The Impact of Item-Writing Flaws on Difficulty and Discrimination in Item Response Theory

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ABSTRACT

High-quality test items are essential for educational assessments, particularly within Item Response Theory (IRT). Traditional validation methods rely on resource-intensive pilot testing to estimate item difficulty and discrimination. More recently, Item-Writing Flaw (IWF) rubrics emerged as a domain-general approach for evaluating test items based on textual features. However, their relationship to IRT parameters remains underexplored. To address this gap, we conducted a study involving over 7,000 multiple-choice questions across various STEM subjects (e.g., math and biology). Using an automated approach, we annotated each question with a 19-criteria IWF rubric and studied relationships to data-driven IRT parameters. Our analysis revealed statistically significant links between the number of IWFs and IRT difficulty and discrimination parameters, particularly in life and physical science domains. We further observed how specific IWF criteria can impact item quality more and less severely (e.g., negative wording vs. implausible distractors). Overall, while IWFs are useful for predicting IRT parameters-particularly for screening low-difficulty MCQsthey cannot replace traditional data-driven validation methods. Our findings highlight the need for further research on domain-general evaluation rubrics and algorithms that understand domain-specific content for robust item validation.

Keywords

item response theory, item-writing flaws, item analysis, automated qualitative coding, large language models

1. INTRODUCTION

Multiple-choice questions (MCQs) are recognized as an effective and widely used form of assessment across diverse educational domains. Ensuring these questions are of high quality is critical for maintaining validity, reliability, and overall soundness of assessing student learning [36, 11]. In both standardized testing (e.g., GRE, MCAT, SAT) and classroom assessments, rigorous evaluation is applied to re-

tain only the most reliable MCQs [19]. This process allows educators and researchers to make targeted improvements, revising or discarding flawed items to better measure student learning. Among the established methods for evaluating MCQ quality, Item Response Theory (IRT) is often considered the gold standard [5, 40]. By quantifying item performance through parameters such as difficulty and discrimination, IRT provides valuable insights into how students interact with different questions.

While IRT has proven effective at capturing statistical dimensions of item performance, it does not fully explain why certain questions might vary in difficulty or discrimination. It requires substantial student response data and operates post hoc, often identifying poor-quality questions only after students have encountered them [47]. Additionally, IRT parameters may overlook qualitative aspects of question design, such as pedagogical soundness and specific flaws that decrease assessment integrity. Expert review and rubricbased evaluations help address these limitations by detecting specific question design flaws that may skew assessment outcomes [31, 8]. While researchers acknowledge that such flaws influence item performance, a systematic examination of how qualitative shortcomings in item design interact with quantitative IRT measures across different domains remains limited. Empirical evidence linking specific flaws to changes in item discrimination and difficulty could clarify why certain questions perform poorly.

To address this gap, the present study integrates IRT analysis with the standardized Item-Writing Flaws (IWF) rubric [58]—an instrument for expert evaluation of MCQ quality. To explore relationships between IRT- and IWF-based evaluations, we analyze datasets across diverse educational domains: life and earth sciences, physical sciences, and mathematics, encompassing the middle and high school grade levels. These datasets combine 7,126 MCQs with response data of 448,000 students within a large-scale online learning platform. For each question, we compute difficulty and discrimination parameters and automatically apply the 19-criterion IWF rubric. By comparing these quantitative and qualitative evaluations, we aim to demonstrate how specific design flaws influence item performance across subject domains. We investigate three primary research questions:

RQ1 How does the frequency of IWFs correlate with IRT difficulty and discrimination parameters across MCQs from different educational domains?

RQ2 Which IWF criteria are most strongly associated with low-quality questions, as indicated by IRT difficulty and discrimination parameters?

RQ3 To what extent can IWF-based item features be used to (i) predict IRT difficulty and discrimination parameters and (ii) filter out low-quality items?

Beyond generating insights into the connections between IRT and IWFs, this paper introduces a general-purpose analysis methodology that leverages AI-enabled capabilities to scale qualitative evaluations proposed in the learning sciences literature [38, 32, 60, 1], alongside statistical measurements derived from large-scale student data. In the present context, this hybrid framework offers a more comprehensive and rigorous assessment of MCQ quality, equipping educators, test developers, and researchers with actionable insights to design more effective and equitable assessments.

2. RELATED WORK

2.1 IRT-based Item Validation

Item validation is critical to ensure that assessments measure intended constructs, have appropriate difficulty and discrimination properties, and provide fair evaluations across diverse populations (e.g., gender and age groups) [21]. Within the IRT framework, item validation involves conducting pilot studies to collect sufficient student response data for reliable parameter estimation—an expensive and time-consuming process [6]. To reduce the amount of student data needed for reliable estimation, recent work proposed multi-armed bandit algorithms as a more data-efficient approach to adaptively refine item parameters [53]. Additionally, to warrant fairness and equity of assessments, differential item functioning (DIF) is analyzed to ensure that items do not advantage or disadvantage any particular group of test-takers [17].

As an alternative to student data-driven validation methods, researchers have explored natural language processing (NLP) techniques to predict IRT parameters based on an item's syntactic and semantic features [2]. Several studies have applied neural networks, such as LSTMs and Transformers, to analyze item text and estimate discrimination and difficulty (e.g., [13, 9, 46]). These predictions can help mitigate the cold-start problem, reducing the amount of student response data needed for reliable parameter identification [35]. In parallel with the development of the Duolingo English Test, researchers have introduced methods to accelerate IRT parameter initialization, iterative calibration, and assessment item validation [61, 54, 53].

The present study utilizes large-scale student response data to estimate IRT parameters for 7,126 questions and employs an automated approach that combines rule-based methods and LLMs to annotate each question with a 19-criteria learning science rubric for Item-Writing Flaws (IWF) [37]. Unlike prior work focused on improving IRT parameter prediction from textual features, our study aims to enhance our understanding of relationships between IWF-based and IRT-based item validation methods, providing insights into how linguistic characteristics influence psychometric properties.

