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Exploring the Impersonal Judgments and Personal Preferences of Raters in Rater-Mediated Assessments With Unfolding Models

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Abstract

The purpose of this study is to explore the use of unfolding models for evaluating the quality of ratings obtained in rater-mediated assessments. Two different judgmental processes can be used to conceptualize ratings: impersonal judgments and personal preferences. Impersonal judgments are typically expected in rater-mediated assessments, and these ratings reflect a cumulative response process. However, raters may also be influenced by their personal preferences in providing ratings, and these ratings may reflect a noncumulative or unfolding response process. The goal of rater training in rater-mediated assessments is to stress impersonal judgments represented by scoring rubrics and to minimize the personal preferences that may represent construct-irrelevant variance in the assessment system. In this study, we explore the use of unfolding models as a framework for evaluating the quality of ratings in rater-mediated assessments. Data from a large-scale assessment of writing in the United States are used to illustrate our approach. The results suggest that unfolding models offer a useful way to evaluate rater-mediated assessments in order to initially explore the judgmental processes underlying the ratings. The data also indicate that there are significant relationships between some essay features (e.g., *word count, syntactic simplicity, word concreteness*, and *verb cohesion*) and essay orderings based on the personal preferences of raters. The implications of unfolding models for theory and practice in rater-mediated assessments are discussed.

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Keywords

unfolding models, rater judgments, essay features, rater-mediated assessments

Rater-mediated performance assessments are widely used in many countries to measure student achievement. Lane (2016) noted that ''performance assessments that measure critical thinking skills are considered to be a valuable policy tool for improving instruction and student learning in the 21st century'' (p. 369). Performance assessments can be meaningfully viewed as rater-mediated assessments because the ratings modeled in our psychometric analyses are obtained from human judges (Engelhard, 2002). One of the critical concerns for rater-mediated assessments is how to evaluate the quality of judgments obtained from raters.

Previous research on evaluating the quality of ratings in rater-mediated assessments is primarily guided by a paradigm for rater cognition that stresses impersonal judgments and cumulative response processes (Engelhard & Wind, 2018). There are a variety of measurement models that can be used to evaluate the ratings, including hierarchical rater model (Patz, Junker, Johnson, & Mariano, 2002), many-facet Rasch model (Linacre, 1989), rater bundle model (Wilson & Hoskens, 2001), and generalized rater model (Wang, Su, & Qiu, 2014). Generalizability theory (Brennan, 1992) is also popular in exploring the attribution of variation due to a rater facet (Marcoulides & Drezner, 2000). In addition, latent class modeling, including signal detection theory (DeCarlo, 2005), and nonparametric methods, such as Mokken scale analysis (Wind & Engelhard, 2015), have been developed for rater-mediated assessments. Earlier studies have used unfolding models to evaluate accuracy ratings in their analyses (Wang, Engelhard, & Wolfe, 2016). Accuracy ratings can be defined as the difference between observed or operational and criterion ratings given by a panel of expert raters.

In this study, observed polytomous ratings are examined to explore rater response processes. A limitation in earlier studies was the lack of consideration of the underlying response processes and the detection of whether raters might use impersonal judgments as intended or personal preferences that may reflect potential biases. The current study is designed to evaluate if the personal preferences of raters play a role in making scoring decisions and to explore the underlying scale based on an unfolding model.

Distinctions Between Impersonal Judgment and Personal Preferences

Engelhard, Wang, and Wind (2018) proposed a conceptual model for evaluating rater-mediated assessments. They stressed the complementary functions between a cognitive perspective that defines a model of human judgmental process and a psychometric perspective that defines an appropriate measurement model. Within the context of rater evaluation, whether a rater is making an impersonal judgment or personal preference is potentially identifiable by the measurement model selected for conducting the psychometric analysis. The current study focuses on the second model regarding the measurement of rater preferences as a potential source of construct-irrelevant variance and systematic bias in ratings using an unfolding model.

The distinction between impersonal judgments and personal preferences is illustrated with the following example from Andrich and Luo (2017):

> Consider the stimuli to be cups of coffee identical in all respects except for fine gradations of the amount of sugar in them. Two different instructions can be given for making comparative selections. Instruction I: Select the cup in each pair which has *more* sugar; Instruction II: Select the cup in each pair that *you prefer*. (p. 2)

The first instruction is intended to be an impersonal judgment, while the second instruction reflects a personal preference.

In this simple example, the differences between impersonal judgments and personal preferences are shown in the format and design of the questions posed to the raters within a pairwise comparison framework. For rater-mediated assessments in a direct response format rather than a comparative format, we can also use this distinction. Based on the instructions in scoring activities, raters are asked to provide ratings of student performances with various degrees of proficiency based on the set of rubrics used to guide the assessment system. Impersonal judgments are expected in rater scoring activities. In spite of training, human raters may still be influenced by their own characteristics and unique prior experiences so that personal preferences may still influence their ratings.

Many research studies have found various kinds of rater effects (Engelhard, 1996; Myford & Wolfe, 2003, 2004; Wolfe, Jiao, & Song, 2015), and cognitive theory has been applied to explore the factors that can influence rater judgments (Crisp, 2012; Wolfe, 2006). The goal of rater training is to stress impersonal judgments reflected in scoring rubrics and to minimize personal preferences that may increase construct-irrelevant variance in the assessment system. As pointed out earlier, the purpose of this study is to suggest the use of an unfolding model for analyzing observed ratings that can be used to detect personal preferences and potential biases. Modeling personal preferences with an unfolding model can be useful addition to other approaches for evaluating the quality of ratings.

Wang, Engelhard, Raczynski, Song, and Wolfe (2017) investigated rater perceptions toward the textual borrowing feature in an integrated writing assessment. The integrated writing assessment usually asks students to write an essay by integrating the information given in source articles. On one hand, Wang et al. (2017) discovered that some raters did not prefer an essay when the essay included too little evidence relevant to the given passages. These raters explained that this was because the instructions ask the students to incorporate relevant details from the source articles. On the other hand, other raters did not prefer an essay when it had too much overlapping with the source articles—for these raters, too much textual borrowing limited the amount of original writing and development of own ideas. In essence, different raters have assigned a lower score for two completely opposite reasons. To conceptualize these ratings, an unfolding response process provides a framework for identifying raters who assign low ratings for different reasons. Unfolding models allow researchers to explore individual differences in rater preferences and to provide targeted feedback to improve rater training practices.

