TPM Vol. 32, No. S6, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

PRONUNCIATION ERROR DETECTION AND CORRECTION IN NON-NATIVE ENGLISH SPEECH: A PSYCHOLOGICAL AND COMPUTATIONAL APPROACH USING CONTRASTIVE LEARNING

DR. SHIRISHA DESHPANDE
ASSISTANT PROFESSOR, DEPARTMENT OF ENGLISH, CHAITANYA BHARATHI INSTITUTE OF TECHNOLOGY, HYDERABAD-500075, TELANGANA-INDIA., ORCID ID-0000-0002-7218-9303
EMAIL: Shirisha_english@cbit.ac.in

DR.A. VIJAYALAKSHMI
ASSISTANT PROFESSOR, DEPARTMENT OF ENGLISH, CHAITANYA BHARATHI INSTITUTE OF TECHNOLOGY, HYDERABAD-500075, TELANGANA-INDIA., ORCID ID: 0000-0002-3422-6409,
EMAIL: vijayalakshmi_english@cbit.ac.in

DR. B. CHANDANA
ASSISTANT PROFESSOR, DEPARTMENT OF SCIENCES AND HUMANITIES, MATRUSRI ENGINEERING COLLEGE, SAIDABAD, HYDERABAD, EMAIL: gantachandana@matrusri.edu.in, ORCID ID: 0000-0002-6074-3880

DR.M. SAMADHANAM EMIMAL
ASSISTANT PROFESSOR, DEPARTMENT OF ENGLISH, CHAITANYA BHARATHI INSTITUTE OF TECHNOLOGY, HYDERABAD-500075, TELANGANA-INDIA, ORCID ID: 0000-0001-8905-6964.
EMAIL: Samadhanamemimal_english@cbit.ac.in

DR. GITASRI MUKHERJEE
ASSOCIATE PROFESSOR, ENGLISH DEPARTMENT, MUFFAKHAM JAH COLLEGE OF ENGINEERING AND TECHNOLOGY
EMAIL: gita@mjcollege.ac.in, ORCID ID:0000-0002-0865-141X

DR MEENA GULLUR
ASSISTANT PROFESSOR (SR.SC), ENGLISH DEPARTMENT, VASAVI COLLEGE OF ENGINEERING IBRAHIMBAGH, HYDERABAD.500031. EMAIL: g.meena@vce.ac.in

Abstract
Communication competence in English is easily impaired in those non-native speakers due to the error in English pronunciation, which may adversely affect the intelligibility, confidence and general proficiency in the language. This paper is an investigation into a hybrid psychological-computational approach to the detection and correction of pronunciation errors in non-native English speech. Based on the theory of the second language acquisition and psycholinguistics, the study examines the cognitive and psychological issues of learners in generating speech with phonetic correctness. A contrastive learning-based model is constructed on the computational front to learn the subtle differences between the native and non-native pronunciation patterns. The system uses acoustic characteristics, phoneme embeddings and contextual inputs to detect deviations and produce an error feedback mechanism. Policymaking in an experimental environment proves the effectiveness of the model in increasing the accuracy of error detection, and providing adaptive correction strategies depending on the profile of the learner. The combination of psychological understanding makes the system not only a solution of phonetic mistakes but also a decrease in anxiety and a perpetual improvement in pronunciation among the learners. The interdisciplinary approach will lead to the expanding research into the Intelligent Language Learning System and introduce the opportunities of more individualized, empathetic, and efficient speech training.
Keywords: Pronunciation error detection, non-native English speech, contrastive learning, psycholinguistics, computer-assisted language learning, speech correction.

INTRODUCTION

English has now become the most common international communication, education, trade and technology language. Although most users of the English language are non-native, their verbal competence is usually undisputed by the lack of pronunciation errors that undermine intelligibility, understanding, and general communicative skills. In sharp contrast to vocabulary and grammar, pronunciation needs proper coordination of auditory perception, motor control and cognitive consciousness, and can be problematic in cases when a learner whose native language (L1) phonetics are quite different to English. As a case in point, speakers of languages that lack some of the clusters of consonants, or the aspirated ones or even the difference between vowels, might not be able to pronounce or detect them correctly. The result of such difficulties is frequently fossilized error, in which the wrong pronunciation patterns become ingrained regardless of the presence of the correct ones. Such mistakes do not only complicate the process of effective communication but also affect the self-confidence of learners, their interpersonal relationship, and employability, and therefore, training in pronunciation is an essential part of the second language acquisition. Nevertheless, the conventional classroom-based training tends to give insufficient feedback because of time, teacher bias, and the number of learners. This is why there is a growing need of intelligent systems operating in recognition of pronunciation mistakes on the fly and also taking into account the psychological aspect of learning.

