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Computerized Oral Proficiency Test for Japanese: Measuring L2 Speaking Ability with ASR Technology

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ABSTRACT

byubaselinestretch2 Computerized Oral Proficiency Test for Japanese: Measuring Second Language Speaking Ability with ASR Technology

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Developing a time- and cost-efficient method for second language (L2) oral proficiency measurement is one of the research topics that has attracted much attention in recent decades. The purpose of this study is to develop a computerized oral testing system for L2 Japanese using automatic speech recognition (ASR) technology. Two testing methods called elicited imitation (EI) and simulated speech (SS) are proposed to quantify L2 accuracy and fluency via ASR processing. This study also suggests systematic EI item creation leveraging corpus technology and discusses the effectiveness of the test items created through analyses of item difficulty. Further, refinement of the EI grading system is described through a series of statistical investigations. For SS, this study reports the five most influential L2 fluency features identified through machine learning and proposes a method to yield individual SS scores with these features based on previous studies. Lastly, several methods to combine the EI and SS scores are presented to estimate L2 oral proficiency of Japanese.

Keywords: L2 oral proficiency, EI, SS, ASR, computerized oral test

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Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Overview

Development of a reliable and time-efficient second language (L2) oral proficiency test is currently of great interest in the field of language testing. The main reason for this motivation is because a common approach in L2 speaking assessment is to interview a learner. Measuring speaking ability per this approach involves complex processes: (1) a test taker must be able to produce speech samples recorded for evaluation, and (2) two or three human evaluators typically listen to the collected speech samples to evaluate oral proficiency based on a stipulated rubric, and raters' judgments are averaged to produce a single score. Regarding (1) and (2), the following conditions exist during test administration and evaluation from testers' and test takers' perspectives.

Table 1.1: Conditions in Typical Interview-based Tests (cf. Newfields 1994)

	Tester	Test Taker
Test Administration	Needs substantial amount of time to test multiple test takers	Needs to be well-informed about the testing procedure
Test Evaluation	Needs to be well-trained to yield consistent scores or ratings based on a rubric in a short time	Needs to wait longer to obtain a score or rating and feedback with receptive skill tests

As Table 1.1 above indicates, using interview-based tests requires a great deal of work and time for both testers and test takers. Considering this situation, the grading process is especially labor-intensive because a rating is produced through averaging two

or three raters' respective judgments, as mentioned above. Because of this complexity, it is necessary that the raters spend substantial time to yield well-justified ratings. However, this is not acceptable in most language institutions because of the time constraints and the limited availability of qualified raters. Therefore, administering interviews is very difficult, especially in programs for less commonly taught languages, due to limited resources, although it is essential to examine students' oral skill development regularly (Kenyon and Malabonga 2001).

Another issue is the cost of commercially available interview tests. For instance, oral proficiency interviews (OPIs), provided by Language Testing International (LTI), are widely administered tests which have been regarded as a recognized standard for measuring oral proficiency of various target languages. However, the administration of OPIs is very costly: a single OPI costs approximately 130 US dollars for a 30-minute interview and evaluation[1]. Because of the cost, the OPI is regarded as a high-stakes test for learners to demonstrate their L2 oral proficiency for official documentation. Therefore, the OPI is not necessarily suitable to assess L2 speaking ability regularly at language institutions for formative and summative purposes.

To develop a cost- and time-efficient test, it is crucial to identify the problems related to L2 oral proficiency measurement. Furthermore, it is inevitable to utilize some sort of computer technology to realize such efficiency. In the following section, I will focus on two important aspects that are frequently discussed in studies on L2 oral language production, namely, accuracy and fluency.

1.2 Problem: Quantification of Accuracy and Fluency Features

Accuracy and fluency in speech production are essential constructs in measuring L2 oral proficiency (Housen and Kuiken 2009), and many oral proficiency tests take these constructs into account in the test development and evaluation processes (e.g., the Test of Spoken English (TSE) Scale by the Educational Testing Service (ETS); Common European Framework of Reference (CEF) of Council of Europe; see Luoma 2004 for more detail). For example, the OPI guidelines (ACTFL 1999) incorporate accuracy and fluency factors in the

[1] See `http://www.languagetesting.com` for more detail.

descriptions of its rating scale. Table 1.2 enumerates the representative characteristics of L2 accuracy and fluency pointed out in the OPI guidelines:

Table 1.2: Accuracy and Fluency Factors in OPI Guidelines

Accuracy Features	Fluency Features
pronunciation	hesitation patterns
vocabulary choice	turn taking
(morpho-)syntactic formation	length of a narration
discourse structures	discourse management

These accuracy and fluency factors are further explained in detail for the basis of final ratings[2] in the evaluation procedure. As one can imagine, interpreting these descriptions accurately and generating ratings which are consistent with other evaluators requires substantial experience because this type of grading procedure is inevitably subjective (McNamara 2000). Moreover, the manifestation of accuracy and fluency features can be quite different in every interview because the topics to be covered are determined during the initial conversation according to several factors such as test takers' background, and thus the linguistic information gained in an interview is basically unpredictable before it starts. Therefore, multiple raters are inevitably necessary to ensure the high stability of ratings in such disparate testing and grading procedures (Hughes 2003).

The first problem that needs to be addressed in this study is to obtain accuracy and fluency features in a quantifiable manner for the development of an efficient oral test. For this it is necessary to ensure that the testing system is able to retrieve these two types of features from speech samples at a satisfatory level of precision consistently. However, this problem highlights the limitation of current computer technology: It is not possible for a computer system to handle speech samples with unpredictable language usage correctly,

[2]There are ten sublevels in OPI: Namely, Superior, Advanced(High, Mid, Low), Intermediate(High, Mid, Low), and Novice(High, Mid, Low). For raters' final judgment, detailed descriptions on expected performance in each sublevel are provided.

because the performance depends largely on language data, or corpora, provided for the system training (Nagatomo *et al.* 2001). In other words, the level of precision in speech processing with computers is likely to be very limited if the input speech samples are outside the domain of the language data. This situation is highly probable in this study, and in particular, it makes obtaining reliable accuracy features very difficult, because of the nature of L2 speakers' speech samples, which are more unpredictable and unorganized than first language (L1) speakers'.

1.3 Solution: Separation of Accuracy and Fluency Measurement

The computerized oral proficiency test proposed in this study is not designed to function with speech samples collected from random topics because of the limitation of speech processing technology. Thus, it is imperative to use more rigidly regulated testing methods than the interview-based counterpart so that the system can successfully obtain and process the structured speech data to extract accuracy and fluency features. To accomplish this, I propose a testing system using two objective testing methods called elicited imitation (EI) and simulated speech (SS). This approach has two advantages: (1) it limits the variety of learners' speech samples obtained in the testing phase in order to make feature extraction more manageable with the computer system, (2) it allows the computer system to be trained in a domain-specific manner according to the employed testing methods and to process the speech samples in an analytic manner. Figure 1.1 shows the basic concept of this approach.

The main purpose of this study is (1) to develop a fully computerized oral testing system for L2 Japanese using automatic speech recognition (ASR) technology (Jurafsky and Martin 2008), (2) to inform systematic EI test item creation with corpus data, and (3) to evaluate learners' test performance with the EI and SS grading results provided by the system. My approach, however, does not aim to implement the same testing and grading procedures as in interview-based exams, because of the limitation of speech recognition technology mentioned above. The testing system I propose here contains the following capability: (1) it handles multiple test takers concurrently with a computer-mediated test,

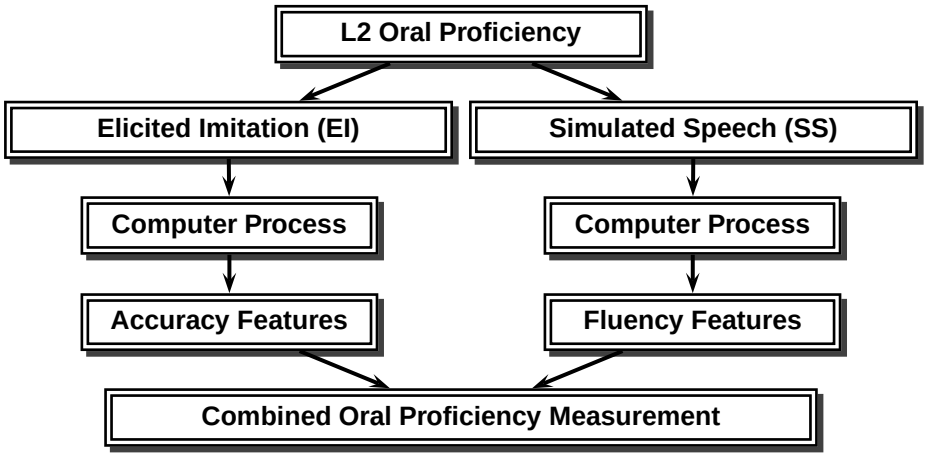


Figure 1.1: Basic Concept of the Proposed Computerized Testing System

and (2) it extracts various linguistic features from collected speech samples without requiring any human labor.

This thesis is organized as follows. In Chapter 2, I will explain the development of EI as an accuracy measurement and SS as a fluency measurement, based on various previous studies. In Chapter 3, the EI item creation procedure with corpus technology will be discussed. In Chapter 4, the system development of the EI grading system will be explained, based on our previous studies. In Chapter 5, I will describe the fluency feature extraction with the grading system and the process of combining EI and SS results to predict overall L2 oral proficiency. Chapter 6 will be the conclusion.

Chapter 2

Review of Literature

In this chapter, I will describe the development and analyses of EI and SS as viable testing methods based on available literature. EI and SS have been investigated based on fundamentally different backgrounds. The former has mainly been used in the fields of language acquisition and psycholinguistics research for several decades as an effective experimental data collection technique, whereas SS has been considered as an alternative testing procedure to labor-intensive interview tests especially for less commonly taught languages. In the following sections, I will explain the strengths of these methods through previous studies and how these two can be combined to measure L2 oral proficiency with ASR technology.

2.1 Elicited Imitation

2.1.1 Basic Concept

Elicited imitation (EI) has been receiving attention as a viable language testing method in various fields, especially in second language acquisition (SLA). Although there are some slight differences in administering EI among various studies, the basic procedure of EI is as follows:

> The procedure involves preparing a stimulus string … that illustrates some grammatical feature …, and subjects are instructed to repeat exactly what they hear. (Chaudron 2003)

This simple process is repeated several times to collect multiple speech samples to examine whether the learner has acquired the target grammatical structures or lexical items incorporated in the model sentences, based on the assumption that "success at exact imi-

tation demonstrates the learner's possession of the target features in his or her linguistic knowledge store" (Chaudron 2003).

Despite its simplicity, EI requires learners to employ multiple linguistic skills to successfully reproduce a series of target sentences. Figure 2.1 and the following descriptions illustrate the fundamental processes that learners need to execute during an EI performance (Vinther 2002).

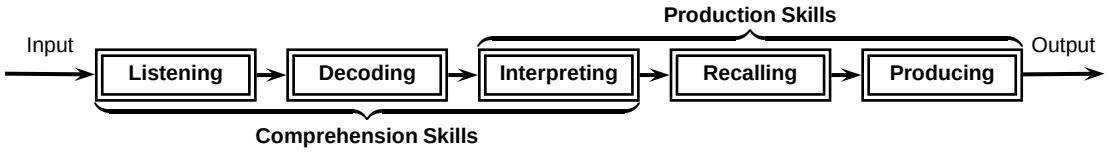


Figure 2.1: EI Processing Model (Based on Vinther 2002)

Listening. The test taker perceives a sound sequence contained in an EI item phonologically to process it as a series of linguistic units (e.g., sound sequences, words, phrases, etc.) in the decoding phase.

Decoding. Bley-Vroman and Chaudron (1994) state that the input is decomposed as chunks, or meaningful linguistic units in the short-term or working memory when it is heard. They say that the size of the chunks varies depending on the test taker's grammatical knowledge: the more familiar the test taker is with the target language, the more accurately he or she is able to process the model sentence at this stage because the knowledge helps form a larger size of chunks and store the linguistic information without exceeding memory capacity.

Interpreting. Vinther (2002) mentions that the meaning of the decomposed units of information are to be syntactically and semantically processed at this stage. She also points out that if the test taker understands the meaning of the stimuli but fails to produce an accurate repetition, it is possible to reason that the grammar system of the target language

has not been developed sufficiently to reconstruct the level of complexity contained in the presented sentence at this stage[1].

Recalling. McDade *et al.* (1982) discuss the relationship between the timing and accuracy level of the performance (either immediate or delayed imitation). Based on their study, they claim that if the test taker fails to interpret model sentences properly, the imitation is significantly hindered even if the test taker is asked to repeat stimuli immediately. On the other hand, sentences that he or she understands are correctly repeated even if there are time intervals between listening and repetition. This result indicates that recalling the stimuli for imitation is highly determined by L2 comprehension capacity or successful processes in the preceding stages. This also implies that it is impossible to produce sentences without internalized productive knowledge and mechanisms of the target language (cf. Levelt 1995).

Producing. Similar to recalling, Vinther (2002) maintains that EI measures production ability, although the accuracy of EI repetitions is highly determined by the preceding comprehension due to the nature of the task. She claims that EI requires developed L2 speaking ability because it is possible that poor imitation occurs even if the subject has been able to understand the model sentences successfully.

Although there are still a number of unknown aspects regarding EI processing, the model above clearly indicates that EI is a highly complex language task that requires several factors of L2 knowledge for successful imitation, not just a memory test. The various applications of EI based on this assumption are reported in the literature. In the following subsection, applications of EI in language testing are discussed.

2.1.2 Applications

EI has been utilized as an experimental data collection method for more than four decades in psychology and language acquisition studies such as child language development (e.g. Fraser *et al.* 1963, McDade *et al.* 1982) and implicit knowledge measurement

[1]I indicate the interpreting stage as both comprehension and production skills because the interpretation is analogous to Levelt's (1995) conceptualizer, which precedes the process to transfer the idea to linguistic representations, according to the explanation of Vinther (2002).

(Ellis 2005, Erlam 2006, Ellis 2008, Erlam 2009) and its instructional impact (see the detailed overview in Ellis 2010). Although the research slowed down temporarily during the 1980s due to severe criticism of the methodology, it regained research attention in the late 1990s again and started being regarded as a viable testing method (Jessop *et al.* 2007).

The noteworthy studies in terms of this present research are those which focus on the application of EI to L2 testing. Naiman (1974) discusses the usefulness of EI for measuring L2 ability. He developed twelve carefully designed EI sentences along with comprehension and production tests and conducted experiments with 112 young students who were learning L2 French in an immersion program. His results show a strong association between scores on imitation and other types of production tests. He claims that EI is a more effective testing method to examine L2 production skills than spontaneous speech counterparts because it is easily implemented to identify L2 learners' morphosyntactic acquisition patterns explicitly and examine the development of their productive grammar effectively.

Bley-Vroman and Chaudron (1994) provide a detailed investigation of previous psycholinguistic and SLA studies and discuss the potential of EI as an L2 proficiency measurement. They delineate the concept of chunking (see 2.1.1) and explain how linguistic representations formed through chunking are stored in the short-term memory. They point out, based on the claim by Forster (1987), that the representations are encoded at stratified control levels, which regulate the interpretation of presented linguistic information in short-term memory. Furthermore, they claim that several control levels are activated during the EI task and a successful or poor EI performance is determined by the intensity of the activation. Based on these theoretical assertions, they maintain that the length of the model sentences has a significant effect on a subject's ability to produce EI repetitions because it provides a direct impact on chunking and representation formation processes regulated by L2 proficiency and short-term memory capacity.

Inspired by Bley-Vroman and Chaudron (1994) and Chaudron's subsequent study (Chaudron *et al.* 2005), research on EI as an L2 proficiency measurement has been conducted by Graham (2006) and others. In a pioneering study, Graham (2006) reports that he and his colleagues developed and refined sixty English EI items with designated syl-

lable lengths (5–25) through the test validation process. They administered the test to 156 students at an intensive English program (IEP) in the US and conducted correlational analyses between EI scores and ratings of other oral tests such as the OPI. They mention that there was a moderately strong correlation between EI and OPI ($r \approx 0.65$) in the experiment and conclude that EI has a potential to be a highly reliable testing technique for oral language skills.

Furthermore, he and his colleagues conducted subsequent studies: Graham *et al.* (2008b), Hendrickson *et al.* (2008), Weitze and Lonsdale (in print), Weitze *et al.* (2009). The important findings of these studies are summarized as follows:

1. Sentence length based on the syllable count (i.e., the number of syllables in an EI sentence) influences L2 learners performance most crucially, which conforms to the claim by Bley-Vroman and Chaudron (1994).

2. Lexical frequency and lexical density (i.e., the number of content words in an EI item) are minor factors that affect EI item difficulty.

3. Morphological density and morphosyntactic features do not account significantly for learners' EI performance.

4. There is a strong association between EI score patterns and the acquisition order proposed by DeKeyser (2005), and the score distributions are highly unified regardless of learners' L1.

5. Overall, EI scores predict OPI ratings within two sublevels of margin of error (between Novice Low and Superior)[2].

2.1.3 Computer Scoring

Scoring EI is one of the important issues discussed in the literature. Although there are some differences among studies, many researchers employ holistic scales as a grading method. As a typical example, Keller-Cohen (1981) uses a 1-to-7 scale continuum (1 for no repetition and 7 for perfect imitation) in the EI study for L1 lexical acquisition. This

[2]See the footnote in 1.2 on OPI ratings.

approach, however, requires complex subjective grading procedures observed in typical interview-based tests and causes the same evaluation problem described in 1.1 and 1.2.

Charting a new direction, Chaudron *et al.* (2005) introduced a scoring method in the development of EI-based language assessment batteries by taking advantage of the limited variety of EI responses. In the scoring process, they counted mispronounced syllables in each repetition to yield a score ranging from four points (the highest) if the repetition is a perfect imitation, to zero if four or more errors are made. Based on this approach, Graham (2006) further proposed a binary scoring method, in which one point is given for each correctly pronounced syllable in an EI utterance and zero otherwise, and the total number of correct syllables in all the items is used as a test score. Obviously, these two scoring methods are highly objective, which does not require graders to be well trained native speakers to ensure consistent scoring. Lonsdale *et al.* (2009) report that agreement in approximately 175,000 double-graded syllable scores yielded by fifty graders (including both native and non-native speakers of English) was as high as 91% with the binary scoring method proposed by Graham (2006).

In concert with the establishment of these objective EI grading methods above, various attempts were made to develop an automated grading system using ASR technology. As a landmark study, Graham *et al.* (2008a) present a detailed validation study with an experimental ASR grading system. They used SPHINX, an ASR engine developed at Carnegie Mellon University (Lee 1989) and recognition grammars designed to score EI items systematically. They conducted correlational analyses against randomly selected human-generated scores reported in Graham (2006). With this method, they reported that they attained an 88% correlation coefficient between human and ASR scores although there are some technical limitations with the proposed system, such as its inability to produce syllable-level scores.

Based on the results shown by Graham *et al.* (2008a), ASR-based systems for Japanese EI have been investigated in a series of our studies. The detailed descriptions of the development of Japanese EI systems will be provided in Chapter 4.

2.2 Simulated Speech

2.2.1 Development

Simulated Speech (SS) is another testing method to measure L2 oral proficiency which has been used for many years in the field of language testing. The basic procedure of this method is described as follows:

> One speaker produces a long turn alone without interacting with other speakers, but they also typically include extracts of situations where the examinees say something in a particular situation, possibly in response to another speaker whose turn is heard … Luoma (2004:44-45)

The tests using this method are frequently referred to as "semi-direct" oral tests (O'Loughlin 2001) in contrast with direct tests such as OPIs discussed in Chapter 1, which involve face-to-face or phone interviews, because those tests requires test takers to speak in a rather communicatively confined environment although they still need to employ their various L2 strategies for production (Shohamy 1994). This testing method started being utilized in 1980s, especially when the simulated oral proficiency interview (SOPI) was introduced for L2 Chinese oral proficiency assessments (Clark and Li 1986). The motivation for the development of SOPI was to make oral proficiency assessment more accessible to learners of less commonly taught languages because it was common that well-trained interviewers of the OPI or other oral interviews for those languages were not readily available at many language institutions. A number of validation studies of SOPI were actively conducted in 1990s. Those studies mainly reported that the high concurrent validity of SOPI, indicating the correlation between OPI and SOPI for various languages ranged from 0.89 to 0.93 (Clark and Li 1986, Stansfield *et al.* 1990, Shohamy *et al.* 1989, among others). Although some of them point out that there are some critical differences between these two types (see Shohamy 1994 and Koike 1998 for more detail) and caution that ratings produced by semi-direct tests are not necessarily equivalent to those of direct tests, many studies indicated that semi-direct oral tests are the optimal second choice for measuring L2 speaking ability if oral interviews are not available (Clark and Li 1986).

Based on the findings of the investigations of SOPI and other semi-direct speaking tests, the possibility of computer-mediated tests has been examined intensively for the last two decades (Malone 2007). The computerized oral proficiency interview (COPI), for example, is a computer-mediated version of SOPI which provides more features than the tape-mediated SOPI was not able to offer, such as an adaptive testing procedures based on the test taker's self-assessment and the test taker's control over preparation and response time (Malabonga *et al.* 2005). The oral proficiency interview by computers (OPIc) is another computer-mediated oral test proposed by the LTI and used in recent years based the concept similar to COPI (Malone and Montee 2010)[3].

2.2.2 Computer Evaluation

The major characteristic of SS discussed in 2.2.1 is that the main focus of this testing method is on the ease of test administration by utilizing technology in lieu of trained interviewers who are not always available, especially for less commonly taught languages. However, this does not mean that rating processes are also eased with this technique. In fact, SOPI, COPI, and OPIc still require human raters who evaluate collected speech samples based on the American Council on the Teaching of Foreign Languages (ACTFL) grading scales which are used for the OPI evaluation. Of course, human evaluation ensures that ratings for these semi-direct tests are comparable to those of OPIs with the same grading rubric. However, this situation makes these tests unaffordable in many cases for most learners and prevents them from being used other than for criterion-referenced purposes. To overcome this issue, various attempts have been made to develop automatic grading systems with computer technology.

This area of research began in the last two decades along with the advancement of computer processing power and the field of natural language processing (NLP) including speech processing technology (Jamieson 2005). Some studies investigate the possibilities of utilizing the technology for automatic evaluation systems. Hansen and Rowe (2006) developed a semi-directed speech testing system called the fully-automated speech test (FAST) based on Hansen (2001), which points out that there are strong associations be-

[3]See `http://www.languagetesting.com/kgic/` for more detail.

tween L2 speaking capability and temporal features such as length of speech and silence time. In this study, they administered computer-mediated semi-direct tests with video prompts to elicit monologic speech samples to 210 English-as-a-second-language (ESL) learners in the US, in order to examine whether the temporal features correctly predict the proficiency levels measured by the placement test offered at the institution. Based on their analyses, they claim that the temporal features they focused on and proficiency levels indicate a strong statistical association and the combination of speech technology with these evaluation features will provide an effective method for L2 ability assessment as well as language acquisition and attrition research.

Similarly, Beigi (2009) reports that he implemented an automatic classification system which distinguishes seven levels of human English OPIc ratings (Novice Low to Advanced) based on temporal features such as the time lengths of audio samples and actual speech segments. In his study, he used 973,000 OPIc speech samples collected in actual OPIc administrations and corresponding human ratings for system training. Based on the results, he mentions that the system attained approximately 53% accuracy of agreements between computer-generated and human ratings although the features concerned in this study were temporal features only.