Distinctions Between Cumulative and Unfolding Response Processes

Cumulative and unfolding models are two alternative scaling techniques for modeling the response processes of raters. We briefly compare these two models using illustrative data sets within the context of writing assessments. Tables 1 and 2 highlight the distinctions between cumulative and unfolding response processes. The rating scale model (Andrich, 1978) is used as a representative model for cumulative response process. The data structure underlying a cumulative scale is shown in Table 1 (Panel A). This structure reflects a perfect Guttman pattern that is not estimable due to the extreme scores. We include a dummy coded essay (i.e., Essay 7) and a dummy coded rater (Rater F) that reverse the Guttman pattern for the analysis (Linacre, 2018). Rater F has a score of 1 for Essay 7 and 0 for the actual six essays. Similarly, Essay 7 receives a score of 1 from the pseudo Rater F and 0 from the actual six raters. Andrich's (1978) rating scale model provides scaled measures for student essays based on writing proficiency and for raters based on scoring severity. Panel B displays the expected score function for Rater C with observed average ratings of the essays. Panel C shows the category response function for Rater C, and each curve displays the probabilities of receiving a certain rating given the location of student essays. Panel D shows the variable map with ordered essays and raters based on the Rasch model.

Table 2 (Panel A) shows the unfolding data structure and scaled measures for raters and student essays based on a hyperbolic cosine model (HCM; Andrich, 1996; Luo, 2001). Panel B displays the expected score function for Rater C with observed average ratings of the essays. The student essays that are located further from Rater C's location tend to receive lower scores from this rater; therefore, a rater's location is viewed as the ideal point for this rater's preferences toward student essays. Panel C shows the category response function for Rater C with each curve representing a score point. The dotted line indicates the location of Rater C. The curve for score of 1 has two peaks (below and above rater's ideal point). Panel D shows the unfolding scale using variable map for the ratings in Table 2. Raters who are located closer to the essays on the unfolding scale provide higher scores that reflect rater preferences toward these essays.

The Joint (*J*) Scale and Individual Rater (*IR*) Scales

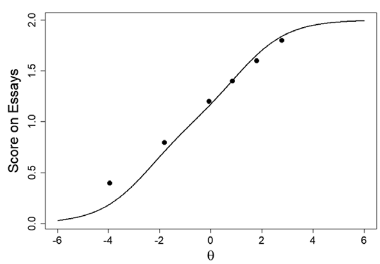
Coombs (1964) introduced unfolding models based on a deterministic framework where person responses are either yes (1) when the distance between a statement and a person's location is within the statement threshold or no (0) if the distance is

Table 1. Illustration of Cumulative Data Structure for Rating Scale (Six Essays and Five Raters).

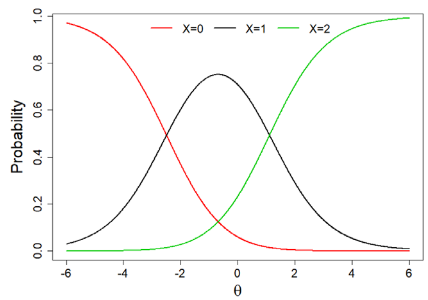
Panel A: Cumulative ratings

	Raters						
Essays	A	B	C	D	E	Proportion	Essay estimate (θ)
1	1	2	2	2	2	.90	2.77
2	1	1	2	2	2	.80	1.78
3	1	1	1	2	2	.70	0.84
4	0	1	1	2	2	.60	−0.07
5	0	0	1	1	2	.40	−1.82
6	0	0	0	1	1	.20	−3.95
Proportion	.25	.42	.58	.83	.92		
Rater estimate (λ)	2.36	0.75	−0.69	−3.01	−3.95		

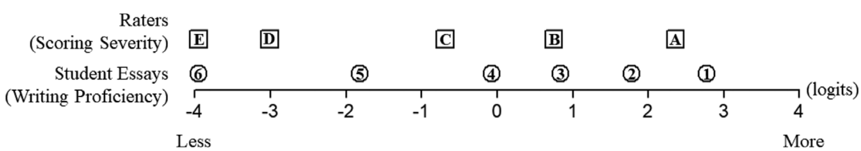
Panel B: Expected curve for Rater C



Panel C: Category response function for Rater C



Panel D: Variable map based on Rasch scale



Note. Proportion refers to the proportion of observed sum scores in maximum sum scores.

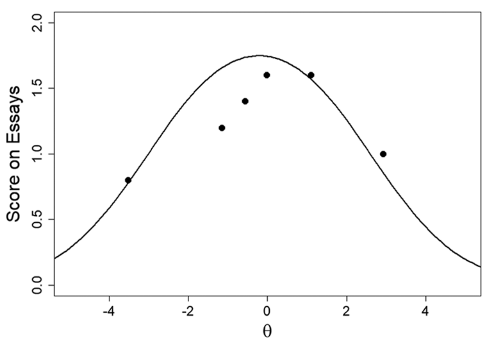
outside the threshold. Coombs (1964) used a *Joint (J) scale* to represent the common underlying continuum that orders persons and statements in a consistent fashion. By folding a *J* scale at a person's location, an *Individual (I) scale* can be obtained that shows a person's personal preferences toward all the statements. Numerically, the absolute distance between a person's location and the location of each statement

Table 2. Illustration of Unfolding Data Structure for Rating Scale (Six Essays and Five Raters).

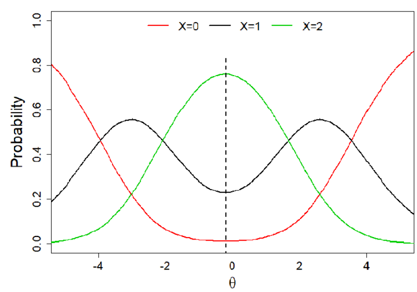
Panel A: Unfolding ratings (X)

Essays (θ)	Raters (λ) A	B	C	D	E	Proportion	Essay estimate (θ)
1	2	1	1	1	0	.50	2.92
2	2	2	2	1	1	.80	1.10
3	1	2	2	2	1	.80	−0.02
4	1	1	2	2	1	.70	−0.56
5	0	1	2	2	1	.60	−1.15
6	0	0	1	1	2	.40	−3.53
Proportion	.50	.58	.83	.67	.50		
Unfolding estimate (λ)	2.73	1.26	−0.21	−0.68	−3.10		

Panel B: Expected curve for Rater C

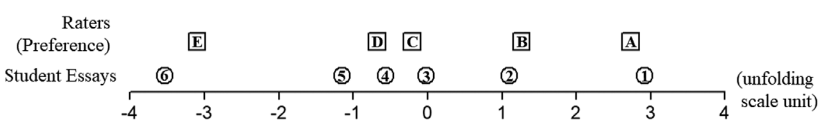


Panel C: Category response function for Rater C



Panel D: Variable map based on unfolding scale

J scale for preferences



Note. Proportion refers to the proportion of observed sum scores in maximum sum scores.

determines the ordering of the statements on an *I* scale. Within the context of rater-mediated assessments, the *J* scale reflects the joint calibration of raters and essays, and it can be represented by a traditional visual representation—the variable map (Table 2, Panel D). Each rater has an *Individual Rater (IR) scale* that represents the

