ETS®

TOEFL®

Research Reports

Report 73
February 2004

Beyond Essay Length: Evaluating e-rater®'s Performance on TOEFL® Essays

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RR-04-04

Abstract

This study examines the relation between essay length and holistic scores assigned to Test of English as a Foreign Language™ (TOEFL®) essays by e-rater®, the automated essay scoring system developed by ETS. Results show that an early version of the system, e-rater99, accounted for little variance in human reader scores beyond that which could be predicted by essay length. A later version of the system, e-rater01, performs significantly better than its predecessor and is less dependent on length due to its greater reliance on measures of topical content and of complexity and diversity of vocabulary. Essay length was also examined as a possible explanation for differences in scores among examinees with native languages of Spanish, Arabic, and Japanese. Human readers and e-rater01 show the same pattern of differences for these groups, even when effects of length are controlled.

Key words: automatic essay scoring, writing assessment, Test of English as a Foreign Language, TOEFL, e-rater, essay length

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Acknowledgments

We wish to thank Chi Lu for assistance with data preparation and e-rater analysis. We are grateful to the following for their helpful comments on an earlier version of this report: Hunter Breland, Brent Bridgeman, Fred Davidson, Yong-Won Lee, and Larry Stricker.

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Introduction

Automatic systems for scoring essays have been available for decades, but only in the past few years has automatic scoring been used in large-scale high-stakes testing, such as on graduate school admissions exams, or in low-stakes environments, such as Web-based assessment of practice writing (see Burstein & Chodorow, 2002, for an overview). Four scoring systems are currently available commercially: e-rater®, developed at ETS; Project Essay Grade (PEG), offered by Tru-Judge, Inc.; Intelligent Essay Assessor, offered by Knowledge Assessment Technologies; and IntelliMetric, offered by Vantage Learning. Each system trains on essays that human readers have assigned a holistic score (a single number that represents the quality of writing). From the training examples, the system learns which features are the best predictors of essay score. For each new essay, it measures these features and uses the measurements to make its prediction. The differences among the systems lie in the particular features that they extract and in the ways in which they combine the features in generating a score.

Scoring performance is usually measured by comparing the predicted scores on a cross-validation set of essays to the scores assigned by human readers. For current systems, these comparisons have shown impressively high levels of agreement with human reader scores (Burstein & Chodorow, 1999; Elliot, 2002; Herrington and Moran, 2001; Landauer, Laham, & Foltz, 2002; Page, 2002), often comparable to the rates found between two human readers. Recently, however, Sheehan (2001) has argued that such results may be misleading. She notes that much of the variability in essay score can be accounted for by a simple surface feature—essay length—and she suggests that only if we first control for effects of length can we produce an accurate picture of how well an automatic scoring system measures the quality, as opposed to the quantity, of writing.

In this report, we consider the effects of length when evaluating the performance of the e-rater system on essays written for prompts (topics) used in the computer-based Test of English as a Foreign Language™ (TOEFL®). These essays, which are currently scored by human readers, are written by thousands of nonnative English speakers, or speakers of another variety of English (such as a regional dialect), who take the TOEFL exam when applying for admission to U.S. colleges and universities. As part of the test, they are given 30 minutes to write an essay on a prompt that has been randomly drawn from a large set of possible topics. The prompts used in the current study are shown in Table 1.

Table 1

TOEFL-CBT Prompts

Topic	Prompt
A	Do you agree or disagree with the following statement? Playing a game is fun only when you win.
B	Do you agree or disagree with the following statement? It is more important for students to study history and literature than it is for them to study science and mathematics.
C	Neighbors are the people who live near us. In your opinion, what are the qualities of a good neighbor?
D	Do you agree or disagree with the following statement? All students should be required to study art and music in secondary school.
E	Some young children spend a great amount of their time practicing sports. Discuss the advantages and disadvantages of this.
F	Some people pay money for the things they want or need. Other people trade products or goods for what they need. Compare the advantages of these two ways of obtaining things. Which way do you prefer?
G	You have enough money to purchase either a house or a business. Which would you choose to buy?

Our goal is to determine the effect of length on e-rater and human reader scores on essays for these prompts, and then statistically remove that effect so that other variables of interest can be studied. With length controlled, we will ask (1) how much agreement is there between e-rater and human readers in assessing the quality of writing, and (2) which features of writing does e-rater rely on in scoring essays? In a previous study (Burstein & Chodorow, 1999), we considered the first of these questions, but without controlling for essay length. At that time, data were available from just two TOEFL prompts representing only a small number of essays. Also, the version of e-rater in use then (e-rater99) did not include the full set of features that were later incorporated. The current study thus gives us an opportunity to compare performance of the current operational version of e-rater (e-rater01) with the earlier version, and to do so on more prompts and with more essays.

The TOEFL Test of Written English Guide (ETS, 1996) reports mean essay score by native language for the more than 100 native languages spoken by TOEFL examinees. To what degree might the differences in score among these language groups be a reflection of differences in essay length? More specifically, we will ask (3) is there an effect of native language that is independent of essay length, and, if so, does e-rater show the same pattern of differences across native language groups as that seen in the scores of human readers?

We begin with a description of essay scoring by humans and by e-rater.

Human Reader Scores

The purpose of the TOEFL essay is to assess the examinee's proficiency in writing English. Each essay is read and scored independently by two trained human readers who use a six-point scoring rubric, with 1 denoting an essay of the lowest quality and 6 indicating the highest quality.[1] The scoring guide (www.toefl.org/educator/edtwegui.html) lists criteria for scores of 5 and 6 that include the properties "is well organized," "uses clearly appropriate details to support a thesis," "demonstrates syntactic variety," and shows "a range of vocabulary." By contrast, 1s and 2s show "serious disorganization or underdevelopment" and may show "serious and frequent errors in sentence structure or usage." Notably, the scoring guide does not refer to essay length as a basis for evaluation. (See Appendix A for the complete list of current scoring guide criteria and www.toefl.org/toeflcbt/cbscrsvc.html for additional information.)

The score assigned to an essay (referred to here as the human reader or HR score) is the mean of the two readers' scores (H1 and H2), provided that these scores do not differ by more than one point. In the event of a larger discrepancy, a third reader is asked to grade the essay, and the final score is the mean of the adjacent or matching scores. For example, suppose H1 is 3 and H2 is 5. If the third reader gives the essay a 4, then HR will be 4 (the mean of 3, 4, and 5). If the third reader gives a 5, HR will be 5, since two scores match. If the third reader gives a 6, HR will be 5.5, the mean of the two adjacent scores 5 and 6.

E-rater Scores

As noted earlier, automatic scoring systems, such as e-rater, require training data. E-rater measures numerous features of writing in its training essays and then uses a stepwise linear regression procedure to select the features (usually a small set of 8 to 10) that are most predictive of essay score for each prompt. While the overall feature set is highly varied, it contains no direct measure of essay length. As we described it in 1999,

> The driving concept that underlies e-rater is that it needs to evaluate the same kinds of features that human readers do. This is why from the beginning of its development, we made it a priority to use features from the scoring guide and to eliminate any direct measures of essay length. Even though length measures can be shown to be highly correlated with human reader essay scores, length variables are not scoring guide criteria. (Burstein & Chodorow, 1999, p. 69)

Although some researchers have suggested adding explicit measures of length to improve correlations with human readers, the assessment community is generally concerned about the effect this would have on coachability.

E-rater features are based on four general types of analysis: syntactic, discourse, topical, and lexical.

Syntactic analysis. The basis for syntactic analysis is parsing—the process of making explicit the syntactic structure of sentences. This requires tagging each word in the essay with its appropriate part of speech and then assembling the words into phrases and clauses. (One important improvement in e-rater01 has been in the quality of its syntactic analysis, due primarily to improved part-of-speech tagging.) The parser identifies several syntactic structures, such as subjunctive auxiliary verbs (e.g., *would*, *should*, *might*), and complex clausal structures, such as complement, infinitive, and subordinate clauses. Recognition of these features yields information about the essay's syntactic variety. The parsed sentences also provide the input for discourse analysis.

Discourse analysis. Organization of ideas is another criterion that the scoring guide asks human readers to consider in assigning essay score. E-rater contains a lexicon based on the conceptual framework of conjunctive relations from Quirk, Greenbaum, Leech, and Svartik

(1985) in which cue terms, such as *In summary* and *In conclusion*, are classified as conjuncts used for summarizing. The conjunct classifiers contain information about whether or not the item is a kind of discourse development term (e.g., *for example* and *because*), or whether it is more likely to be used to begin a discourse statement (e.g., *First*, *Second*, or *Third*).