2.2 Learning Science Rubrics

Rubrics play a central role in education by providing a structured means of evaluating quality, whether in student submissions or instructional and assessment materials [3]. When applied by trained individuals, rubrics help ensure consistency and replicability by offering standardized and interpretable evaluation criteria [28]. As a result, rubrics have been used to assess the quality of student-facing resources, including hints, short-answer questions, and multiple-choice questions (MCQs) [43, 24, 40]. For example, Arif et al. [5] employed six question-level metrics-including relevance, answerability, and difficulty-to evaluate the quality of LLMgenerated MCQs. However, some rubric criteria involve a degree of subjectivity, such as relevance, which may affect inter-rater reliability and make replication more challenging. Factors such as language preference, prior knowledge, and personal definitions of difficulty may lead to inconsistencies in applying the same criteria [55]. Additionally, even relatively short rubrics can be time-consuming and cumbersome to apply across large content pools, limiting scalability [22].

Despite the challenges of rubric-based evaluations, one prominent instrument that has been widely adopted for MCQ assessment is the Item-Writing Flaws (IWF) rubric [22, 58, 16]. Applicable across subject areas, the IWF rubric detects flaws such as gratuitous detail, grammatical cues, and implausible or disproportionately long distractors. Two previous studies in the domain of medical education have shown that the presence of IWFs correlates with psychometric properties such as difficulty and discrimination, with flawed items introducing construct-irrelevant variance that can disadvantage students and reduce test validity [18, 48]. Compared to simpler automated measures (e.g., diversity, perplexity), the IWF rubric provides a more targeted and pedagogically grounded assessment of MCQ quality [37]. To address the time-intensive nature of manually applying the IWF's 19 distinct criteria to each MCQ, recent research has focused on automation, enabling IWF rubric application at scale [39, 37]. This automated approach achieved an overall accuracy of 94% on a dataset of 271 MCQs spanning five educational domains, each annotated with a gold-standard human application of the IWF rubric. In addition to accelerating the evaluation process, this method enhances consistency and detail in assessments by mitigating some of the inherent subjectivity in human-applied rubrics [42].

Rubrics are widely used in education, whether for grading assignments or evaluating educational technologies, but they often lack quantitative evidence to demonstrate their effectiveness [26]. In this work, we address this gap by providing quantitative proof that the IWF rubric criteria influence both question difficulty and discrimination. Unlike previous research that compared automatically identified IWF criteria with human-applied labels, our approach relies on an automated application that has already been validated [39, 37]. Consequently, we apply these verified annotation methods to thousands of real MCQs drawn from a variety of domains, using student response data to go beyond mere frequency counts. This enables us to offer deeper insights into how specific IWFs differentially affect question quality.

Table 1: Dataset overview. The first three rows indicate the number of concepts, questions and multiple-choice questions (MCQs). The next three rows describe the number of students, practice sessions and responses providing data to fit the IRT parameters. The last two rows show the average number of students and questions in each concept.

	All	Life/Earth	Physical	Math
# of concepts	1,033	563	336	134
# of questions	$13,\!158$	7,212	4,331	1,649
# of MCQs	7,126	3,792	2,206	1,128
# of students	448k	265k	169k	44k
# of sessions	1.9M	1.1M	0.6M	0.15M
# of responses	21.1M	12.6M	7.0M	1.6M
# stud./conc.	1,848	1,983	1,902	1,155
# quest./conc.	12.8	12.8	12.9	12.3

3. METHODOLOGY

3.1 Study Context and Dataset

Our analyses utilize a dataset from the CK-12 Foundation, a US-based nonprofit that provides millions of students with free access to educational resources. CK-12 actively develops and hosts the FlexBook 2.0 system¹, an online tutoring platform offering courses across diverse subjects and grade levels. Each course consists of a series of concepts, analogous to a textbook chapter and typically consisting of one to four learning objectives. Each concept is associated with a broader lesson topic and with a practice section designed to develop and assess students' understanding of that concept. For instance, in a Life Science course, a lesson might be "Genetics," with "Punnett Squares" as a concept within it. We focus on popular concepts within middle and high school courses, spanning topics in physical sciences (e.g., physics, chemistry), mathematics (e.g., algebra, geometry), and life and earth sciences, using data from 2023 and 2024.

Overall, our study uses data from 448,000 students interacting with 13,158 questions to fit IRT parameter sets for 1,033 distinct concepts (Table 1). All questions were written by human domain experts. As the Item-Writing Flaw (IWF) rubric studied in this paper is designed specifically for multiple-choice questions (MCQs) [58], we assess the relationships between IWFs and question-specific difficulty and discrimination parameters based on the 7,126 MCQs within the content pool. The following discusses the IRT parameter estimation and IWF annotation processes in detail.

3.2 Item Response Theory

Item Response Theory (IRT) is a methodological framework commonly used in high-stakes assessments, such as college entrance exams (e.g., SAT and GRE) [17]. Formally, IRT models interactions between students and a set of test items (i.e., questions) under binary response outcomes ($\{0,1\}$). The idea is to assign each student a latent ability parameter that explains their response probabilities, estimated using probabilistic inference. The relationship between student ability and response correctness probabilities is modeled by fitting a sigmoid function for each item, commonly referred to as item response function (IRF).

For each item j, its IRF reaches its steepest slope at a specific point on the x-axis, representing the item's difficulty δ_j . The steepness of the IRF reflects the item's discrimination property, denoted as α_j . Given student ability θ_i , along with item difficulty and discrimination parameters, the probability of student i answering item j correctly is defined as

$$\mathbb{P}(X_{i,j} = 1 \,|\, \theta_i, \, \alpha_j, \, \delta_j) = \frac{1}{1 - e^{-\alpha_j(\theta_i - \delta_j)}}, \tag{1}$$

where $X_{i,j}$ indicates the binary response outcome. X is the potentially sparse item response matrix capturing all interactions between students and items. Given student response data X, the parameters of the IRT model defined by Equation 1 are fitted via maximum likelihood estimation.