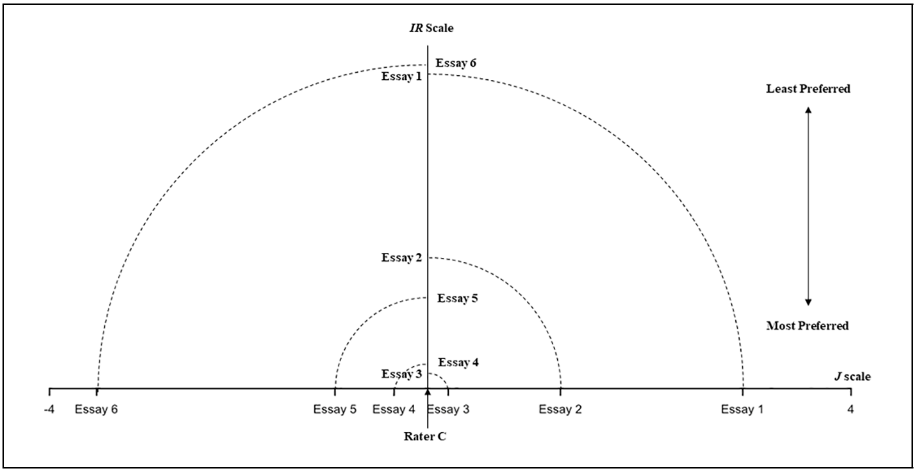


Figure 1. The joint (*J*) scale with individual rater (*IR*) scale for Rater C.

preference orderings toward the essays. An *IR* scale can be obtained by folding the *J* scale at a rater's location. Theoretically, the construction of a *J* scale is based on unfolding *IR* scales of all the raters. When good model–data fit is met, the *J* scale can be used to predict the preference orderings of each individual rater based on their locations on the *J* scale.

The unfolding model is constructed by folding the extreme categories of cumulative response process so that the model can better correspond to the data (Andrich & Luo, 1993). Within the context of rater-mediated assessments, we use HCM for polytomous responses (HCM-P) to examine whether the ordering of essays by raters leads to the creation of a meaningful *J* scale. In other words, we want to know if the unfolded *IR* scales can construct a single *J* scale that indicates a common preference ordering of the essays. This provides the opportunity to empirically detect the underlying response process used by raters. In the second part of this study, we explore the features of essays along the continuum defined by the *J* scale that may influence rater preference.

The *J* scale based on the hypothetical data in Table 2 is plotted in Figure 1. The *IR* scale for C illustrates how the locations on the *J* scale reflect this rater's preferences toward the essays. The *IR* scale is constructed by folding the *J* scale at Rater C's ideal point. The ordering of the essays on the *IR* scale is based on the absolute distance between locations of essays and Rater C reflecting preference proximity of the essays to the raters. A smaller absolute distance indicates a higher preference of Rater C for an essay. Therefore, Essay 3 is preferred over the other essays by Rater C and Essay 6 is the least preferred. Figure 2 shows the *IR* scales for all raters. Each rater's preference orderings can be read from bottom to top on an *IR* scale with essay index.

In this study, we suggest that the cognitive processes underlying rater scoring activity can be viewed as preferences with rating categories implying an ordering

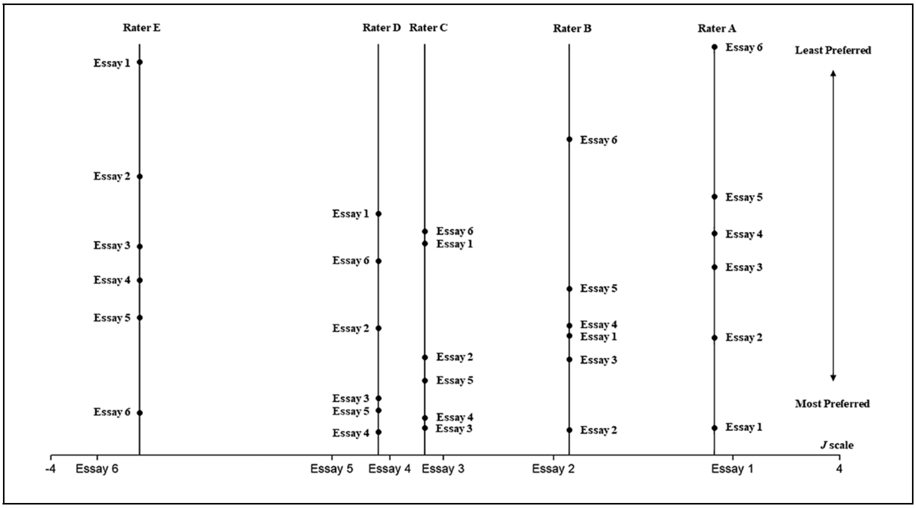


Figure 2. The joint (*J*) scale with all individual rater (*IR*) scales.

from the least preferred to the most preferred. Even though raters are expected to use a cumulative rating process, some raters might still assign lower ratings to the essays that they prefer less and higher ratings to the ones they prefer more due to a variety of biases. Individual rater preferences may lead to higher or lower ratings for essays than deserved based on the intended scoring rubrics. The unfolding scale defines a continuum with the potential for detecting differential ordering of the essays due to personal preferences.

Purpose of Study

The purpose of this study is to describe the use of an unfolding model for evaluating the psychometric quality of rater-mediated assessment system. Specifically, we examine (a) if raters are using personal preferences to inform their ratings and (b) if raters are being influenced by their personal preferences for certain aspects of student performance.

To address these two research questions, we use a HCM-P to analyze observed ratings in a writing assessment. Next, we use the essay feature indices obtained with the Coh-Metrix text analyzer (McNamara, Louwerse, Cai, & Graesser, 2005) to explore the substantive interpretation of the underlying continuum represented by the common *J* scale.

Method

Data Description

We conducted a secondary analysis of data presented in Wang, Engelhard, Raczynski, Song, and Wolfe (2017). These data are based on ratings obtained in a large-scale writing assessment for Grade 7 students. Among the items in the instrument, the essay item being examined in this study is designed to evaluate students' narrative skills in writing based on two reading passages. Twenty trained operational raters scored 100 student essays on two domains. The first domain evaluated the idea development, organization, and coherence (IDOC) features of the essays with five rating categories (0-4). A second domain evaluated the language usage and convention (LUC) features of the essays with three rating categories (0-2). Separate data analyses were conducted for each domain (IDOC and LUC) to provide more detailed information.