Research on the automatic evaluation system called SpeechRater^{SM}, which has been investigated at ETS for several years, is one of the most current and comprehensive studies regarding computer evaluation for semi-direct oral tests (Xi *et al.* 2008, Zechner *et al.* 2009, Yoon *et al.* 2010, Higgins *et al.* 2011, among others). In their most recent study, Higgins *et al.* (2011) used more than 20,000 L2 English speech samples (45 to 60 seconds each) obtained from the Internet-based Test of English as a Foreign Language (TOEFL-iBT) and TOEFL Practice Online (TPO) test for the ASR-based grading system development. First, they examined three multiple regression models as possible score estimators, which generated numerical values predicting test scores based on the five most influential speech features in human rating. They obtained moderately strong correlations ($r \approx 0.7$) with all three regression models between human and machine scores in this step. Based on these results, they further developed a logit scoring model with 90% prediction intervals to provide approximate score ranges that the test taker is likely to gain with human-

generated scores. These ETS studies will be used as the basis of the fluency measurement with SS in Chapter 4.

2.3 EI and SS: Testing Methods for Accuracy and Fluency Measures

The most important aspect of the previous EI and SS studies cited in 2.1 and 2.2 is to explicate how EI and SS function to measure L2 oral accuracy and fluency in terms of the development of the oral proficiency testing system in this research. The critical characteristic of EI is that test takers are required to use particular grammatical features presented in the test items in their production. Therefore, it is reasonable to think that avoiding or failing to reproduce the features accurately indicates tangible information on the limitation of learners' current oral production capability. Regarding this aspect, Naiman (1974:34) describes as follows:

> The advantage of using imitation as a technique for collecting data comes from the fact that whatever sound or grammatical structures the researcher wishes to look at can be elicited without having to record hours of spontaneous speech …. Spontaneous speech data … suggest that speakers of a second language will go to considerable length to avoid the use of a sound or grammatical structure that is particularly difficult for them.

In other words, the test taker of EI is forced to produce sentences with specific features regardless of whether he or she has already acquired those features in the target language. Therefore, as described in 2.1.1 and Vinther (2002), both comprehension and production are hindered significantly if those features are absent in the current interlanguage, which leads to less accurate production in the EI task. Because of the objective grading with EI mentioned in 2.1.2, the differences in production accuracy can be distinguished with quantified scores. This is the basis for the assumption in this study that EI is a powerful technique to tap the test taker's L2 oral accuracy. At the same time, this fact further indicates that (1) creating EI test items which are able to classify learners' L2 accuracy in a gradable manner is very crucial in developing an effective EI test, and (2) dictating EI responses with ASR accurately is crucial to attain precise objective grading

proposed by Graham (2006). Regarding these issues, I will propose a proceduralized item development technique in Chapter 3 and an optimal language model development for EI grading using ASR in Chapter 4.

The main reason that I chose SS for fluency measurement is rather obvious. A substantial number of studies have been conducted to measure L2 fluency based on various features. Typically, these studies examine several quantifiable fluency features to illustrate the role of fluency observed in production activities and indicate the relationship between those features and L2 oral proficiency (Koponen and Riggenbach 2000, Segalowitz 2010). Table 2.1 shows the empirical and theoretical fluency studies and their focused features.

Table 2.1: L2 Fluency Studies and Focused Features

Study	Features
Ellis (1993)	temporal variables and hesitation phenomena
Laver (1994)	filled and unfilled pauses
Freed *et al.* (2004)	speech rate, total words spoken, duration of speaking time, etc.
García-Amaya (2009)	speech rate, repetitions, repairs, total number of words, etc.
Chambers (1997)	number of pauses, length of run, place of pauses, L1 transfer of pause patterns, etc.
Kormos and Dénes (2004)	speech rate, phonation-time ratio, mean length of runs, etc.

Interestingly, these fluency features play critical roles in measuring oral proficiency in computer-based SS tests such as the TOEFL test. See Table 2.2, which shows the L2 proficiency features investigated in Higgins *et al.* (2011).

Note that the majority of variables indicated in Table 2.2 are fluency-related features. Therefore, the computer-generated scores in Higgins *et al.* (2011) are fundamentally based on fluency features obtained through semi-direct test items used in their study. Further, retrieving most temporal features mentioned in Table 2.2 with ASR does not require

Table 2.2: Oral Proficiency Variables in Higgins *et al.* (2011)

Variable Name	Feature Type	Feature Description
wpsec	Fluency	Speech articulation rate
tpsecutt	Fluency and Vocaburary	Unique words normalized by speech duration
tpsec	Fluency and Vocaburary	Unique words normalized by total word duration
wdpchk	Fluency	Average length of speech chunks
wdpchkmeandev	Fluency	Mean absolute deviation of chunk lengths
longpmn	Fluency	Mean duration of long pauses
silmean	Fluency	Mean duration of silences
silpwd	Fluency	Duration of silences normalized by response length in words
lmscore	Grammar	Language Model score
longpwd	Fluency	Number of long pauses normalized by response length in words
amscore	Pronunciation	Acoustic Model score

the high-precision dictation capability because those features are basically determined by the presence or absence of utterances in the speech samples, regardless of learners' L2 speaking ability. In other words, the ASR settings for fluency measurement are not necessarily trained with ample L2 acoustic and corpus data to obtain such information. Because of these reasons, it is safe to say that retrieving fluency features from an SS test with ASR is an optimal approach considering the limitation on the available ASR capability.

In Chapter 3, I will focus on the creation of optimal EI test items with a systematic procedure based on corpus technology.

Chapter 3

EI Item Creation

3.1 Systematic Item Creation

Creating optimal EI items is the first important stage for the development of effective EI tests. Several studies which discuss criteria for EI item creation are found in SLA and psycholinguistics literature. The following items indicate some of the typical conditions pointed out in those previous studies on this issue:

Sentence Length: EI items must exceed participants' short-term memory capacity to avoid rote repetition. This includes controlling sentence length based on the number of syllables or words (Jessop *et al.* 2007).

Target Features: Lexical and morphological features in EI items must be carefully chosen because they may make items too easy or difficult for learners to imitate, which greatly affects EI performance and scores (Tomita *et al.* 2009).

Feature Positions: Ideally, the target features must be placed in the middle position of the stimuli (Erlam 2006).

However, these criteria are rather vague and difficult to interpret in creating items for a particular target language. In the case of Japanese EI, for example, it is reasonable to assume that the maximum sentence length of test items should be considerably longer than those of English items due to the fact that the amount of information contained in a syllable (or mora[1]) is significantly small compared with English (Maddieson 2005). Also, the complex morphosyntactic features are often unavoidable even with a short Japanese sentence because of the agglutinative nature of the language, which causes high morphological complexity due to consecutive morpheme attachment in single words

[1] A mora (pl. morae) is a phonological unit used for the binary scoring in this study. See Chapter 4 in Tsujimura (2007) for detailed description from a linguistic viewpoint.

(e.g., causative passives, see Shibatani 1990). Further, verb formation and compounding constructions are linguistically significant characteristics of Japanese (Kageyama 1993, Matsumoto 1996) but those features are almost always located at the end of the sentence because the language is typologically verb-final. Undoubtedly, these language-specific characteristics should be taken into account in the production of optimal Japanese EI items along with the suggestions on item creation above.

Moreover, it is important to develop a method to constantly create a sufficient number of new items with various difficulty levels in order to avoid the practice effect (Brown 1988) that comes from multiple exposure to the same prompts over time. Also, it is necessary to proceduralize an item management system to classify test items according to difficulty levels and to properly reflect test takers' oral proficiency by using such assorted items retrieved from the item database. Logistically, this involves much time and effort if the process relies solely on native speakers' intuition. Therefore, developing a systematic procedure is imperative to address such a issue.

In this chapter, I will propose a structured method to create quality EI items from a linguistic and pedagogical point of view, based on the study conducted by Christensen *et al.* (2010). Further, I will examine the effectiveness of newly created items with two statistical analyses.

3.2 Previous Study

Christensen *et al.* (2010) examined a method to create English EI items utilizing various NLP techniques, based on the item creation criteria suggested by Jessop *et al.* (2007). They point out that manually created items found in previous studies such as Graham *et al.* (2008b) and Valian and Prasada (2006) significantly lack naturalness due to excessive emphasis on specific features such as word order and lexical complexity for the sake of the research purpose. They claim that such artificial test items do not necessarily reflect learners' L2 proficiency and emphasize the use of sentences that occur in corpora to ensure accurate predictions of L2 oral proficiency. To systematically produce EI items which contain target features from L1 corpus data, they developed a comprehensive NLP tool leveraging various language resources to retrieve test item candidates. This tool exam-

ines lexical density, word frequency, syllable length and grammatical features in queries in the process of sentence searches from the various corpora they used. They report that the correlation of the scores of EI items selected with this tool to the ratings of an oral proficiency test administered at an English-for-academic-purposes (EAP) institution was significantly stronger than those of the manually created EI items in Graham *et al.* (2008a). They further mention that this item creation method is far more time-efficient than the manual creation approach and enables them to create EI tests for specific purposes by using different types of corpora as needed.

Interesting aspects of their study include EI items based on natural language instances obtained from a spoken data corpus and on the effectiveness of corpus-based EI items in measuring oral proficiency. I claim that their approach is also desirable to Japanese EI item creation because (1) some of the similar tools and language resources used in their study are also available to replicate this study, and (2) this approach may open a path to overcome the ceiling effect seen in Matsushita and LeGare (2010) (see also 4.3) more easily than addressing it with a manual item creation approach.

However, this item creation method is not applicable unconditionally because of the language-specific aspects mentioned in 3.1 above. To customize this approach to Japanese item creation, the following points should be considered:

(1) Christensen *et al.* (2010) mainly focused on sentence length, lexical frequency and complexity, and morphological features based on the annotation information provided by the language resources used in their study. However, I argue that these features are not enough to create optimal Japanese EI items which draw clear distinctions, especially between those who are rated as Advanced Mid and Advanced High or Superior under the OPI criteria. This is mainly because the inflectional morphemes are largely salient and regular in Japanese (Kageyama 2010), and thus it is unlikely that those features affect difficulty in EI performance significantly[2]. In terms of Japanese EI item creation, there is a strong need to take into considera-

[2]Matsushita *et al.* (2010) reported that the EI test used in Matsushita and LeGare (2010) did not differentiate between advanced learners and native speakers based on the comparison between EI scores and OPI ratings. We claimed that this was mainly because the test items used in the study focused solely on grammatical features.

tion a higher level of language phenomena based on a viewpoint of theoretical and empirical linguistics in order to incorporate desirable difficulty levels in EI items.

(2) To accomplish (1), it is necessary to list language phenomena that contribute to the enhancement of item quality in a systematic manner. To address this task, identifying such language phenomena through careful examination of (psycho)linguistic literature and statistical item analyses with the empirical data are important. Further, establishing an effective procedure to identify item candidates that contain such phenomena with existing and/or custom-made corpus tools is also important.

(3) It is essential to create EI items according to the needs and interests of learners and instructors. Therefore, using grammatical features taught in a language program as criteria for item development should also be considered. Regarding this, the method suggested by Christensen *et al.* (2010) is useful because the typical features covered in language programs are identifiable with most NLP resources available in public use.

In the rest of this chapter, I discuss the item creation process based on (1) – (3) above. In this particular study, I developed thirty corpus-based Japanese EI items according to (a) the scheduled acquisition order based on the topics covered in the textbooks used in the Japanese program at Brigham Young University (BYU), and (b) the syntactic and semantic phenomena which are unique to the language and not covered in the textbooks specifically. Section 3.3 will discuss the theoretical background of syntactic and semantic phenomena in (b) above. Section 3.4 will illustrate the item engineering approach discussed in Matsushita *et al.* (2010) as a comparison with the corpus-based approach discussed in the subsequent sections. The rest of the sections will discuss the corpus-based approach and the statistical analyses based on an empirical study.

3.3 Syntactic and Semantic Features in Japanese

There are numerous linguistic features that make the Japanese language distinct from other languages. However, it is impossible to enumerate all of them and examine whether they are ideal for EI item creation in this single study. In this section, I discuss

only three linguistic phenomena: noun-modifying clauses, embedded clauses containing *pro*-dropped pronouns, and evidentiality based on several theoretical and empirical linguistic studies.

3.3.1 Noun-Modifying Clauses

Various psycholinguistic studies indicate that Japanese relative clauses are one of the complex syntactic structures that require high memory load and cause a garden path effect (Carroll 2008). For example, Sawa (2005) reports on a study of reading time and comprehension in a self-paced reading test containing various relativized sentences with 22 native speakers of Japanese. He indicates that SS and SO sentences[3] delayed reading speed and SS sentences resulted in the highest error rates in comprehension tasks. He ascribes these results to the garden path effect caused by these sentence structures. Interestingly, Sawasaki (2009) conducted a similar study with 84 L2 Japanese speakers and reported that SS and SO sentences also caused the longest reading time.

Further, Comrie (2010) explains the unique characteristic of Japanese relative clauses compared to their English counterparts. The following examples illustrate the difference in the flexibility of NP extraction in the process of relativization between Japanese and English:

(3.1) a. The person who kept the dog died.

b. *The dog [that the person who kept died] came to the station every evening to greet his master.

(3.2) a. Inu o kawaigatte kureta hito ga nakunatta.

b. [Kawaigatte kureta hito ga nakunatta] inu ga maiban eki made kainusi o mukae ni kita.

(Comrie 2010:41)

[3]SS: the head noun serves as a subject in both relative and matrix clauses; SO: the head noun serves as an object in the relative clause and as a subject in the matrix clause.

There are several syntactic frameworks which describe the phenomenon above. For instance, from the government and binding (GB) perspective (see Chomsky 1981), (3.2b) is called a violation of subjacency (Chomsky 1977) and cannot be perceived as a relative clause for the English counterpart depicted in (3.1b). Therefore, Comrie (2010) refers to such relative clauses as noun-modification clauses which are distinctively different from the conventional relativization patterns discussed in Keenan and Comrie (1977). As a similar case, Nakayama (2002) introduces a pragmatic complex NP, an example of which is shown below:

(3.3) *[Yuumei-na haiyuu-ga nesshin-ni shashin-o totta] sakuhinshuu-ga*
famous actor-NOM ardently photo-ACC take-PST collection-NOM
saikin chuumoku-sare-ta.
recently attention-CAU-PST
'The collection of the photos the famous actor took recently attracted attention.'

(Nakayama 2002:410)

The interesting aspect of this structure is that there is no empty category that has a connection with the head noun to indicate an argument role in the relativized clause in the bracket. However, the embedded clause still behaves as a modifier of the head noun following it. Regarding the processing of these noun-modification formations, Nakayama (2002) indicates that L1 speakers address such complex NPs based on the valency information of the verbs inside the modifying clauses while parsing the sentences and make constant predictions of the sentence endings based on the saturation of argument requirements.

Regarding EI item development, there are several advantages to using such noun-modification clauses. First, the structure makes it possible for verb constructions to locate in the middle of prompt sentences by utilizing the prenominal modification in Japanese. Second, unlike English, creating short sentences with noun-modification clauses is relatively easy with *pro*-drop (Tsujimura 2007), which makes it possible to create syntactically complex EI prompts with a few simple lexical items. Third, these structures are very common in Japanese, which enables a corpus search tool to provide a substantial number of instances effectively.

The *pro*-drop phenomenon is also a very common linguistic feature in Japanese and provides an interesting syntactic and semantic influence to structurally complex sentences. The following subsection will discuss the relationship between embedded clauses and *pro*-drop.

3.3.2 Embedded Clauses and *pro*-Drop

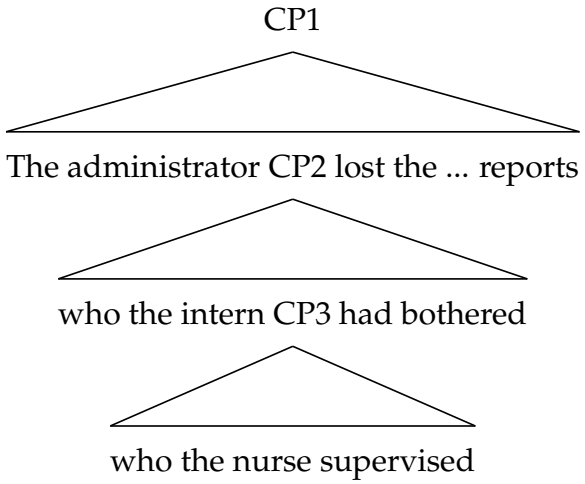
Along with the noun-modification constructions, sentence embedding and its effects are extensively discussed in the field of cognitive science. Regarding embedded clauses, Bader and Bayer (2006) discuss sentence structures which are not processable for most native speakers of English because of the memory overload with multiple nominative NPs. As shown in (3.4), the following type of sentence is very difficult to process although it is perfectly grammatical:

(3.4) #The administrator who the intern who the nurse supervised had bothered lost the medical reports.

(Bader and Bayer 2006:21)

They explain that this is mainly because the embedded clauses are nested hierarchically, which causes memory overload in processing the sentence. See the following diagram:

(3.5)



(Bader and Bayer 2006:21)

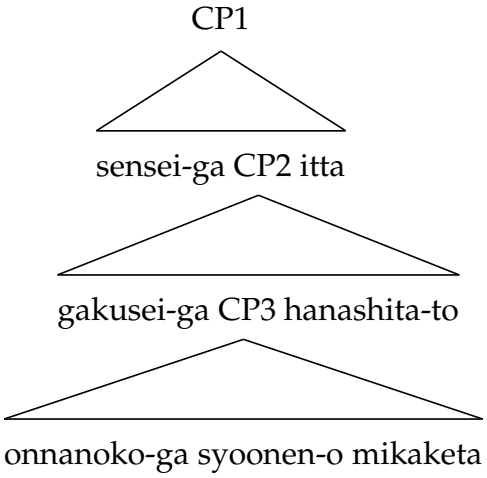
Miyamoto (2008) also discusses the same issue in the case of Japanese. He mentions that the following Japanese sentence is not processable for most native speakers of Japanese either:

(3.6) #*Sensei-ga* *gakusei-ga* *onnanoko-ga* *syoonen-o* *mikake-ta-to* *hanashi-ta-to*
teacher-NOM student-NOM girl-NOM boy-ACC say-PST-that tell-PST-that
it-ta.
say-PST
'The teacher said that the student told that the girl saw the boy.'

(Miyamoto 2008:240)

The hierarchical structure of (3.7) is analogous to the one shown in Bader and Bayer (2006):

(3.7)

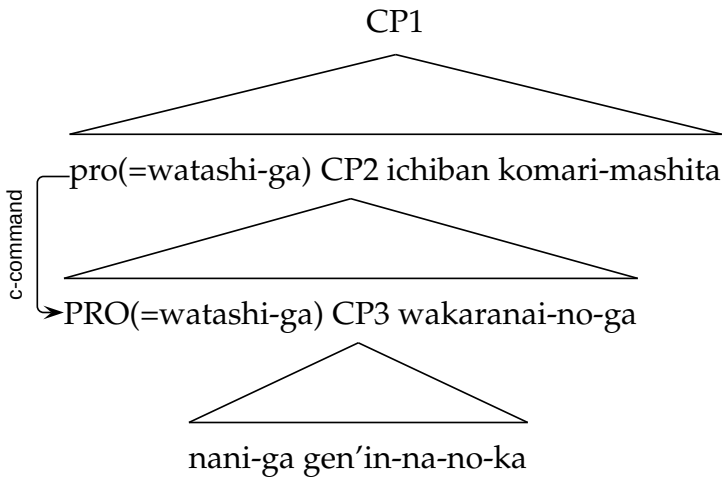


(Based on Bader and Bayer 2006)

This center-embedding construction, however, is not completely impossible in Japanese. With *pro*-dropped pronouns mentioned above, the following sentence is perfectly sound and processable for native speakers:

(3.8) ∅ *nani-ga* *gen'in-nano-ka* ∅ *wakara-nai-no-ga*
pro(=I) what-NOM cause-COP-Q PRO(=I) understand-NEG-COMP-NOM
ichiban *komari-mashita.*
most trouble-PST
'What baffled me most is that I didn't know what caused it.'

(3.9)



Comrie (2010) mentions that semantically vacuous lexical morphemes such as *-no* may be linked to the flexible structures in noun-modification structures discussed 3.3.1. This explanation may be applicable to this center-embedded construction above, along with *pro*-drop. However, the concrete reasons for this phenomenon remain to be seen, and it is not the main focus of this study. The main focus here is whether L2 speakers of Japanese, especially those who speak English as their L1, are capable of repeating such sentences in EI if the structure is not possible in their L1 in any case. Based on this perspective, this structure is also considered in item development in this study.

3.3.3 Evidentiality

The semantic feature I chose for this study is evidentiality (McCready and Ogata 2007). Japanese evidentials imply sources of information the speaker relies on. Different evidentials exhibit different connotations according to the sources. The following examples show typical evidentials and subtle differences among them. These evidentials are not clearly distinctive, but each evidential can be used to cover a specific domain of semantic types of references.

(3.10) a. *Kono* *kusuri-wa* *yoku* *kiku* *rashii.*
PROX medicine-TOP well work-INF EVID
'I infer from what I heard that this medicine works well.'

b. *Kinoo* *mo* *daremo* *ko-na-katta* *node,* *kyoo* *mo* *daremo*
yesterday also anyone come-NEG-PST so today also anyone
ko-nai *mitai* *da.*
come-NEG EVID COP
'No one came yesterday, so it seems that no one will come today, either.'

c. *Koizumi-sooridaijin-wa* *aitsu-o* *kubi* *ni* *suru* *soo* *da.*
Koizumi-PM-TOP him-ACC neck to do EVID COP
'Prime Minister Koizumi is going to fire him (I heard).'

McCready and Ogata (2007:154–160)

The examples above show a critical difference between epistemic modals and evidentials. In (3.10a), the speaker implies that (s)he has come to realize the efficacy of the medicine through some inference based on reading an advertisement, and so forth. The speaker in (3.10b), on the other hand, makes the statement based on his or her previous experience gained the day before. In (3.10c), the speaker makes this comment based on hearsay. According to McCready and Ogata (2007), each evidential is perceived as an indirect inferential, a judgmental, or a hearsay type respectively, and none of these are deterministic on the facts implied with the main clauses. Because of this, native Japanese speakers can perceive these statements not only as epistemic but also as referential expressions which indicate where the knowledge comes from.

Evidentials are also one of the salient features, and the combination with a complex sentence structure, as in (3.10b), commonly occurs in Japanese. In this study, this feature is considered in the item creation process.

3.3.4 Application of the Theoretical and Empirical Notions to Item Creation

The linguistic features in the preceding subsections are discussed in the theoretical and empirical linguistics literature. However, there are few previous studies applying these features to Japanese EI or other similar testing methods. We (Matsushita *et al.* 2010) recently investigated these syntactic and semantic features with the item engineering or manual item creation approach and compared them with items used in Matsushita and LeGare (2010), which were selected from the Simple Performance-Oriented Test (SPOT,

Kobayashi *et al.* 1996, Ford-Niwa and Kobayashi 1999)[4], in order to examine the effectiveness of those items. The following section will sketch some findings of the study and describe the direction toward corpus-based item creation proposed in the present study.

3.4 Item Engineering Approach

Matsushita *et al.* (2010) examined additional eight EI items containing the aforementioned linguistic features along with those selected from SPOT. The item creation with this approach is as follows:

1. Select target syntactic and semantic features as described in 3.3.
2. Create several item candidates for each target feature.
3. Consult with several native speakers. Examine the naturalness of each sentence. Decide which candidate sounds most plausible.
4. Adjust sentence length and lexical items as needed.

Based on this process, the new items were carefully designed to contain approximately the same mora lengths as the SPOT items used in Matsushita and LeGare (2010). The lexical items in these new sentences were also carefully chosen from basic vocabulary lists used in the introductory courses to avoid excessive influence from the lexical items on EI performance. With these EI items, we compared the scores yielded by the binary scoring method proposed by Graham (2006) to those of the SPOT items. We administered these eight items along with the sixty SPOT items to 157 subjects using a computer-delivered testing tool in Winter 2010[5]. Figure 3.1 shows the score difference among three groups classified according to the courses that the subjects enrolled at the time of the data collection (100: first-year, 200: second-year, and 300: third-year Japanese courses)[6].