Our study utilizes the R package MIRT [15] to estimate a separate set of IRT parameters for each of the 1,033 concepts within our dataset. Following guidance from de Ayala [17], we ensure a robust IRT parameter estimation by focusing on concepts that meet the following criteria: at least 500 students (each submitting a minimum of 5 responses) and at least 10 questions (each receiving a minimum of 500 responses). While we use data from multiple question types (e.g., short-answer and multiple-choice) for the initial parameter estimation process, the subsequent analysis of the relationship between IWFs and IRT parameters focuses solely on MCQs (details in Table 1).

3.3 Item-Writing Flaws Application

We evaluate the quality of MCQs based on the 19-criteria IWF rubric [58] (see Table 2). This learning science rubric is domain-agnostic, and prior research has validated its utility in medical education, mathematics, and science domains [22, 58, 16]. Given the immense resources required for domain experts to annotate the more than 7,000 MCQs in our dataset, we utilize the Scalable Automatic Question Usability Evaluation Toolkit (SAQUET) [37], an open-source method that facilitates the automated application of the IWF rubric.

SAQUET has been shown to closely align with expert human application of the rubric, achieving an overall accuracy of 94% when applied to MCQs across five subject areas [37]. Compared to human evaluators, it is more likely to classify an MCQ as having an IWF, making it a stricter tool that errs on the side of caution. Additionally, the study demonstrated that SAQUET offers a more comprehensive evaluation of the quality of the question than traditional automated approaches, such as perplexity or cognitive complexity. The toolkit combines rule-based approaches with Large Language Model (LLM) verifications (via GPT-4o [25]) to determine whether an item satisfies or violates each of the rubric's 19 criteria [39]. For surface-level flaws or those that pertain to wording, such as identifying the presence of none of the above options or vaque terms, SAQUET employs rulebased techniques that rely on verb tense detection, keyword matching, and other straightforward heuristics. For criteria requiring domain-specific or pedagogical judgment, such as evaluating whether the text contains gratuitous information, the system incorporates a final verification step using the LLM to provide a "judgment call". This step involves prompting the LLM (GPT-40) to confirm or refute the suspected flaw based on the item's content.

¹https://www.ck12.org

Table 2: Definitions of the 19-criteria within the Item-Writing Flaw (IWF) rubric [58].

IWF Criteria	Definition
Ambiguous/Unclear	The question text and options should be written in clear, precise language to avoid confusion
Implausible Distractors	All incorrect answer choices should be realistic and plausible
None of the Above	Avoid using any variation of "none of the above" since it primarily tests students' ability to
	identify wrong answers
Longest Option Correct	The correct answer should not be noticeably longer or contain more detail than the other options,
	as this can unintentionally guide students to the correct answer
Gratuitous Information	Avoid unnecessary details in the question text that do not contribute to answering the question
True/False Question	Avoid answer choices structured as a series of true or false statements
Convergence Cues	Ensure answer choices do not contain overlapping words that might hint at the correct answer
Logical Cues	Avoid clues in the stem and the correct option that can help the test-wise student to identify
	the correct answer
All of the Above	Avoid using any variation of "all of the above" as students can guess the correct answer just by
	recognizing one correct option
Fill in the Blank	Avoid missing words in the middle of a sentence, as this forces students to rely on partial
	information
Absolute Terms	Avoid extreme words like "always" or "never" in answer choices, as these are usually false
Word Repeats	Ensure words or phrases from the question text are not repeated only in the correct answer, as
	this can inadvertently reveal the right choice
Unfocused Stem	The question text should be clear and specific so that students can understand it without needing
	to read the answer choices
Complex or K-type	Avoid overly complex questions that require selecting from a number of possible combinations
	of the responses, as they may test strategy rather than knowledge
Grammatical Cues	All options should be grammatically consistent with the question text and should be parallel in
	style and form
Lost Sequence	Arrange options in a logical order (e.g., chronological or numerical) to improve readability and
	fairness
Vague Terms	Avoid the use of vague words (e.g. frequently, occasionally) in the options as their meaning can
	be subjective
More than One Correct	In single-answer multiple-choice questions, ensure there is a single best answer to avoid ambiguity
Negative Wording	Avoid usage of negative wording in the question text, as it can confuse students

The output of SAQUET is a labeled dataset in which each item (i.e., MCQ) is annotated with a vector $\mathbf{x}_i \in \{0,1\}^{19}$ of binary indicators, specifying the presence or absence of a specific flaw as characterized by the 19-criteria rubric.

3.4 Analysis Methodology

After using student data for IRT parameter estimation and SAQUET for IWF rubric application, we define our analysis dataset as $D = \{(\alpha_i, \delta_i, \boldsymbol{x}_i)\}_{i=1}^{7126}$. Here, each MCQ i in the content pool is characterized by its discrimination parameter α_i , difficulty parameter δ_i , and a binary vector $\boldsymbol{x}_i \in \{0,1\}^{19}$ indicating which flaws apply. We further define domain-specific datasets $(D_{\text{Life/Earth}}, D_{\text{Physical}}, D_{\text{Math}})$ to study potential differences across subject areas (Table 1). Using these datasets, we address our research questions through a mixed methodology that combines traditional regression analysis with modern machine learning algorithms.