Description of a HCM-P

The HCM-P (Andrich, 1996; Luo, 2001) is used in this study, and it was formed by folding Andrich's (1978) rating scale model. The specification of HCM-P for observed ratings was proposed by Luo (2001):

$$P\left(X_{ij}=k\right)=\frac{\left[\cosh\left(\theta_i-\lambda_j\right)\right]^{m-k}\prod_{l=1}^{k}\cosh\left(\rho_{jl}\right)}{\sum_{k=0}^{m}\left[\cosh\left(\theta_i-\lambda_j\right)\right]^{m-k}\prod_{l=1}^{k}\cosh\left(\rho_{jl}\right)}, \tag{1}$$

when $k=0$, $\prod\limits_{l=1}^{k}\cosh\left(\rho_{jl}\right)\equiv 1$; where k = 0, …, m with m rating categories; X_{ij} = rating score for student essay i from rater j; θ_i = writing proficiency reflected by student essay i and i = 1, . . ., I; λ_j = preference of rater j, and j = 1, . . ., J; ρ_{jl} = rater threshold parameter that was constrained to be equally distanced, so that $\rho_{jl}-\rho_{j(l+1)}=\zeta_j$, and ζ_j we call the rater unit parameter reflecting the latitude of preference for rater j.

Model Analysis and Fit Statistics

The RateFOLD software (Luo & Andrich, 2003) is used for the data analyses. Joint maximum likelihood estimation with an iterative Newton–Raphson algorithm is implemented in the RateFOLD computer program. An overall test of fit is available based on a Pearson χ^2 statistic:

$$\chi^2=\sum_{i=1}^{I}\sum_{g=1}^{G}\frac{\left(\sum\limits_{i\in g}f_{ij}-\sum\limits_{i\in g}P_{ij}\right)^2}{\sum\limits_{i\in g}P_{ij}\left(1-P_{ij}\right)}, \tag{2}$$

where $g=1,\ldots,G$ with G intervals. Student essays were classified into intervals. $\sum\limits_{i\in g}f_{ij}$ refers to the observed proportion of interval g, and $\sum\limits_{i\in g}P_{ij}$ represents the expected value based on the parameter estimates for interval g. We used five class intervals (i.e., $G=5$). A nonsignificant test indicates good overall model–data fit.

The rater unit parameter can be set to be equal across raters. Whether raters share a common unit parameter was examined using a likelihood ratio test. We denoted the likelihood obtained with variant units as $L_{\hat{\rho}_j}$, and the likelihood with a common unit as $L_{\hat{\rho}}$. The null hypothesis is that the unit parameter is the same for every rater ($\rho_1 = \cdots = \rho_{20} = \rho$). A chi-square statistic can be used and shown below.

$$\chi^2 = -2\log\left(L_{\hat{\rho}}/L_{\hat{\rho}_j}\right). \tag{3}$$

Coh-Metrix Essay Feature Indices

We calculated essay feature indices for 100 essays using the Coh-Metrix text analyzer (McNamara et al., 2005). Graesser, McNamara, and Kulikowich (2011) performed a principal component analysis on 54 Coh-Metrix indices for 37,520 texts in the Touchstone Applied Science Associates corpus. They extracted eight components that accounted for 67.30% of the variation in the text. These eight components are *narrativity, syntactic simplicity, word concreteness, referential cohesion, deep cohesion, verb cohesion, connectivity*, and *temporality*. In this study, we used the *z* scores provided in Coh-Metrix 3.0 for the eight components. In addition, a descriptive measure, *word count*, was also obtained. This variable is on a raw score metric reflecting the number of words in a text. The descriptions of these nine features from the Coh-Metrix official website are included in the appendix (McNamara et al., 2005).

Dowell, Graesser, and Cai (2016) emphasized the importance of data cleaning before using Coh-Metrix software for text analysis, and they provided two standards for doing it properly. First, there should be a good reason to remove anything from the original text. Second, the researcher should be consistent in conducting data cleaning for all texts. In this study, all 100 essays were originally handwritten by students. Two researchers conducted the transcription of the essays by following three rules that were specified ahead of time: (a) no title, (b) do not correct any spelling mistake or typo, and (c) no extra line break after each paragraph. In addition, a randomly selected set of 59 essays were transcribed by both researchers and compared for consistency in following the rules. Based on initial screening using the Coh-Metrix analyzer, the sentences and paragraphs were correctly separated and counted for all essays.

Results

The results section has three parts. First, we discuss Domain 1 related to IDOC. Next, we examine Domain 2 related to LUC. Finally, we describe relationship between the *J* scales for each domain and a set of Coh-Metrix Essay Feature Indices.

Unfolding Measures for Domain 1: Idea Development, Organization, and Coherence

The overall test of fit for the ratings on IDOC domain indicated that the observed ordering of the essays conforms to the expected orderings based on the HCM-P,

Table 3. Summary of Parameter Estimates for Rater and Essay Facets Based on Hyperbolic Cosine Model for Polytomous Responses (HCM-P).

	IDOC domain			LUC domain		
	Rater location (λ_j)	Rater unit (ρ_j)	Essay location (θ_i)	Rater location (λ_j)	Rater unit (ρ_j)	Essay location (θ_i)
N	20	20	100	20	20	100
Mean	.00	1.50	−1.78	.00	1.87	1.43
SD	.26	0.07	3.18	.25	NA	2.66
Minimum	−.52	1.36	−5.64	−.30	1.87	−5.39
Maximum	.53	1.57	5.94	.61	1.87	5.04

Note. The rater unit parameter is constant for the LUC domain with a value of 1.87. IDOC = idea development, organization, and coherence; LUC = language usage and convention.

$\chi^2(76) = 58.86, p = .96$. In other words, the individual preference scales of raters can be unfolded to represent a common *J* scale. The likelihood ratio test showed that the model with variant rater unit estimates fit significantly better than the model with a common unit for raters, $\chi^2(18) = 44.58, p < .05$. This suggests that raters have varying latitudes of preferences, and it implies a potential inconsistent use of rating scales in the IDOC domain. Therefore, different unit parameters were estimated for each rater.

The range of the essay distribution was wider than the range of rater location estimates (Table 3). Table 4 lists the rater locations, unit parameter estimates, and fit statistics for individual raters. The variable map for the unfolding scale for IDOC domain is shown in Panel A of Figure 3. The summary statistics and the variable map indicate that raters shared similar preference orderings on their *IR* scales. In addition, the rater unit parameters had a mean of 1.50 with a standard deviation of .07. Even though varying unit parameters were found based on the likelihood ratio test, the differences were not very large.

Figure 4 (Panel A) presents the category response function and the expected curve with average ratings of five essay groups for Rater 1. In the category response curve, rater location determines the center of the curves on the scale and the unit parameter tunes the width. Each curve is single-peaked so that the probability of preferring an essay declines monotonically from a rater's location on the *J* scale. The expected function curves and chi-square tests can be used as rater fit measures. For instance, Rater 1 had a chi-square value of 0.76, which was not significant, and this indicates that Rater 1 had good fit to the model. In summary, the chi-square values of all 20 raters ranged from 0.76 to 6.06 and none of them had a significant *p* value. Therefore, all the raters had good model fit indices.