Psychologically, pronunciation learning is affected by a variety of factors such as anxiety, motivation, cognitive load and the attitude of the learner towards the target language. The studies of psycholinguistics revealed that the problem of pronunciation is not the mechanical one but the issue closely intertwined with the existence of the perceptual biases and affective variables. As an example, students usually replace an unknown phoneme with the nearest phonemes in their native language, which is described by the Contrastive Analysis and Speech Learning Theory. Moreover, the anxiety about possible mispronunciation of words in front of other people may increase the level of anxiety, causing a person to evade verbal communication and other possible training opportunities. Such psychological obstacles emphasize the importance of creating pronunciation correcting systems that are both technically correct and friendly, sympathetic, and helpful to the learner to be less stressful and promote the regular practice. An intensive framework that merges both the psychologic and computational instruments, therefore, promises tobe fruitful in tackling both the cognitive and affective parts of the pronunciation learning.

Recent research on artificial intelligence and machine learning has provided possibilities to speech processing and computer-assisted language learning on the computational side. Automatic Speech Recognition (ASR) systems have been long applied to transcribe learner speech, and they do not always identify any subtle phonetic errors, particularly with varying accents, background noise. Phoneme recognition models are trying to detect mispronunciations at a more finer level but are usually limited by small labeled data and inconsistency in non-native speech patterns. In order to conquer these difficulties, the contrastive learning has come into the scene as an effective paradigm, and the models have the ability to learn discriminative representations through the comparison of positive and negative pairs of speech samples. Contrastive learning may be used in the setting of pronunciation error detection to distinguish between native-like and non-native pronunciations that inherently capture fine acoustic and temporal differences that may be missed by traditional models. Through large-scale unlabeled data by utilizing a contrastive learning task that aligns the unlabeled data with an expert-labeled corpus, stronger generalization relative to speakers, accents, and the linguistic backgrounds is enabled.

This paper suggests an innovative interdisciplinary methodology consisting of psychological principles of pronunciation-learning and the use of computational methods based on contrastive learning. Its structure is aimed at identifying the pronunciation mistakes, offering a corrective feedback and fitting the profile of particular learners. Contrary to the traditional systems that provide fixed and generic corrections, the model proposed incorporates psychological knowledge, such that feedback is personal, non-threatening and motivating. As an illustration, the system might not only flag errors, but can also emphasize small progress, recommend low-anxiety practice activities and supply multimodal cues, like visual articulation animations or slowed acoustic patterns. It combines the human-like compassion and machine accuracy, and the pronunciation correction becomes more interactive and sustainable to the learners.

This study is important because it can have implications on both the theory and practice. In theory, it brings forward the knowledge of synthesizing the psychological and computational views to the solution of a sophisticated problem of learning a language. In practice, it provides scalable solutions to a variety of contexts, including online learning, mobile-supported language learning apps, and training programs in the workplace where individualized feedback tends to be constrained. Besides, the structure meets the demands of multilingual students in such countries as India, China, and the whole Europe where knowledge of English is a key to academic and professional achievements. By referring to pronunciation - a long-overlooked, yet vital aspect of language competency, this study will equip students with the means to speak with increased confidence and effectiveness in the global environment.

Conclusively, the background of this research lays significant emphasis on the need to handle pronunciation mistakes in non-native English speech as a two-fold psychological and computational concept. Although the processes of learning pronunciation are influenced by both perceptual and affective aspects of pronunciation learning that necessitate both sensitive and accommodating strategies, the learning errors of pronunciation need to be detected and corrected by complex computational models that can accommodate the variability and complexity of non-native speech. Contrastive learning offers a good avenue of constructing such models, and in conjunction with psychology, it offers an avenue that can change the future of creating more intelligent, empathetic and productive pronunciation correction systems. The study, thus, not only supports the development of computer-assisted language learning but also supports overall educational objectives of inclusivity, access, and well-being of the learners in the digital era.

LITERATURE REVIEW

Studies in the area of pronunciation error detection and correction have increased significantly in the last two decades with sources in psycholinguistics, second language acquisition, computer-assisted language learning (CALL), and artificial intelligence. The available body of literature depicts the mental deterrence encountered by the learners as well as the technological advancements in developing systems capable of identifying and reporting on the pronunciation. The review presents a summarization of the previous literature in three thematic categories: (1) Pedagogical and psychological models of pronunciation learning, (2) Computational models of error detection and correction and (3) Emerging trends in machine learning and natural language processing models to learn pronunciation.