[4]The reasons that we chose SPOT for item selection are because (1) the test procedure is very similar to EI: the test taker listens to a series of prompts while reading the same sentences on the answer sheet and fills in blanks in the printed sentences very quickly (two seconds for each item), and (2) therefore, the lengths and the morphosyntactic features contained in those SPOT sentences are sufficiently processable for L2 learners in EI tasks as well.

[5]Refer to 4.2 in Chapter 4 for more detail on the testing tool.

[6]See also 3.6.1 in this chapter for further descriptions on these courses and the textbooks.

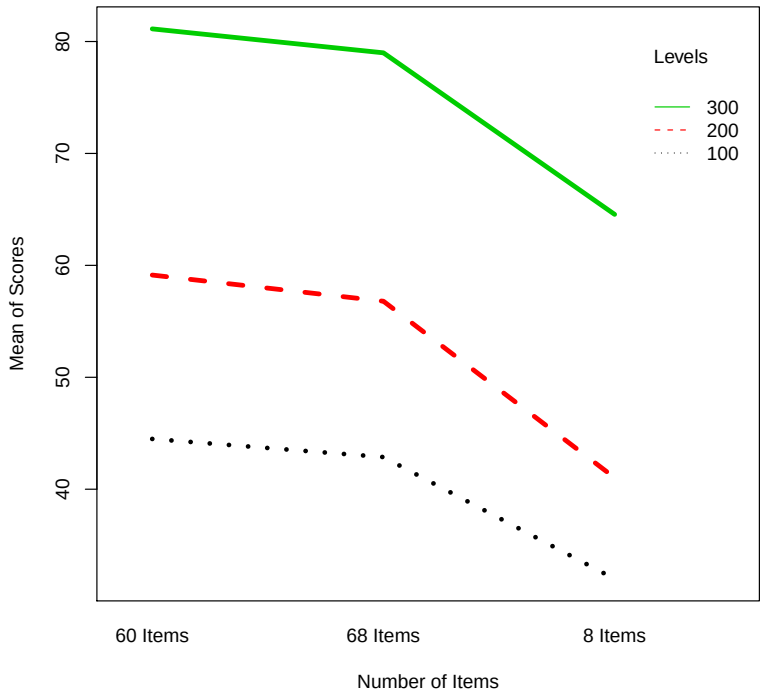


Figure 3.1: New and Old Item Score Comparison (Matsushita *et al.* 2010)

Clearly, the additional eight items with complex syntactic and semantic features were more challenging than the SPOT items for all the subject groups based on these mean score patterns. Further, we showed the detailed score differences of the high achievers in these subject groups, as seen in Table 3.1.

As indicated, only subjects 78, 38, and 76 achieved higher scores on the eight new items than on the SPOT items. According to a pre-test survey the participants answered, these three learners were near-native speakers who received formal education in Japan, whereas all of the others had limited or no overseas experience. Matsushita *et al.* (2010) point out that these eight items effectively distinguished learners with substantial L2 capability from those with less L2 experience and concluded that the ceiling effect was greatly lessened by these carefully engineered EI items.

Table 3.1: Comparison of Top 10 Scores of SPOT Items and New Items (Matsushita *et al.* 2010)

Subject ID	SPOT Items (%)	New Items (%)
78	99.21	100.00
38	98.07	100.00
42	97.89	84.02
76	97.81	100.00
80	97.54	82.25
28	96.84	64.50
43	96.14	72.78
66	95.88	78.11
41	95.00	64.50
70	94.74	92.31

These results indicate that the item feature identification based on language-specific phenomena is effective for optimal EI test creation. However, item creation based on the item engineering approach is time-consuming, and it is difficult to develop multiple items with the same linguistic features in a short time. The corpus-based approach is a method that overcomes these disadvantages. I will discuss the basic procedure of item creation with this approach in the following section.

3.5 Corpus-Based Approach

The basic concept of corpus-based item creation is depicted in Figure 3.2. As the figure indicates, the process of the corpus-based approach is simple. Using annotated corpora, multiple sentences with particular target features are retrieved based on various corpus queries. Then optimal item candidates are selected among those retrieved sentences and modified according to EI item criteria such as the maximum mora length if necessary. The important aspect of this approach is the corpus tool which enables us to identify desirable sentences contained in the corpora in an efficient manner.

For this study, I used ChaKi.NET (Iwatate *et al.* 2011) as a corpus tool. This tool contains a wide variety of functions to enable users to search for sentences in a similar manner to Christensen *et al.* (2010). Figure 3.3 shows the screenshot of ChaKi.NET.

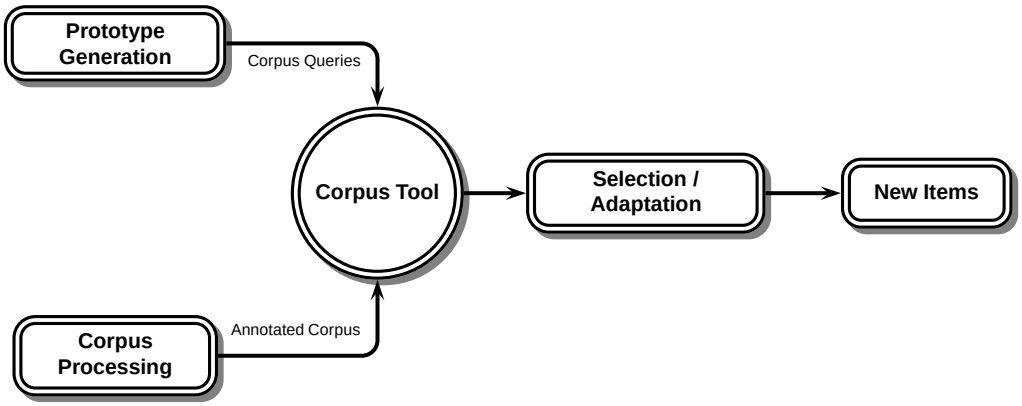


Figure 3.2: Schema of Corpus-Based Item Creation

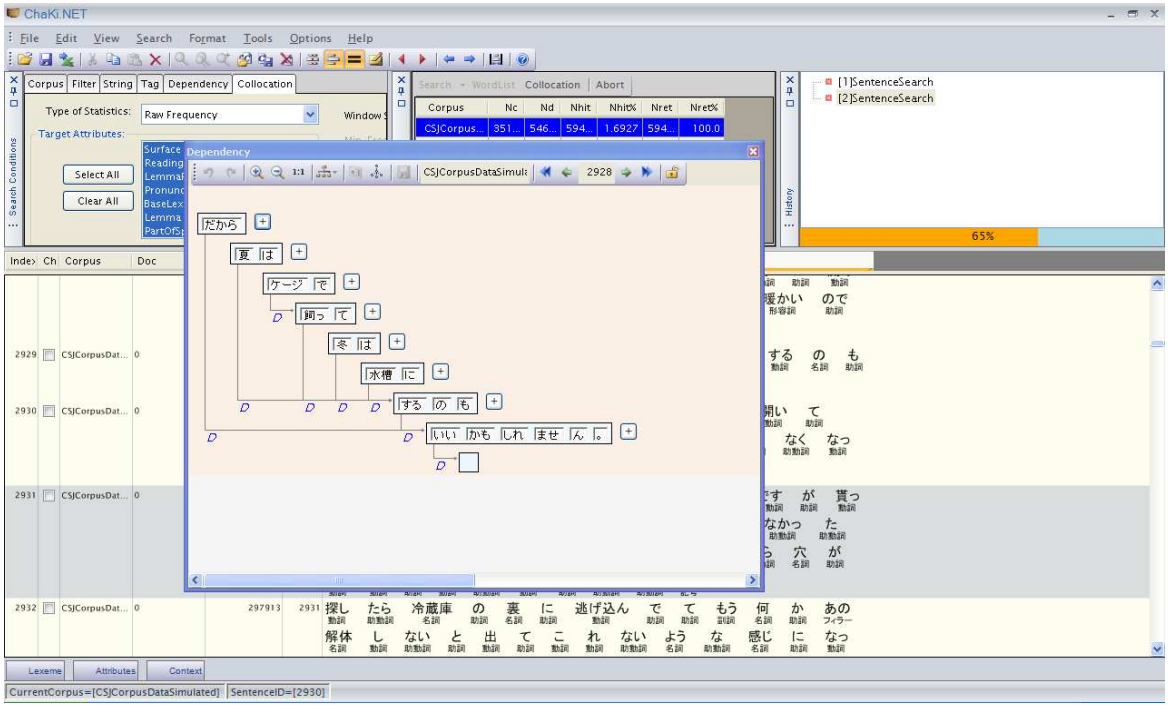
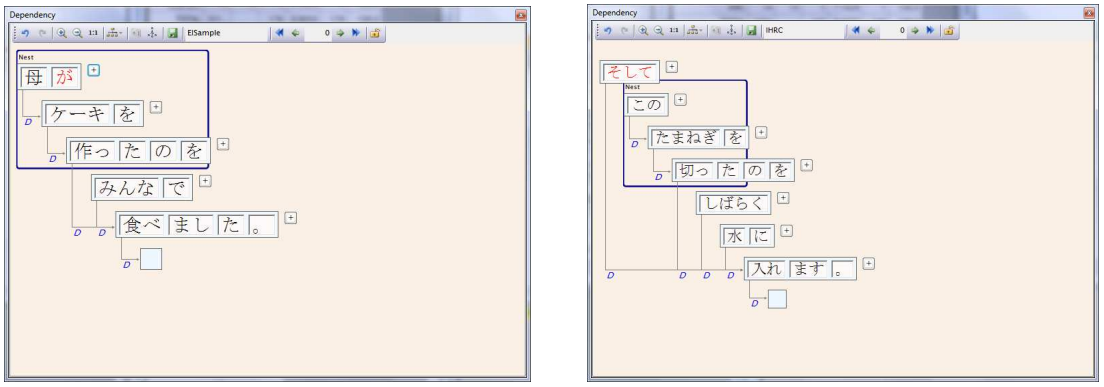


Figure 3.3: ChaKi.NET

Matsushita *et al.* (2010) discuss the possibility of using such a corpus tool to find item candidates with the item retrieval procedure shown in Figure 3.2. As an example, we identified a sentence with a internally headed relative clause (IHRC, see Tsujimura 2007) from a collection of large-sized spoken data called the Corpus of Spontaneous Japanese

(CSJ, Maekawa 2003, Furui *et al.* 2005)[7] based on the sentence with the syntactic structure in their study as a prototype. Figure 3.4 shows the engineered and CSJ-based sentences.



(a) Engineered Sentence (b) CSJ Sentence

Figure 3.4: Internally Headed Relative Clause of Japanese (Matsushita *et al.* 2010) (a) IHRC sentence manually engineered by native speakers (b) IHRC sentence retrieved from CSJ data

In 3.5.1, I will describe each stage of the corpus-based approach and the item analysis in detail.

3.5.1 Prototype Generation

As shown in Figure 3.2, the first stage of item creation is to generate prototypical cases that embody the target constructions for a corpus search, based on the identified linguistic features discussed in 3.3. This process involves such tasks as creating sample sentences and extracting the common syntactic constructions in those sentences. In this respect, the corpus-based approach is exactly the same as the item engineering approach. However, the advantage of this corpus-based approach is that perfectly formed prototypes are not necessary at this stage because the prototypes are used as search queries and acceptable only if sentence fragments are generated for the corpus search.

Based on those prototypes, search queries are created. Chaki.NET covers most of the search functions utilized in Christensen *et al.* (2010): regular expressions, dependency

[7]Refer to 4.3 for further descriptions on CSJ.

search, word list search, and so forth. Figure 3.5 shows an example of the dependency search query for simple relative clauses[8].

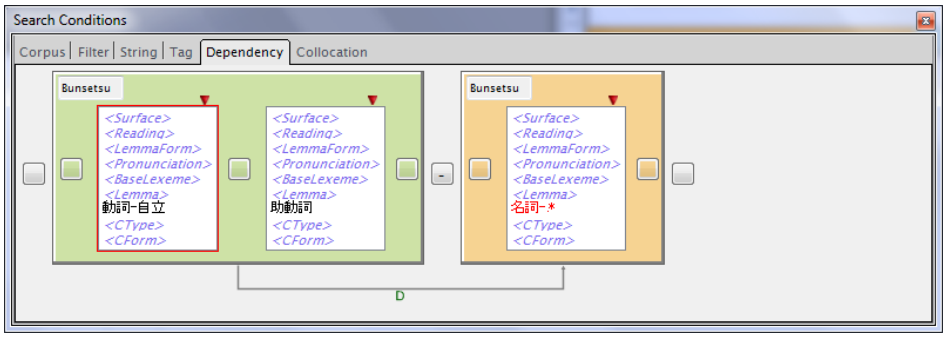


Figure 3.5: Example of Dependency Search Query

Of course, the tool suggests multiple sentences based on the queries. Therefore, it is necessary for humans to examine the appropriateness of those sentences as possible EI items. In 3.5.3, I will describe the selection and adaptation process using an actual sentence.

3.5.2 Corpus Processing

Along with prototype generation, corpus processing is a preparatory stage for corpus searching. As Christensen *et al.* (2010) indicate, plain corpora need to be annotated with morphological and syntactic information in order to search for sentences with various strategies. In this study, I used the morphological analyzer Mecab 0.98[9] to decompose the CSJ sentences into morphemes and add lexical information (part of speech (POS), pronunciation, conjugation and declension classes, etc.) to the morphemes[10]. Further, I used

[8] As shown in 3.5, ChaKi.NET utilizes a dependency grammar framework to manage the constituency relations (see Yamada and Matsumoto 2003). In the field of Japanese NLP as well as linguistics, using a syntactic unit called *bunsetsu* is the mainstream approach for syntactic analysis, and the concept is incorporated in this tool as well. Kurohashi and Nagao (2003) illustrate the application of *bunsetsu* to corpus annotation and parsing with detailed description based on their large-scale automatic corpus annotation project.

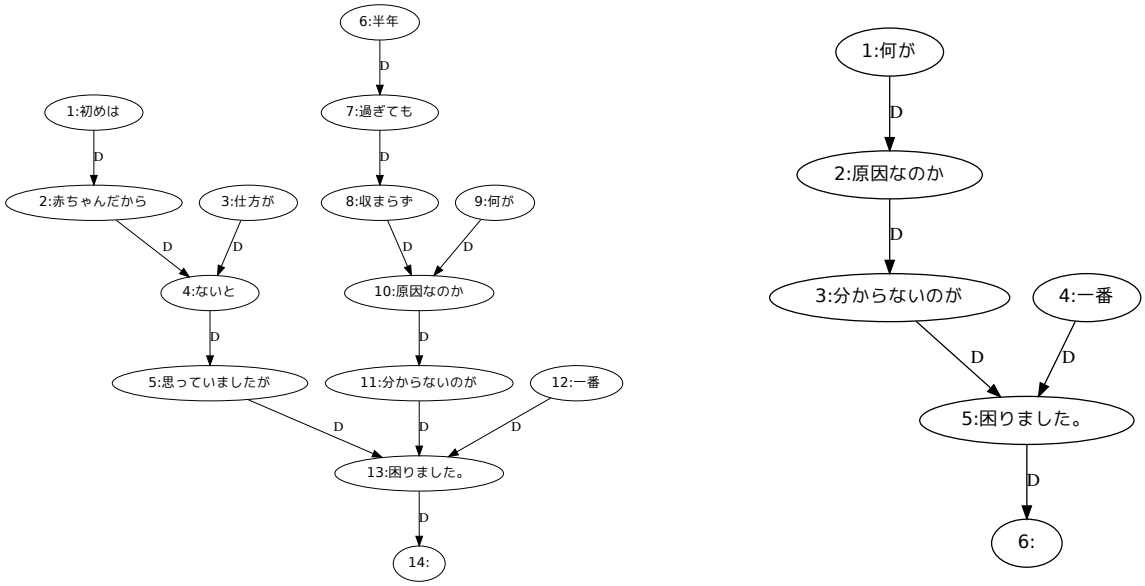
[9] `http://mecab.sourceforge.net/`

[10] Although CSJ is annotated with detailed information, I processed it with the tools discussed above because the tagging and dependency strategies of CSJ are slightly different from the format used for ChaKi.NET. In a future study, I will investigate a method to incorporate the CSJ annotation information directly in ChaKi.NET.

the Japanese dependency structure analyzer CaboCha 0.53[11] to create dependency relations of the morphemes decomposed with MeCab.

3.5.3 Selection / Adaptation

Ideal items are selected at this stage among the suggested sentences through the process discussed in 3.5.1. However, it is unlikely to find optimal EI items directly in the corpus data in many cases because those sentences tend to contain undesirable lexical items and mora lengths excessive for EI test items. Therefore, it is necessary to do some minor modification to tailor those sentences manually. For example, the sample sentence used to explain the relationship between *pro*-drop and the center-embedded structure in Example 3.8 was actually found in CSJ using the corpus-based item creation approach discussed here. See Figure 3.6.



(a) Original Sentence (b) Tailored Sentence

Figure 3.6: Center-Embedded Clause Sentence as an EI Item (a) Center-embedded clause sentence found in CSJ (b) Center-embedded clause sentence tailored for EI use (D denotes "dependent")

[11] `http://chasen.org/~taku/software/cabocha/`

Figure 3.6(a) shows the sentence directly retrieved from CSJ (67 morae, 13 bunsetsu). Obviously, this sentence is not ideal for EI use because of the length and complexity. However, the tree structure clearly shows that the sentence can be shortened while retaining the center-embedded feature by trimming the two branches (the one with 1 to 5 and the other 6 to 8). With this simple process, the sentence is modified as 3.6(b) (27 morae, 5 bunsetsu). The graphical dependency relations of the tailored sentence is shown in Figure 3.7.

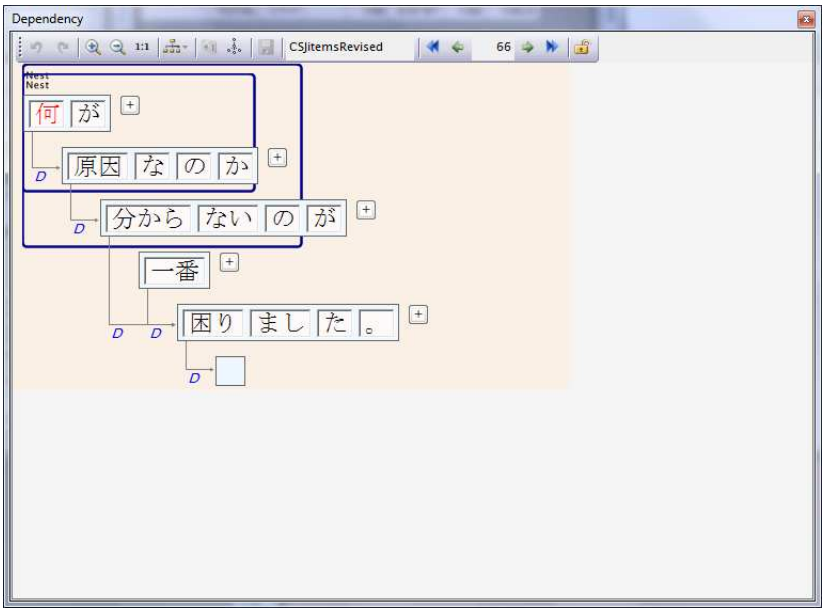


Figure 3.7: Graphical Diagram of an EI Item with Center-Embedded Clause Structure

By conducting this selection and adaptation process cyclically, it is possible to produce multiple EI items with the same feature with relative ease and in a short period of time. The search queries, selected sentences, and tailored sentences can be saved in the database[12] for future use.

Although this corpus-based approach still requires native speakers' linguistic intuition throughout the procedure, the burden on item creation is lighter than the item engineering approach because actual spoken sentences are used as models, rather than

[12]ChaKi.NET contains SQLite as its component.

sentences generating manually. The other advantage is authenticity. Because these sentences were actually used in speech by native speakers, they are more natural than those artificially generated based on linguistic notions only.

With this process, I created thirty EI items to examine the effectiveness of this approach. In the following section, I will discuss in detail the statistical analyses of the items created with this method.

3.6 Item Effectiveness Analyses

3.6.1 Method

Using EI items created with the corpus-based approach, a study was conducted to analyze item effectiveness. The method is described as follows.

Items. The items were created based on the textbooks used in the courses offered at BYU (the 100 level: first-year, focusing on basic vocabulary, conversation, and grammar skills; the 200 level: second-year, focusing on further practice in conversation and basic reading and writing skills; and the 300 level: third-year, focusing more on reading, writing, and culture). Refer to Jorden and Noda 1987, Jorden and Noda 1988, Jorden and Noda 1990, Watabe 1979, Watabe 1982 for the content covered in these courses. Also, items with the syntactic and semantic features described in 3.3 were also created. Both types of items were found through the corpus-based process discussed in the previous section. In this study, 26 textbook-based EI items were selected with grammatical features covered in those textbooks and four sentences with the aforementioned syntactic and semantic features. The textbook-based items were classified according to the class number and item level as shown in Table 3.2 (see also Table 4.6) and the other four were categorized as superior based on the assumption that their difficulty exceeds the other 26 items. The breakdown of items is summarized in Table 3.2.

The total number of subjects examined in the analyses below is 231. The test was administered with the testing tool mentioned in 3.4 above. The EI scores were generated using the latest version of the EI grading system called System III. Thus, the statistical

Table 3.2: Corpus-Based EI Items

Item Level	Class Number	# Items	# Morae	# Bunsetsu
100 Level	101	4	13–14	2–4
	102	4	13–15	3–4
200 Level	201	4	17–20	4–5
	202	4	17–20	3–4
300 Level	301	5	22–24	4–5
	302	5	24–25	4–5
Superior		4	25–31	5–6

analyses discussed below are based on results obtained through this grading system. Refer to 4.4.3 for other details on the subjects, test administration, and grading system.

3.6.2 Factorial ANOVA

Figure 3.8 illustrates the scores according to the item levels indicated in Table 3.2 and the class levels of subjects mentioned in 4.4.3. As indicated in Figure 3.8, the mean scores of the 100-level, 200-level, and 300-level subject groups decreases significantly as the item level increases whereas those of the native subject group are stable. Also, the score decrease trends are uniquely different from one group to the next. As the interaction plot indicates, there is an interaction between class and item levels ($F_{\text{Class Level}}(3,222) = 337.85$, $p < 0.0001$ and $F_{\text{Item Level}}(3,222) = 225.67$, $p < 0.0001$, respectively). Therefore, it is safe to say that these corpus-based EI items functioned effectively to classify these subjects according to their proficiency levels.

Table 3.3 below shows the Tukey post-hoc test based on the factorial ANOVA analysis above. Along with Figure 3.8, this table indicates that the score differences of respective class level pairs are uniquely distributed. In other words, these results indicate that each level of items functioned effectively to differentiate these subject groups.