Figure 5 shows the relationship between observed proportions of essay scores and HCM-P essay location estimates on IDOC domain. The observed proportions were obtained by dividing the sum of raw ratings by the maximum score (i.e., 20 × 4 = 80). A polynomial curve was fit, and it explained 96.94% of the variantion. This

Table 4. Rater Parameter Estimates Based on Hyperbolic Cosine Model for Polytomous Responses (HCM-P) Within Each Domain.

	IDOC Domain						LUC Domain[a]			
					Fit statistic				Fit statistic	
Rater	Location	*SE*	Unit	*SE*	χ^2	*p*	Location	*SE*	χ^2	*p*
1	−.22	.07	1.57	.03	0.76	.94	−.01	.08	2.12	.71
2	−.02	.07	1.41	.03	0.96	.91	.07	.08	6.07	.17
3	.53	.07	1.46	.02	5.73	.20	−.13	.08	4.75	.30
4	−.27	.07	1.57	.03	3.90	.40	−.27	.08	1.37	.84
5	−.24	.07	1.50	.03	1.93	.74	.09	.08	0.82	.93
6	−.19	.07	1.56	.03	0.87	.93	.61	.09	5.20	.25
7	−.28	.07	1.52	.03	1.20	.87	−.07	.08	0.81	.94
8	.09	.07	1.51	.03	1.43	.83	.43	.09	4.39	.34
9	.33	.07	1.47	.03	2.08	.71	−.26	.08	9.40	.03
10	.27	.07	1.57	.03	6.06	.17	−.02	.08	2.72	.59
11	.26	.07	1.57	.03	4.05	.38	.15	.08	1.92	.74
12	−.09	.07	1.42	.03	1.99	.73	−.30	.08	7.26	.10
13	−.07	.07	1.36	.02	3.19	.51	−.12	.08	2.78	.59
14	.23	.07	1.48	.03	3.30	.50	.46	.09	7.79	.08
15	−.22	.07	1.57	.03	3.12	.53	.03	.08	7.00	.11
16	.24	.07	1.53	.03	4.12	.37	−.19	.08	4.59	.31
17	−.52	.07	1.57	.03	4.84	.29	−.18	.08	2.96	.55
18	.06	.07	1.40	.02	3.32	.49	−.10	.08	2.16	.70
19	.20	.07	1.51	.03	4.23	.36	−.09	.08	3.71	.43
20	−.09	.07	1.47	.03	1.78	.77	−.11	.08	4.07	.38

Note. IDOC = idea development, organization, and coherence; LUC = language usage and convention; *SE* = standard error.
[a]The rater unit parameter is constant for the LUC domain with a value of 1.87.

serves as an important indicator of good fit of HCM-P to the data. As indicated by this polynomial relationship, essays with higher scores had HCM-P location measures closer to zero, and those with lower scores were on either of the two sides of the continuum.

Unfolding Measures for Domain 2: Language Usage and Convention

Based on the analyses of ratings for the LUC domain, we found good overall model–data fit, $\chi^2(76) = 81.90, p = .30$. The test for a common unit parameter for raters was not significant, $\chi^2(18) = 13.25, p = .78$, indicating raters shared similar latitude of preferences toward the essays.

Next, a summary of rater and essay parameter estimates are shown in Table 3. A common unit parameter was estimated for all raters with a value of 1.87. The distribution of raters was much more centralized than the distribution of student essays,

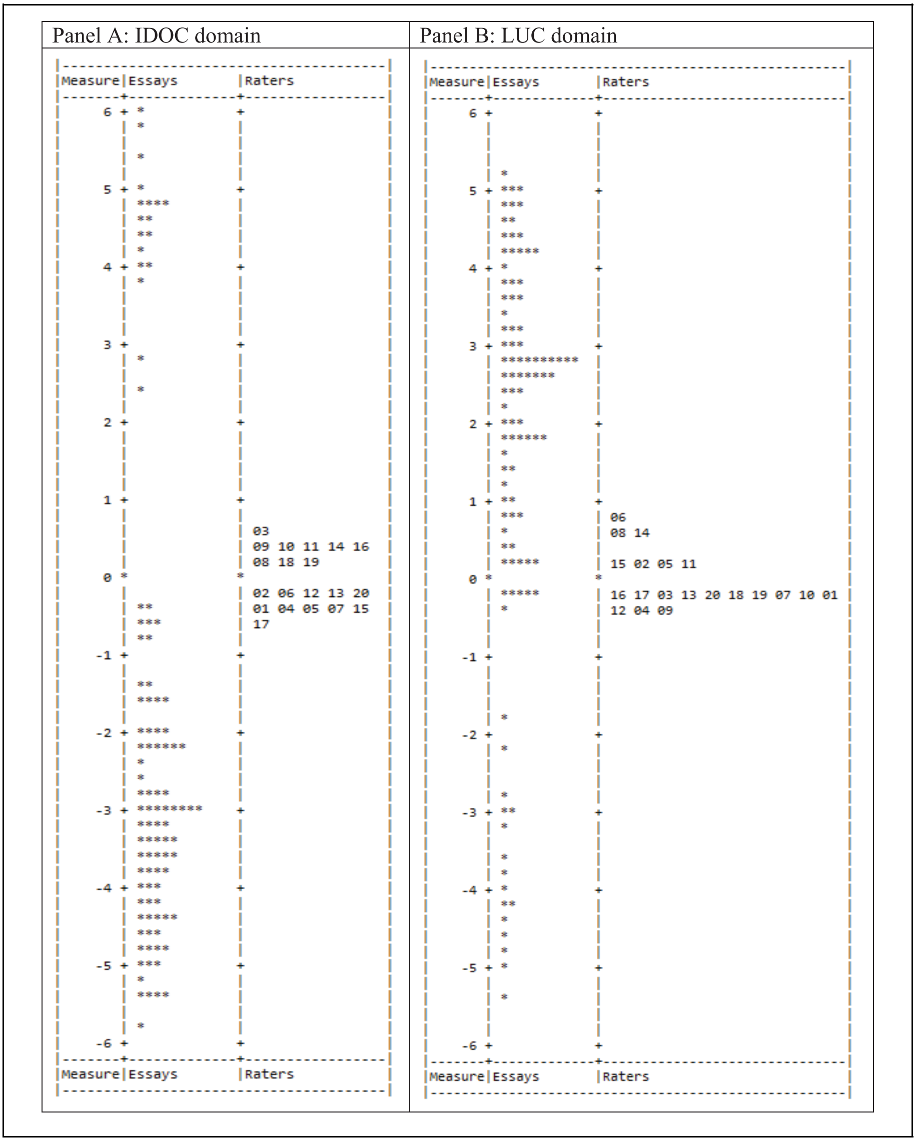


Figure 3. The variable maps based on hyperbolic cosine model for polytomous responses (HCM-P) for each domain.