One of the hardest areas of learning English as a foreign language is pronunciation. Hassan (2014) reviewed the concrete pronunciation issues of Sudan University of Science and Technology (English students) and discovered the issues with vowel quality, intonation, and consonant clusters. These problems were strongly associated with the pronunciation system of the first language (L1) of the learners, which reassured the old Contrastive Analysis Hypothesis. Likewise, Syafrizal, Wahyuni, and Syamsun (2022) compared the cases of silent consonant errors by junior high school students, evidencing that learners tend to omit or misread sounds, which do not exist in their L1 repertoire. These results highlight the fact that there are psychological barriers to perception and production that may cause errors to be fossilized in the absence of corrective actions.

Pedagogically, research highlights the importance of using technology to enhance training of pronunciation. Gambari, Kutigi, and Fagbemi (2014) demonstrated that the use of computer-assisted instructional methods in teaching pronunciation in Nigeria secondary schools significantly enhanced oral English performance especially when it was combined with the verbal performance of the learners. The findings imply that individualized adaptive systems are capable of improving engagement and learning. In the study of English learning in Senegalese and the United States to examine the effects of globalization, Poggensee (2016) has additionally pointed to the exposure of learners to various English accents as a factor in the development of pronunciations, identity, and confidence. Put together, these works emphasize the psychological aspect of learning pronunciation, such as motivation, anxiety, and the social identity of accent in accent creation.

An increasing literature has used automatic speech recognition (ASR) and algorithmic techniques to identify mispronunciations. Tepperman et al. (2006) created a pronunciation checking system in the speech of children and showed that it is helpful in the evaluation of literacy. Their work has defined the pronunciation verification as not only a language-learning problem but also applicable to the early learning situation. The same line of inquiry was further developed by Molina et al (2009), who proposed ASR-based pronunciation assessment using classifier fusion, and they demonstrated that robustness was enhanced automatically through the generation of competing vocabulary. Likewise, to avoid the use of manually prepared pronunciation dictionaries, McGraw, Badr, and Glass (2012) proposed models of pronunciation mixtures, which help learn lexicons by simply listening to speech.

More recent work is by Lu, Ghoshal, and Renals (2013), who came up with an acoustic data-based pronunciation lexicon to large vocabulary speech recognition. Their methodology dealt with individual variability in non-native accents by drawing the pronunciations out of the acoustic data. Rutherford, Peng and Beaufays (2014) investigated crowdsourcing pronunciation learning of named entities, indicating the usefulness of human-in-the-loop techniques. Li, Chen, Siniscalchi, and Lee (2017) utilized multi-source information and deep learning models (LSTMs) to detect mispronunciation and performed better than the traditional models because they used contextual linguistic characteristics in addition to acoustic cues. Collectively, these studies reveal an incremental transformation in the method of pronunciation error detection between the dictionary-based and the data-driven and neural-based methods.

The last several years were characterized by the rapid development of interest in machine-learning-based models of pronunciation errors. Kotani and Yoshimi (2018) applied machine learning to categorize pronunciation difficulty in English learners, and the authors note that computational models can predict the areas most prone to difficulty in learners. The paper by Lai and Chen (2022) assessed the precision of speech recognition software among young Taiwanese learners and pointed to the potential and restrictions of the available commercial tools in the education sector. Lee (2016) suggested language-independent approaches to computer-assisted training of pronunciation which is a significant step in constructing universal systems that can be adapted to linguistic conditions.

In the meantime, the use of sophisticated natural language processing (NLP) has been applied not only to speech recognition but to the affective aspects of language learning. Nijhawan, Attigeri, and Ananthakrishna (2022) showed the detection of stress based on machine learning during social interactions, which, although it is not directly related to the method of pronunciation, may be of great interest in terms of integrating psychological well-being into talking-based systems. In the same vein, Paula et al. (2022) demonstrated how machine learning and NLP may be adopted to design experiments in unrelated areas of science through data, highlighting the flexibility and scalability of these computing tools.

Primary contributions to the assessment of pronunciation were made by Peabody (2011) and Weinberger and Kunath (2011) towards the typology of accent. The procedure of assessing pronunciation in CALL systems was described by Peabody and the Speech Accent Archive by Weinberger and Kunath presented a typology of the English accents that could be used to compare the pronunciation systems. Their effort is still essential to create corpora that are input to machine learning models of pronunciation.

In addition to going directly into core systems of computation, blended and hybrid learning environments have been considered to support pronunciation teaching. Zrekat (2021) explored the blended education in the EFL setting of Arab Open University and noted that performance and engagement of the learners were improved significantly as compared to traditional teaching. These results indicate that pronunciation correction computational models implemented as part of blended learning systems can be a game changer as far as the result of learners is concerned.