For RQ1, we employ linear regression analysis to study how the number of flaws relates to each MCQ's difficulty and discrimination parameters. In particular, we fit two models

$$\delta_i = \beta_0 + \beta_1 \| \boldsymbol{x}_i \|_1 + \epsilon_i, \quad \alpha_i = \gamma_0 + \gamma_1 \| \boldsymbol{x}_i \|_1 + \eta_i$$
 (2)

where δ_i and α_i are the difficulty and discrimination for MCQ i. The predictor variable is the total number of identified flaws $\|\boldsymbol{x}_i\|_1$. The coefficients β_1 and γ_1 capture the direction and magnitude of the association between the num-

ber of flaws and each IRT parameter. The error terms ϵ_i and η_i account for unexplained variance. By fitting these models separately for the full dataset and each domain-specific subset, we investigate how flaw prevalence influences difficulty and discrimination across educational domains.

For RQ2, we use linear regression analysis to identify which IWF criteria are most strongly associated with MCQ difficulty and discrimination. Specifically, for each IWF rubric $f \in \{1, ..., 19\}$ we fit two models:

$$\delta_i = \beta_{0,f} + \beta_{1,f} x_{i,f} + \epsilon_{i,f}, \quad \alpha_i = \gamma_{0,f} + \gamma_{1,f} x_{i,f} + \eta_{i,f} \quad (3)$$

where $x_{i,f}$ indicates the presence of flaw f in MCQ i. The coefficients $\beta_{1,f}$ and $\gamma_{1,f}$ quantify the relationship between each IWF criteria and the difficulty and discrimination parameters, respectively. The error terms $\epsilon_{i,f}$ and $\eta_{i,f}$ account for residual variance. By estimating these models, we examine the extent to which each IWF contributes to variations in difficulty and discrimination across the datasets.

For RQ3, we investigate the extent to which IWF rubricbased evaluations, derived solely from item text, can serve as a proxy for traditional validation methods that require student response data to estimate IRT parameters. Specifically, we assess the predictive power of the flaw indicator vector \mathbf{x}_i in two tasks: (i) predicting an item's difficulty (δ_i) and discrimination (α_i) ; and (ii) predicting items with

Table 3: Hyperparameters considered during model training.

Model	Parameters
Regression	$penalty_weight \in \{10^i\}_{i=-4}^4$, penalty: 12
Random	$n_estimators \in \{50, 100, 200, 300\}$
Forest	$max_depth \in \{None, 5, 10, 20\}$
	$min_samples_split \in \{2, 5, 10\}$
Gradient	$n_estimators \in \{50, 100, 200, 300\}$
Boosting	$learning_rate \in \{0.001, 0.01, 0.1, 0.2, 0.3\}$
	$max_depth \in \{3, 5, 7, 10\}$
Multi-layer	$hidden_layer_sizes \in \{10, 50, 100\}^{\{1,2\}}$
Perceptron	$activation \in \{\text{relu}, \text{tanh}\}$
	$earning_rate_init \in \{10^i\}_{i=-4}^0$

low discrimination ($\alpha_i < 0.5$), low difficulty ($\delta_i < 2$), and high difficulty ($\delta_i > 2$) [6]. To this end, we train machine learning models to determine whether rubric-based flaw annotations provide sufficient predictive power to support automated item pre-screening across educational domains. We do not train models for identifying high-discrimination questions, as high discrimination is not an item flaw.

Our evaluations consider a diverse range of parametric and non-parametric machine learning algorithms, including linear/logistic regression, random forest, gradient boosting, and multi-layer perceptron (MLP), using implementations from the Python package scikit-learn [41]. For the regression tasks, we evaluate model fit using root mean squared error (RMSE) and assess predictive power using explained variance (\mathbb{R}^2) and Pearson correlation (r). For the classification tasks, we measure performance using accuracy (ACC), area under the curve (AUC), and F1-score. Given the class imbalance—where approximately 90% of items exhibit "benign" IRT parameter values—AUC and F1-score are particularly relevant, as they provide a more robust evaluation of model performance in imbalanced classification tasks.

Our results report average performance metrics across a 5-fold cross-validation. In each fold, 80% of the items in the dataset are used for model training and grid search-based hyperparameter selection, and 20% are used for testing. Thus, all results are based solely on predictions for items that were not observed during training. Table 3 outlines the hyperparameter spaces considered for each algorithm.

4. RESULTS

Using data from 448,000 students, we fitted IRT models for each of the 1,033 concepts. Assessing discrimination and difficulty parameters of all 7,126 MCQs, we flagged 789 (11.1%) for low discrimination, 773 (10.8%) for low difficulty, and 134 (1.9%) for high difficulty (Table 4). Across the domainspecific datasets, we observed that Life/Earth Sciences and Math showed the highest and lowest proportions of flagged questions, respectively (low discrimination 12.1% vs. 7.3%, low difficulty 10.5% vs. 4.3%, and high difficulty 7.3% vs. 1.6%). These findings suggest that Math MCQs within individual concepts have more homogeneous difficulty levels compared to Science MCQs. Overall, we find that the vast majority of MCQs exhibit desirable IRT parameters. This implies that our item screening models have to manage class imbalance when trying to predict whether an item has desirable difficulty and discrimination (RQ3).

Table 4: Analysis Overview. The first section details the total number of questions and those flagged for low discrimination and low/high difficulty based on IRT analysis. The second section reports the total number of IWFs identified and average number per question. The last section highlights the five most common IWFs and their prevalence across domains.