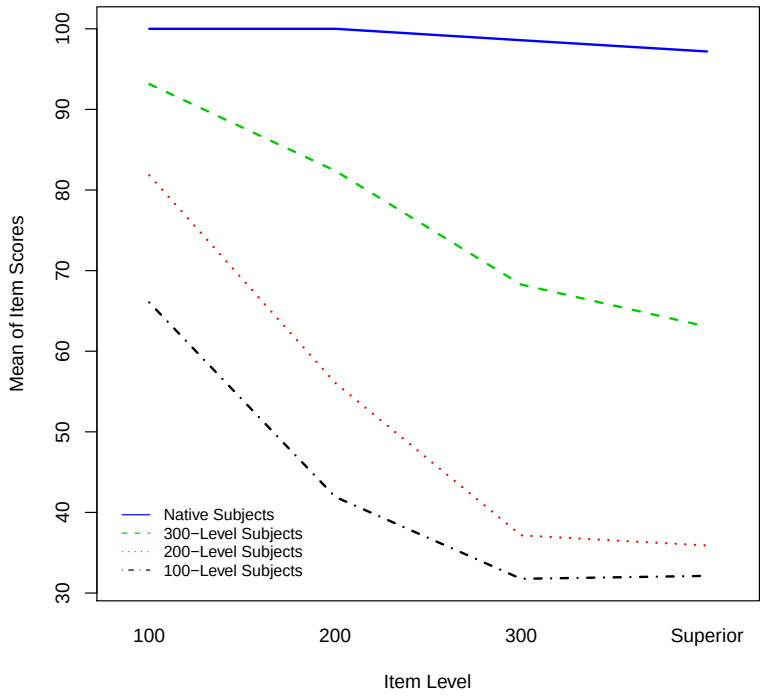


Figure 3.8: Interaction of Subject and Item Levels

Table 3.3: Score Difference Analysis with Tukey HSD between Subject Groups (the numbers in the table are mean differences; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$)

Subject Groups	100 Level Items	200 Level Items	300 Level Items	Superior Items
L200-L100	15.78***	14.15***	5.39	3.76
L300-L100	27.10***	40.46***	36.50***	30.92***
Native-L100	33.96***	58.07***	66.81***	65.05***
L300-L200	11.32***	26.31***	31.12***	27.15***
Native-L200	18.18	43.92***	61.43***	61.29***
Native-L300	6.86	17.60	30.31**	34.14**

3.6.3 Rasch Model Analysis

Another method used in this study to examine item effectiveness is a Rasch model. The main purpose of this analysis, however, is different from the conventional approach used in the item response theory (IRT) analysis, which is a commonly used statistical analysis method for item effectiveness evaluation (see also Doran 2005). Rather than focusing on the difficulty of each item here, I treat these EI items as components of individual test batches classified according to the item levels described in 3.6.1, in order to enable EI to measure oral proficiency in a discrete manner. See Figure 3.9.

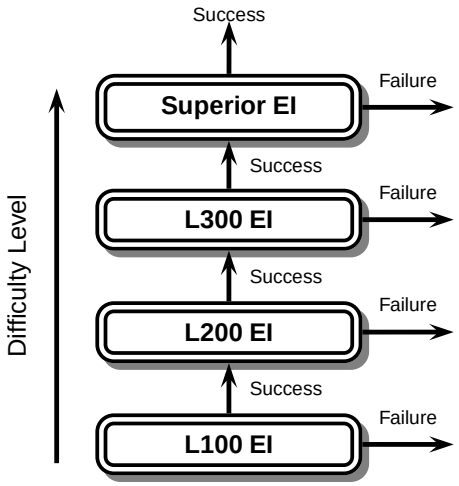


Figure 3.9: Alternative EI Testing Approach

This figure indicates that the person who can reproduce EI items of a certain item level with satisfactory accuracy will be considered as a successful learner at that level; otherwise, the learner is considered unsuccessful at that level and to not have reached that level of proficiency. The rationale for this alternative EI testing method is described as follows:

1. The binary scoring method in Graham (2006) (see also Equation 4.1) does not provide information on which item level is difficult for learners to repeat because it treats all the morae in a test equally in its calculation procedure. On the other hand,

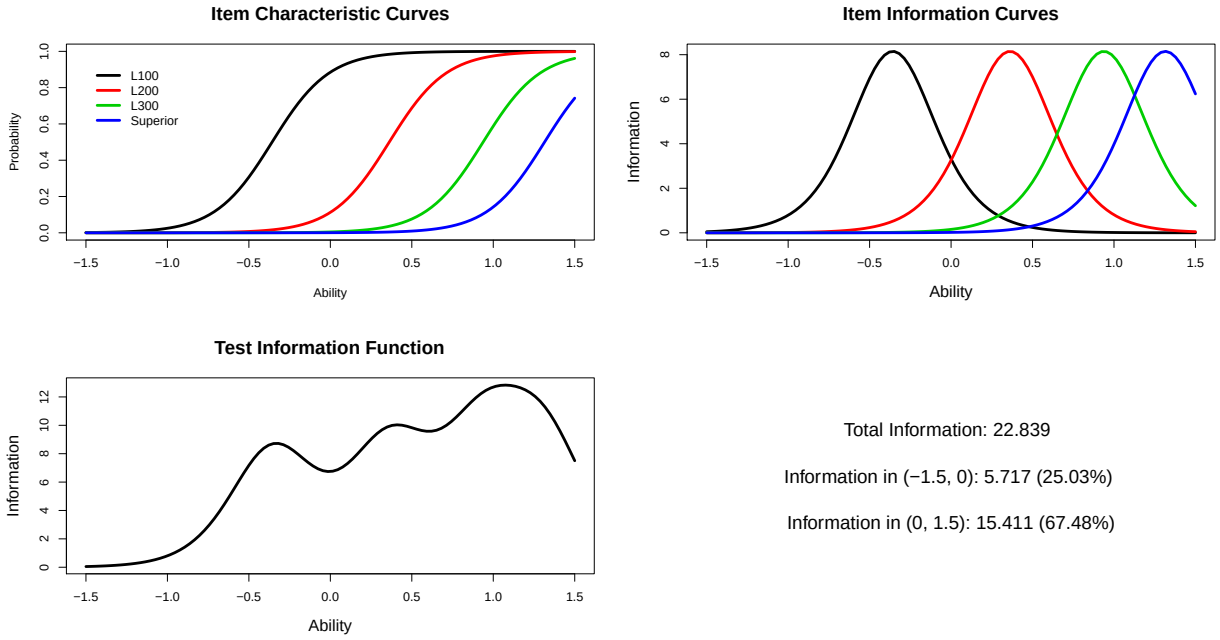
this approach enables us to identify the particular level of items that posed a challenge for learners. If these items are created effectively based on stratified difficulty levels, this approach will also show the effectiveness of these items as well.

2. In this item effectiveness study, I used only thirty corpus-based items. This approach will tell us whether this number is sufficient to examine learners' ability.

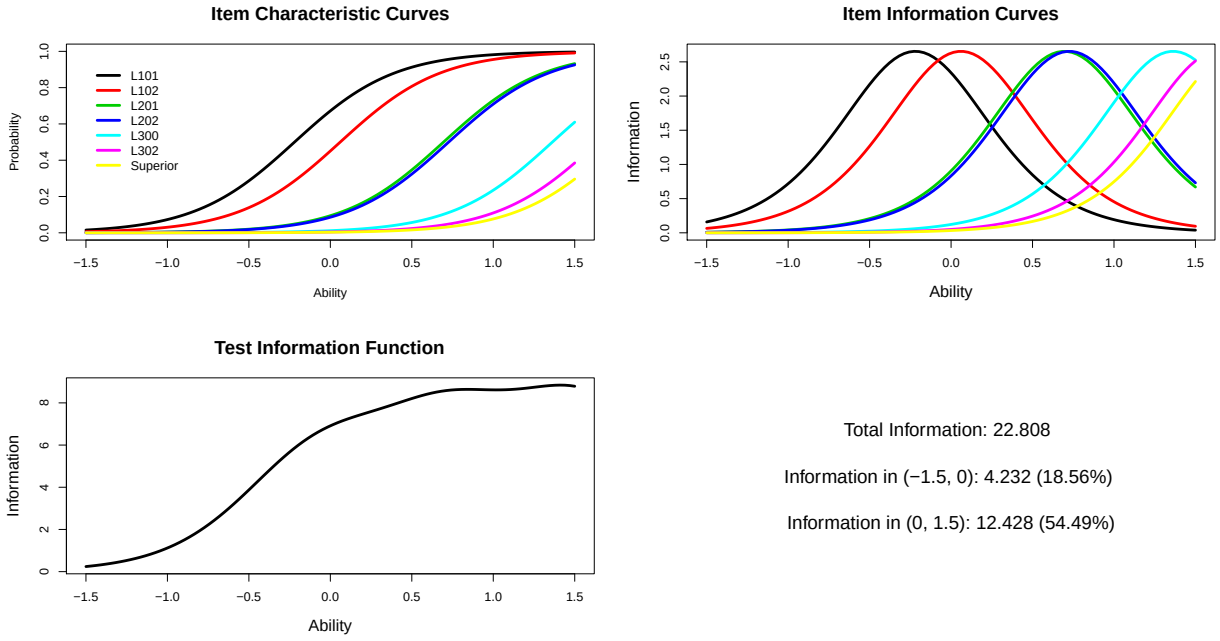
Based on these perspectives and the approach depicted in Figure 3.9, I categorized the EI items according to (1) item levels and (2) class numbers described in Table 3.2, and conducted an one-parameter unconstrained Rasch model analyses. As mentioned, each item is regarded as a component of item sets categorized according to class levels or class numbers, and raw scores calculated with Equation 4.1 are not accumulated. In this analysis, if a test taker achieves more than 80% for all items in the item level or class number, the person is considered as successful, which is denoted as 1 in the parameter, and 0 otherwise. The item information criteria plots with the Rasch model in Figure 3.10 show the respective results. Figure 3.10(a) indicates that the item level difficulties differentiate the subjects' ability. The test information function, however, depicts a fluctuated curve, which may indicate the item-level categorization does not function with these test items. Figure 3.10(b) indicates that the subjects' ability is also clearly differentiated according to the class number, except for 200-level item groups, due to identical trends in the item characteristic curves. The item information function, which reaches its peak at around 1.5, is rather stable. In terms of the Rasch model analysis, it is probably safe to say that the class number approach is more reliable than the item level counterpart for the discrete grading process in Figure 3.9.

3.7 Discussion

The item analyses in the previous section clearly show that the corpus-based items function effectively for this test in both the conventional scoring method and the item level classification method illustrated in Figure 3.9. Regarding the Rasch model approach above, it is reasonable that class number categorization functions more effectively than the item level counterpart because it reflects the scheduled acquisition order designed in



(a) Item Level



(b) Class Number

Figure 3.10: Item Information Criteria Analyses of Corpus-Based Items

the Japanese program. Pedagogically speaking, this approach is more suitable to observe students' progress in the program longitudinally.

The superior items with syntactic and semantic complexities functioned effectively in this study. In both factorial and Rasch model analyses, these items required high L2 capability to be reproduced accurately. Interestingly, native speakers' performance was not significantly hindered with these items although their scores slightly decreased as the item level increased. This is also a promising result because these items are totally acceptable for these native speakers despite the syntactic and semantic complexities inherent in the language while non-native speakers' performance is greatly affected by the difficulties.

In the next chapter, I will discuss the development of the ASR-based EI grading system in detail.

Chapter 4

Japanese EI Grading System and Results

4.1 System Development

As mentioned in Chapter 2, another important aspect in the development of the automatic EI grading system is attaining high accuracy of dictation for reliable score generation based on the binary scoring protocol proposed by Graham (2006). To accomplish this, we conducted a series of studies to develop a robust grading system through the investigation of optimal language model (LM) creation. The first approach (System I) uses LMs with very limited language resources based on the assumption that variation in EI responses is small enough to produce desirable EI dictation with such LMs. The second approach (System II), on the other hand, utilizes a large L1 corpus coupled with the language resources used in System I to gain wider coverage to handle unexpected EI repetitions. The third approach (System III) adds artificially created learner corpora to System II to increase the capability to deal with interlanguage-influenced EI responses more accurately. In this chapter, I will depict each approach according to the findings from the previous Japanese EI studies and propose a method to enhance robustness of the grading system.

4.2 System I: Grammar-Based Approach

Matsushita and LeGare (2010) investigated an ASR-based grading system for Japanese EI (System I[1]) based on English EI studies conducted by Graham *et al.* (2008a) and Lonsdale *et al.* (2009). In this study, we selected sixty Japanese EI items with appropriate sentence lengths (10 – 25 morae) containing semantically generic lexical items (i.e., free from gender-oriented words, proper nouns and interjections) from SPOT (see 3.3.4).

[1]I call this System I to compare it easily with subsequent systems (System II and System III).

We administered this SPOT-based EI test to 98 learners of Japanese enrolled in Japanese courses at various proficiency levels at BYU in Fall 2009 and scored the collected speech samples with System I. Table 4.1 shows the ASR specifications in this study.

Table 4.1: System I Specifications (Matsushita and LeGare 2010)

Component	Description
ASR Engine	Julius 4.1.4[3]
LM Training Tool	Palmkit 1.0.31[4]
Language Models	Sixty LMs with correct EI sentences and those with different case marking (*kaku-joshi*) and binding particle (*kakari-joshi*)[5] patterns
Acoustic Models	Hidden Markov Model (HMM) triphone model trained with 20,000 sentences (*Mainichi Shimbun* newspaper corpus) read aloud by 120 native speakers of Japanese

In this design, each LM was specifically trained with each model sentence and its case marking variations based on the assumption that learners' EI repetitions are very similar to the model prompts with slight modifications such as case marking patterns. Because of this assumption, it is safe to say that the recognition with these LMs is basically equivalent to a finite-state grammar approach (Shikano *et al.* 2007), which stipulates a number of possible morpheme sequences in speech samples represented by a finite set of states and transition paths in a form of a directed graph, with limited-sized dictionaries[5]. During dictation, the grading system switched LMs one after another because each grammar-based LM was specifically trained according to a specific EI item to be processed for the sake of precise dictation. For comparison with ASR-generated scores, seven raters (four native and three non-native speakers of Japanese) scored the same speech data via a browser-mediated grading tool. Both ASR and human grading processes were conducted

[2]Available at `http://julius.sourceforge.jp/`. See also Lee and Kawahara (2009) for more technical details.

[3]Available at `http://palmkit.sourceforge.net/`.

[4]See Chapter 4 (Morphology) in Tsujimura (2007) on case particles.

[5]From now on, I call this approach grammar-based recognition in this study for the sake of simplicity.

based on the binary scoring method proposed by Graham (2006). The screenshots of ASR and human graders are shown in Appendix A.

In this grading process, either zero or one was assigned to each mora of all the collected EI responses. To generate individual item and/or subject scores, Equation 4.1 below is used:

$$\text{EI Score} = \frac{\sum_i M_i}{\sum_j M_j} \times 100 \qquad (i \leq j) \tag{4.1}$$

where $\sum_i M_i$ indicates the total number of correctly pronounced morae and $\sum_j M_j$ indicates the total number of morae in an item or an entire test.

Based on the human- and ASR-generated binary values and EI scores with Equation 4.1, Matsushita and LeGare (2010) conducted two statistical analyses to examine the effectiveness of System I. First, we produced the inter-rater reliability (IRR) statistics based on Lonsdale *et al.* (2009) to observe differences between ASR and human binary scores. We then analyzed the correlations of subject- and item-level scores to examine the strength of the linear relationship. See Table 4.2 and the corresponding regression and residual analyses shown in Figure 4.1.

Table 4.2: IRR and Correlation Analyses between Human and System I Scores in Matsushita and LeGare (2010)

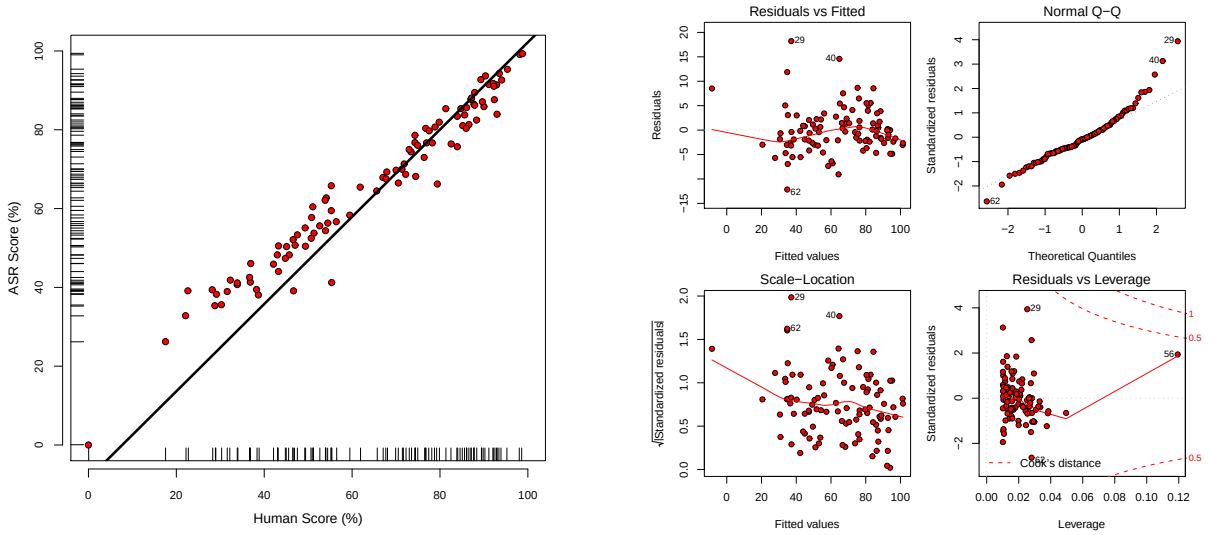
(a) IRR Analysis

IRR Statistic	Value
Robinson's R (%)	84.3
Unweighted κ	0.65
Rater Bias	0.53

(b) Correlation Analysis

	n	r	r^2	p
Subject-Level	98	0.98	0.9604	2.2×10^{-16}
Item-Level	5880	0.84	0.7056	2.2×10^{-16}

The strong correlation shown in Table 4.2 and Figure 4.1 above indicates that System I is capable of yielding reasonably accurate subject-level scores with the simple LMs.



(a) Regression Analysis

(b) Residual Analysis

Figure 4.1: Regression Analysis of Matsushita and LeGare (2010) (a) the scatterplot and corresponding regression line and with human- and ASR-generated subject-level scores and (b) the corresponding residual analysis (Cook's distance < 0.5)

However, the results also exhibit problems inherent in the grammar-based recognition. As shown in 4.1(a), the lower-half of the ASR scores are rather favorably generated compared with the human counterparts. Figure 4.2 depicts the situation more clearly.

As indicated in the first histogram, low ASR scores generally start around 40% whereas human scores spread to lower than 40%, although the mean and standard deviation of both scores are almost identical to each other. We concluded that this favorable grading was caused by the grammar-based LMs, which lacked wider coverage to dictate highly inaccurate EI responses due to learners' low proficiency. Due to this limited dictation capability, System I assigned wrongly pronounced morphemes to correct ones in the recognition process, which led to better ASR scores than those of humans. Further, these descriptive statistics indicate that there were a large number of high score achievers in this EI test which caused a ceiling effect (Hughes 2003) with this SPOT-based EI test. Matsushita and LeGare (2010) assumed this was because of low difficulty of the chosen EI items. Refer also to Section 3.4 regarding this item difficulty issue.

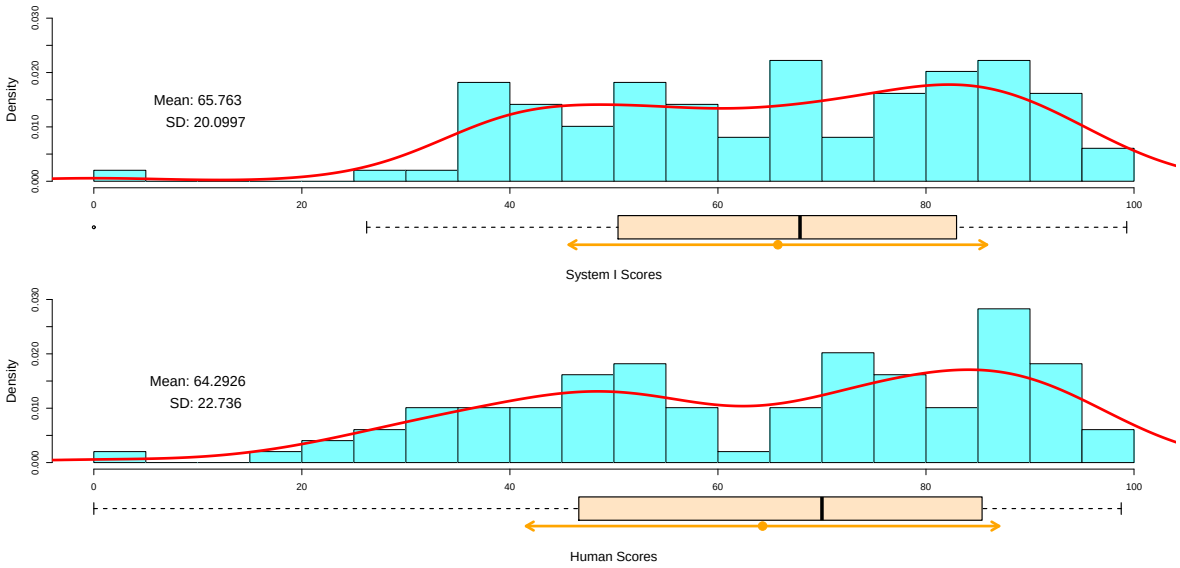


Figure 4.2: Distribution of System I and Human Scores (Matsushita and LeGare 2010) (the points and arrows below the boxplots indicate the mean values and one standard deviation ranges)

To overcome the favorable grading issue above, Matsushita (2010) and Matsushita *et al.* (2010) proposed a new grading system (System II) with LMs incorporating a large-scale L1 speech corpus. I will discuss details of System II in the following section.

4.3 System II: Corpus-Based Approach

Based on the findings in Matsushita and LeGare (2010), Matsushita (2010) and Matsushita *et al.* (2010) investigated a new approach in developing a grading system (System II) to produce fair scores throughout all the levels of proficiency. The main foci of these studies are as follows:

(a) Our basic assumption was that it is necessary to include additional language resources to attain wider coverage than that of System I in order to cope with EI repetitions which are unexpectedly different from the model prompts. However, it is essential to identify optimal corpora that have the capability to augment the previous system effectively.

(b) Increasing LM coverage leads to more perplexity, or a increased number of possible choices at any given point in the speech recognition processes, which may cause the grading system to become more sensitive to subtle mispronunciations and cause harsher grading even on EI responses deemed essentially correct by human raters. Therefore, it is important to manipulate the distribution of word occurrences in the training corpora to retain the dictation capability of System I.

Regarding (a), these studies chose to use CSJ, a large-scale corpus, briefly explained in 3.5. Matsushita *et al.* (2010) report that CSJ has several advantages for EI system grading: (1) the corpus is composed of large-sized pure spoken data rather than written texts such as newspapers, which is desirable in dealing with variations of EI responses as described in 4.2, (2) a wide variety of speech-specific language phenomena including disfluency features (e.g., fillers and fragments, repairs, word coalescence, vowel devoicing, etc.) are precisely annotated, and (3) the language data are stored in an XML database, which enables users to easily customize the provided linguistic information at their disposal. Table 4.3 below summarizes the contents of the CSJ[6].

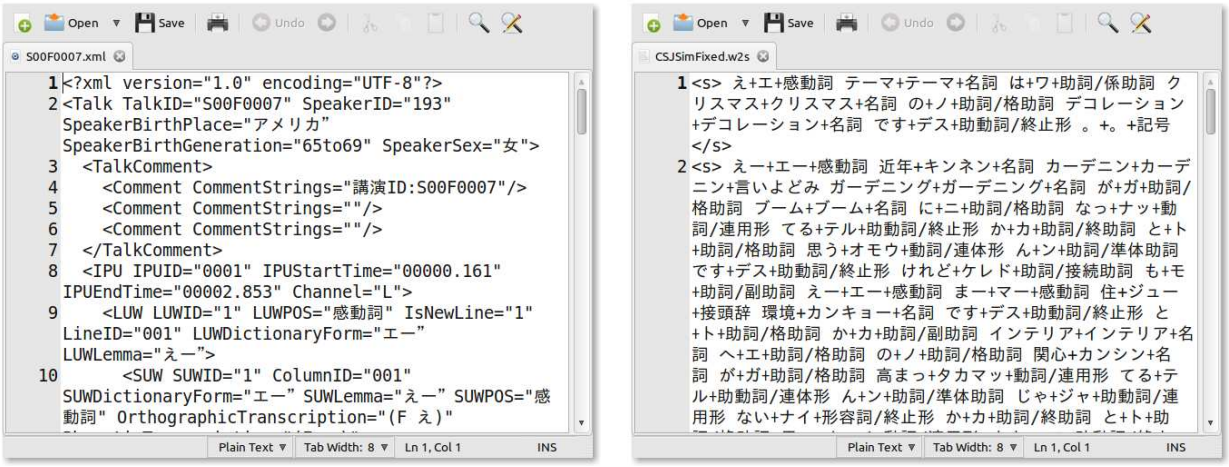
Table 4.3: Summary of the Content of CSJ

Characteristic	Description
# Speakers	1,417 (947 males and 470 females)
Types	academic presentations, extemporaneous presentations, interviews, dialogues, reading transcriptions, etc.
# Hours	658.8
# Tokens	7.5 million

To incorporate the CSJ language data in the grading system, the lexical items and corresponding annotation information were retrieved and converted to the text format for LM training. A simple Perl script was used to retrieve the necessary language data (morphemes, pronunciation, POS information, and so on) in 3,286 XML files in the CSJ

[6]The detailed specifications of CSJ are found in NINJAL (2006).

package and to reorganize the information according to the Cambridge-CMU toolkit format[7], as shown in Figure 4.3.