E-rater also contains heuristics that define the syntactic or essay-based structures in which these terms must appear to be considered as discourse markers. For example, for the word *first* to be considered a discourse marker, it must not be a nominal modifier, as in the sentence, “The first time I went to Europe was in 1982,” in which *first* modifies the noun *time*. Instead, *first* must occur as an adverbial conjunct to be considered a discourse marker, as in the sentence, “First, it has often been noted that length is highly correlated with essay score.” The lexicon of cue terms and the associated heuristics are used by e-rater to automatically annotate a high-level discourse structure of each essay. These annotations are also used by the system to partition each essay into separate arguments, which are input to the topical analysis component.

Topical analysis. Good essays are relevant to the assigned topic. They also tend to use a more specialized and precise vocabulary in discussing the topic than do poorer essays. We should therefore expect a good essay to resemble other good essays in its choice of words and, conversely, a poor essay to resemble other poor ones. To capture use of vocabulary or identification of topic, e-rater uses content vector analyses that are based on the vector-space model commonly found in information retrieval applications (Salton, 1989). Training essays are converted into vectors of word frequencies, and the frequencies are then transformed into word weights, where the weight of a word is directly proportional to its frequency in the essay but inversely related to number of essays in which it appears. For example, *the* is typically the most frequent word in an essay but because it is found in all essays, its computed weight is extremely low. To calculate the topical analysis of a test essay, the essay is converted into a vector of word weights, and a search is conducted to find the training vectors most similar to it. Similarity is measured by the cosine of the angle between two vectors. For one feature, called *topical analysis by essay*, the test vector consists of all the words in the essay. The value of the feature is the mean of the scores of the most similar training vectors. The other feature, *topical analysis by argument*, evaluates vocabulary usage at the argument level. The discourse analysis is used to partition the essay into its main points of discussion, and a vector is created for each. These argument vectors are individually compared to the training set so that a topical analysis score can be assigned to each argument. The value for this feature is a mean of the argument scores. (See Burstein & Chodorow, 1999, for details of these procedures.)

Analysis of lexical (text) complexity. While the topical analysis features compare the *specific* words of the test essay to the words in the scored training set, the lexical (or text) complexity features treat words more abstractly (Larkey, 1998). Each essay is described in terms of the number of unique words it contains, the average length of its words, the number of words it has with five or more characters, with six or more characters, and so on. These numerical values reflect the range, frequency, and morphological complexity of the essay's vocabulary. For example, longer words are less common than shorter ones, and words beyond six characters are more likely to be morphologically derived through affixation. Larkey has shown that these text complexity features contribute significantly to predicting scores of essays written for the Graduate Management Admission Test® (GMAT®). E-rater99 did not include the text complexity features, but they are part of e-rater01.

In order to predict score, e-rater measures more than 50 features of the kinds described above in each training essay. It then computes a stepwise linear regression to select those features that make significant contributions to the prediction of essay score. Thus, for each prompt, the result of training is a regression equation that can be applied to the features of a new test essay to produce a predicted value. This value is rounded to the nearest whole number to yield the predicted score. Performance is assessed by predicting scores of essays that are not in the training set (cross-validation essays) and comparing them to HR scores.

E-rater scores are currently used in several kinds of applications. Since February 1999, ETS has used e-rater as one of the two initial readers for the GMAT writing assessments, and, in this capacity, it has scored more than 1 million essays. E-rater's scores either match or are within one point of the human reader scores about 96% of the time. ETS is using *e-rater* to score essays for numerous educational institutions across middle school, high school, college, and graduate school populations. In these lower-stakes environments, where students are practicing their writing skills, e-rater is often the sole scorer of the essays.

The Study

Data Sets

For the current study, 265 training essays were used for each of the seven prompts shown in Table 1. Selection of essays was without regard to the native language of the writer. In each training set, there were 15 essays that had received an HR score of 1 (a rare score for TOEFL essays) and 50 essays for each of the HR score points 2–6. There were 500 essays in a "mixed" cross-validation set for each prompt. These essays were selected through stratified random sampling so that the distribution of scores would be comparable to those in the general TOEFL population. For the score points 1–6, the proportions are 0.01, 0.04, 0.20, 0.37., 0.26, and 0.12, respectively.[2] The essays were selected without regard to the native language of the writer and so represent a mix of native languages. Spanish, Japanese, and Arabic language groups were used for the study because their essays constituted the largest non-English samples in electronic form available at the time of data collection. About 13% of the examinees reported Spanish as their native language, 8% Japanese, 4% Arabic, and the remainder a variety of non-English languages. In addition to the mixed cross-validation sets, language-specific sets were also identified at the time of data collection. These consisted of all the essays by Spanish, Arabic, and Japanese examinees that had not been included in the training or mixed cross-validation sets. The sizes of the data sets are summarized in Table 2.

Table 2

Training and Cross-validation Set Sizes (Numbers of Essays)

Prompt	Training	Mixed	Spanish	Japanese	Arabic	Cross-validation total
A	265	500	485	261	144	1,390
B	265	500	502	267	135	1,404
C	265	500	482	286	150	1,418
D	265	500	578	295	169	1,542
E	265	500	406	247	119	1,272
F	265	500	388	204	136	1,228
G	265	500	428	277	138	1,343
Total	1,855	3,500	3,269	1,837	991	9,597

Essay Score and Essay Length

In the following, we look at essay score and length in two ways. The first approach, similar to Sheehan (2001), is an indirect one that compares e-rater scores and HR scores to those produced by a model that uses only length information derived from training essays. Here, the question is, do e-rater and HR differ significantly from the length-only model in terms of performance? The second approach is more direct. It compares e-rater scores to HR scores using partial correlations to remove the length effects.

Longer TOEFL essays tend to receive higher scores from human readers than shorter essays receive. This relation between quantity and quality is not too surprising, since many of the criteria for high scores (e.g., details used to support a thesis, syntactic variety, and range of vocabulary) are difficult to produce in a short essay. Figure 1 shows the typical relation between essay length and human reader score in the mixed cross-validation data, in this case for prompt C. Polynomial regressions using essay length were computed for all the mixed cross-validation sets and showed significant linear (i.e., number of words) and quadratic (number of words squared) components (all *p*s $< .001$).[3] The polynomial regression line is superimposed on the data in Figure 1, where it accounts for .60 of the score variance.

We will use the term "length-based" to refer to polynomial regression models that use the number of words and the number of words squared as predictors. For each prompt, we computed a length-based regression model from the 265 essays of its training set and then used the model to predict each of the 500 HR scores in its mixed cross-validation set. The rationale for this is to see what performance would be like if only length information were extracted from the training set and used for predicting score. Table 3 gives the proportion of score variance accounted for by the predictions. Also shown are "exact agreement," the proportion of times the predicted score exactly matched the HR score when both were rounded to the nearest integer, and "adjacent agreement," the proportion of times the prediction was within one point of the HR score. The bottom row shows the values obtained when the essays from the seven data sets are combined into a single set. The confusion matrix for this combined set is included in Appendix B.