	All	Life/Earth	Physical	Math
# of questions	7,126	3,792	2,206	1,128
- low discrimination	773	459	232	82
- low difficulty	789	538	203	48
- high difficulty	134	78	38	18
# of IWFs	10,537	5,647	3,062	1,828
IWFs per quest.	1.479	1.489	1.388	1.621
ambiguous/unclear	31.3%	27.8%	30.0%	45.9%
fill in the blank	22.4%	29.2%	18.4%	7.8%
multiple correct	14.1%	14.3%	14.4%	12.7%
none of the above	12.5%	15.9%	10.8%	4.1%
lost sequence	10.1%	2.8%	13.6%	28.1%

In the IWF application, we found that most questions had either no flaws or very few, with 82.5% containing at most two (Figure 1). Among the three domains, Life/Earth Sciences featured the highest proportion of flawless MCQs at 22.0%. Math exhibited the highest average number of IWFs per question at 1.62. Still, all three domains demonstrated a similar distribution of IWF numbers, with an overall average of 1.48 IWFs per question. Additional details are provided in Table 4, which highlights the prevalence of the five most common IWFs within each domain. The most frequent flaw identified across all domains was "ambiguous/unclear language" in the question text or answer options, affecting 31.3% of all MCQs. We found "fill-in-the-blank" (fitb) and "none-of-the-above" (nota) formulations to be more prevalent in the Life/Earth (29.2% fitb, 15.9% nota) and Physical Science (18.4% fitb, 10.8% nota) domains, compared to Math (7.8% fitb, 4.1% nota). The "lost-sequence" flaw, which indicates that answer options break chronological or numerical order, was significantly more common in Math MCQs at 28.1%. We continue by assessing the impact of IWF numbers and specific IWF criteria on MCQ's IRT difficulty and discrimination parameters (RQ1 and RQ2).

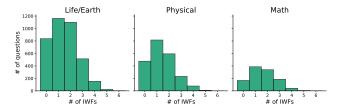


Figure 1: Histograms illustrating the number of IWFs identified per question across the three domain-specific datasets.

4.1 RQ1: IWF Correlations with IRT

We conducted regression analyses to study how the number of IWFs relates to IRT discrimination and difficulty parameters across aggregated and domain-specific datasets (Table 5). First, focusing on the aggregated dataset containing all 7,126 MCQs, we observe a significant negative relationship between IWF frequencies and discrimination parameters ($\hat{\gamma}_1 = -0.080, p < 0.001$), indicating that items with

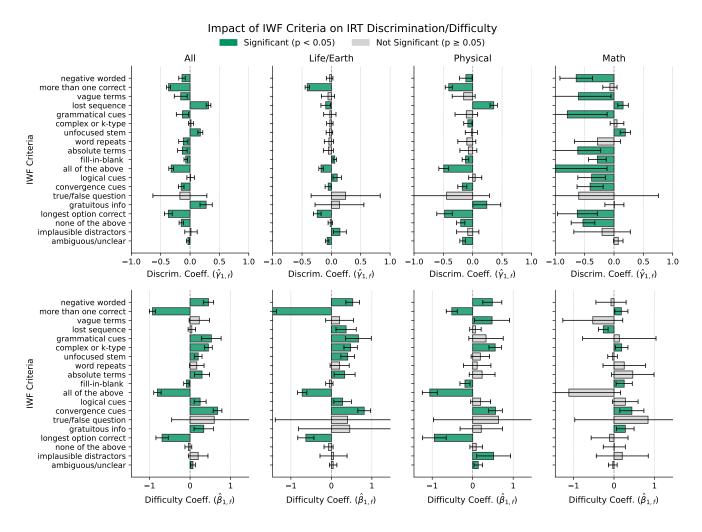


Figure 2: Linear regression analysis examining the strength of association between each IWF criterion and IRT discrimination and difficulty parameters across the domain-specific datasets. The figure indicates estimated coefficients, 95% confidence intervals, and highlights statistically significant relationships (p < 0.05) in green.

Table 5: Linear regression analysis examining relationships between the number of IWFs and IRT discrimination and difficulty parameters across domains. We report estimated coefficients, 95% conf. intervals, and corresponding p-values.

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Parameter	All	Life/Earth	Physical	Math
Discrimination	-0.080	-0.075	-0.139	-0.016
	(± 0.011)	(± 0.012)	(± 0.020)	(± 0.037)
	p = 0.000	p = 0.000	p = 0.000	p = 0.393
Difficulty	-0.042	-0.093	0.019	0.030
	(± 0.025)	(± 0.036)	(± 0.045)	(± 0.050)
	p = 0.001	p = 0.000	p = 0.417	p = 0.239

higher discrimination were less likely to contain IWFs. This pattern was consistent across Life/Earth ($\hat{\gamma}_1 = -0.075$, p < 0.001) and Physical Sciences ($\hat{\gamma}_1 = -0.139$, p < 0.001), suggesting that well-discriminating items in these domains were generally written with fewer flaws. The relationship between IWF frequencies and difficulty parameters showed mixed results. In Life/Earth, the domain with the most questions, there was a significant negative association ($\hat{\beta}_1 = -0.093$,

p < 0.001), indicating that easier items were more prone to contain flaws. However, in Physical Sciences and Math, we did not find significant relationships between difficulty parameters and IWF frequencies (p = 0.417 and p = 0.239, respectively). This suggests that in these domains, the number of IWFs may not be a reliable predictor of item difficulty.

4.2 RQ2: Identifying High-Impact IWFs

The second regression analysis aimed to identify which specific IWF criteria are most strongly associated with question discrimination and difficulty parameters. For each dataset and IWF criteria $f \in \{1, \dots, 19\}$, Figure 2 presents the estimated discrimination $(\hat{\gamma}_{1,f})$ and difficulty coefficients $(\hat{\beta}_{1,f})$ along with their 95% confidence intervals. Statically significant coefficients (p < 0.05) are highlighted in green. Examining the combined dataset of 7,126 MCQs, we found significant associations between IRT discrimination and 15 of the 19 IWF criteria, while 13 criteria were significantly associated with difficulty. Among domain-specific datasets, Math exhibited the highest number of significant discrimination coefficients (12), despite having the smallest sample size

Table 6: Regression Task. We train models that employ IWF features to predict MCQ's discrimination and difficulty parameters.
All Pearson correlation coefficients (r) are statistically significant at $p < 0.001$.