(a) XML Format (b) Cambridge-CMU Toolkit Format

Figure 4.3: Format Conversion of CSJ Data

Regarding the perplexity issue mentioned in (b) above, Matsushita *et al.* (2010) report that the occurrence of correct EI items in the LMs was increased to make those sentences stochastically dominated in the training copora (at least 70% of the total size) to ensure that the correct sentences would be favorably recognized. The other specifications of System II are summarized in Table 4.4.

With this system, Matsushita *et al.* (2010) conducted the IRR and correlational analyses with the same dataset used in Matsushita and LeGare (2010). Additionally, a second round of human grading was conducted by three more native and non-native speakers of Japanese for comparison. The results of the analyses are shown in Table 4.5 and Figure 4.4.

[7]See `http://mi.eng.cam.ac.uk/~prc14/toolkit.html`. Palmkit, the LM toolkit used in our studies, conforms to this format as well.

[8]Compared with the acoustic model used in Matsushita and LeGare (2010), Matsushita (2010) reports that the recognition accuracy of EI responses was significantly improved with this CSJ model. See also Nanjo *et al.* (2004) for more technical details.

Table 4.4: System II Specifications (Matsushita *et al.* 2010)

Component	Description
ASR Engine	Julius 4.1.4
LM Training Tool	Palmkit 1.0.31
Language Models	Sixty LMs with CSJ and EI item sentences
Acoustic Models	CSJ acoustic model[9], an HMM triphone model trained with 2496 conference presentation data (486 hours worth)
Dictionary Size	20,000

Table 4.5: IRR and Correlation Analyses with Human Scores in Matsushita *et al.* (2010) (H-H: Human-Human Comparison; H-I: Human-System I Comparison; H-II: Human-System II Comparison)

(a) IRR Analysis

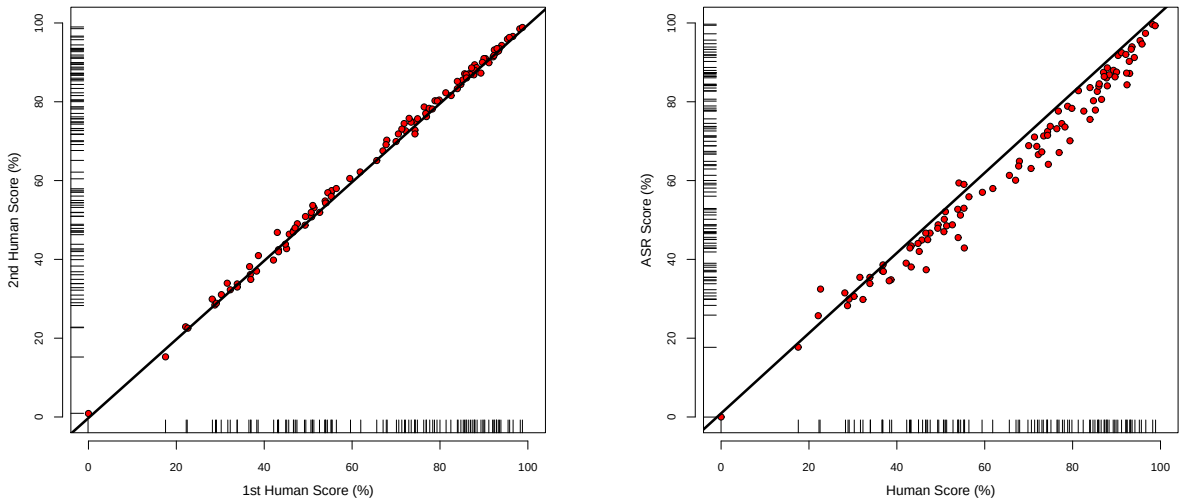
	H-H	H-I	H-II
Robinson's R (%)	93.8	84.6	83.6
Unweighted κ	0.86	0.66	0.64
Rater Bias	0.53	0.57	0.44

(b) Correlation Analysis

	H-H	H-I	H-II
Correlation Coef.	0.9986	0.9840	0.9886
Mean Residual	0.94	3.16	2.89

Figure 4.4(b) and Table 4.5 indicate that the regression model with System II fits better than that of System I in Figure 4.1(a) although the IRR statistics are slightly lower than System I counterparts.

Note that the mean residual is also improved with System II although it is still considerably larger than that of human scores. This indicates that the biased ASR grading for low scores is lessened due to the additional language information provided with CSJ. Figure 4.5 also show that System II treated low scores more appropriately than System I. As shown in Figure 4.5 below, the overall score distribution of System II became more similar to that with human scores, without causing much distortion in mean and standard deviation from those of human and System I scores.



(a) Human-Human Regression (b) Human-System II Regression

Figure 4.4: Regression Analysis of Matsushita *et al.* (2010) (a) the scatterplot and regression line of 1st and 2nd human-graded scores and (b) 1st human and System II Counterpart (cf. Figure 4.1(a))

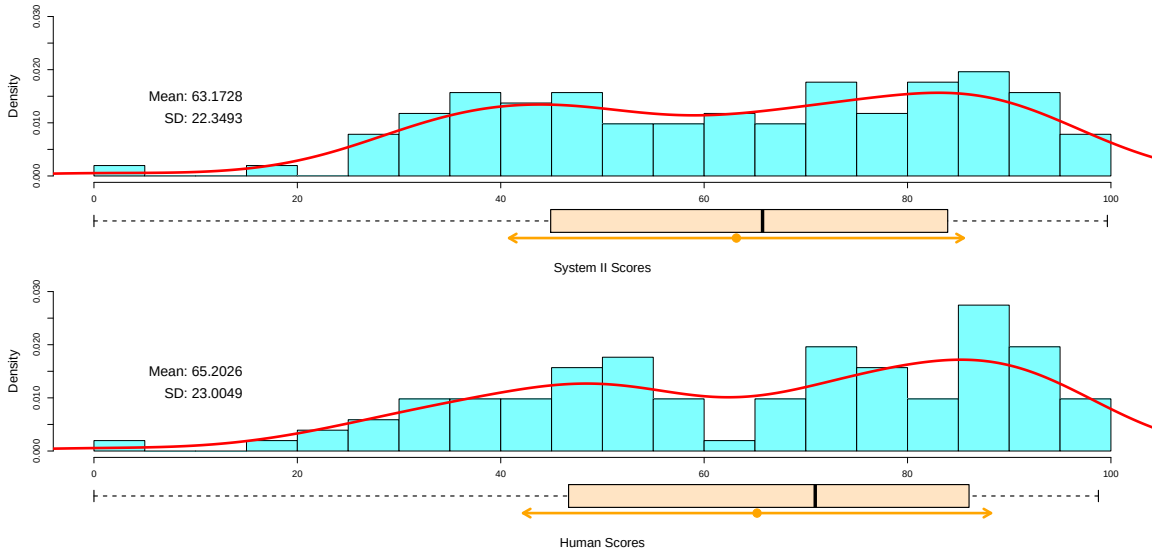


Figure 4.5: Distribution of System II and Human Scores (Matsushita *et al.* 2010) (cf. Figure 4.2)

The newly emerging issue is that the majority of ASR scores over 60% are lower than those from humans, as shown in Figure 4.4(b). It is obvious that System II was in-

fluenced by the perplexity associated with the CSJ data, although the occurrences of correct sentences were significantly increased in the LMs. A possible explanation of this is that disfluency phenomena (repair, fillers, etc.) and collocations that were unlikely in the training data caused deviation from the actual EI responses due to the lack of such information in the LMs while the system was determining word sequences based on n-gram representations[9]. This assumption also indicates that there is a significant discrepancy between L1 and L2 production which cannot be filled with L1 speech corpora such as CSJ. Therefore, it is necessary to consider incorporation of L2 language data to System II to overcome the problem. In the following section, I discuss another grading system using a machine-learning mechanism to maximize the effect of small learner corpus data.

4.4 System III: Analogical-Modeling Approach

This section will describe the most current grading system developed in the series of Japanese EI studies so far, based on Matsushita and Tsuchiya (2011). The significant characteristic of System III is the incorporation of EI transcription data using a machine-learning system called analogical modeling (AM, Skousen 1989, Skousen *et al.* 2002). In the following subsections, I will depict the rationale for this approach, compare this system with the previous versions, and suggest future directions with this approach.

4.4.1 AM-Generated Corpora: AM as a "Virtual" Learner

The most reasonable solution to the problems observed by Matsushita *et al.* (2010) is to integrate learner corpora in order to capture the speech patterns that occur particularly in L2 production. The questions that need to be addressed here are (1) what types of learner corpora are optimal for EI grading and (2) how can those corpora can be incorporated in the existing grading system to enhance its evaluation capability without losing original advantages.

Regarding (1), it is obvious that the most reliable language resource for the system development is EI transcription data obtained from past test administrations. The main reason is that the most probable L2 irregularities that are likely to occur in the EI task

[9]See Manning and Schütze (2002:441) on beam search for more detail.

are easily obtained from the EI speech samples, whereas learner corpora available for public use do not necessarily contain such L2 phenomena because of the high possibilities of avoidance (Laufer and Eliassona 1993) if the language sources are from spontaneous speech (e.g., Uemura 1998). Also, multiple speech samples of the same model prompts are available from EI transcription data. This enables us to identify error patterns of particular EI items that can be incorporated in new LMs.

The problem with the use of available transcription data is that the size is still significantly small, which means that using the raw data for LM training does not provide a probabilistic impact in the LMs especially when it is merged with large-scale corpora such as CSJ. Therefore, it is necessary to develop a method to identify the characteristics of EI speech observed in the transcription data and to artificially create EI responses containing those characteristics in a systematic manner. A conventional approach to address such a problem is creating either rule-based grammars or statistical n-gram models based on the obtained data to enumerate all the possible sentence patterns. However, generalizing grammars manually is quite difficult especially with L2 data, and it is also difficult to obtain reasonable outputs with n-gram models based on such a small dataset as EI transcription. To address this issue, Matsushita and Tsuchiya (2011) proposed use of analogical modeling (AM, Skousen 1989, Skousen *et al.* 2002), an exemplar-based machine learning system. The advantages of AM for creating artificial EI responses are summarized as follows:

1. AM captures regularities in seemingly irregular language phenomena in a small amount of language data. As described in 2.1.1, learners are highly likely to commit certain speech errors in the EI repetitions when they imitate sentences in which the contained morphosyntactic features exceed their current linguistic knowledge. Further, it is natural to assume that the error patterns in EI responses exhibit some sort of unified patterns unlike open-ended speech, if not perfectly regular, considering the confined environment in the EI task. If this assumption is correct, AM is an ideal tool to identify such regularities and suggest reasonably possible EI speech patterns with the small amount of transcription data.

2. AM predicts multiple outcomes if the linguistic behaviors conditioned by the training dataset are nondeterministic. This feature makes it feasible to create a larger number of artificial EI responses than the original data size.

Based on these advantages, Matsushita and Tsuchiya (2011) propose the following process to create an artificial learner corpus with AM via bootstrapping.

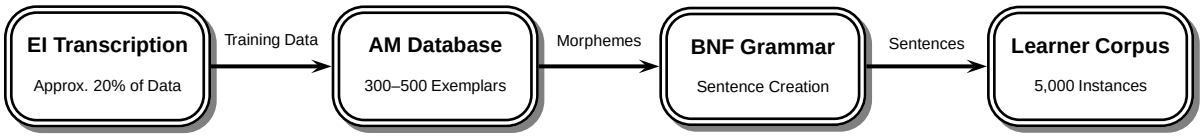
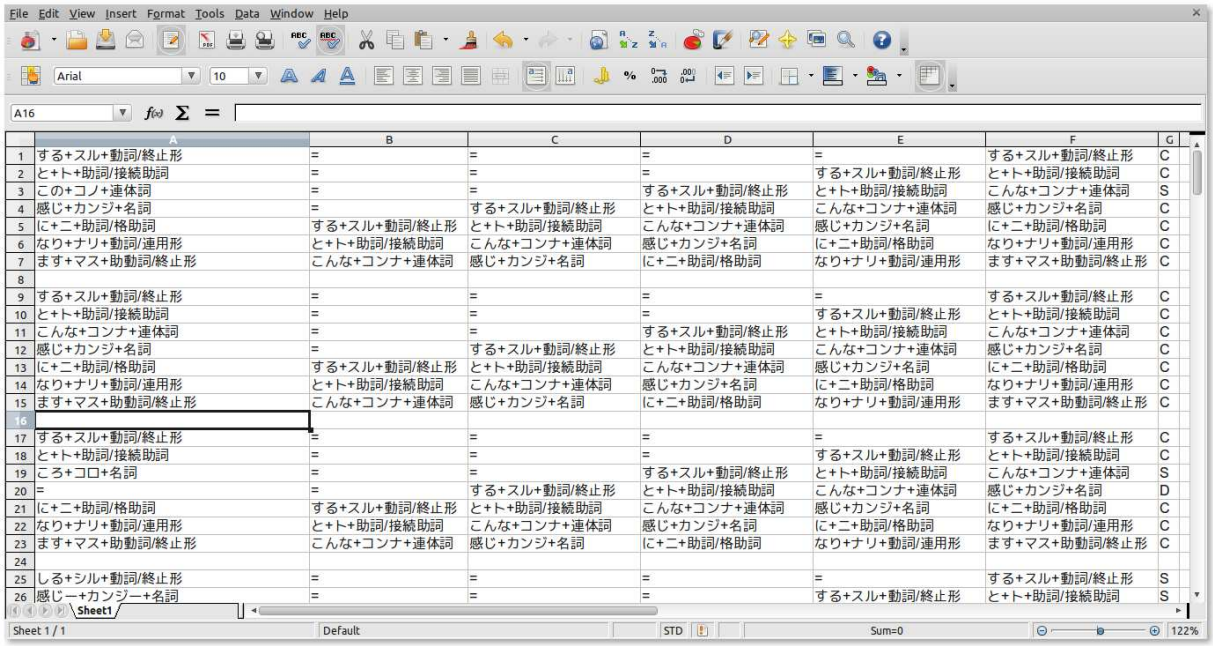


Figure 4.6: AM-Based Learner Corpus Creation (Matsushita and Tsuchiya 2011)

Matsushita and Tsuchiya (2011) report that about 20% of the transcribed responses for each corresponding EI prompt were randomly selected to create 300 – 500 AM exemplars as a training dataset. Each transcribed EI response was first decomposed into morpheme sequences. Each morpheme in the sequence was used as an outcome in an exemplar and aligned with the corresponding morphemes in the prompt sentence and with the output pattern information (correct (C), insertion (I), deletion (D), and substitution (S)) to form a feature vector. This process was repeated to create an AM dataset for each EI item used in this study. An example screenshot of the dataset is shown in Figure 4.7.

The test sets for the prompt sentences were manually created to obtain the possible outcomes based on the datasets using the AM system written in Perl[10]. The feature vectors in the test set were basically identical except for the fact that the same feature vectors with different output pattern information were applied to obtain as many possible morpheme predictions at every morpheme position in the EI input as possible. With this method, AM behaved as a virtual learner, performing EI tasks one morpheme at a time according to the knowledge provided by the datasets. The morpheme outcomes were categorized according to the positions in the sentence. Taking the AM outcomes as

[10] Available at `http://humanities.byu.edu/am/`.



	A	B	C	D	E	F	G
1	する+スル+動詞/終止形	=	=	=	=	する+スル+動詞/終止形	C
2	と+ト+助詞/接続助詞	=	=	=	する+スル+動詞/終止形	と+ト+助詞/接続助詞	C
3	この+コノ+連体詞	=	=	する+スル+動詞/終止形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	S
4	感じ+カンジ+名詞	=	する+スル+動詞/終止形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	感じ+カンジ+名詞	C
5	に+ニ+助詞/格助詞	する+スル+動詞/終止形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	感じ+カンジ+名詞	に+ニ+助詞/格助詞	C
6	なり+ナリ+動詞/連用形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	感じ+カンジ+名詞	に+ニ+助詞/格助詞	なり+ナリ+動詞/連用形	C
7	ます+マス+助動詞/終止形	こんな+コンナ+連体詞	感じ+カンジ+名詞	に+ニ+助詞/格助詞	なり+ナリ+動詞/連用形	ます+マス+助動詞/終止形	C
8							
9	する+スル+動詞/終止形	=	=	=	=	する+スル+動詞/終止形	C
10	と+ト+助詞/接続助詞	=	=	=	する+スル+動詞/終止形	と+ト+助詞/接続助詞	C
11	こんな+コンナ+連体詞	=	=	する+スル+動詞/終止形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	C
12	感じ+カンジ+名詞	=	する+スル+動詞/終止形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	感じ+カンジ+名詞	C
13	に+ニ+助詞/格助詞	する+スル+動詞/終止形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	感じ+カンジ+名詞	に+ニ+助詞/格助詞	C
14	なり+ナリ+動詞/連用形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	感じ+カンジ+名詞	に+ニ+助詞/格助詞	なり+ナリ+動詞/連用形	C
15	ます+マス+助動詞/終止形	こんな+コンナ+連体詞	感じ+カンジ+名詞	に+ニ+助詞/格助詞	なり+ナリ+動詞/連用形	ます+マス+助動詞/終止形	C
16							
17	する+スル+動詞/終止形	=	=	=	=	する+スル+動詞/終止形	C
18	と+ト+助詞/接続助詞	=	=	=	する+スル+動詞/終止形	と+ト+助詞/接続助詞	C
19	ころ+コロ+名詞	=	=	する+スル+動詞/終止形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	S
20	=	=	する+スル+動詞/終止形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	感じ+カンジ+名詞	D
21	に+ニ+助詞/格助詞	する+スル+動詞/終止形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	感じ+カンジ+名詞	に+ニ+助詞/格助詞	C
22	なり+ナリ+動詞/連用形	と+ト+助詞/接続助詞	こんな+コンナ+連体詞	感じ+カンジ+名詞	に+ニ+助詞/格助詞	なり+ナリ+動詞/連用形	C
23	ます+マス+助動詞/終止形	こんな+コンナ+連体詞	感じ+カンジ+名詞	に+ニ+助詞/格助詞	なり+ナリ+動詞/連用形	ます+マス+助動詞/終止形	C
24							
25	しる+シル+動詞/終止形	=	=	=	=	する+スル+動詞/終止形	S
26	感じー+カンジー+名詞	=	=	=	する+スル+動詞/終止形	と+ト+助詞/接続助詞	S

Figure 4.7: Screenshot of AM Dataset

transitions, finite-state grammars notated in Backus Naur Form (BNF), a widely used syntactic rule notation format for computer languages (see also Jurafsky and Martin 2008), were created. These grammars were used to produce 5,000 sentences by permuting morpheme patterns provided by AM. The created artificial sentences for EI prompts were then recorded as artificial learner corpora in the text files. Figure 4.8 shows one of the AM-based corpora.

With this method, the small-scale EI transcription data are increased systematically for incorporation into statistical LMs in the new grading system, System III. To retain the capability of System I and System II, the correct EI sentence and CSJ data were also added to the LMs as well. In the following subsection, I will describe the components of System III.

4.4.2 System Components

As mentioned, System III is a combination of System I and System II with AM-generated learner corpora. Therefore, the acoustic model, LM tool, and speech recog-

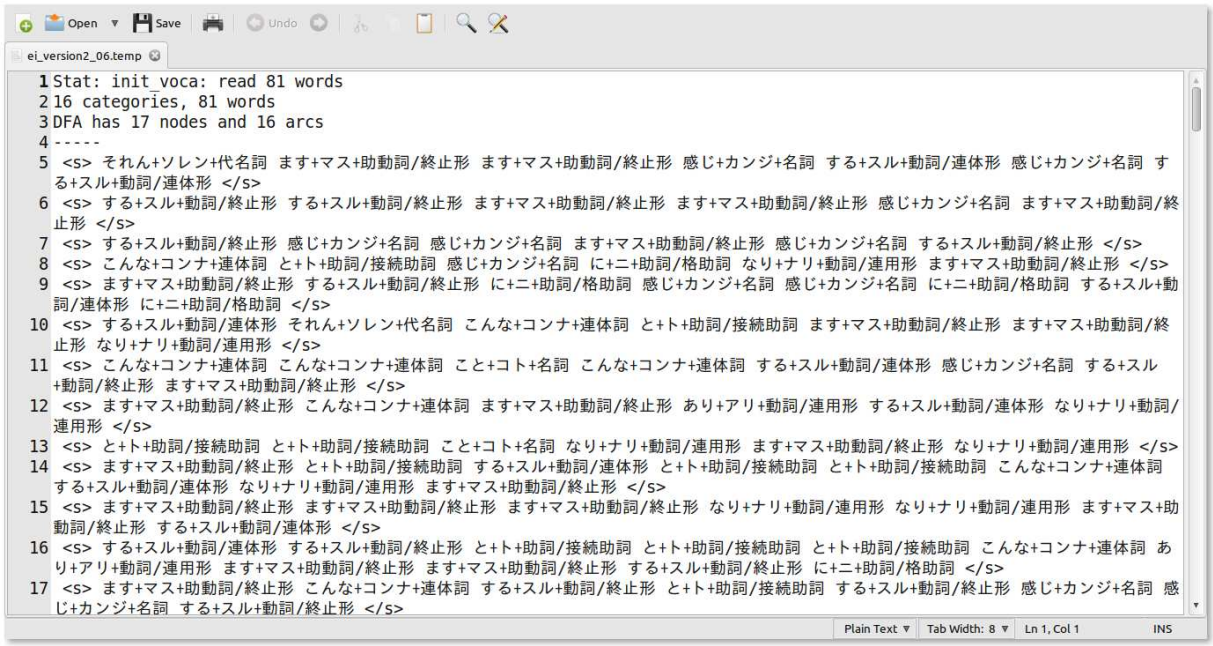


Figure 4.8: Example of AM-Generated Learner Corpus

nition engine are the same as System II, described in Table 4.4[11]. Figure 4.9 shows the schematic representation of System III. Note that EI sentences, CSJ, and AM-generated corpora were all incorporated to create an item-specific LM to grade each EI item. This process was repeated according to the number of EI items, as described in 4.2.

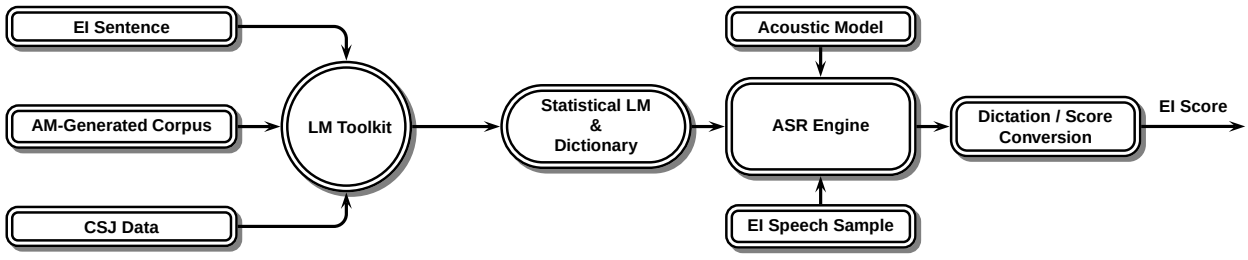


Figure 4.9: System III Schema (Matsushita and Tsuchiya 2011)

[11]Julius 4.1.5.1 was used for this study instead, but the functionality of it was about the same as the previous version.