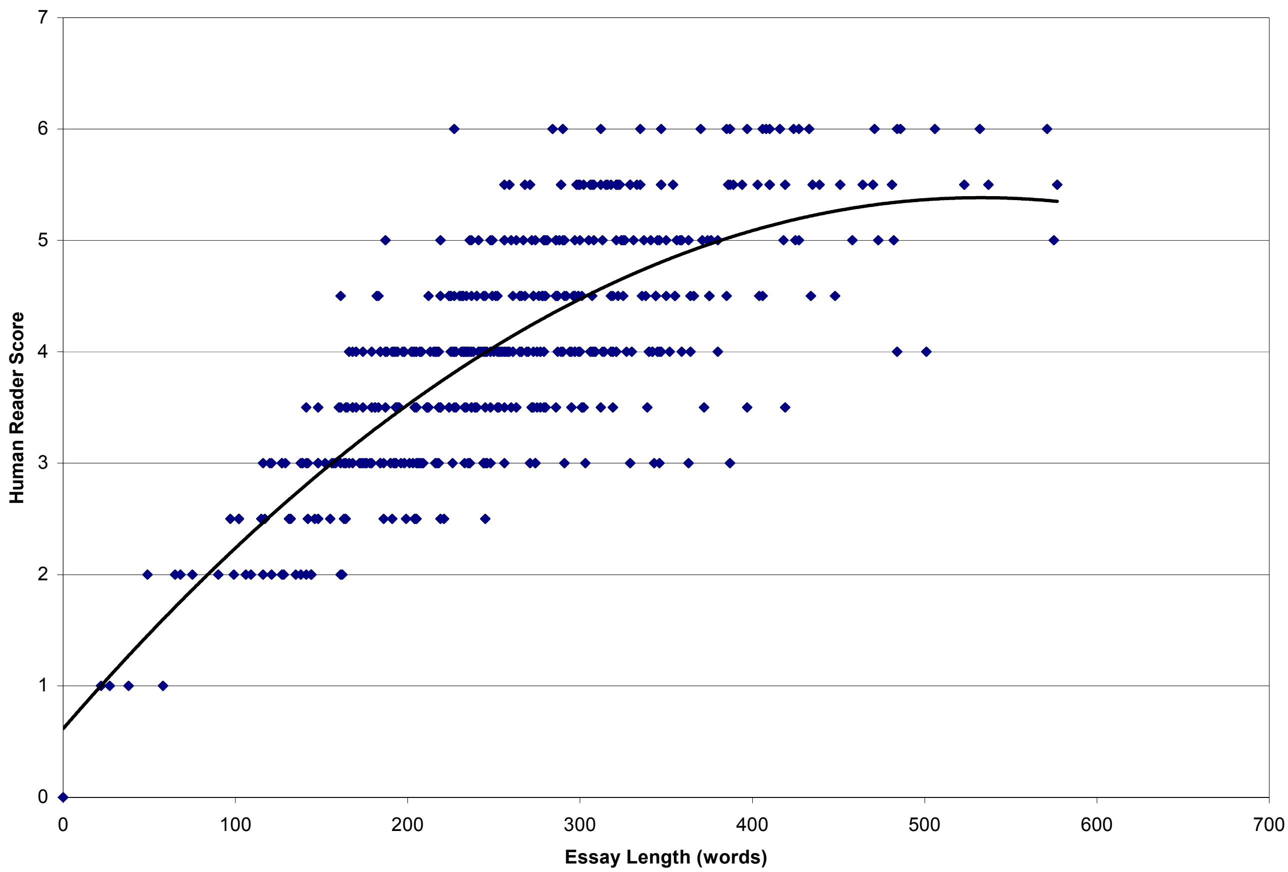


Figure 1. **Essay length and human reader score for Prompt C.**

There are no significant differences in R^2 across prompts ($\chi^2(6, N = 3{,}500) = 1.139$, $p >$ 0.10). The length-based models account for .53 of the variance in HR score when all of the cross-validation sets are combined, exactly matched the HR score about one-half of the time, and are within one point of it .95 of the time. Just how should this level of performance be interpreted? In other words, to which baseline should it be compared?

Table 3

Predicting HR Scores in Mixed Cross-validation Sets Using Length-Based Regression Models Estimated From Training Sets: Multiple Correlations and Agreement Proportions (Kappas)

Prompt	Multiple R^2	Exact agreement (κ)	Adjacent agreement (κ)
A	.51	.49 (.30)	.95 (.82)
B	.54	.55 (.39)	.95 (.85)
C	.54	.48 (.29)	.96 (.88)
D	.51	.50 (.32)	.96 (.85)
E	.54	.49 (.30)	.94 (.82)
F	.53	.45 (.25)	.95 (.83)
G	.53	.49 (.30)	.95 (.84)
Combined	.53	.49 (.31)	.95 (.84)

An appropriate baseline ought to take the amount of agreement between the length-based model scores and the HR scores and deduct from it the amount of agreement that would be expected by chance if the two sets of scores had been generated independently. For example, if the proportion of HR scores of 4 in prompt A is .37, and the proportion of essays assigned 4 by the length-based model is .40, then the probability that the two will agree in their assignment of 4s by chance is $.37 \times .40 = .148$, since the joint probability of two independent events (HR score of 4 and length-based model score of 4) is the product of their separate probabilities. Similar computations for the other score points permit us to calculate the proportion of chance agreement over the whole score range. Performance can then be expressed as kappa (κ), the proportion of actual agreement between length-based model scores and HR scores after chance agreement has been removed (Cohen, 1960), as shown below.

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

Here, P_o is the proportion of agreement observed, and P_e is the proportion expected by chance.

Kappas of the length-based models are shown in parentheses in Table 3. They are all significantly greater than zero, indicating better performance than expected by chance alone. (For exact match, the smallest z value is $z = 10.11$, $p < .001$, and for adjacent match, the smallest is z

= 6.42, $p < .001$; see Fleiss, 1981, for significance tests involving kappa.) This, of course, is not surprising, given the significant correlation between HR score and essay length. However, a kappa less than about 0.40 is considered to show poor agreement, while one above 0.75 indicates excellent agreement (Landis & Koch, 1977). Using these criteria, the length-based models show poor exact agreement with HR but excellent adjacent agreement.

There are no direct measures of length in e-rater's feature set, but many of its features are likely to be correlated with the number of words in the essay and could therefore serve as proxies of length in the regression model that e-rater builds. This, in fact, is what Sheehan (2001) has argued is the case for e-rater99, and it is the motivation for the analyses of the length-based models in Table 3, which can be compared to Table 4. The latter shows the performance of e-rater99 for the seven prompts when trained on the 265 essays of the training set and tested on the cross-validation set. (See Appendix B for the confusion matrix of the combined data.)

Table 4

Predicting HR Scores in Mixed Cross-validation Sets Using e-rater99: Correlations and Agreement Proportions (Kappas)

Prompt	r^2	Exact agreement (κ)	Adjacent agreement (κ)
A	.44	.37 (.16)	.91 (.72)
B	.49	.49 (.31)	.92 (.75)
C	.53	.46 (.28)	.92 (.75)
D	.48	.45 (.25)	.93 (.78)
E	.53	.47 (.29)	.92 (.77)
F	.56	.45 (.27)	.93 (.80)
G	.49	.50 (.32)	.92 (.75)
Combined	.50	.46 (.27)	.92 (.76)

There are no significant differences in r^2 across prompts ($\chi^2(6, N = 3{,}500) = 9.570$, $p >$ 0.10). E-rater99 accounts for half of the HR score variance overall, and its kappas for exact and adjacent agreement with HR are significantly greater than zero (for exact agreement, the smallest z is $z = 6.55$, $p < .001$, and for adjacent, the smallest is $z = 6.15$, $p < .001$). It does not, however, fare well in a comparison with the length-based approach.

E-rater99 accounts for significantly less of the HR score variance (0.50) than the length-based models (0.53), $t(3497) = 2.62$, $p < .01$, (Hotelling's test of the difference between two nonindependent *r*s, as cited in Edwards, 1960, p. 85). It should be noted, though, that this difference (.04 in Fisher's Z units) represents less than a small effect size. E-rater99 also produces a lower combined kappa for exact agreement (.27) than the length-based models (.31), χ^2 (1, $N = 3{,}500$) = 8.79, $p < .01$ (Fleiss, 1981). For adjacent agreement, e-rater99's performance is lower than the length-based models on all the prompts, but the difference in overall kappas (.76 versus .84) is not significant ($\chi^2(1, N = 3{,}500) = 1.57$, $p > .10$). In summary, e-rater99 does a worse job than the length-based models do in accounting for score variance and in exactly matching HR scores.

Table 5 gives the results for e-rater01. (See Appendix B for the confusion matrix of the combined data.)

Table 5

Predicting HR Scores in Mixed Cross-validation Sets Using e-rater01: Correlations and Agreement Proportions (Kappas)

Prompt	r^2	Exact agreement (κ)	Adjacent agreement (κ)
A	.59	.53 (.36)	.96 (.88)
B	.60	.54 (.38)	.97 (.91)
C	.57	.47 (.29)	.95 (.85)
D	.58	.55 (.39)	.97 (.90)
E	.59	.52 (.36)	.96 (.87)
F	.62	.51 (.34)	.97 (.90)
G	.62	.59 (.44)	.95 (.85)
Combined	.60	.53 (.37)	.96 (.88)

There are no significant differences in r^2 across prompts ($\chi^2(6, N = 3,500) = 2.792$, $p > 0.10$). E-rater01 accounts for .60 of the HR score variance overall, and its kappas for exact and adjacent agreement are significantly greater than zero (for exact agreement, the smallest z is $z = 12.10$, $p < .001$, and for adjacent, the smallest is $z = 7.16$, $p < .001$). It also performs better than the length-based approach. First, it accounts for more of the variance in HR scores (0.60) than is accounted for by the length-based models (0.53), $t(3,497) = 7.18$, $p < .001$, in a test of the difference between nonindependent *r*s, though the effect size is small (0.11 in Fisher's Z units). E-rater01 produces higher combined kappa for exact agreement (0.37) than the length-based models produce (0.31), $\chi^2(1, N = 3,500) = 19.26$, $p < .001$. For adjacent agreement, the difference in overall kappas for e-rater01 and the length-based models (.84 versus .88) is not significant, $\chi^2(1, N = 3,500) < 1$.