Parameter	All		Life/Earth		Physical			Math				
	RMSE	R^2	r	RMSE	R^2	r	RMSE	R^2	r	RMSE	R^2	r
Discrimination												
Lin. Regr.	0.491	0.121	0.348	0.396	0.129	0.359	0.476	0.178	0.422	0.666	0.071	0.269
Rnd. Forest	0.487	0.138	0.373	0.396	0.131	0.362	0.475	0.185	0.430	0.666	0.071	0.268
Grad. Boost.	0.485	0.142	0.377	0.395	0.132	0.364	0.472	0.192	0.439	0.666	0.071	0.268
MLP	0.486	0.141	0.375	0.396	0.130	0.361	0.474	0.187	0.433	0.666	0.072	0.273
Difficulty												
Lin. Regr.	1.128	0.115	0.338	1.161	0.189	0.435	1.099	0.102	0.319	0.914	0.017	0.141
Rnd. Forest	1.067	0.209	0.457	1.109	0.259	0.510	1.054	0.174	0.420	0.917	0.012	0.156
Grad. Boost.	1.064	0.213	0.462	1.111	0.257	0.507	1.062	0.161	0.405	0.914	0.018	0.136
MLP	1.062	0.216	0.465	1.106	0.264	0.514	1.043	0.192	0.438	0.908	0.030	0.176

(N=1,128), suggesting stronger associations with IWF criteria compared to Earth/Life (9) and Physical Sciences (11). In contrast, difficulty coefficients were more frequently significant for Life/Earth (10) and Physical Sciences (10) than for Math (6), highlighting differences in how IWFs impact IRT parameters across educational domains.

Shifting our focus on individual IWFs, we found that the flaws most negatively associated with IRT discrimination and difficulty parameters were "longest option correct" ($\hat{\gamma}_{1,f}$ = $-0.370, \ \hat{\beta}_{1,f} = -0.691),$ "more than one correct" $(\hat{\gamma}_{1,f} =$ -0.366, $\hat{\beta}_{1,f} = -0.928$), and "all of the above" ($\hat{\gamma}_{1,f} =$ $-0.322, \hat{\beta}_{1,f} = -0.806$). These flaws likely introduce textual cues that inadvertently hint at the correct answer, diminishing the quality of test items. We observed that the "lost sequence" criteria had a positive discrimination coefficient $(\hat{\gamma}_{1,f} = 0.314)$ and was also significant for two of the three domain-specific datasets. Several IWFs were associated with increased question difficulty, including "convergence cues" $(\hat{\beta}_{1,f}=0.679)$, "grammatical cues" $(\hat{\beta}_{1,f}=0.526)$ and "negative wording" ($\hat{\beta}_{1,f} = 0.454$), suggesting that these flaws may contribute to cognitive load or confusion beyond the intended subject knowledge assessment.

4.3 RQ3: IWF-Based IRT Predictions

Using the IWF annotations as input features, we trained machine learning models to predict questions' difficulty and discrimination parameters. The performance of the resulting models, as shown in Table 6, varied across educational domains and predicted parameters. For the discrimination parameter, when trained on the dataset comprising all 7,126 MCQs, the models achieved Pearson correlation coefficients (r) ranging from 0.348 to 0.377 and explained variance (R^2) ranging from 0.121 to 0.141, indicating moderate predictive strength. For the difficulty parameter, the Random Forest and MLP models showed the highest Pearson correlations (r = 0.457 and r = 0.465, respectively) and explained variance ($R^2 = 0.209$ and $R^2 = 0.216$, respectively), suggesting more effective utilization of the IWF features. Notably, non-linear models (Random Forest, Gradient Boosting, and MLP) consistently outperformed the linear regression model, indicating that modeling non-linear interactions between IWF features can improve predictive accuracy. We observed substantial differences between the domain-specific models. For instance, in Life/Earth sciences, the Random

Table 7: Classification task. We train models that employ IWF features to predict MCQs with low discrimination and low/high difficulty. To highlight class imbalance, we include a baseline assigning all MCQs to the majority class in gray.

Task	L	ife/Eart	h	Physical			
	ACC	AUC	F1	ACC	AUC	F1	
Disc. Low	0.879	0.500	0.000	0.895	0.500	0.000	
Log. Regr.	0.880	0.736	0.249	0.909	0.784	0.435	
Rnd. Forest	0.890	0.746	0.344	0.907	0.781	0.403	
Grad. Boost.	0.888	0.741	0.354	0.910	0.799	0.432	
MLP	0.882	0.730	0.364	0.908	0.779	0.400	
Diff. Low	0.858	0.500	0.000	0.908	0.500	0.000	
Log. Regr.	0.910	0.818	0.649	0.934	0.778	0.516	
Rnd. Forest	0.910	0.809	0.636	0.932	0.760	0.498	
Grad. Boost.	0.910	0.825	0.644	0.933	0.784	0.506	
MLP	0.908	0.808	0.639	0.932	0.757	0.514	
Diff. High	0.979	0.500	0.000	0.983	0.500	0.000	
Log. Regr.	0.979	0.684	0.000	0.983	0.789	0.000	
Rnd. Forest	0.979	0.706	0.000	0.983	0.618	0.000	
Grad. Boost.	0.979	0.688	0.000	0.983	0.727	0.000	
MLP	0.979	0.681	0.021	0.983	0.675	0.000	

Forest model achieved the highest Pearson correlation (r=0.510) and explained variance ($R^2=0.259$). However, in Math, all models struggled with both discrimination (max $R^2=0.071$) and difficulty predictions (max $R^2=0.030$).