4.4.3 Method

The research design for this study is described below.

Participants. Two hundred and thirty nine learners who were enrolled in introductory- to graduate-level Japanese courses offered at BYU in Fall 2010[12] participated in this study. The majority of the participants (approx. 93%) are native speakers of English. The rest of them are native speakers of Korean, Spanish, Chinese, or Japanese. The proficiency levels of those learners were divided according to course numbers (100, 200, and 300 or above) as follows.

Table 4.6: Subject Demographic

Class Level	# Participants
100	82
200	35
300 or above	120
Native	2

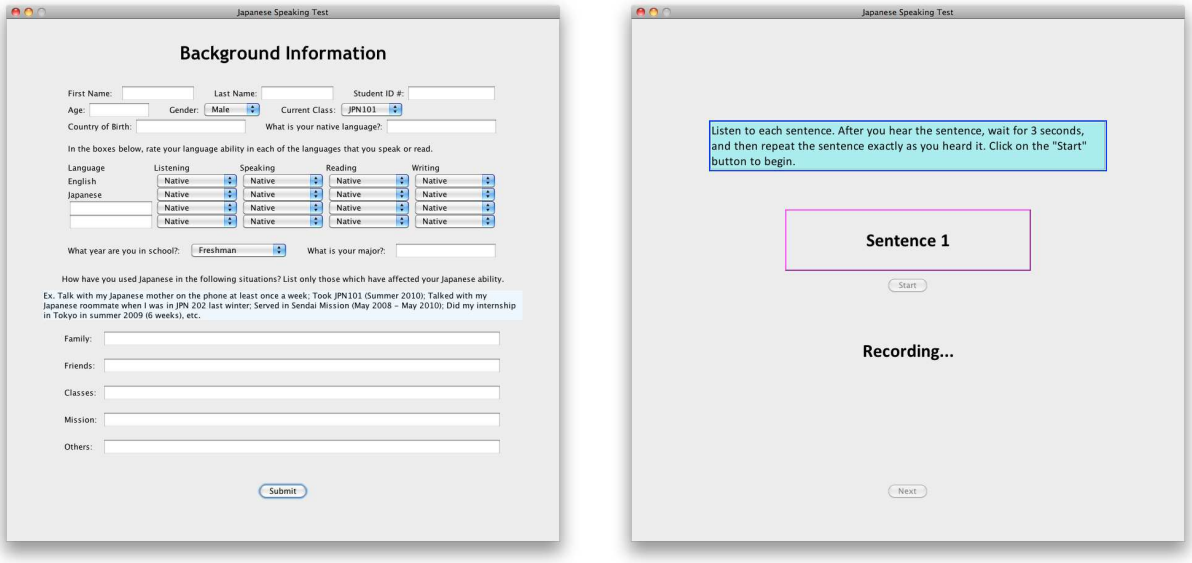
Test Administration. The participants were asked to take the test during the two weeks close to the end of the semester. The test was administered with Macintosh desktop computers at the testing lab. The newly created sixty EI items[13] were presented using a computer-mediated testing tool, shown in Figure 4.10 below. This tool was preinstalled in those lab computers before the test administration. The EI responses of the participants were recorded as uncompressed .wav audio files and stored locally, and then uploaded to server space with an applescript.

Grading. The audio files were downloaded from the server space to a local computer for grading. Sampling frequencies, volumes, and bit rates were converted with SoX[14],

[12]The number of subjects used in the analysis was decreased to 231 due to the poor quality of some recordings in the data collection process.

[13]Along with the thirty corpus-based test items described in Chapter 3, additional thirty items retrieved directly from the textbooks cited in 3.6.1 were also used in this study.

[14]`http://sox.sourceforge.net/`



(a) Pre-Test Survey (b) EI Test

Figure 4.10: EI Tester

ffmpeg[15] and normalize-audio[16] for dictation with Julius. The grading system then processed each audio file to produce dictation texts of EI responses and convert them to the binary scores with a Perl script. The item- and subject-level EI scores were generated with Equation 4.1. In addition, two native speakers of Japanese the transcribed EI responses manually to facilitate IRR analyses shown in Table 4.7 below. The transcription data were decomposed to morae with MeCab[17], a Japanese morphological analyzer and a Perl script to conduct the binary grading. for score generation, and the binary scores were calculated with the same grading protocol as ASR scores with Equation 4.1.

4.4.4 Results

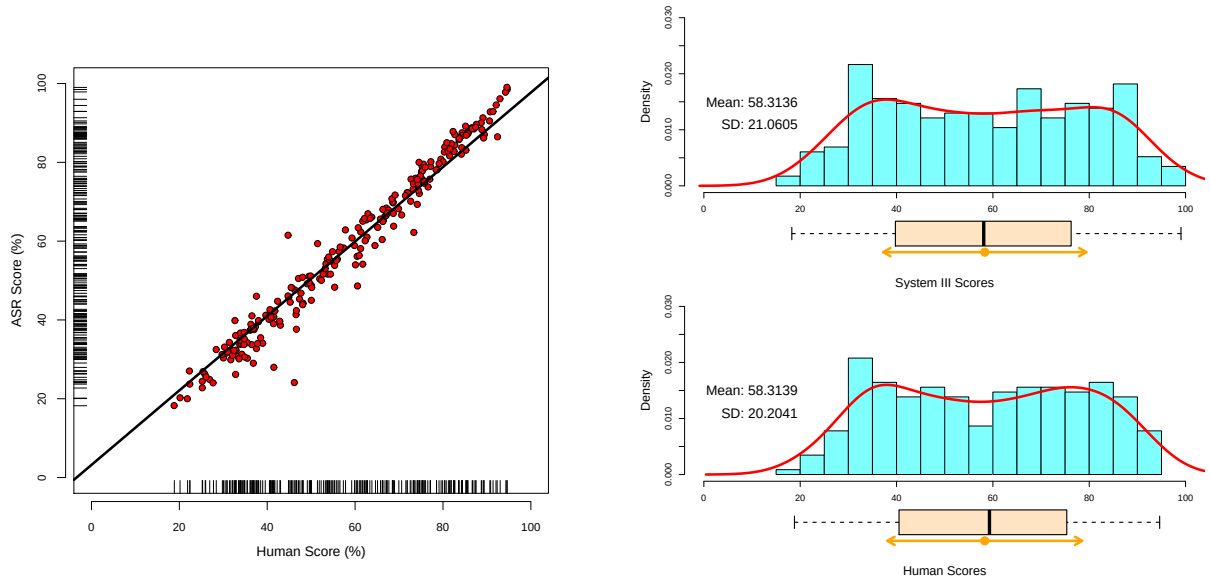
The scores generated by the three grading systems were compared with IRR and correlation analyses as in the previous studies (Matsushita and LeGare 2010, Matsushita *et al.* 2010). As shown in Table 4.7, scores generated with System III exhibit the best agree-

[15] `http://www.ffmpeg.org/`
[16] `http://normalize.nongnu.org/`
[17] `http://mecab.sourceforge.net/`

ment and correlation coefficient against human scores among the three systems. The discrepancies in terms of human and ASR scores observed in Figure 4.1(a) and 4.4(b) are also rectified as shown in Figure 4.11(a). The means and standard deviations in Figure 4.11(b) are almost identical, although there are some differences in the score distributions.

Table 4.7: IRR and Correlation Statistics with Human-Generated Scores of Three Grading Systems

	System I	System II	System III
Robinson's R (%)	84.8	83.8	86.0
Unweighted κ	0.686	0.669	0.713
Rater Bias	0.550	0.441	0.500
Item-Level r	0.9024	0.8940	0.9088
Subject-Level r	0.9815	0.9799	0.9852



(a) Regression Analysis (b) Score Distribution

Figure 4.11: Regression and Score Distribution Analyses of System III

4.5 Discussion

In this chapter, I have discussed the development of the three ASR-based EI grading systems. As shown in 4.4, System III using AM for learner corpus creation is the most effective grader among the three approaches. The significant aspect of System III is that it improved the IRR and correlation statistics with only 20% of the entire transcription data. Therefore, it is possible to enhance grading accuracy further by incorporating more transcription data in the AM exemplars as more test iterations are conducted with the same items. The best practice to ensure consistent grading performance with System III is to use newly created items along with the actual items in test administrations in order to obtain substantial transcription data with the collected speech samples. This process is also useful to examine difficulty levels of those experimental items, thereby determining whether they are optimal for future use. Therefore, both item and system development can be investigated concurrently with this approach. See Figure 4.12.

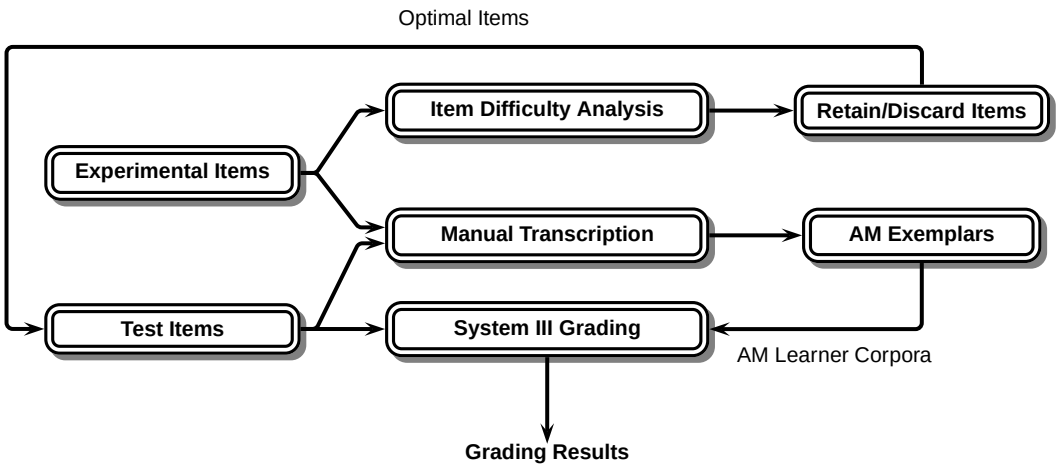


Figure 4.12: System III and Item Development Cycle

Further, the corpus-based item development approach discussed in Chapter 3 can be combined effectively with the process of grading system refinement. Figure 4.13 shows the comprehensive schema which combines Figure 4.12 and Figure 3.2. As shown in Figure 4.13 below, the item creation process is connected to the item analysis and man-

ual transcription through EI test administration. The effectiveness of the experimental items is investigated as conducted in this study, and the result will return to the prototype generation as feedback to the next item creation. Regardless of whether the experimental items are optimal or not, the transcription data can be utilized for AM learner corpus creation for the augmentation of System III, if the transcription contains ample interlanguage-influenced production phenomena.

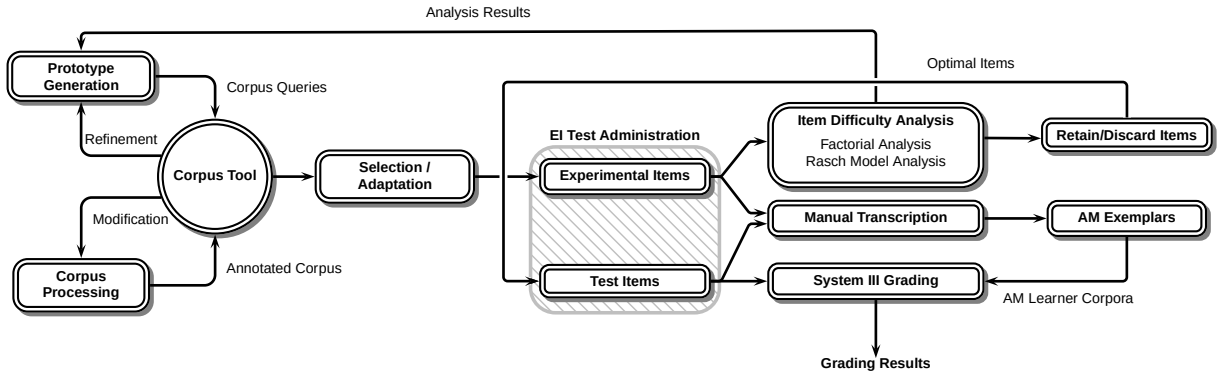


Figure 4.13: Combination of Corpus-Based Item Creation and System III

Thus, System III and the test items used in Chapter 3 are the components of the current version of the testing and grading system developed through a series of Japanese EI studies. Although there is still much room for improvement, this Japanese EI testing system provides valuable information on learners' proficiency in terms of L2 accuracy based solidly on the targeted linguistic concepts using an automatic grading procedure. The scores generated with this testing system integrate L2 accuracy information with SS scores as fluency measurement for L2 proficiency assessment.

In the following chapter, I will discuss the SS system and the combination of EI and SS results to measure L2 oral proficiency.

Chapter 5

Japanese Simulated Speech and its Combination with EI

5.1 Japanese Simulated Speech: Basic Approach

As described in Chapter 2, Simulated Speech (SS) is another method for oral proficiency measurement used in the field of language testing. In the previous two chapters, I mentioned that EI is used to measure L2 oral accuracy by designing test items which reflect learners' L2 capability effectively and by carefully setting up the ASR system to yield precise grading results. In this chapter, I will discuss the use of SS to measure L2 oral fluency, which is another aspect of L2 oral proficiency addressed by this system. In Matsushita (2010), we investigated several fluency factors with EI speech samples, but this attempt has not been fruitful simply because EI speech samples are too short to extract desirable fluency features. The time lengths of EI repetitions produced by typical learners range from one to thirteen seconds with the prompts used in the current Japanese EI test. Although some relevant features are observable with those EI speech samples (e.g., hesitation, fillers, length of repetitions, etc.), it is still difficult to retrieve a majority of the fluency features enumerated in Table 2.2 from such short speech samples. On the other hand, SS allows us to obtain various fluency features due to the less controlled speech environment provided with this testing method, as discussed in 2.2.

There are several considerations in processing SS speech samples with ASR: (1) it is unlikely that precise dictation with such open-ended speech samples will be accomplished, especially with samples produced by non-native speakers, and (2) learners' performance in SS depends on a wide variety of latent factors other than their pure L2 capability (e.g., prior knowledge of and/or experience with the topics presented by the test items, etc.), which requires complex procedures to design appropriate test items for fair grading (see Luoma 2004).

As mentioned in Chapter 1, the main reason for the separation of accuracy and fluency measures with EI and SS is to overcome the limitation of ASR capability. By relegating EI to L2 production accuracy measurement, the ASR system for SS is dedicated solely to fluency feature extraction, and the problem (1) above is not as significant with this approach. Although the SS system is still required to process speech samples with a certain level of precision in dictation to retrieve several fluency features, this approach enables us to develop the ASR system with more generic specifications than the EI counterpart.

The item difficulty issue mentioned in (2) above is beyond the scope of this study and still remains to be addressed in future studies. Therefore, I chose existing SS items available for public use rather than creating original items, for the sake of simplicity. The following section will describe the selected test items for this study.

5.2 SS Test Items

Test items used in this study were selected from the Japanese SOPI test (CAL 1995), with permission from the Center for Applied Linguistics. The effectiveness of these test items has been thoroughly tested in actual SOPI administrations and they are deemed viable items based on the analyses developed in a series of previous studies on SOPI items for other languages (see Clark and Li 1986 and Stansfield *et al.* 1990).

These items are categorized in three groups according to task type: picture tasks, topic tasks, and situation tasks (four picture tasks, five topic tasks, and five situation tasks are enclosed in the test package). In the picture tasks, test takers are asked to provide detailed descriptions on the topics related to the presented pictures according to the questions asked by a native speaker. In the topic tasks, questions on particular topics (e.g., school life) are given, and the subjects are asked to answer the questions and give the justifications for their answers. In the situation tasks, subjects are asked to imagine that they are in particular situations described in the test directions and to play roles (e.g., offering advice, apologies, etc.) in the hypothetical situations. These items are also classified as Intermediate, Advanced, and Superior based on the anticipated task difficulty. There are three Intermediate, eight Advanced, and three Superior items in the test.

Among these fourteen items, I chose five for the computerized SS test. Table 5.1 provides descriptions of the selected items.

Table 5.1: SS Test Item Descriptions (CAL 1995)

Test Item	Level	Prep. Time	Response Time	Task Type
Picture 1	Intermediate	15 sec.	1 min. 20 sec.	Describe a typical shopping mall to a Japanese tourist
Topic 1	Intermediate	15 sec.	45 sec.	Give a description of the kind of weather he or she likes
Situation 1	Intermediate	10 sec.	45 sec.	State what kind of hotel room he or she wants, state the length of stay, and ask about restaurant hours
Topic 3	Advanced	20 sec.	1 min. 15 sec.	Give a step-by-step description of how a Japanese student can find a summer job
Situation 3	Superior	20 sec.	1 min.	Apologize to a host mother for returning home very late after missing the last train home

The criterion for choosing these test items is familiarity of the topics to the subjects. All three Intermediate items were chosen for the Japanese SS test to ensure that even low-level learners are able to produce a certain amount of speech with these tasks. I also selected the other two high-level items based on consultation with an experienced teaching assistant in the Japanese program, in order to select items with topics which are covered in the class materials. The related assumption is that learners are able to perform well in the test by applying their learning experience to these high-level but familiar topics.

With these items, a study was designed to investigate the effectiveness of the proposed Japanese SS system. I will describe the experiment, the system specifications, and targeted fluency features in the following section.

5.3 Method

The overall data collection procedure and subject demographics were already described in 4.4.3. The following sections provide additional detail concerning the SS test administration in this study.

Participants. In addition to the 231 subjects described in Table 4.6, SS data were also collected from twelve additional native speakers of Japanese using the same testing tool explained in 4.4.3. Further, nineteen non-native subjects were randomly selected among the 231 subjects to take OPI tests for comparison with EI and SS scores.

Testing Procedure. The testing procedure used in this study was basically identical to the Japanese SOPI besides the fact that ours was computer-delivered. The SS items were presented to the subjects as the second portion of the speaking test following the completion of the EI test discussed in Chapter 3 and Chapter 4. At the beginning, general instructions were provided with the test administration tool to briefly explain the nature of SS. The written instructions for each test item taken from the SOPI booklet were displayed on the screen when the audio description of the item started. A picture was also presented in a separate window for the picture task. After the audio instruction was completed for an item, the preparation and response time were displayed in a countdown clock on the screen in order for the test takers to be able to pace their thinking and speaking processes. When the test takers reached the last five seconds in the response time, a small warning beep sounded. Once they finished an item, they were requested to press a button to proceed to the next item. Figure 5.1 shows an example screenshot of the picture task.

The data management process is the same as described in 4.4.3. The SS speech samples were saved as .wav files on the local desktops and uploaded to the designated server space with a batch script along with the EI speech files.

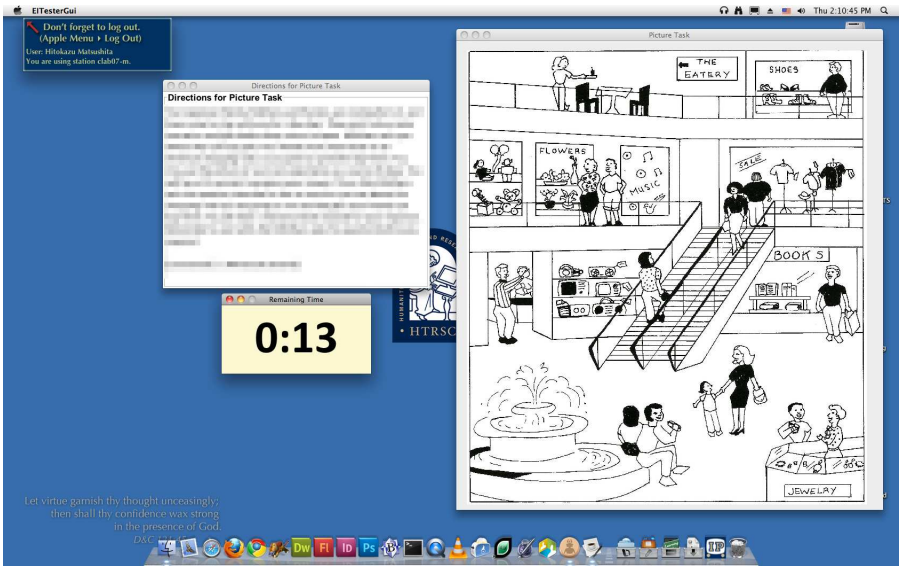
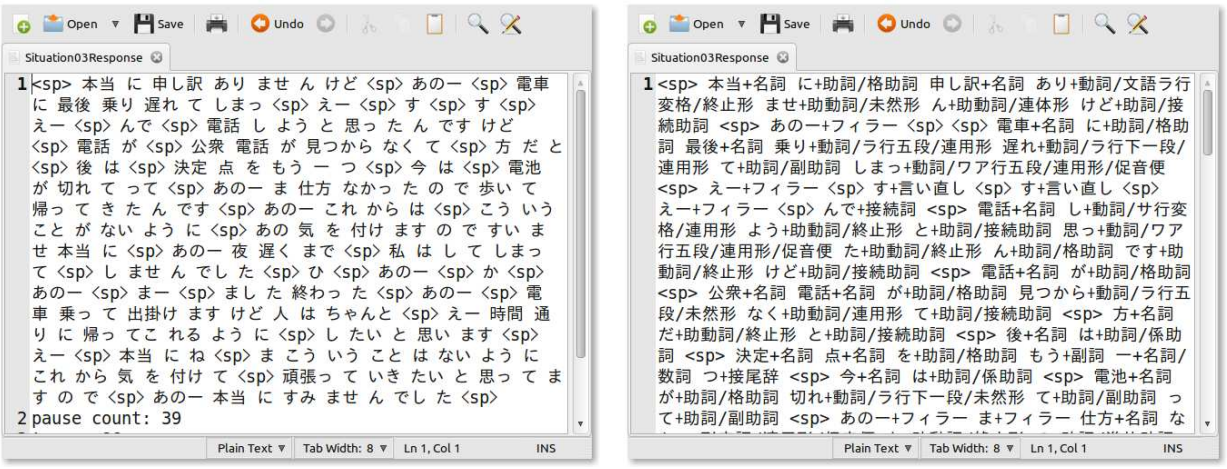


Figure 5.1: Screenshot of Computer-Based Japanese SS Test

ASR Specifications for Fluency Feature Extraction. Because the collected data consisted of open-ended speech, generic ASR components of Julius were used for fluency feature extraction. A single language model trained with CSJ data (see 4.3 for more detail) was incorporated in Julius to dictate all five test items. The acoustic model was the same as the one used for Systems II and III, described in Table 4.4. By utilizing various types of information provided in the dictation process, the following fluency features were extracted with Julius. The time frame counts (100 milliseconds per frame) provided during the forced alignment processes were used to measure speech and silence lengths. Also, the number of phonemes were counted in the test items from the forced alignment information as well. Regarding pauses, I used 400 milliseconds as a threshold to divide continuous speech runs, based on the study by Freed *et al.* (2004). Julius denoted such pauses as "<sp>" (i.e., a short pause) in the dictation outputs when it encountered silence spans which exceeded the threshold in the recognition processes, as indicated in Figure 5.2(a).

The number of pauses, tokens (the total number of morpheme instances), and types (the number of unique morphemes) were counted by parsing the dictation results with a Perl script in the post-processing stage. Regarding filled pauses, dictation results



(a) Output for Type, Token and Pause Counts

(b) Output for Filler Counts

Figure 5.2: Screenshots of Dictated Speech Samples

with POS information tagged to the dictated morphemes (see 5.2(b)) were produced separately to identify the filler instances efficiently. The information on the number of tokens, types, and filled pauses provided by ASR dictation outputs was regarded to be satisfactorily accurate, if not perfectly precise, for the analyses of L2 fluency in this study because the main purpose of the ASR dictation for SS is to roughly differentiate types of morpheme instances in the speech samples[1] along with the extraction of temporal features. Therefore, it is reasonable to assume that the approximate estimates of these L2 fluency phenomena are readily attainable with this type of generic ASR system.