E-rater01 is better than the length-based models in exactly matching HR scores. In terms of performance, if e-rater01 were to serve as the sole scorer for the seven prompts (for example, in an application where students practice their writing on the computer), then we would expect it to agree with the HR score 53% of the time and to be within one point of the HR score 96% of the time.

We have looked at the relation between e-rater scores and HR scores, but have said nothing of the agreement between human readers. Table 6 shows the proportion of shared variance and agreement rates for H1 and H2 in the cross-validation sets of the same seven prompts. (The confusion matrix for the combined data is included in the Appendix B.)

Table 6

Correlations and Agreement Proportions (Kappas) Between H1 and H2 in Mixed Cross-validation Sets

Prompt	r^2	Exact agreement (κ)	Adjacent agreement (κ)
A	.65	.63 (.51)	.96 (.89)
B	.64	.61 (.48)	.97 (.91)
C	.58	.59 (.45)	.95 (.86)
D	.60	.58 (.43)	.97 (.90)
E	.59	.55 (.39)	.96 (.87)
F	.54	.51 (.35)	.95 (.84)
G	.54	.48 (.31)	.95 (.86)
Combined	.59	.56 (.42)	.96 (.86)

Across prompts, the proportions of shared variance are not all the same ($\chi^2(6, N = 3{,}500) = 14.435$, $p < 0.05$). The range of r^2 values (.54 to .65) is broader than that seen for e-rater01 and HR (.57 to .62). For five of the seven prompts, H1 and H2 show more exact agreement than is shown by e-rater01 and HR; for one prompt (G), the opposite is true; and for one (F), they show the same amount. The difference between the combined kappas for H1 and H2 (0.42) and for e-rater01 and HR (0.37) is significant ($\chi^2(1, N = 3{,}500) = 13.61$, $p < .001$. Finally, the difference in combined adjacent agreement kappas for H1 and H2 (0.86) compared to e-rater01 and HR (0.88) is not significant, $\chi^2(1, N = 3{,}500) < 1$.

In summary, compared to the length-based models, e-rater99 accounts for less variance and shows lower exact agreement; e-rater01 accounts for more variance and shows higher exact agreement. H1 and H2 are more variable across prompts but show greater exact agreement with each other than e-rater01does with HR. It should be noted that the performance differences of e-rater01 and the human readers are probably underestimated by comparing the results in Table 6 with those in Table 7, because HR, as a mean score, is more reliable than H1 or H2 individually.

Removing Length Effects

The results in Tables 3, 4, and 5 are useful for comparing the performance of e-rater99 and e-rater01 to length-based models, but they do not directly assess the relation between essay length and e-rater score. In fact, the length-based models of Table 3 were built from training sets that are not representative of the TOEFL population in terms of essay lengths. As noted, the training sets give equal representation to score points 2–6 (in contrast to their actual distributions), and they overrepresent the rare score of 1. As a result, the distribution of lengths in the training essays does not match the distribution in the cross-validation sets.

An alternative approach that avoids this shortcoming is to look at the relation between e-rater scores and HR scores in the mixed cross-validation sets while using partial correlation to control for the effects of length. Partial correlation allows us to use length information (number of words and number of words squared) to predict HR scores, and also to predict e-rater scores. The residual or difference between the HR score and its length-based prediction represents the part of the HR score that length cannot explain. Similarly, the residual between the e-rater score and its length-based prediction represents the part of the e-rater score that length cannot explain. We can then ask if a correlation exists between these residuals. If it does, e-rater must be using at least some information that is independent of length in predicting human reader scores. If it does not, then e-rater's performance is no better than that of a model that uses only the number of words and the number of words squared.

Table 7 shows the variance in HR scores accounted for by e-rater99 and e-rater01 when the length measures have been partialed out. For comparison, it also shows the shared variance between H1 and H2 with the effects of length removed in the same way.

Table 7

Partial Correlations in Mixed Cross-validation Sets After Removing Length and Length Squared

Prompt	Partial r^2 e-rater99 w/ HR	Partial r^2 e-rater99 w/ single H[a]	Partial r^2 e-rater01 w/ HR	Partial r^2 e-rater01 w/ single H[a]	Partial r^2 H1 w/ H2
A	.06	.05	.14	.12	.37
B	.03	.02	.14	.11	.32
C	.05	.04	.10	.08	.24
D	.03	.02	.12	.08	.28
E	.08	.06	.14	.11	.23
F	.12	.09	.16	.12	.18
G	.03	.02	.18	.13	.20
Combined	.06	.04	.15	.11	.26

[a]Values represent average of partial correlations computed separately with H1 and H2.

All of the partial correlations are statistically significant (ps < .01), but those between e-rater99 and HR are small, accounting for only about .06 of the variance that remains after the effects of the length measures are removed. This is consistent with Sheehan's (2001) conclusion that e-rater99's predictions of score are based largely on length. However, e-rater01 performs better than its predecessor for each prompt, although it still shares less variance with HR scores (.15) than readers H1 and H2 share with each other (.26). Table 7 also shows the partial correlations between e-rater and individual human readers. As expected, they are somewhat lower than the partial correlations with the more reliable HR score, and they highlight the disparity between e-rater and human readers. Future research should focus on the sources of these remaining differences in performance.

E-rater Features and Essay Length

A typical e-rater model consists of about 8-10 features from the more than 50 that e-rater measures. It would be useful to know which of these are most sensitive to essay length and which are not. Table 8 shows the features that occur in four or more of the e-rater99 and e-rater01 models built for the seven TOEFL prompts. As noted earlier, e-rater01 has an extra set of lexical complexity features that were not part of e-rater99.

Table 8

Features Appearing in Four or More E-rater Models

System/ Type	Feature	# prompts	Description
E-rater99			
D	Ad_con_p	4	Number of argument development contrast phrases
T	Topic_essay	5	Score from topical analysis by essay
D	Ad_ving	6	Number of argument development words verb+ing
T	Topic_arg	7	Score from topical analysis by argument
S	Aux_verb	7	Number of auxiliary verbs in essay
S	Raux_wd	7	Number of auxiliary verbs divided by number of words in essay
E-rater01			
D	Ad_pg1	4	Number of argument development words in first paragraph
T	Topic_arg	4	Score from topical analysis by argument
S	Aux_verb	5	Number of auxiliary verbs in essay
L	Diffwords	7	Number of different word types in essay
L	Bw5-8	7	Number of words of various lengths: 5, 6, 7, 8 characters

Note: Feature types: S = syntactic, D = discourse; T = topical; L = lexical complexity.

Many of these features are counts of words that meet various criteria (e.g., number of auxiliary verbs, number of argument development verbs ending in *-ing*, number of different word types). Since word counts are expected to increase as essay length increases, it might be the case that these features are predictive of score solely because of their relation to essay length. If so, then they will have no significant correlation with score once the length effects have been removed. By contrast, the topical features are not word counts but are based on *proportions* of overlapping vocabulary between essays. Accordingly, we expect them to be less sensitive to length. Table 9 shows the squared partial correlations between some of these features and HR score, controlling for essay length and length squared.

Table 9

Squared Partial Correlations Between E-rater Features and HR Scores in Mixed Cross-validation Sets After Removing Length and Length Squared

Prompt	Aux_verb	Raux_wd	Ad_ving	Topic_arg	Topic_essay	Diffwords	Bw7
A	.003	.002	.005	.051	.080	.168	.165
B	.022	.014	.017	.083	.059	.101	.260
C	.001	.002	.008	.064	.066	.079	.130
D	.004	.007	.026	.072	.057	.103	.226
E	.006	.002	.018	.068	.085	.099	.195
F	.009	.009	.012	.119	.085	.083	.159
G	.008	.006	.017	.103	.086	.106	.099
Combined	<.001	<.001	.011	.076	.075	.099	.134

Note: Df = 496 for each prompt; $p < .05$ for values greater than .008; $p < .001$ for values greater than .013; Df = 3,496 for combined prompts; $p < .05$ for values greater than .001.

The three features that account for the least variance—Aux_verb, Raux_wd, and Ad_ving—are those that appear most often in the e-rater99 models. This was also noted by Sheehan (2001). The topical analysis measures, Topic_arg and Topic_essay, account for more variance, as expected. Interestingly, the lexical complexity word counts computed by e-rater01, Diffwords and BW7 (words with seven or more characters), account for the greatest amount of variance. Word counts, then, can capture information that is independent of length. In this case, they no doubt reflect the scoring rubric's criterion that a good essay is one that shows a range of vocabulary usage.