We evaluate the utility of IWF features for predicting MCQs with low discrimination and low/high difficulty in Life/Earth and Physical Science datasets, where the prior regression analysis confirmed the predictive power of IWFs. Table 7 shows that models trained on IWF features achieve AUC scores of up to 0.746 (random forest) and 0.799 (gradient boosting) for low discrimination, and 0.825 (gradient boosting) and 0.784 (logistic regression) for low difficulty. While the AUC scores suggest strong predictive performance, F1 scores remain relatively low for low-discrimination MCQs (peaking at 0.364 for Life/Earth and 0.435 for Physical Sciences), indicating challenges due to class imbalance (Table 4). In contrast, F1 scores for low-difficulty questions are considerably higher, with logistic regression achieving 0.649 for Life/Earth and 0.516 for Physical Sciences, suggesting that IWFs are particularly informative for identifying lowdifficulty MCQs. In contrast, none of the classifiers trained to predict high difficulty MCQs outperformed a baseline that

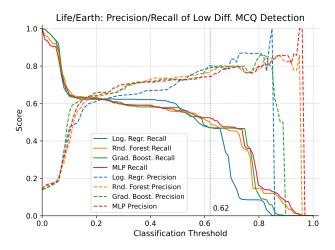


Figure 3: Precision and recall curves for predicting low-difficulty Life/Earth Science MCQs for different classifiers. The curves show trade-off between precision and recall across classification thresholds. Using a threshold of 0.62, logistic regression achieves a precision of 0.801 and a recall of 0.472.

always predicts the majority class. This is likely due to class imbalance and the fact that IWFs are not designed to assess the knowledge required to answer domain-specific questions.

Since the IWF-based classification models demonstrated the highest predictive performance for identifying low-difficulty MCQs in the Life/Earth Science dataset, we conducted a follow-up analysis to assess their potential for automated item pre-screening. Figure 3 illustrates the trade-offs between precision and recall across different classification thresholds. Recall represents the proportion of low-difficulty MCQs correctly identified by the models, while precision reflects the fraction of flagged MCQs that genuinely belong to the lowdifficulty category. By setting the classification threshold to 0.62, the logistic regression model achieves a high precision of 0.801 while maintaining a moderate recall of 0.472. This balance underscores the practical utility of IWF-based classifiers in supporting experts in test item development by enabling early identification of low-difficulty questions, potentially lowering the need for student data collection.

5. DISCUSSION

Our study integrated statistical and machine learning methodologies with large-scale student data, capturing interactions with thousands of questions. This approach provided insights into how qualitative aspects of question design influence traditional measures of question performance derived from item response theory (IRT) [17]. Specifically, we examined the relationships between the standard 19-criteria IWF rubric [58] for MCQs and IRT parameters across various educational domains (e.g., math and natural sciences). Our findings offer quantitative evidence demonstrating how the frequency and specific types of IWFs impact question discrimination and difficulty. Additionally, we validated the utility of IWF evaluations as features for predicting IRT parameters and for identifying low-difficulty questions.

Across the three domains we examined, the frequency of

IWFs consistently relates to item discrimination, yet its relationship to item difficulty appears to be domain-specific. MCQs with fewer flaws tended to show higher discrimination, indicating that IWFs can diminish a question's reliability. As noted in prior work, certain IWFs may inadvertently aid students in guessing the correct answer (e.g., "longest answer correct" or "all of the above") [58, 22], while others add confusion unrelated to the content itself. In either case, such flaws can distort how accurately the question discriminates between more- and less-knowledgeable students. In Life/Earth Sciences, we observed that easier items contained more flaws, suggesting the frequent presence of the flaws that may effectively simplify questions; however, this trend did not surface in Physical Sciences or Math. This discrepancy underscores the possibility that IWFs and item difficulty interact in a domain-dependent manner. It may also reflect variations in how effectively the automated IWF detection methods operate across different subject areas, aligning with previous findings that showed stronger performance in Humanities and Healthcare than in Chemistry [37]. Consequently, while IWF frequency appears to be a reliable indicator of item discrimination overall, its utility in predicting item difficulty likely hinges on both the domain and the strengths or limitations of automated detection techniques.

Our findings indicate that most IWF criteria significantly influence both item discrimination and difficulty, though certain flaws exhibit particularly strong and consistent effects. Specifically, flaws such as "longest option correct" and "all of the above" show the most substantial negative associations with both metrics. This is likely because they introduce cues that enable students to guess the correct answer without engaging with the intended knowledge. In contrast, the "lost sequence" flaw had a positive effect on discrimination across multiple datasets, suggesting that sequencebased tasks may require more focused reasoning skills, thus better distinguishing between higher- and lower-performing students. Additionally, flaws such as "convergence cues". "grammatical cues", and "negative wording" were associated with higher item difficulty. This suggests that these flaws may elevate cognitive load by requiring students to navigate complex text structures rather than directly demonstrating their domain knowledge. Consistent with previous work, the presence of "all of the above" as an answer choice decreased the difficulty of the question [48] While some flaws consistently diminish both question quality and rigor, our findings highlight how specific IWFs exert their influence differently. They might make questions easier to guess or introduce additional cognitive demands that may confuse students. Others appear to have more nuanced effects, warranting further investigation into their role in shaping assessment validity and fairness.

Machine learning models trained to predict question discrimination and difficulty parameters based on IWF annotations achieve moderate predictive power, with performance varying across subject domains (Table 6). Notably, prediction accuracy was higher for Life/Earth and Physical Science questions compared to Math, particularly for difficulty estimation. This aligns with our regression analysis, which revealed stronger associations between IWFs and difficulty parameters in the Science domains (Table 2). Across all prediction tasks, non-linear models (e.g., Gradient Boosting

and MLP) consistently outperformed linear models, highlighting the need to capture complex interactions between individual IWF features. To assess the practical utility of IWF features for item screening, we evaluated classification models designed to identify questions with low discrimination, low difficulty, and high difficulty. Our results suggest that by selecting a classification threshold that balances precision and recall, IWF-based models can assist domain experts in identifying low-difficulty questions early. In particular, criteria such as "all of the above" and "longest option correct" showed strong associations with low item difficulty, likely explaining why our classifiers performed significantly better at predicting low-difficulty MCQs compared to highdifficulty ones. The latter task likely requires models to assess the specific knowledge needed to answer a question within a given domain, underscoring the limitations of IWF features for difficulty prediction.

