to fund team member Hongwei Wang and her friend Ph.D. Fernando G. Quintana for their help.
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Received: April 25, 2020

Accepted: July 20, 2020

Cite as: Jia, B., He, D., & Zhu, Z. (2020). Quality and feature of multiple-choice questions in education. *Problems of Education in the 21st Century, 78*(4), 576-594. https://doi.org/10.33225/pec/20.78.576

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**Bing Jia**
Assistant Professor, Teacher Education and Training Center, Beihua University, Jilin, China.
E-mail: jia.bing@foxmail.com

**Dan He**
Associate Professor, School of Education Science, Beihua University, Jilin, China.
E-mail: 15337614@qq.com

**Zhemin Zhu**
PhD, Associate Professor, School of Education Science, Beihua University, Jilin, China.
E-mail: zhuzhm485@nenu.edu.cn