Note. IDOC = idea development, organization, and coherence; LUC = language usage and convention.

which can also be seen in Figure 3 (Panel B). Therefore, raters shared relatively consistent preferences toward the student essays on the LUC domain. The category response curve and expected score function for Rater 9 are shown in Panel B of

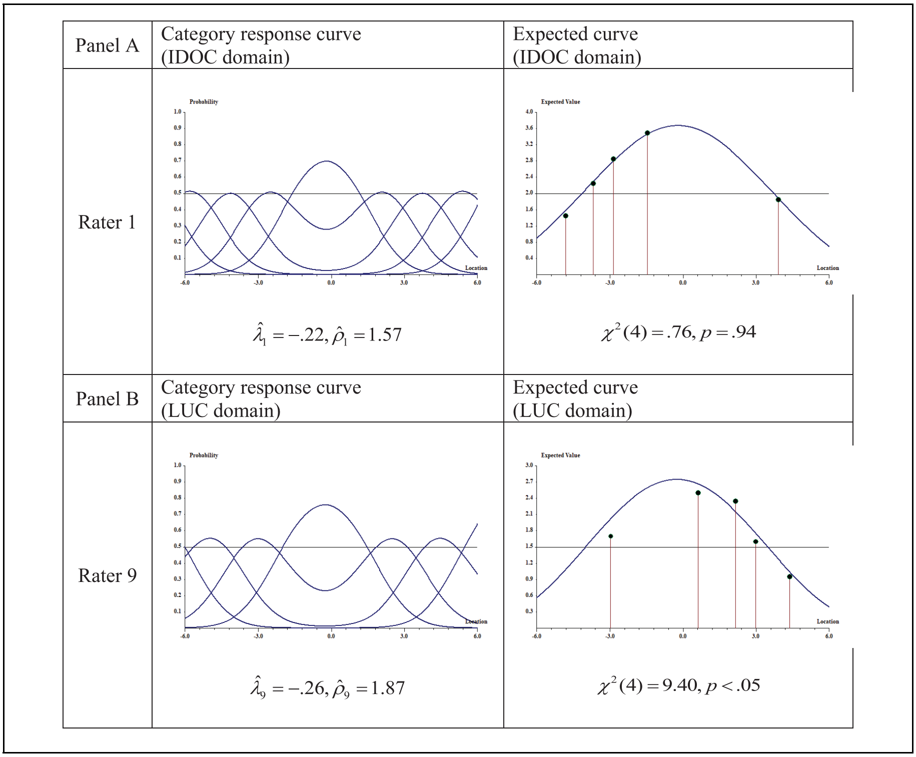


Figure 4. Category response curves and expected score curves for two raters.
Note. IDOC = idea development, organization, and coherence; LUC = language usage and convention.

Figure 4. The rater fit statistics reflected by chi-square values ranged from 0.81 to 9.40 (Table 4). Rater 9 is diagnosed as a misfitting rater on the LUC domain. The other raters had acceptable fit to the model in the LUC domain.

Figure 6 shows the relationship between observed proportions and HCM-P essay location estimates for LUC domain. A polynomial curve explained 97.14% of the variation in this relationship. Student essays with higher scores were located in the middle of the scale, and those with lower scores were on the two tails. This finding applied to both domains that HCM-P divided the essays with lower scores into two observable subsets. Next, we used essay feature indices to explore a substantive explanation for the underlying unfolding continuum (i.e., *J* scale).

Exploring Unfolding Scales Using Coh-Metrix Essay Feature Indices

To explore a substantive interpretation of the unfolding *J* scale, we examined the relationship between the Coh-Metrix essay feature indices and essay location measures based on HCM-P. We treated the unfolding measures for the essays as an independent

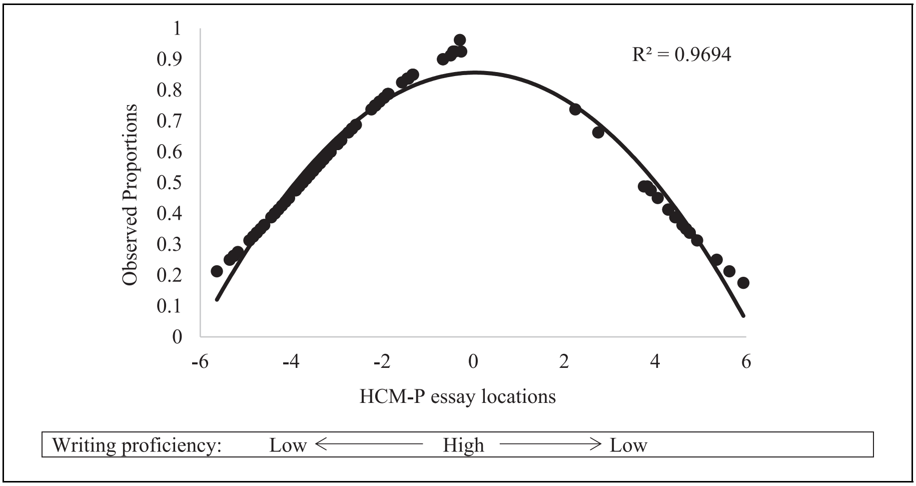


Figure 5. Relationship between unfolding essay locations and observed proportions on idea development, organization, and cohesion (IDOC) domain.

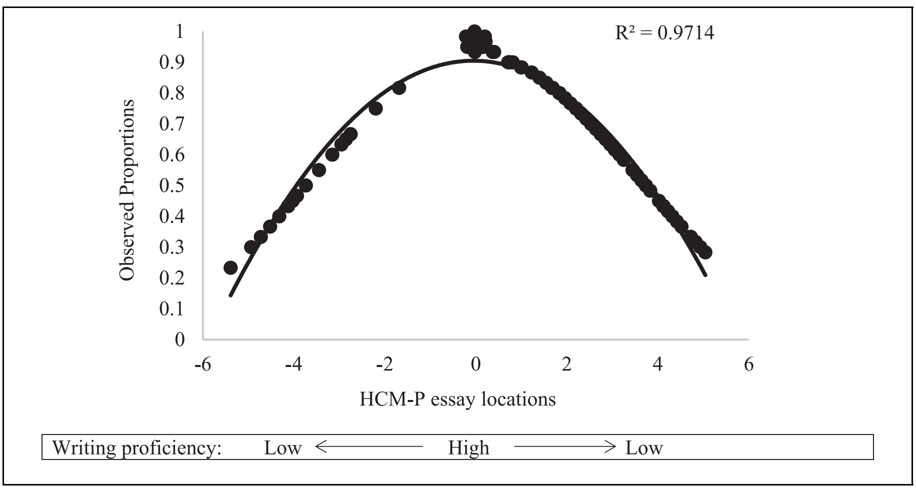


Figure 6. Relationship between unfolding essay locations and observed proportions on language usage and convention (LUC) domain.

variable (x-axis) and Coh-Metrix measures as dependent variables (y-axis). Both linear and quadratic regression functions were fit for each essay feature with HCM-P essay location measures in each domain separately. Two situations were considered: (a) the quadratic term of a second-order polynomial regression function was significant at .05 alpha level and (b) the quadratic term of a second-order polynomial curve was not significant, and meanwhile the slope parameter of a linear regression function was significant at .05 alpha level. The other situations were omitted for brevity where neither the slope of a linear function nor the quadratic term of a polynomial curve were statistically significant.