Future improvements in e-rater will require the development of new features that measure more of the criteria in the scoring rubric. For example, Leacock and Chodorow (2001) report a relationship between HR score and the prevalence of low probability sequences of parts-of-speech in TOEFL essays. These sequences (e.g., plural noun followed by singular verb, such as *books is*) are often associated with grammatical errors, something that human readers are almost certainly sensitive to in assessing the quality of sentence structure, but that e-rater99 and e-rater01 do not measure.[4]

Native Language and Essay Length

In an earlier study (Burstein & Chodorow, 1999), we reported significant essay score differences among Arabic, Chinese, Spanish, and English language groups. We also found a significant interaction between rater and language group. For that dataset, e-rater99 assigned higher scores than HR assigned to essays written by native speakers of some languages, and it assigned lower scores than HR assigned to essays written by native speakers of other languages. Sheehan (2001) argues that this interaction of rater and language reflects the tendency of e-rater to rely more on essay length than human readers do. Here we examine the relation between rater, native language, and length for our seven prompts.

Table 10 shows mean HR, e-rater99, and e-rater01 scores by native language group and prompt.

Table 10

Mean Essay Score by Native Language Group, Rater, and Prompt

Language Rater	A	B	C	D	E	F	G	Mean
Mixed	3.96	4.00	3.95	3.99	3.94	3.92	3.93	3.96
HR	4.03	4.01	4.01	3.99	3.98	3.96	3.95	3.99
E-rater99	3.85	3.92	3.86	3.88	3.83	3.80	3.84	3.86
E-rater01	4.01	4.08	3.97	4.10	4.01	3.99	3.99	4.02
Arabic	3.52	3.86	3.78	3.74	3.80	3.52	3.38	3.66
HR	3.54	3.84	3.85	3.78	3.75	3.46	3.31	3.65
E-rater99	3.43	3.84	3.64	3.65	3.73	3.46	3.31	3.58
E-rater01	3.60	3.89	3.84	3.79	3.92	3.64	3.51	3.74
Japanese	3.51	3.69	3.47	3.85	3.70	3.55	3.53	3.61
HR	3.54	3.67	3.52	3.82	3.70	3.48	3.48	3.60
E-rater99	3.42	3.67	3.46	3.84	3.66	3.49	3.58	3.59
E-rater01	3.56	3.71	3.42	3.89	3.74	3.69	3.52	3.65
Spanish	3.97	4.04	3.91	4.03	4.01	3.97	3.91	3.98
HR	4.02	4.03	3.99	4.08	4.05	4.03	3.94	4.02
E-rater99	3.81	3.95	3.75	3.89	3.88	3.85	3.82	3.85
E-rater01	4.07	4.13	3.99	4.10	4.10	4.04	3.99	4.06
Mean	3.74	3.90	3.78	3.90	3.86	3.74	3.69	3.80
HR	3.78	3.89	3.84	3.92	3.87	3.73	3.67	3.81
E-rater99	3.63	3.85	3.68	3.82	3.77	3.65	3.64	3.72
E-rater01	3.81	3.95	3.81	3.97	3.94	3.84	3.75	3.87

These data were analyzed using a mixed model repeated measures ANOVA with one within-group variable, Rater (HR, e-rater99, and e-rater01), and two between-group variables, Language (Mixed, Arabic, Japanese, and Spanish) and Prompt (A-G). The main effect of Rater is significant ($F_{(2, 19138)} = 157.85$, $p < 0.001$, partial $\eta^2 = .016$), as are the main effects of Prompt ($F_{(6, 9569)} = 8.20$, $p < 0.001$, partial $\eta^2 = .005$) and Language ($F_{(3, 9569)} = 78.17$, $p < 0.001$, partial $\eta^2 = .024$). Tukey HSD comparisons show a significant difference between Mixed and Arabic, Mixed and Japanese, Spanish and Arabic, and Spanish and Japanese language groups. Also significant are the interactions of Rater × Language ($F_{(6, 19138)} = 12.27$, $p < 0.001$, partial $\eta^2 = .004$), Rater × Prompt ($F_{(12, 19138)} = 3.62$, $p < 0.001$, partial $\eta^2 = .002$), and Language × Prompt ($F_{(18, 9569)} = 5.92$, $p < 0.01$, partial $\eta^2 = .004$). The three-way interaction of Rater × Language × Prompt is marginally significant ($F_{(36, 19138)} = 1.40$, $p < 0.06$, partial $\eta^2 = .003$).

Because of the interactions with Prompt, separate ANOVAs were computed for each prompt. In these analyses, there was one within-group variable (Rater) with just two levels (HR and either e-rater99 or e-rater01), and one between-group variable (Language). Figure 2 shows the Rater (HR and e-rater99) × Language interactions for the seven prompts.

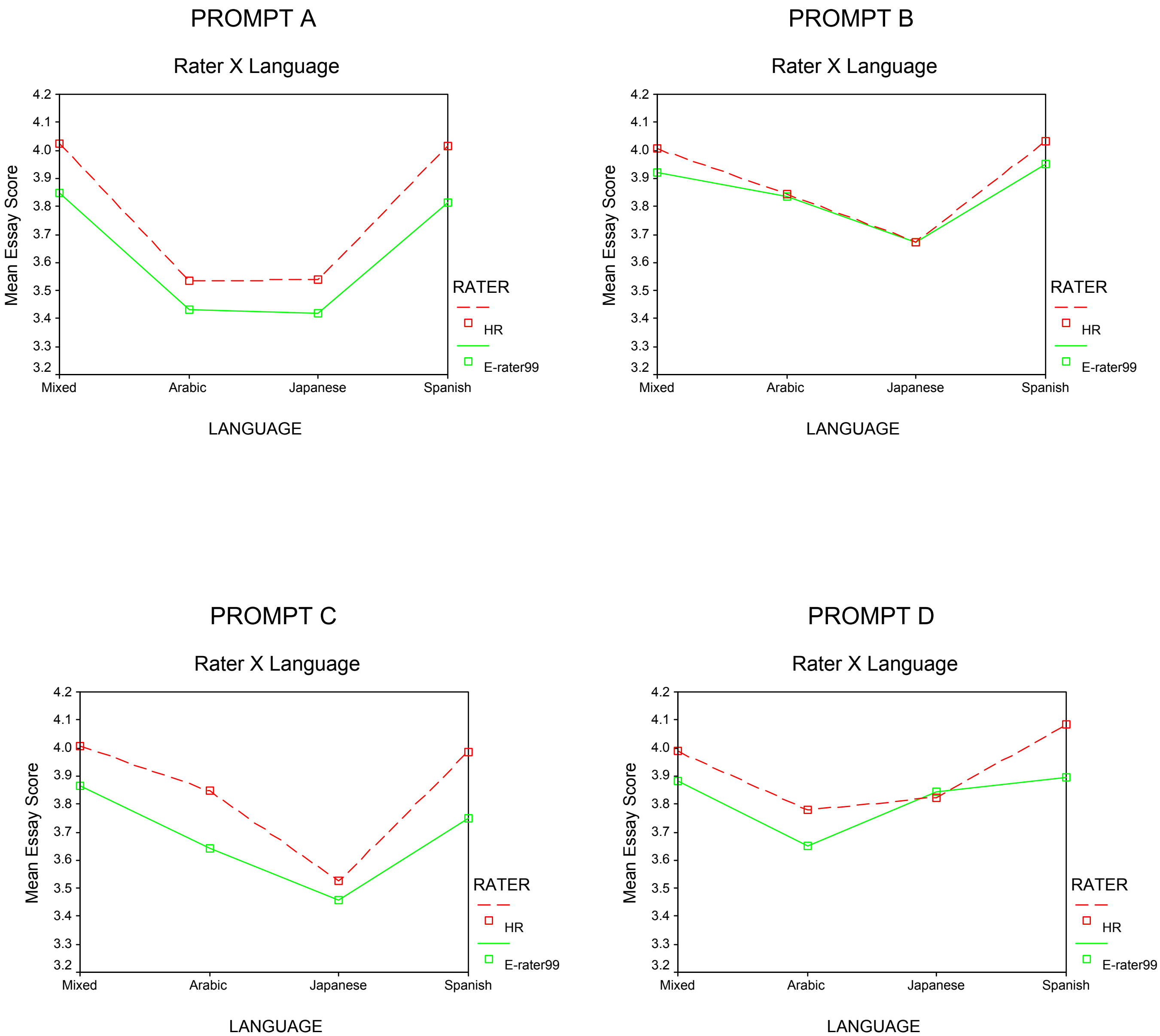
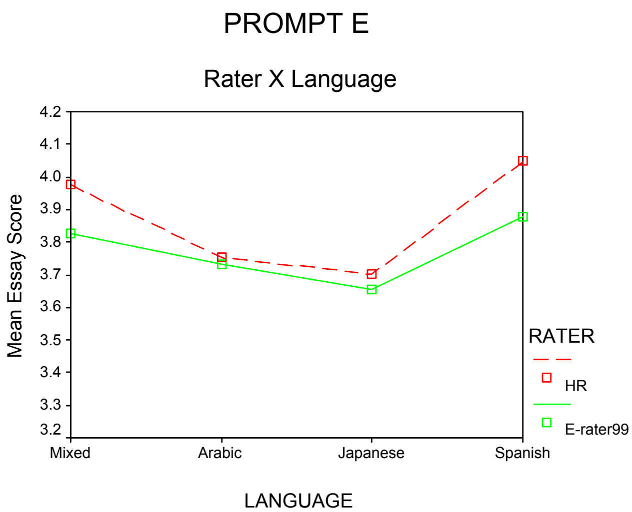
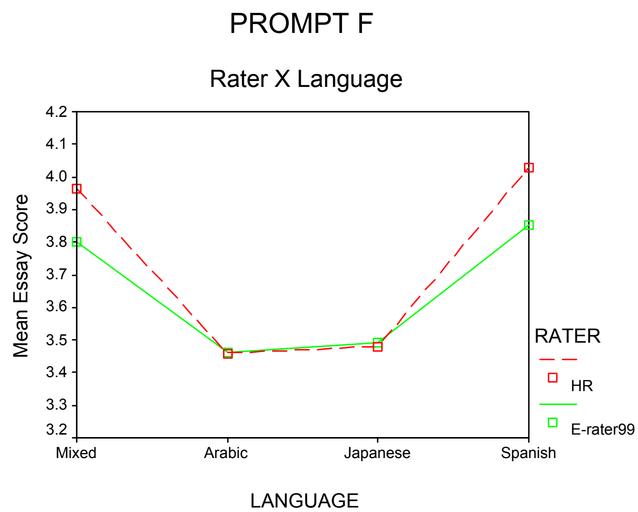