Feature Descriptions. Based on the dictation results obtained through the ASR procedure above, the eleven fluency feature values listed in Table 5.2 were obtained. As mentioned in 2.3, the rationale for extracting these features for fluency measurement are based on previous studies by Xi *et al.* (2008) and Higgins *et al.* (2011), which assert that these fluency features provide critical information on L2 proficiency in the evaluation process using semi-direct oral tests such as SS.

[1]See the ASR output (Situation 1) shown in 5.2(a) to confirm the accuracy level of the dictation.

Table 5.2: Fluency Features Extracted with SS

Feature	Description
(1) # Tokens	Number of morpheme tokens in a test item
(2) # Types	Number of morpheme types in a test item
(3) # Pauses	Number of short pauses in speech
(4) Speech Length	Total speech duration in a test item
(5) Silence Length	Total length of silence in a test item
(6) Speech Rate	Number of phonemes per second
(7) # Fillers	Number of filled pauses in a test item
(8) # Runs	Number of fluent speech runs in a test item
(9) Tokens per Run	Number of tokens normalized by fluent speech runs
(10) Speech Time per Run	Speech length normalized by fluent speech runs
(11) Types per Speech Length	Number of types normalized by speech length

5.4 Analysis

In this section, I examine the eleven fluency features described in the previous section in an effort to develop an optimal SS grading method using a two-step approach. First, I use two machine learning (ML) systems to determine the most influential features for score calculation. Second, based on the study conducted by Higgins *et al.* (2011), a simple score generation model with the selected features is proposed.

5.4.1 First Stage: Machine Learning Process

Unlike EI analyses laid out in Chapter 3 and 4, there are no human-evaluated scores or ratings for benchmarks in this SS study. Therefore, a different approach to process the data is required for the development of SS score generation. The first step I use for SS scoring is using two ML systems to identify the most significant fluency factors. For this approach, I use TiMBL (Daelemans and van den Bosch 2005), and WEKA (Hall *et al.* 2009), ML tools extensively utilized to address NLP problems.

TiMBL is a a memory-based machine learning system based on the *k*-nearest neighbor (*k*-NN) algorithm. This tool is frequently used to address problems with language phenomena which are unsolvable with conventional rule-based, theoretical approaches (e.g., Ernestus and Baayen 2003). The strength of this system is the use of a statistical model based on the given unstructured data to predict the general behavioral patterns based on the model. This tool is desirable for this SS analysis because it has the capability to order the features according to the amount of information gained in the training process. This capability enables us to identify the most influential features for SS score generation.

To analyze the obtained fluency data with TiMBL, the feature vectors were created and stored as input files, as shown in Figure 5.3.

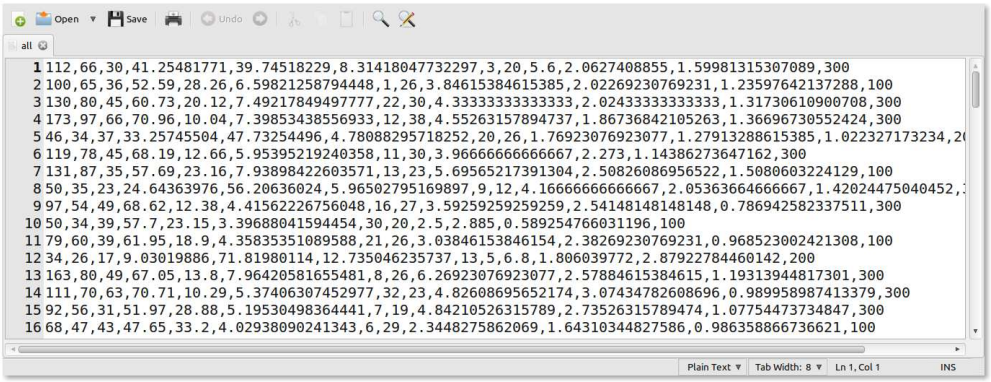


Figure 5.3: TiMBL Feature Vectors

The eleven fluency features of each test item response were aligned according to the order shown in Table 5.2 to form a feature vector. Here the class level of the subject in Table 4.6 was considered as the output of each vector, based on the assumption that the class level is an approximation of the subject's proficiency level. The class level information was placed at the end of each vector.

The formed feature vectors were consolidated to create datasets for statistical learning. The datasets were classified as (a) those with the twelve additional native speakers' data mentioned in 5.3 and (b) those without them. The learning process was conducted

with these datasets containing the vectors for each test item and those with all the test items combined. For the analysis, I used the leave-one-out validation process to obtain the results.

Table 5.3 shows the results of the TiMBL predictions. As shown, the prediction accuracy of (a) is higher than (b), due to the addition of twelve native speakers. The most important aspect of these results is the five influential factors indicated in the last two columns. Although the order of the variables is slightly different, the same five fluency features (# Tokens, # Types, # Pauses, # Fillers, and # Runs) are considered as influential in all the datasets.

Table 5.3: TiMBL Results (the numbering of variables corresponds to Table 5.2; the order of the five variables is according to the information gain ratio/values)

Test Item	(a) With 12 NS	(b) Without 12 NS	Top 5 Influential Variables (a)	(b)
Picture 1	0.754630	0.710744	2, 7, 8, 3, 1	8, 2, 7, 3, 1
Topic 1	0.768519	0.702479	3, 8, 2, 7, 1	8, 3, 2, 7, 1
Situation 1	0.717593	0.661157	7, 2, 8, 3, 1	8, 2, 7, 3, 1
Topic 3	0.800926	0.753086	8, 3, 2, 7, 1	3, 8, 2, 1, 7
Situation 3	0.708333	0.669421	8, 2, 3, 7, 1	8, 7, 3, 2, 1
All	0.922517	0.715670	2, 8, 3, 1, 7	

Further, to confirm that the five features found with the TiMBL models are also influential in the other framework, the same datasets were processed with WEKA, a data mining system using various decision tree models constructed via the support vector machines (SVM, see Burges 1998).

The J48 classification method (C4.5 decision tree models) was used for this analysis. The results in Table 5.4 show the prediction accuracy rates based on the created decision trees. It clearly shows that the prediction rates between the trees with all the features and with the five features are almost identical. This trend is shown in datasets both with and without the twelve additional native speakers. Therefore, it is safe to say that these five fluency features are the most dominant factors in making predictions about

learners' proficiency levels and other features are inconsequential for score generation in this study.

Table 5.4: WEKA Results

Test Item	Prediction Accuracy Rate (%)			
	With 12 NS		Without 12 NS	
	All Features	5 Features	All Features	5 Features
Picture 1	86.1111	82.8704	80.5785	80.1653
Topic 1	82.4074	79.6296	78.9256	76.4463
Situation 1	80.5556	79.1667	76.4463	71.9008
Topic 3	84.2593	81.4815	81.4185	78.6008
Situation 3	83.3333	81.9444	80.5785	76.8595
All	89.3916	82.0593	79.8061	74.7981

5.4.2 Second Stage: Score Generation

In the second stage, the fluency features identified with the ML processes above are used to generate SS scores for individual subjects. Unlike EI, calculation is not straightforward because it is necessary to identify a particular calculation formula with these features to combine them and yield reasonable scores. Again, the conventional regression model is not appropriate for this analysis due to the lack of human-graded scores.

Higgins *et al.* (2011) analyzed the features in Table 2.2 to develop a multiple regression model with human- and ASR-generated scores of the TOEFL iBT speaking test items. Table 5.5 shows the features that they selected according to statistical significance in the model and the associated mathematical treatment to normalize each feature and to yield the best fit with the regression model. Note that these score calculation features in Table 5.5 aside from amscore and lmscore[2] include the majority of the ML-selected features in Table 5.3.

[2]Zechner *et al.* (2009) mention that although these features were incorporated in their scoring process as in 5.5, they cannot be significant numbers even with the mathematical treatment because of the probabilistic nature. Therefore, I simply ignore these features in this study.

Table 5.5: Features of Regression Model and Mathematical Treatment in Higgins *et al.* (2011) (see also Table 2.2)

Feature	Calculation	Assigned Weight	Transformation
amscore[3]	$\log P(\mathbf{x}\|\mathbf{w})$	4	Inverse
wpsec	$\frac{\text{\# Tokens}}{\text{Item Time Length}}$	2	—
tpsecutt	$\frac{\text{\# Types}}{\text{Speech Length}}$	2	—
wdpchk	$\frac{\text{\# Types}}{\text{\# Runs}}$	1	Logarithmic
lmscore	$\alpha \times \log P(\mathbf{x}) + \beta \times N$	1	Inverse

It is reasonable to assume that these weights and mathematical treatments in Table 2.2 are also applicable to the SS score generation in this study. One concern about their approach is, however, that the calculation of *tpsecutt* and *wdpchk* are highly likely to interact with each other due to the same numerator used in the calculation. Therefore, I change one of the these formulas by incorporating the # Fillers feature, which is not incorporated in this table. Thus, the SS score generation formula is defined as in Table 5.6.

Table 5.6: SS Score Generation Features

SS Score Factor	Calculation
Factor 1 (f_1)	$2 \times \frac{\text{\# Tokens}}{\text{Item Time Length}}$
Factor 2 (f_2)	$2 \times \frac{\text{\# Tokens} - \text{\# Tokens}}{\text{Speech Length}}$
Factor 3 (f_3)	$\log\left(\frac{\text{\# Types}}{\text{\# Runs}}\right)$
	$\text{SS Score} = \sum_i f_i$

[3]See Kawahara and Lee (2005) for the detail of the probabilistic calculation of AM and LM scores.

Pauses is not incorporated in this formula. The reasons for this are because (1) I assume that pause counts generally interact strongly with # Runs because they appear alternatively in speech samples, and (2) this feature seems not to behave monotonically (either a constant increase or decrease according to the class levels), which makes it quite complex to develop a particular mathematical treatment for it. Figure 5.4 depicts the distribution of pauses made by the subjects in all five SS items. Interestingly, this pause count feature is salient only with the 300-level subjects in terms of the mean and distribution, but other subject groups' are similarly distributed. Because of this peculiar characteristic, this feature is excluded for the calculation in this study.

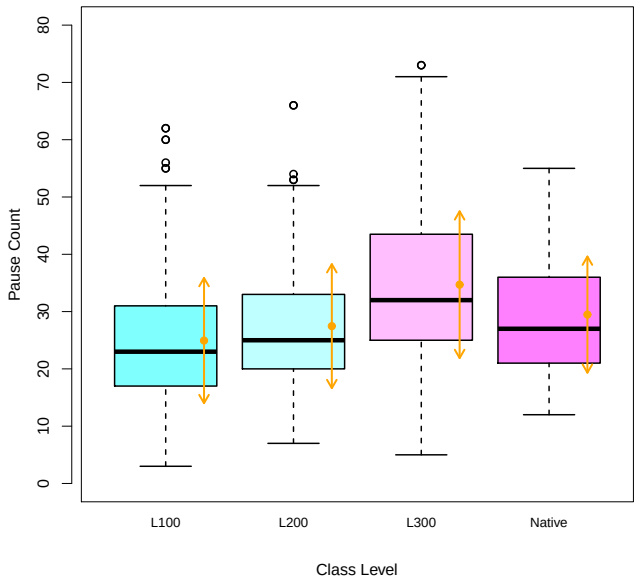
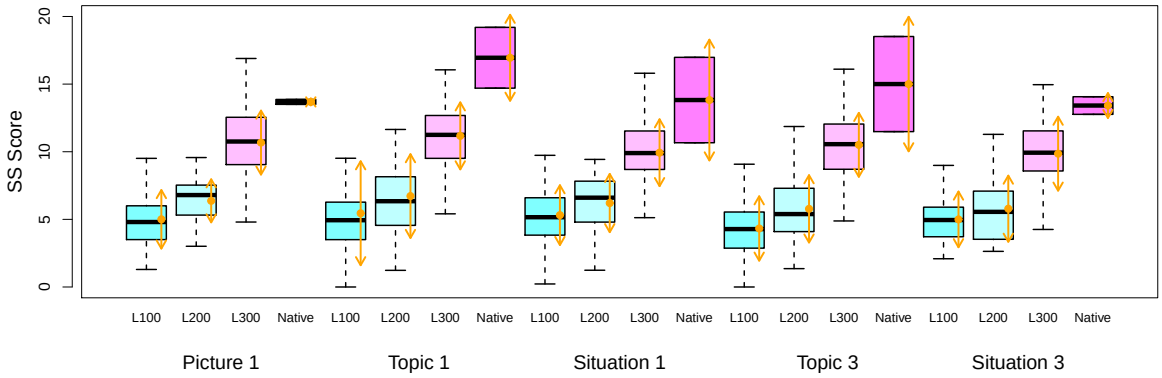


Figure 5.4: Pause Count Distribution (the points and arrows on the boxplots indicate the mean values and one standard deviation ranges)

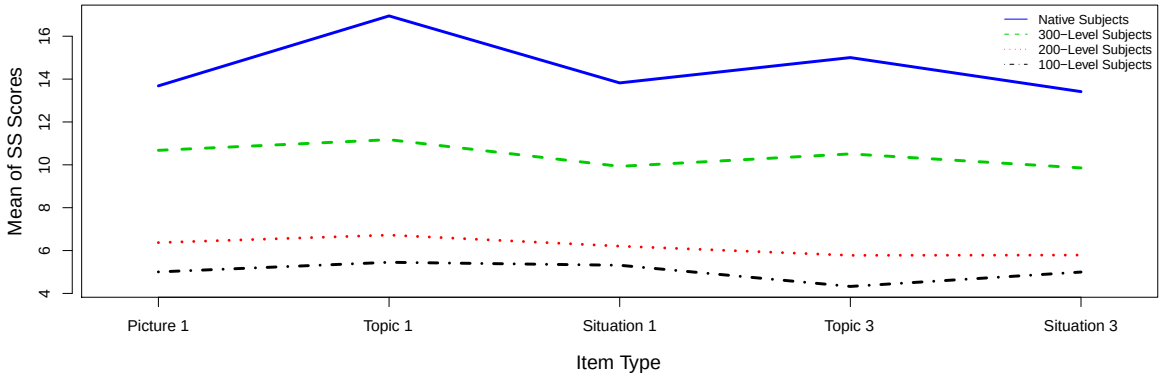
5.4.3 Results

Based on the formula in Table 5.4.2 above, SS scores for the 231 subjects were generated. Figures 5.5(a) and (b) show the SS item score differences according to class

levels and the interaction between the item type and the class level based on the associated factorial ANOVA results. The differences for test items and for class levels are both statistically significant ($F_{\text{Item Type}}(4,222) = 4.5478$, $p < 0.001$ and $F_{\text{Class Level}}(3,222) = 311.2628$, $p < 0.0001$, respectively). However, the differences in test items are not uniformly significant according to the Tukey post hoc test (only Topic 1–Situation 1 and Topic 3–Topic 1 pairs, $p < 0.01$). Therefore, the stipulated item difficulties of the five SOPI items used in this study (see Section 5.2) do not affect subjects' SS scores generated with the calculation method above.



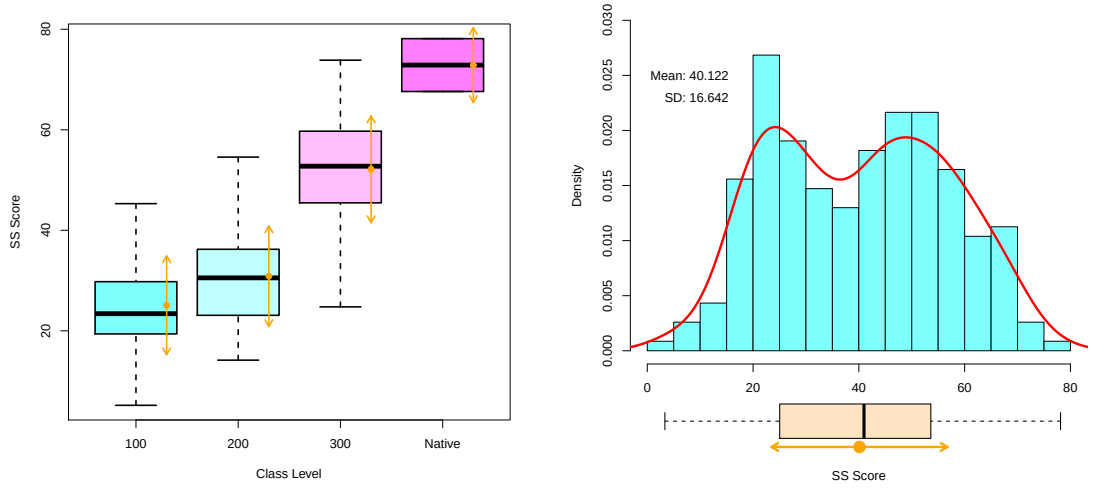
(a) SS Item Score Distribution



(b) Item Type – Class Level Interaction

Figure 5.5: SS Score Distribution (a) the score differences according to item type and class level (b) the interaction between item type and class level

Figures 5.6(a) and (b) show the differences and distribution of the total scores of the five SS items. The ANOVA analysis shows that the difference between the class level groups are significantly different ($F_{\text{Class Level}}(3,222) = 108.1$, $p < 0.0001$). Also, the associated Tukey HSD analysis indicates that the differences among all the subject groups are significant (the p values are ranging from 0.03 to less than 0.0001). Further, the score distribution exhibited in Figure 5.6(b) seems bimodal, but the Anderson-Darling (AD) test indicates its strong normality with $p < .0001$ ($A = 2.297$). Therefore, it is safe to say that this SS score generation method is reasonably useful in measuring learners' performance concerning the ML-selected features in an efficient manner.



(a) Score Differences (b) Score Distribution

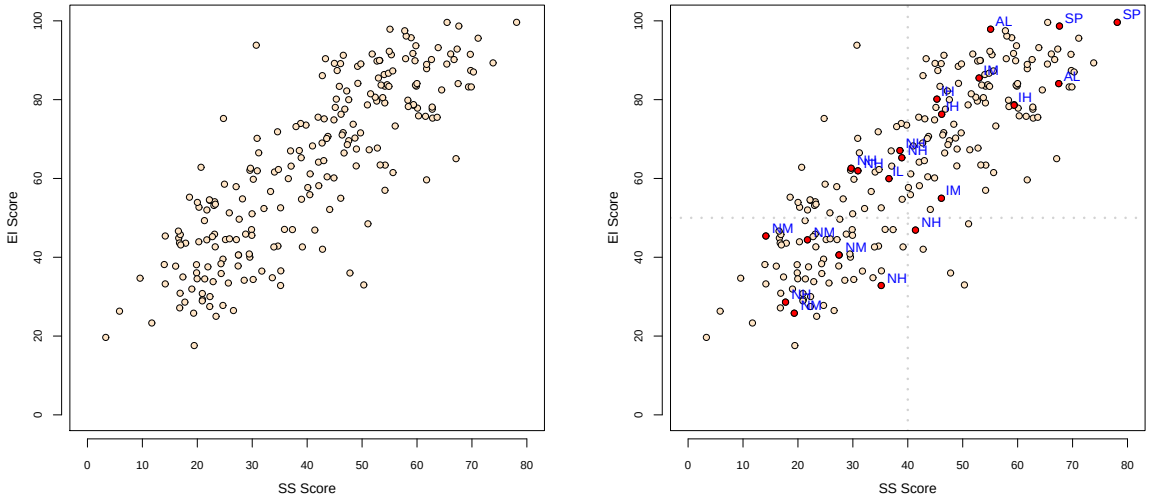
Figure 5.6: SS Total Score Differences (a) Total score differences according to class levels (b) Distribution of SS scores

5.5 Combination of EI and SS Scores

Finally, I will discuss the combination of the EI scores obtained with System III, discussed in Chapter 4, and the SS scores above. Figure 5.7(a) indicates the simple two-dimensional distribution of these scores. There is a moderate correlation between these scores ($r = 0.83$), but the regression model itself is not statistically significant ($p = 0.974$).

This is promising because it indicates that these two types of language testing methodologies focus on different but weakly related aspects of L2 oral production.

Figure 5.7(b) shows the same scatterplot superimposed with nineteen subjects' OPI ratings on the associated EI–SS scores. The OPI ratings are indicated with the initials (NM: Novice-Mid, NH: Novice-High, IL: Intermediate-Low, IM: Intermediate-Mid, IH: Intermediate-High, and AL: Advanced-Low). Additionally, the two native speakers are regarded as Superiors in this analysis, and their scores are marked as SP. As shown, the Novice-level scores are clustered in the lower-left portion of the graph; the Intermediate-level scores are on the middle to the upper-right portion; and the Advanced to Superior scores are located around the upper-right edge. Interestingly, EI scores for one subject with an AL rating are almost identical to the native speakers', but the corresponding SS score is clearly lower than theirs. The opposite phenomenon can be observed with another AL subject's SS score: the SS score is close to the those of native speakers', but the corresponding EI score is lower than theirs. Therefore, it is possible to observe some characteristics associated with OPI ratings and EI–SS scores with this simple score alignment method.



(a) Scatterplot

(b) Scatterplot with OPI Ratings

Figure 5.7: Scatterplot of EI and SS Score (a) the simple scatterplot of EI and SS scores and (b) the scores superimposed with the associated OPI ratings

An alternative comparison strategy is to use the discrete EI scoring method discussed in 3.6.3 to differentiate proficiency groups more clearly. To illustrate the score distribution, I calculated EI binary scores based on the following procedure:

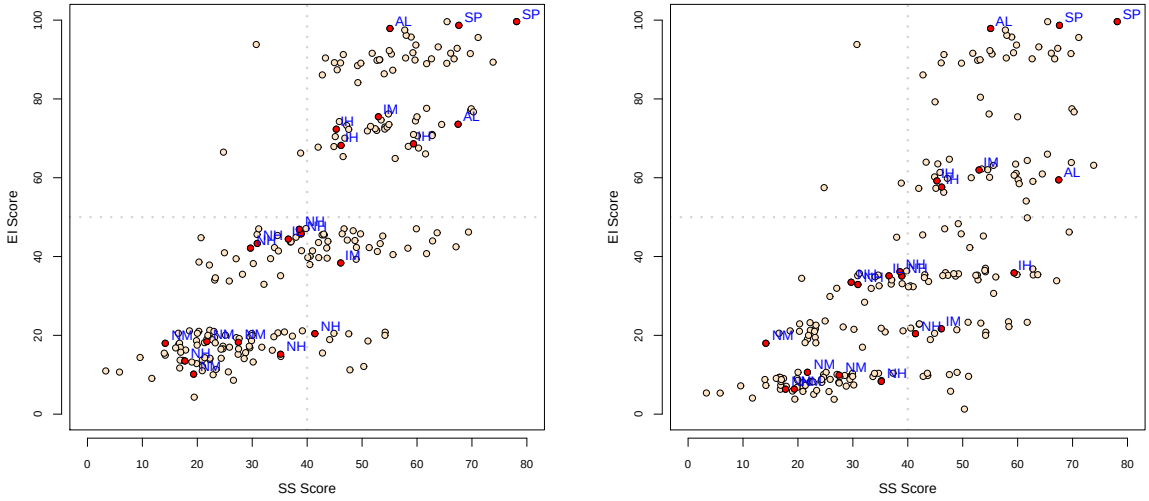
1. As described in 3.6.3, the item scores are separated according to the item levels and and class numbers in Table 3.2.

2. The binary scores are added if the subject attains 80% of accuracy on all the items in the item level or class number. If this is not the case, the scores are not included in the total scores.