Figure 7 shows the results for three essay features—*word count, syntactic simplicity*, and *word concreteness*. Each of these had a significant quadratic term in a second-order polynomial regression function of HCM-P essay measures in IDOC domain. The fitted values are displayed on the y-axis, and the HCM-P essay location measures are shown on the x-axis. The estimates for the quadratic term and the variation explained by the curve (R^2) are reported. Regarding *word count*, longer essays were generally preferred by the raters and shorter essays were less preferred. In terms of *syntactic simplicity*, essays comprising sentences in simpler and more familiar syntactic structures were preferred over the essays using unfamiliar syntactic structures. As to *word concreteness*, essays containing more abstract words received higher scores, and those using more concrete words received lower scores.

Figure 8 displays the relationship between Coh-Metrix indices and HCM-P essay location measures of LUC domain. Similar results were found on the same three essay features—*word count, syntactic simplicity*, and *word concreteness*. Furthermore, we observed linear relationship for *deep cohesion* and *verb cohesion* indices with HCM-P essay measures on LUC domain. *Deep cohesion* had a significant negative slope estimate implying that the essays containing more or fewer causal and intentional connectives were less preferred than the essays with a medium-level usages of these connectives. A significant negative slope parameter estimate was also reported for *verb cohesion*, indicating that raters preferred essays with medium usage of overlapped verbs in the text over essays having too many or too few uses of repeated verbs.

A unique feature of unfolding models is the generation of *IR* scales for each rater and the opportunity to explore factors influencing individual preference orderings of the student essays. By calculating the absolute distances from a rater's location to 100 essays' locations, we obtained two *IR* scales for each rater on two domains separately. To investigate an individual rater's preferences, we can examine the relationship between essay locations (i.e., absolute distances) on an *IR* scale and Coh-Metrix essay measures. For instance, based on the *IR* scale of Rater 1 on IDOC domain, the correlation between HCM-P essay locations on *IR* scale and Coh-Metrix measures was −.82 for *word count*, −.34 for *syntactic simplicity*, and .40 for *word concreteness*. This indicated that Rater 1 preferred the essays with longer length, more familiar syntactic structures, and more abstract words.

It is worth noting that the raters who participated in this study received intensive training before they started scoring the essays. As expected, the raters had close locations on the *J* scale relative to student essays, and this provides evidence that they share similar *IR* scales with preference orderings of essays. However, different rater unit parameter estimates were suggested for ratings in the IDOC domain, and this reflected different latitudes of preference toward certain aspects of the essays. For

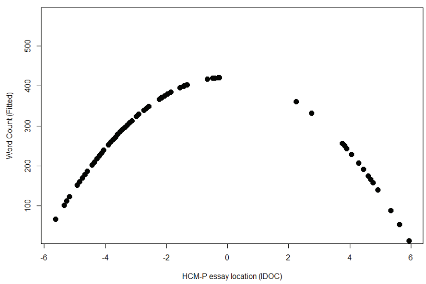
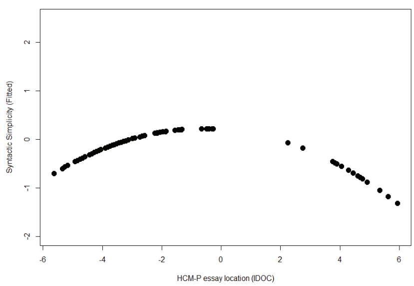
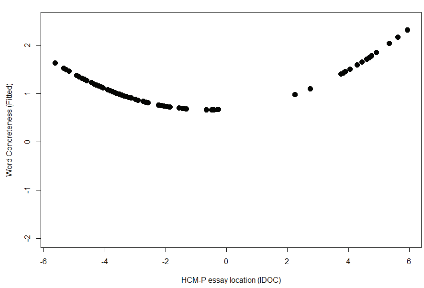
Essay feature	Relationship	Estimates
Word count		Quadratic term = -983.22 (SE = 68.43), $t = -14.37, p < .05$. $R^2 = .68$
Syntactic simplicity		Quadratic term = -3.12 (SE = .84), $t = -3.69, p < .05$. $R^2 = .15$
Word concreteness		Quadratic term = 3.31 (SE = .82), $t = 4.05, p < .05$. $R^2 = .18$

Figure 7. Relationship between Coh-Metrix essay feature indices and unfolding essay measures on idea development, organization, and cohesion (IDOC) domain.
Note. SE = standard error.

instance, a rater with larger unit parameter would prefer a wider range of word counts. For the LUC domain, a common rater unit parameter was estimated, and rater locations were slightly more centralized compared with those of IDOC domain. Therefore, raters had more consistent preferences on the LUC domain. With *IR*

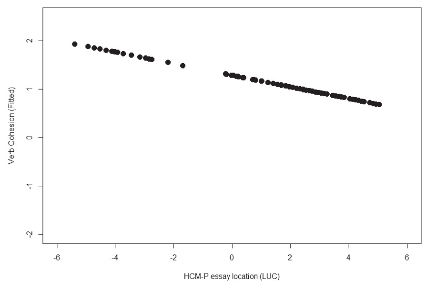
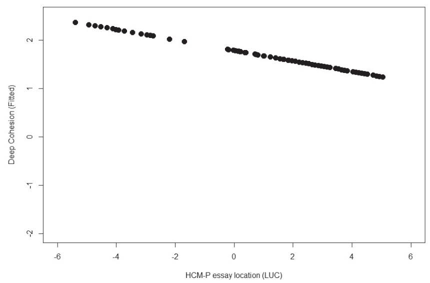
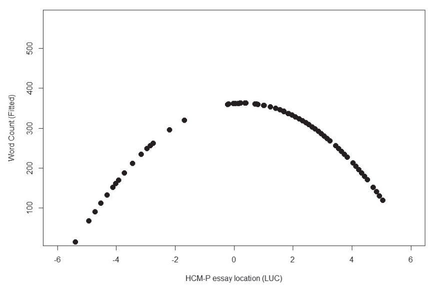
Essay feature	Relationship	Estimates
Verb cohesion		Linear term (slope) = -.12 (SE = .03), $t = -3.64, p < .05$. $R^2 = .12$
Deep cohesion		Linear term (slope) = -.11 (SE = .05), $t = -2.09, p < .05$. $R^2 = .04$
Word count		Quadratic term = -817.12 (SE = 88.33), $t = -9.25, p < .05$. $R^2 = .47$

Figure 8. (continued)

scales, unfolding models can provide more tailored training for each individual rater based on their unique preference orderings.