Figure 2. **Rater (HR and e-rater99) × Language for seven prompts.**





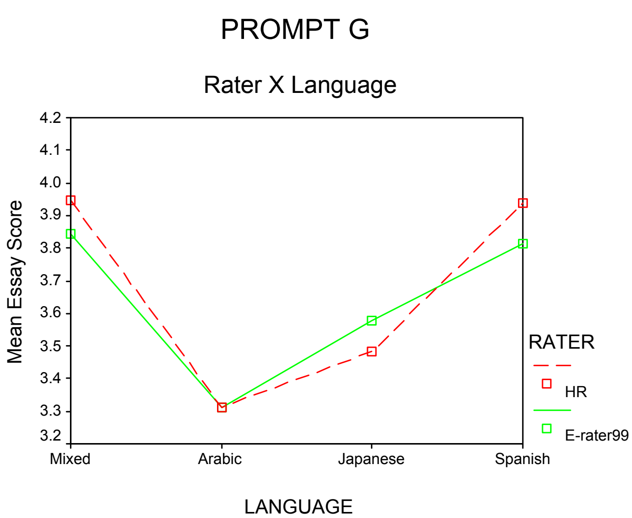


***Figure 2.* (continued)**

Table 11 contains the results for the main effects and interactions in these analyses.

Table 11

Analyses of Rater (HR and E-rater99) × Language for Seven Prompts

Effect	A	B	C	D	E	F	G
Rater							
Df	1, 1386	1, 1400	1, 1414	1, 1538	1, 1268	1, 1224	1, 1339
F	32.77	3.42	47.72	18.61	14.59	11.12	1.88
p	<.001	.065	<.001	<.001	<.001	.001	.170
Partial η^2	.023	.002	.033	.012	.011	.009	.001
Language							
Df	3, 1386	3, 1400	3, 1414	3, 1538	3, 1268	3, 1224	3, 1339
F	19.02	7.13	13.57	4.12	5.05	14.73	20.85
p	<.001	<.001	<.001	.006	.002	<.001	<.001
Partial η^2	.040	.015	.028	.008	.012	.035	.045
Rater x Language							
Df	3, 1386	3, 1400	3, 1414	3, 1538	3, 1268	3, 1224	3, 1339
F	0.78	0.96	3.06	4.37	2.17	4.51	5.28
p	.508	.408	.027	.005	.090	.004	.001
Partial η^2	.002	.002	.006	.008	.005	.011	.012

There is a significant main effect of Language in all of the prompts and of Rater in five of them. Consistent with our previous results (Burstein & Chodorow, 1999), four prompts show a significant Rater × Language interaction.

Table 12 contains the main effects and interactions for these analyses.

Table 12

Analyses of Rater (HR and E-rater01) × Language for Seven Prompts

Effect	A	B	C	D	E	F	G
Rater							
df	1, 1386	1, 1400	1, 1414	1, 1538	1, 1268	1, 1224	1, 1339
F	2.54	8.43	2.22	6.02	9.69	20.42	15.18
p	.111	.004	.137	.014	.002	< .001	< .001
Partial η^2	.002	.006	.002	.004	.008	.016	.011
Language							
Df	3, 1386	3, 1400	3, 1414	3, 1538	3, 1268	3, 1224	3, 1339
F	22.29	10.10	19.52	6.57	7.42	14.54	24.24
P	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Partial η^2	.046	.021	.040	.013	.017	.034	.052
Rater x Language							
df	3, 1386	3, 1400	3, 1414	3, 1538	3, 1268	3, 1224	3, 1339
F	0.89	0.49	1.52	1.97	1.23	5.09	1.99
p	.444	.690	.290	.117	.298	.002	.114
Partial η^2	.002	.001	.003	.004	.003	.012	.004

Figure 3 shows the Rater (HR and e-rater01) × Language interactions for the seven prompts.