3. The accumulated binary scores satisfying the condition in (2) are processed with Equation 4.1.

Figures 5.8(a) and (b) depict the EI–SS score distribution with the discrete scoring method above. Overall, the class number approach is more conservative than the item level counterpart, and the majority of the EI scores in Figure 5.8(b) are lower than (a). The ratings on the right side of each score cluster tend to be higher than those on the left side. The significant aspect of this grading approach is that the AL rating with the low EI score is more clearly separated from those of native speakers in both Figure 5.8(a) and (b) than that in Figure 5.7, which enables us to observe the difference of advanced-level learners from (near-)native speakers more easily.

Although it is still impossible to discriminate test takers in the same classification levels as the OPI (i.e., ten sublevels), this EI–SS approach provides a good estimation of the L2 oral proficiency in a very effective manner. Lastly, Figure 5.9 shows the approximate OPI rating distribution pattern according to Figure 5.8(b). Because of the scarcity of OPI ratings in this study, OPI ratings with Novice Low, Advanced Mid, Advanced High were not available. Therefore, the OPI distribution clusters including those ratings shown in Figure 5.9 are based solely on my assumption. Definitely, more data are needed to investigate the effectiveness of this EI–SS approach in further research.



(a) Class Level (b) Class Number

Figure 5.8: Discrete EI Scoring and OPI Ratings (a) The OPI distribution in the class level EI and SS scores (b) The OPI distribution in the class number EI and SS scores

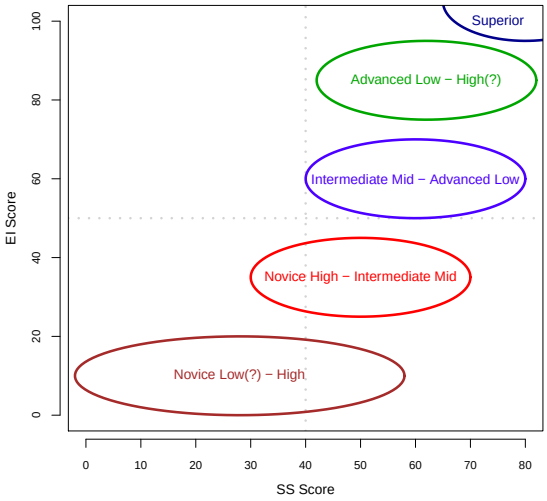


Figure 5.9: Approximate OPI Rating Distribution in EI–SS Scoring Method

Chapter 6

Conclusion

6.1 Significance of This Study

In this study, I discussed an approach to measuring L2 oral proficiency using two separate testing and scoring methods, and I addressed the effectiveness of these two methods from various perspectives. This proposed approach is innovative compared to many of the existing computer-mediated oral language testing systems because these systems put great emphasis only on structured speech tasks which heavily circumscribe the speech patterns of test takers (e.g., Bernstein *et al.* 2010, Müller *et al.* 2009) or on completely open-ended speech tasks (Cucchiarini *et al.* 2000). The two most significant aspects of this study are (1) combining structured and open-ended speech tasks, namely EI and SS, as a joint speaking test and administering it with a computer-based testing system, and (2) evaluating the speech samples obtained through the test administration with two ASR-based grading systems, which are configured independently to maximize the ASR capability to observe L2 oral proficiency globally, as schematized in Figure 1.1.

From a language administration point of view, there are several advantages of using EI and SS as an integrated test battery as follows:

1. Unlike typical oral interviews, test takers are allowed to have multiple "fresh starts" (Hughes 2003) during the EI/SS test by providing a substantial number of test items (thirty EI and five SS items), which is frequently pointed out as one of the characteristics of effective oral tests.

2. The combination of EI and SS helps increase the face validity of the test, which is hardly guaranteed with only structured speech tasks such as EI.

3. The test administration is very time-efficient. The required time for completion of a single test is less than thirty minutes. This indicates that a substantial number of test takers are able to complete the test within a day if multiple computers with good quality headsets are available.

Also, the following are advantages from the perspective of test evaluation:

1. The grading process is virtually automatic with the ASR systems. Although it takes several hours to complete the entire grading process, this is much more time- and cost-efficient than evaluating the speech samples with human labor, which is favorable for language institutions with fewer resources.

2. Unlike criterion-referenced tests, the EI/SS results are strictly numeric due to the objective and analytic nature of the test. Therefore, the test results are applicable to both longitudinal and cross-sectional studies to examine learners' progress and compare their performance.

3. The speech samples collected in the test administration can be used later for qualitative studies as well. These samples are useful in various situations such as when educators or researchers need to investigate learners' particular characteristics (e.g., error-making patterns) in the EI and SS tasks. It is also possible to conduct similar qualitative studies to the one illustrated in 3.4 (see also Matsushita *et al.* 2010), examining the relationship between learners' test performance and their learning experience. In fact, the findings obtained through such qualitative analyses are highly important and necessary for further testing and grading procedure refinement.

These advantages clearly indicate that the ASR-based EI/SS testing system developed in this study is a solution for the time- and cost-efficiency problems posed in Chapter 1. However, it is still premature to say that this testing system is a satisfactory alternative to existing interview-based tests, which can offer us more details regarding L2 oral proficiency. The following discussion will describe some of the limitations of the system proposed in this research.

6.2 Limitations of This Study

The following points summarize some of the issues that have not been addressed in this study:

1. Clearly, not all the L2 accuracy factors listed in 1.2 are encompassed in EI. For example, pronunciation accuracy is not considered in this study although this factor plays some role in the ASR processing. To refine EI grading, it is necessary to investigate what types of pronunciation patterns were unacceptable to human graders and how those phonologically abnormal EI responses were treated with the EI grading system through qualitative analyses. Also, no accuracy factors related to social and cultural appropriateness, such as vocabulary choice in a particular context, are taken into account in either EI or SS due to the test format and grading capability. Therefore, it is not possible to incorporate such factors with the current EI and SS grading criteria. Ideally, these features should be obtained and processed through SS, which provides test takers with a less-controlled speech environment; however, it is not feasible for the current SS system to accurately capture and incorporate such factors in evaluation due to its heavy emphasis on fluency features and the system configuration. Presumably, this may be the main reason that there were no significant differences in SS scores among the five SS items, as indicated in Figure 5.5(a).

2. Related to the issue above, the critical disadvantage of the current SS grading method is that the system is not able to scrutinize the content of the produced speech before extracting fluency features for grading. Therefore, there is no method to identify situations where learners speak about unrelated matters and to avoid grading such speech samples.

3. Further, this study does not discuss a systematic method for SS item creation although this is also a critical aspect for constantly developing new versions of the test for the future administrations.

4. Test score calibration processes against existing oral tests such as OPIs have not been thoroughly conducted. In this study, I mainly used class levels as rough approxi-

mations for proficiency levels, which are obviously not perfect correlates with OPI ratings. Therefore, it is critically important to conduct further statistical analyses to increase the reliability and validity of the EI/SS test and produce scores closely comparable with such oral tests.

The limitations enumerated above clearly show that there are still many issues to be addressed to improve the current EI/SS testing system in order to ensure more effective testing and grading processes. Needless to say, it is critically important to conduct further literature review and data collection in order to identify possible solutions to these issues.

6.3 Future Work

Along with the limitations described in the previous section, the development of new tools and the addition of language resources are the other issues to be considered in future studies. To realize more fine-tuned testing and scoring systems, the following future work and suggested possible approaches need to be investigated.

6.3.1 Manual Transcription Tool

Regarding the EI grading system, manual transcription is essential to create AM training datasets for LM development and to identify new optimal EI items through item analyses, as schematized in Figure 4.13. The problem inherent in this process is, however, that it is difficult to unify the transcription notations (e.g., *kanji* vs. *hiragana*, etc.) among human transcribers, which often makes annotation with NLP tools unstable and consequently impede the AM exemplar creation process. To stabilize transcription processes, the development of a comprehensive transcription tool to assist transcribers is necessary. One could envision a tool that suggests desirable transcription notations according to the transcribers' input based on the previously transcribed data and conducts annotation of the transcribed EI responses under the CSJ annotation standard concurrently.

6.3.2 SS Scoring Improvement

In this study, I used the formula proposed by Higgins *et al.* (2011) to generate SS scores based on the fluency features selected by TiMBL and WEKA, the ML systems. Although this approach satisfactorily functioned for proficiency estimation, there is much room for further improvement of score generation in various aspects. For example, I did not take into account the weights on relevant fluency features provided by TiMBL, which may contain important information for SS scoring, because the order of the fluency features are uniquely varied for each test item. In this study, I treated these features equally in the scoring process. This might be another reason that there were no significant difference among item types in terms of score distribution, as indicated in Figure 5.5(a). Therefore, it is reasonable to assume that the combination of these weights and the feature values may yield more effective SS item and total scores than the current version's. Also, it may be possible to integrate the # pauses feature into the score calculation, which was not attempted in this study due to the peculiar distribution pattern illustrated in Figure 5.4, by utilizing its corresponding weight in the calculation process. To investigate this, it is necessary to develop or improve the current score calculation methods. This study should be conducted be conducted in the immediate future.

6.3.3 Simultaneous EI/SS Scoring

It is desirable to grade EI and SS items during the test administration in order to provide test takers with scores upon the completion of the test. This is also advantageous for test administrators as well because it accelerates the entire evaluation procedure by delegating the scoring processes to multiple local computers used for testing, rather than spending several hours for grading with a single computer. This is attainable by incorporating the core libraries of Julius to the test administration tool described in 4.4.3. In theory, it is possible that the incoming speech is processed as direct input via microphone and the dictation results for binary scoring are produced as each item is completed. The audio input can be exported as .wav files at the same time for other processes such as

transcription. This is reasonably attainable by leveraging incorporated functions in the Julius libraries and plugins.

6.3.4 Acoustic Model Training

Dealing with speech samples containing the test takers' English utterances[1] with the current ASR system is another problem with the grading processes. Although it is impossible to identify all the possible L1 utterances that can occur in the EI and SS tasks, incorporating common English expressions often used during EI and SS performance in the acoustic model can reduce the influence on grading results. de Wet *et al.* (2010) conducted a study of acoustic model development to process accented English speech samples with ASR. They report that incorporating accent features to the acoustic model does not significantly increase overall recognition accuracy. However, considering the appreciable difference in the phonological patterns between English and Japanese, it is worthwhile to investigate integration of English speech instances to the CSJ acoustic model using HTK Toolkit[2] in future studies.

6.3.5 Language Model Training for SS grading

In this study, I used a generic LM trained only with the CSJ data for the SS feature extraction procedure, based on the rationale mentioned in 5.3. However, it is still necessary to increase recognition accuracy to ensure retrieval of more accurate token, type and pause counts, which are among the most influential fluency factors in this study. Also, recognition accuracy in SS grading is inseparably tied to the issues of the vocabulary pattern identification for discrimination of unrelated speech (see section 6.2). To improve the grading system in this respect, it is important to incorporate corpus data containing instances related to SS item topics. The main issue for this LM development is collecting appropriate corpus data. A possible approach for this task is selecting language data with a web tool based on context-vector models (see Billhardt *et al.* 2002), frequently used in

[1] I focus only on English here because the majority of our subjects are native speakers of English.
[2] `http://htk.eng.cam.ac.uk/`

information retrieval. If this LM augmentation approach is possible, we will be able to integrate pragmatic and sociolinguistic factors into the current SS evaluation criteria, which are considered as important aspects of L2 proficiency along with accuracy and fluency in many interview tests.

6.3.6 EI Item Creation Tool

In Chapter 3, I discussed the corpus-based approach to create optimal EI items and its effectiveness. One of the weaknesses in this approach is that the available corpora are not necessarily able to provide item candidates with particular types of syntactic and semantic structures; therefore, it is possible that users may not find desired sentences with this approach. A possible solution for this problem is creating an item engineering tool which consolidates syntactic fragments obtained from corpora to form possible EI candidates. In some respect, this approach resembles the item engineering method discussed in 3.4. The main difference, however, is developing a method engineering sentences based on corpus data, rather than creating items according to linguistic intuitions only. An eventual solution would require as input various NLP resources such as a lexical conceptual structure (LCS) database[3], Japanese WordNet[4], subcategorization frame dictionaries[5], and so forth.

6.4 Comprehensive EI/SS Schema

Figure 6.1 shows a comprehensive schematic representation of the current EI/SS testing and grading system as it would incorporate the new functions and tools suggested in the previous section. It is necessary to conduct a number of empirical studies and system refinement processes to ensure the robustness of such a system to reach the optimal level of functionality. The ideal system depicted here will probe L2 learners' oral proficiency in a more effective manner and provide valuable information on their L2 speaking ability for various purposes.

[3] http://cl.it.okayama-u.ac.jp/rsc/lcs/
[4] http://nlpwww.nict.go.jp/wn-ja/index.en.html
[5] http://www.gsk.or.jp/catalog/GSK2007-D/catalog.html

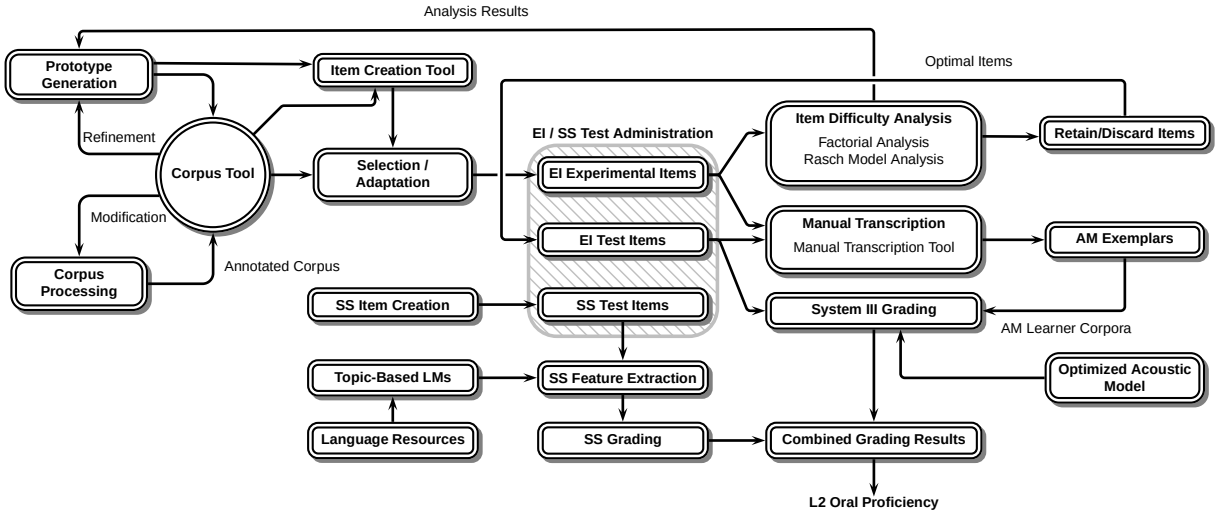


Figure 6.1: Comprehensive Schema of Computerized Japanese Oral Testing System

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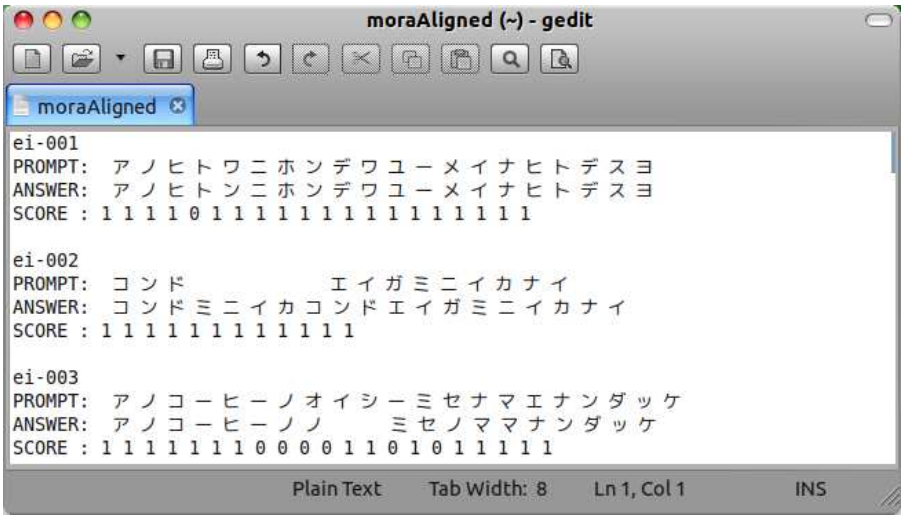
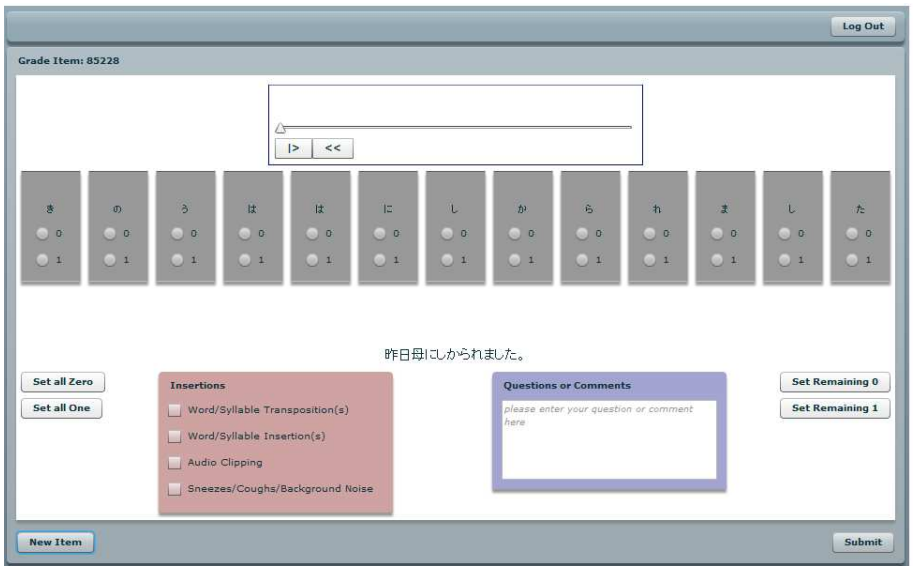
Appendix A

EI Graders



(a) ASR Grader



(b) Human Grader

Figure A.1: ASR and Human Graders (a) Mora alignment of correct and dictated EI items and corresponding binary scores generated by System I (b) Web-based human scoring system with the binary grading method

Appendix B

Decision Trees

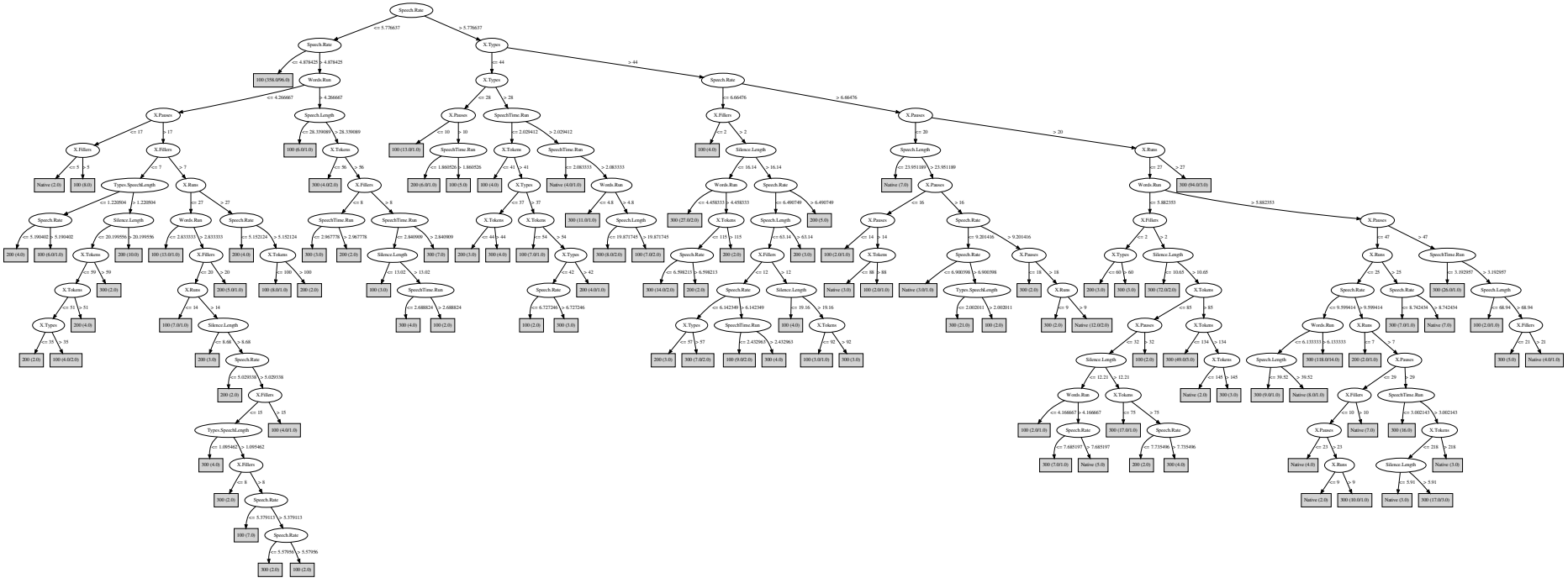


Figure B.1: Decision Tree for All 12 Features

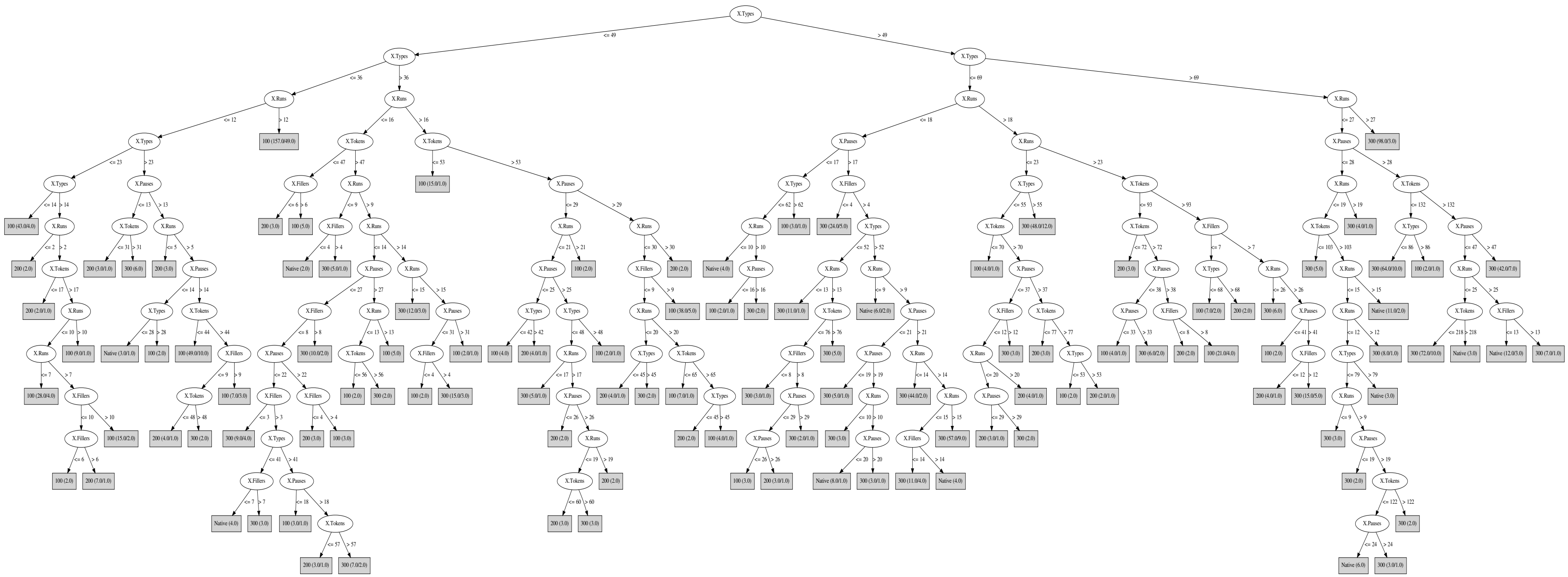


Figure B.2: Decision Tree for 5 Selected Features