Discussion

This study focuses on the use of an unfolding model to explore the personal preferences of raters within the context of rater-mediated assessments. Raters are trained to

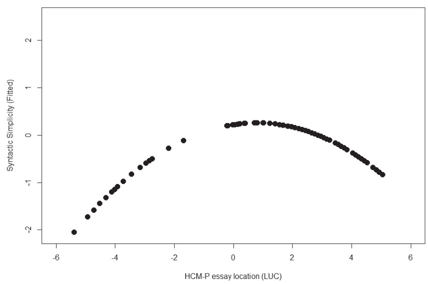
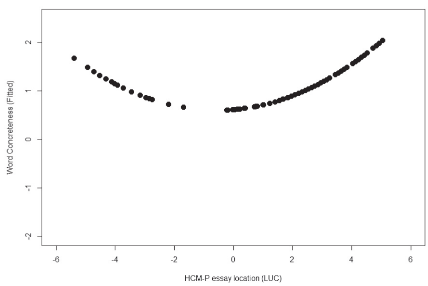
Essay feature	Relationship	Estimates
Syntactic simplicity		Quadratic term = -4.58 (SE = .76), $t = -6.02, p < .05.$ $R^2 = .31$
Word concreteness		Quadratic term = 3.48 (SE = .81), $t = 4.30, p < .05.$ $R^2 = .19$

Figure 8. Relationship between Coh-Metrix essay feature indices and unfolding essay measures on language usage and convention (LUC) domain.
Note. SE = standard error.

provide impersonal judgments with ratings that shall match the rubrics used to guide the assessment system. Even though raters are trained, personal preferences may still appear as sources of construct-irrelevant variance and potential biases.

The HCM-P was used to examine polytomous ratings within the context of a large-scale writing assessment in order to determine whether or not the observed essay ratings can be modeled to uncover a latent continuum of rater preferences. In addition to exploring whether or not raters share a common preference continuum, *J* scale, the characteristics of the essays along this continuum were explored using essay feature indices obtained with the Coh-Metrix text analyzer (McNamara et al., 2005). The preference continuum can also be folded to reveal individual rater preference ordering for essays through the formation of *IR* scale.

In the IDOC domain, the overall test of fit for the ratings indicated that the observed ordering of the essays conforms to the expected orderings based on the HCM-P. In other words, the individual preference scales of raters can be unfolded to represent a consistent *J* scale reflecting common criterion. The summary statistics and the variable map indicated that raters share similar preference orderings on their *IR* scales. Similar results were found for the LUC domain. There was good overall model–data fit with only one diagnosed as a misfitting rater (Rater 9) on the LUC domain. All the other raters had acceptable fit to the model in both domains.

A preference continuum (*J* scale) was created to represent the personal preferences of raters. If the raters used objective judgments based on the scoring rubrics, then the raters theoretically should share comparable ideal points on the preference scale. In addition, all the individual rater preference scales would be the same. To explore the substantive explanations of the *J* scale, we used Coh-Metrix essay feature indices based on text analysis of the essays. We found a second-order polynomial relationship for essay locations with three features—*word count, syntactic simplicity*, and *word concreteness*—on both IDOC domain and LUC domain. A linear relationship with HCM-P essay measures of LUC domain was observed for two essay features—*deep cohesion* and *verb cohesion*. This linear relationship would not be detected by assuming a cumulative response process and ordering essays using a cumulative model. In this case, an unfolding model provided additional information not detected in models assuming cumulative response processes in the exploration of rating quality.

In summary, this study explored the use of an unfolding model to discover the underlying response processes used by raters. Specifically, we used an unfolding model (a) to determine whether raters used personal preferences in making scoring decisions and (b) to explore possible factors that may influence raters and their personal preferences for certain aspects of student essays. The results of this study support the exploration of unfolding models for observed rater judgments that can be used to detect personal preferences and biases. Modeling personal preferences with an unfolding model provides a useful addition to other approaches for evaluating the quality of rater judgments in rater-mediated assessments.

We have several suggestions for future research using unfolding models to evaluate rater preferences. First, researchers should carefully consider the conceptualization of the continuum for unfolding models. Additional work is needed on the substantive interpretation of the latitude of preference parameter that can be included in the HCM. Issues of substantive interpretations of parameters in unfolding models in general need further development, and they also offer challenges when modeling rater responses. We argue that the evaluation of personal preferences with unfolding models is a promising way to look at another class of rater errors that are not evaluated by current measurement models for rater judgments. Future research can apply this research idea within other contexts, such as performance assessments of teaching as well as assessment of student proficiency in science and mathematics.

Another important issue to be addressed in future research is the development of model–data fit indices for unfolding models. We strongly encourage research studies focusing on the development of fit indices for unfolding models especially for HCMs. Research to examine the invariance properties of the *J* and *IR* scales should be conducted related to characteristics of raters, such as prior experience in teaching, expertise in a particular content area, speed in scoring, and English fluency. The quality of handwriting may also be a factor in assessments with a combination of handwritten and typed responses.

Appendix Description for Coh-Metrix Essay Features.

Essay feature	Description
Word count	This is the total number of words in the text.
Narrativity	Narrative text tells a story, with characters, events, places, and things that are familiar to the reader. Narrative is closely affiliated with everyday, oral conversation. Nonnarrative texts on less familiar topics lie at the opposite end of the continuum.
Syntactic simplicity	This component reflects the degree to which the sentences in the text contain fewer words and use simpler, familiar syntactic structures, which are less challenging to process. At the opposite end of the continuum are texts that contain sentences with more words and use complex, unfamiliar syntactic structures.
Word concreteness	Texts that contain content words that are concrete, meaningful, and evoke mental images are easier to process and understand. Abstract words on the other end are more difficult to process.
Referential cohesion	A text with high referential cohesion contains words and ideas that overlap across sentences and the entire text, forming explicit threads that connect the text for the reader.
Deep cohesion	This dimension reflects the degree to which the text contains causal and intentional connectives when there are causal and logical relationships within the text. These connectives help the reader to form a more coherent and deeper understanding of the causal events, processes, and actions in the text. If the text is high in deep cohesion, then those relationships and global cohesion are more explicit.
Verb cohesion	This component reflects the degree to which there are overlapping verbs in the text. When there are repeated verbs, the text likely includes a more coherent event structure that will facilitate and enhance situation model understanding.
Connectivity	This component reflects the degree to which the text contains explicit adversative, additive, and comparative connectives to express relations in the text.
Temporality	Texts that contain more cues about temporality and that have more consistent temporality (i.e., tense, aspect) are easier to process and understand.

Source. McNamara, D. S., Graesser, A. C., McCarthy, P. M., & Cai, Z. (2014). Automated evaluation of text and discourse with Coh-Metrix. New York, NY: Cambridge University Press. (pp. 85-86).

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