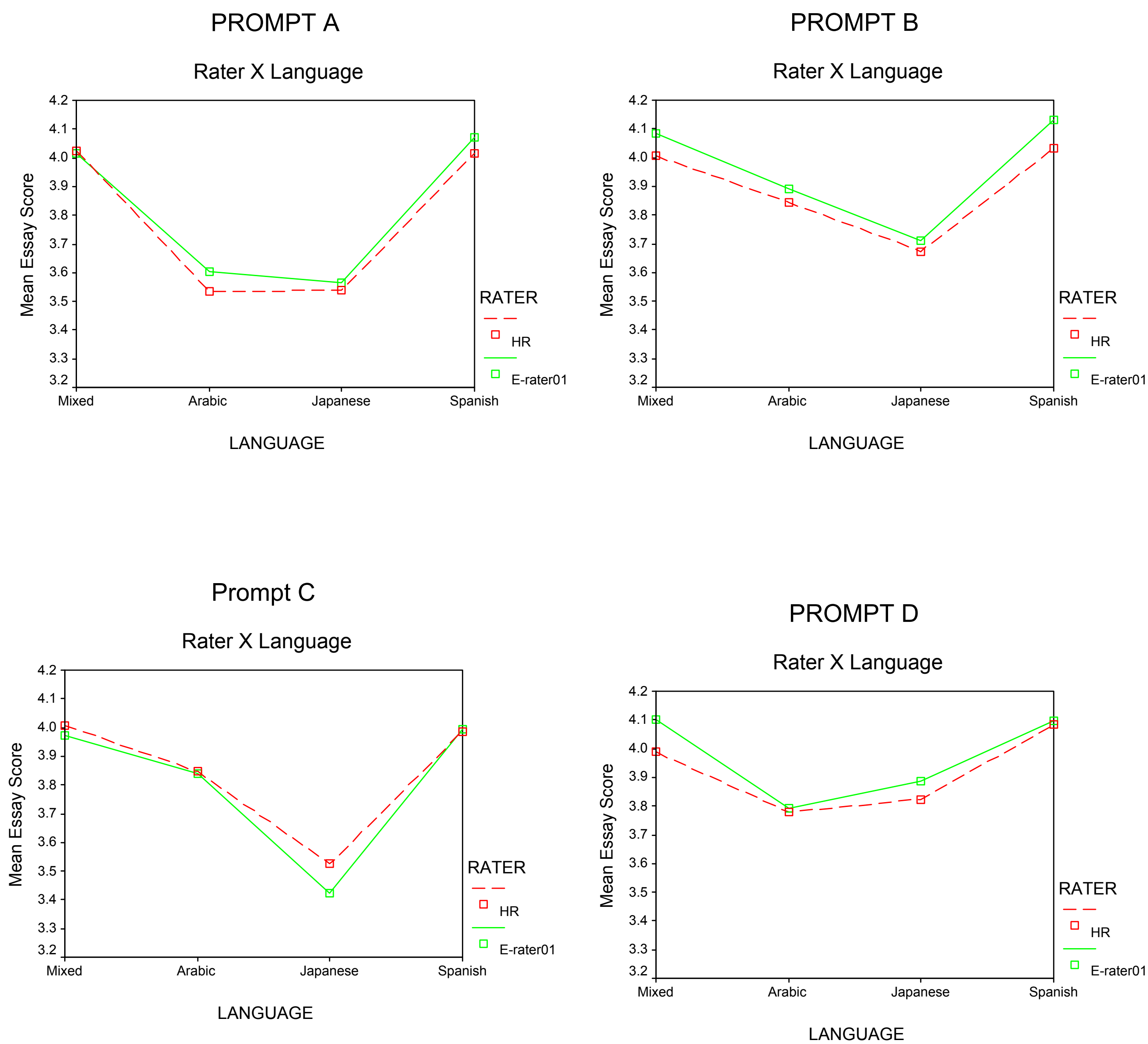
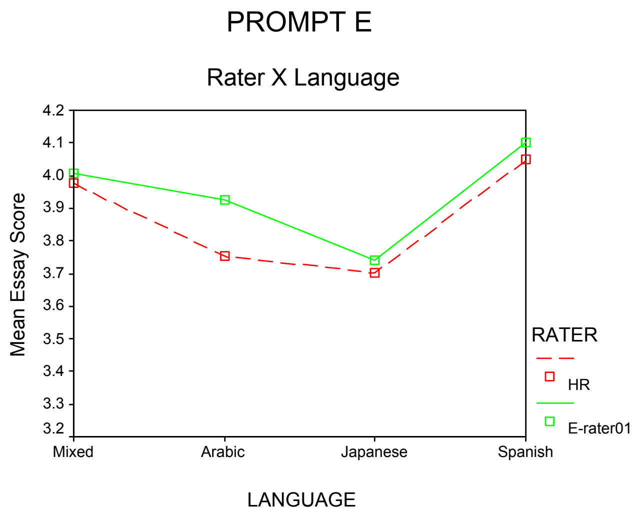
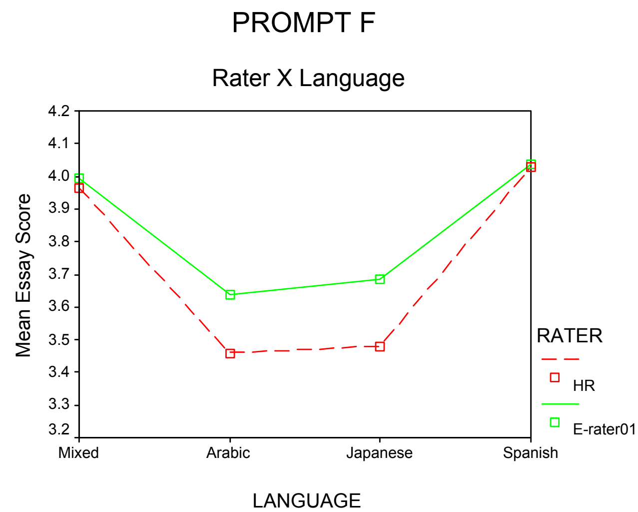


Figure 3. **Rater (HR and e-rater01) × Language for seven prompts.**





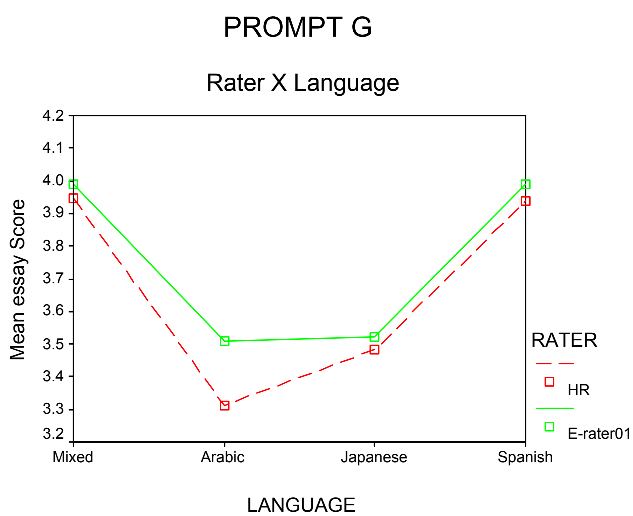


Figure 3. **(continued)**

In these analyses, as in those of Table 11, Language is a significant main effect for all of the prompts and Rater is significant for five of them. However, in contrast to the previous results, there is only one significant interaction of Rater × Language (for Prompt F). Although far from conclusive, this suggests that e-rater01 may be more likely than e-rater99 to produce a pattern of scores among language groups that is similar to the pattern found in HR.

Not only do scores differ between Language groups and Prompts, but essay lengths differ too, as shown in Table 13.

Table 13

Mean Number of Words in Essay by Native Language Group and Prompt

Language	A	B	C	D	E	F	G	Mean
Mixed	244	232	250	233	242	246	238	241
Arabic	215	229	236	222	237	224	206	224
Japanese	216	208	220	225	229	215	220	219
Spanish	243	238	251	231	246	253	236	243
Mean	236	229	243	230	240	241	231	232

An analysis of variance on essay lengths shows a significant main effect for Language ($F_{(3, 9569)} = 40.14$, $p < 0.001$, partial $\eta^2 = .012$) and for Prompt ($F_{(6, 9569)} = 4.75$, $p < 0.001$, partial $\eta^2 = .003$), and a marginal interaction of Language × Prompt ($F_{(18, 9569)} = 1.60$, $p = 0.052$, partial $\eta^2 = .003$). Tukey HSD tests showed significant differences in essay length between Mixed and Arabic, Mixed and Japanese, Spanish and Arabic, and Spanish and Japanese.

The two language groups with the shortest essays, Arabic and Japanese, are also the groups with the lowest scores (see Table 10). This raises the possibility that the Language effects on score, for human readers and for e-rater, are simply the result of differences in essay length among the groups. To examine this, we can control for differences in length and length squared in an analysis of covariance. Unfortunately, one of the basic assumptions of the ANCOVA procedure is violated in our data. As in the partial correlations reported earlier, the ANCOVAs use length-based regression to predict essay score. Residuals, the differences between actual scores and those predicted by the regression, represent the part of the score that is independent of length. But if the regression lines, which are computed in this process, differ in slope among the various language groups, then the ANCOVA procedure cannot be used (Mertler & Vannatta, 2001). This is the case for all seven prompts.[5] An examination of the data arranged by length showed a small number of essays that were empty or almost empty (containing less than 10 words) and a small number with more than 550 words (greater than three standard deviations above the mean essay length). With these very short and very long essays removed (less than 1% of the total number of essays), the homogeneity of slopes assumption was satisfied for six of the seven prompts (all but prompt C) for HR and e-rater01 data, and analyses of covariance were computed for these sets.

In the covariance analyses, there was one within-group variable, Rater (HR and e-rater01), one between-group variable, Language, and two covariates, words and words squared. Table 14 contains the results for the main effects and interactions of these six analyses.

Table 14

Analyses of Rater (HR and E-rater01) × Language for Six Prompts, With Effects of Covariates Length and Length Squared Removed

Effect	A	B	C	D	E	F	G
Rater							
df	1, 1376	1, 1387		1, 1528	1, 1257	1, 1217	1, 1330
F	7.00	0.06		0.08	3.44	1.72	0.44
p	.008	.808		.781	.064	.190	.834
Partial η^2	.005	< .001		< .001	.003	.001	< .001
Language							
df	3, 1376	3, 1387		3, 1528	3, 1257	3, 1217	3, 1330
F	11.12	3.56		8.31	5.21	3.55	27.01
p	< .001	.014		< .001	.001	.014	< .001
Partial η^2	.024	.008		.016	.012	.009	.057
Rater x Language							
df	3, 1376	3, 1387		3, 1528	3, 1257	3, 1217	3, 1330
F	1.04	0.13		1.74	1.24	6.40	2.59
p	.373	.944		.157	.292	< .001	.052
Partial η^2	.002	< .001		.003	.003	.016	.006

The main effect of Language is significant for all six prompts, although effect sizes are somewhat smaller in these analyses than in the previous ones, which did not control for length (see Table 12). The main effect of Rater is much less prevalent when effects of length are removed. In Table 12, five of seven prompts show a difference between HR and e-rater01, but in the current analyses, the Rater difference is significant for only one of six prompts. Finally, as in the previous results, the Rater × Language interaction is significant for only one prompt. This general absence of Rater × Language interactions means that HR and e-rater01produce similar patterns of language group differences.