By examining how qualitative question design guidelines [58] align with robust statistical measurements derived from large student datasets, our study contributes to ongoing research efforts on characterizing effective instructional design principles [29]. From a learning science perspective, rubrics serve as distilled representations of expert knowledge used to assess the quality of educational materials and instruction (e.g., [44, 59, 32]). Understanding the relationship between expert evaluation rubrics and student learning is crucial, especially as AI-driven learning technologies increasingly rely on textual descriptions of effective pedagogical strategies [56, 52, 45, 27].

6. LIMITATIONS AND FUTURE WORK

While this study established relationships between a domaingeneral IWF rubric [58] and statistical measures of question difficulty and discrimination derived from IRT [17], several limitations should be considered. First, our analysis was limited to science and mathematics courses within a large-scale online tutoring platform at the middle and high school levels. Future research should explore the applicability of these findings across other subject areas, including language, humanities, and social sciences. Additionally, further validation is needed in higher and professional education contexts, particularly in medical education, where MCQ-based assessments are widely used [18, 48]. Finally, beyond education, IWFs may influence the reliability of other assessments, such as psychological evaluations of personality traits and mental states, where MCQs play a central role [49]. Investigating these broader implications would enhance our understanding of IWFs across diverse testing environments.

Although the IWF rubric provides a domain-general methodology for experts to assess the pedagogical soundness of test items without relying on student data [58], our findings indicate that its features are only moderate predictors of MCQ difficulty and discrimination parameters (Table 6). By design, IWFs focus on broad design principles, such as ensuring that all distractors are plausible, but do not capture domain-specific nuances related to the knowledge required to solve a particular test item. An item may fully adhere to IWF guidelines yet still exhibit high or low difficulty levels depending on the complexity of the subject knowledge it assesses. To address these limitations, future research could explore hybrid approaches that combine the interpretability

of IWF-based evaluations with the predictive power of deep learning models, which estimate IRT parameters based on semantic analyses of question text [2]. Another promising direction is the development of enhanced evaluation rubrics that integrate human domain expertise with data-driven insights generated by machine learning algorithms, thereby improving their predictive accuracy [30, 34, 7].

Across the courses examined in this study, the IWF analysis identified an average of 1.48 writing flaws per MCQ (Table 4). While many of these flaws may have minimal impact on student learning outcomes, addressing them remains essential for ensuring content quality. Future work will focus on developing AI-assisted content authoring tools to support domain experts in MCQ generation and refinement [37]. Recent advancements in LLM-enabled pipelines for question generation and validation offer promising directions [10, 33, 23]. To enhance the efficiency of question validation, future research will explore natural language processing and reinforcement learning algorithms to reduce the amount of student response data required for reliable IRT parameter identification [35, 61, 54, 53].

Lastly, we emphasize the broader utility of evaluation methodologies that integrate generative AI to scale qualitative assessments based on learning science rubrics with statistical measures derived from student data. This hybrid approach can generate robust and actionable insights for improving educational practice. Future research will extend this framework to evaluate other types of educational materials, such as hints [44, 51, 57], textbooks [59], and illustrations [4]. Additional directions include examining the predictive validity of rubric-based evaluations in educational domains such as project-based learning [14, 20, 1], discourse analysis [32, 12] and programming education [14, 50].

7. CONCLUSION

This paper explored relationships between the 19-criteria Item-Writing Flaws (IWFs) rubric, a domain-general qualitative method for question validation [58], and item response theory (IRT), a traditional, data-driven approach to assessing question quality [17]. Using an automated method, we applied the rubric to over 7,000 multiple-choice questions spanning mathematics, physical sciences, and life/earth science domains, analyzing how the number and types of IWFs impact question difficulty and discrimination parameters. Three key findings emerged. First, a higher number of IWFs was associated with lower item difficulty and discrimination in life/earth sciences, while the relationship was less consistent in mathematics and physical sciences. Second, specific IWF criteria strongly correlated with question difficulty, such as "longest option correct" for easier items and "convergence cues" for harder ones, demonstrating how superficial textual cues can compromise an otherwise well-designed question. Third, while models trained on IWF features did not match the precision of IRT-based methods, they showed promise for preliminary screening, particularly in identifying low-difficulty questions.

These findings show the dual role of domain-agnostic and domain-specific factors in developing high-quality test items. On the one hand, a rubric that flags generic writing flaws can serve as a scalable "first pass", helping content authors

identify potential design issues before pilot testing. On the other hand, IWF features alone are only moderate predictors of IRT parameters, with predictive strength varying across educational domains. This highlights that IWF-based evaluation cannot replace traditional student data-dependent methods, such as those embodied in IRT. Future work could explore hybrid approaches that integrate the interpretability of human-readable rubrics with the flexibility of machine-learning models capable of capturing semantic information related to domain-specific knowledge to enhance the accuracy of IRT parameter predictions. This systematic alignment of qualitative rubrics with quantitative validation not only helps improve item quality at scale but also ensures that computer-assisted assessments support fair, reliable, and pedagogically meaningful testing.

Acknowledgments

We thank Microsoft for support in the form of Azure computing and access to the OpenAI API through a grant from their Accelerate Foundation Model Academic Research Program. We thank the CK-12 Foundation (ck12.org) for providing access to their learning materials and to data on student responses to those materials. This research was supported in part by the AFOSR under award FA95501710218.

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