The results, then, indicate that the effect of native language is not entirely due to differences in essay length, as Language is still a significant factor for all six prompts. Instead, other aspects of writing must be responsible for the higher sores of the Spanish and the lower scores of the Arabic and Japanese examinees. Future research should look for distinctive patterns of feature values that can characterize the writing of these and other groups.

Summary and Conclusions

We return now to our original three questions about e-rater and essay length.

1. With the effects of length removed, how much agreement is there between e-rater and human readers in assessing the quality of writing?
   - E-rater99 performs no better than a model that uses only the number of words and the number of words squared to predict score. Partial correlations show that it accounts for only .05 of the variance in HR score when effects of length are removed.
   - E-rater01 is significantly better than length-based models and accounts for .14 of the HR variance when length is partialed out.
   - Human readers have slightly higher levels of exact agreement (0.56) than that which is found e-rater01 and HR (0.53), but there is no difference in adjacent agreement proportions. With length partialed out, H1 and H2 share .26 of their variance, a value that is greater than the partial shared variance of e-rater01 and HR (.15).

2. Which features of writing does e-rater rely on in scoring essays?
   - The regression models of e-rater99 rely heavily on counts of argument development words and auxiliary verbs, as well as on topical analysis features. When length is

partialed out, it is primarily the topical analysis features that account for a significant proportion of variance.

- The regression models of e-rater01 rely largely on topical analysis features and lexical complexity measures. Although the latter include word counts of various sorts, these measures still account for a significant proportion of the variance when length is removed.

3. Is there an effect of native language on score that is independent of essay length, and, if so, does e-rater show the same pattern of differences across native language groups as HR scores show?
   - There is a main effect for language in the data of the current study. The mixed and Spanish groups have higher scores on average than the Arabic and Japanese. These differences remain even when length is removed.

   For most of the prompts, e-rater01 shows the same pattern of differences across native language groups as HR, even with length differences partialed out. Future work should include additional language groups to see if these results generalize.

In practical terms, e-rater01 differs from human readers by only a very small amount in exact agreement, and it is indistinguishable from human readers in adjacent agreement. But despite these similarities, human readers and e-rater are not the same. When length is removed, human readers share more variance than e-rater01 shares with HR. The human readers must be sensitive to additional characteristics of writing that the machine is not. This suggests that the greatest improvements in machine scoring will come from the development of new features for as-yet unmeasured aspects of composition. The improvement in performance from e-rater99 to e-rater01 reflects the addition of lexical complexity features, and recent advances in automatic detection of grammatical errors (Leacock & Chodorow, 2001) have provided measures of syntactic proficiency and word usage that e-rater02 models use.[4] The goal of future work should be to make available an even larger and more sophisticated array of features. Not only will this lead to better scoring performance, but it will also let us capture more of the richness and diversity of human language.

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Notes

[1] A score of 0 can also be assigned to indicate that the essay contains little or no text, or that it is not on the assigned topic.

[2] Less than 0.5% of the essays in the mixed cross-validation sets have a score of 0.

[3] Only one prompt, E, had a significant cubic component.

[4] A newer version of e-rater, e-rater02, not evaluated here, uses number of low probability part-of-speech sequences in its prediction of essay score.

[5] Homogeneity of regression slopes was tested with an analysis of variance that included in its model an interaction term for language*words*words^2. Significance of this interaction indicates a violation of the assumption of homogeneous regression slopes (Keppel, 1991; Mertler & Vannatta, 2001).

Appendix A

TOEFL Writing Scoring Guide

The content of this appendix is excerpted from the *TOEFL Test of Written English Guide* (ETS, 1996).

6 An essay at this level

- effectively addresses the writing task
- is well organized and well developed
- uses clearly appropriate details to support a thesis or illustrate ideas
- displays consistent facility in use of language
- demonstrates syntactic variety and appropriate word choice though it may have occasional errors

5 An essay at this level

- may address some parts of the task more effectively than others
- is generally well organized and developed
- uses details to support a thesis or illustrate an idea
- displays facility in the use of language
- demonstrates some syntactic variety and range of vocabulary, though it will probably have occasional errors

4 An essay at this level

- addresses the writing topic adequately but may slight parts of the task
- is adequately organized and developed
- uses some details to support a thesis or illustrate an idea
- demonstrates adequate but possibly inconsistent facility with syntax and usage
- may contain some errors that occasionally obscure meaning

3 An essay at this level may reveal one or more of the following weaknesses:

- inadequate organization or development
- inappropriate or insufficient details to support or illustrate generalizations
- a noticeably inappropriate choice of words or word forms
- an accumulation or errors in sentence structure and/or usage

2 An essay at this level is seriously flawed by one or more of the following weaknesses:

- serious disorganization or underdevelopment
- little or no detail, or irrelevant specifics
- serious and frequent errors in sentence structure or usage
- serious problems with focus

1 An essay at this level

- may be incoherent
- may be undeveloped
- may contain severe and persistent writing errors

0 A paper is rated 0 if it

- contains no response
- merely copies the topic
- is off-topic
- is written in a foreign language
- consists of only keystroke characters

Appendix B

Confusion Matrices for Essay Scores Combined Across Mixed Cross-validation Sets for Seven Prompts

Table B1

Score Predicted by Length-based Models Estimated From Training Sets

HR Score	0	1	2	3	4	5	6	Total	Proportion
0	7	0	0	0	0	0	0	7	0.002
1	6	18	3	0	1	0	0	28	0.008
2	0	17	71	43	6	3	0	140	0.040
3	0	0	86	419	168	21	0	694	0.198
4	0	0	11	336	727	199	18	1,291	0.369
5	0	0	0	35	426	381	57	899	0.257
6	0	0	1	3	71	265	101	441	0.126
Total	13	35	172	836	1,399	869	176	3,500	1.000
Proportion	0.004	0.010	0.049	0.239	0.400	0.248	0.050	1.000	

Note. Scores are rounded to the nearest integer.

Table B2

Score Predicted by E-rater99

HR Score	0	1	2	3	4	5	6	Total	Proportion
0	5	1	0	1	0	0	0	7	0.002
1	4	12	11	0	1	0	0	28	0.008
2	0	13	77	44	6	0	0	140	0.040
3	0	2	112	428	142	9	1	694	0.198
4	1	0	26	459	639	145	21	1,291	0.369
5	0	0	0	91	438	295	75	899	0.257
6	0	0	2	10	105	184	140	441	0.126
Total	10	28	228	1,033	1,331	633	237	3,500	1.000
Proportion	0.003	0.008	0.065	0.295	0.380	0.181	0.068	1.000	

Note. Scores are rounded to the nearest integer.

Table B3

Score Predicted by E-rater01

HR Score	0	1	2	3	4	5	6	Total	Proportion
0	5	2	0	0	0	0	0	7	0.002
1	0	17	10	1	0	0	0	28	0.008
2	0	9	70	56	3	2	0	140	0.040
3	0	0	87	432	162	12	1	694	0.198
4	0	0	8	354	737	173	19	1,291	0.369
5	0	0	1	40	381	373	104	899	0.257
6	0	0	0	0	51	168	222	441	0.126
Total	5	28	176	883	1,334	728	346	3,500	1.000
Proportion	0.001	0.008	0.050	0.252	0.381	0.208	0.099	1.000	

Note. Scores are rounded to the nearest integer.

Table B4

H2 Score

H1 Score	0	1	2	3	4	5	6	Total	Proportion
0	7	0	0	0	0	0	0	7	0.002
1	0	28	7	1	0	0	0	36	0.010
2	0	9	122	89	11	0	0	231	0.066
3	0	0	82	501	250	23	1	857	0.245
4	0	0	10	247	748	244	25	1,274	0.364
5	0	0	2	26	231	386	116	761	0.217
6	0	0	0	3	42	107	182	334	0.095
Total	7	37	223	867	1,282	760	324	3,500	1.000
Proportion	0.002	0.011	0.064	0.248	0.366	0.217	0.093	1.000	

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73313-035288 • Y24E.05 • Printed in U.S.A.
I.N. 990112