Although a lot has been achieved, there are still a number of gaps. First, most computational systems focus on technical accuracy and ignore psychological and affective aspects of learner anxiety and motivation, important in long-lasting pronunciation practice. The mispronunciation errors, as demonstrated by Hassan (2014) and Gambari et al. (2014), do not only rely on the mechanical aspect of the process but are dependent on the psychological scope. Second, machine learning methods including those by Kotani and Yoshimi (2018) and Li et al. (2017) have been effective in error detection but they are frequently constrained by annotated corpus, accent variation, and scalability in profiles, amongst learners. Third, the majority of the currently available research lacks contrastive learning, one of the techniques in the recent deep learning that complements the idea of representation learning by differentiating between similar and dissimilar examples. Contrastive learning has a huge potential in the differentiation of native-like and non-native pronunciation and providing corrective feedback respectively.

The literature indicates that there has been a continuous integration of psychology, pedagogy and computation in addressing the issue of pronunciation error detection and correction. Initial studies (Tepperman et al., 2006; Molina et al., 2009) have utilized the ASR-based approaches, and newer researches (Li et al., 2017; Kotani and Yoshimi, 2018) have used deep learning to get better results. Similar studies in the field of pedagogy (Gambari et al., 2014; Zrekat, 2021) and psychology (Hassan, 2014; Syafrizal et al., 2022) demonstrate the significance of learner-centered practices that decrease anxiety and promote motivation. Nevertheless, there is still a necessity of unified systems that join psychological sensitivity with calculations sophistication. The proposed study exists in this gap by assuming a contrastive learning paradigm guided by the psycholinguistic theories and the objective of providing correct, adaptive and compassionate solutions to pronunciation errors.

Objectives for the study

1. To identify common pronunciation errors in non-native English speech.
2. To examine the psychological factors influencing pronunciation learning.
3. To develop a computational model for pronunciation error detection using contrastive learning.

Hypothesis (H1): Psychological factors such as anxiety, motivation, and learner attitude have a significant influence on pronunciation learning among non-native English speakers.

Null Hypothesis (H0): Psychological factors such as anxiety, motivation, and learner attitude do not have a significant influence on pronunciation learning among non-native English speakers.

RESEARCH METHODOLOGY

The current research is based on a mixed-method research design, which combines psychological investigation and computational experiment to explore the topic of error detection and correction in non-native speech of English. Psychologically, a purposive sample of non-native English learners are surveyed and interviewed to obtain perceptions, the degree of anxiety and motivational forces that impact the pronunciation learning process. Data on the learner attitudes and affective barriers are collected through the use of standardized psycholinguistic assessments and self report questionnaires. At the same time, the part of computing entails the gathering of the speech samples of the same respondents, which are subsequently annotated by skilled phoneticians in order to be correct at the phoneme and word levels. The following samples are used to train and test a contrastive learning-based deep neural network to find and classify pronunciation errors. The acoustic features of the Mel-frequency cepstral coefficient (MFCCs), phoneme embedding, and prosodic cues are obtained as model input. The model is tested based on measures of precision, recall, and F1-score and its correction feedback is compared to human expert-recommended measures. Triangulation strategy can be used to guarantee validity by cross-referencing the results of a study with psychological results and computational results, thus enabling the study to suggest an integrated framework that can respond to both the affective needs of the learner and the accuracy of the technology in the pronunciation correction process.

Table 1: Descriptive Statistics of Psychological Factors Influencing Pronunciation Learning

Variable	N	Mean	Median	Mode	Std. Deviation (SD)	Range	Skewness	Kurtosis
Anxiety	200	3.62	3.70	4.00	0.84	3.80	0.41	-0.32
Motivation	200	4.15	4.20	4.00	0.71	3.20	-0.27	0.18
Attitude	200	3.98	4.00	4.00	0.76	3.40	-0.12	-0.24

Descriptive Statistics

The descriptive statistics of the recorded data demonstrate valuable information about psychological determinants of pronunciation learning in the non-native speakers of English. The findings show the average score in terms of learner anxiety was moderately high (M = 3.62, SD = 0.84 on a 5-point scale), which implies that a significant portion of participants feel noticeably anxious when they have to pronounce a foreign sound in English. Conversely, the levels of motivation were quite high (M = 4.15, SD = 0.71) as it expressed the desire of learners to work on their pronunciation to receive academic, professional, and social benefits. The attitude to the learning of pronunciation was also positively directed (M = 3.98, SD = 0.76), which means that the majority of the learners understand the significance of correct pronunciation in successful communication. The score distributions revealed that anxiety had a small positive skew, i.e. there were fewer learners with very high anxiety, but motivation and the attitude scores showed that the distribution was more normal. Taken together, these descriptive statistics indicate that the non-native learners, in general, show a great level of motivation and positive attitudes towards learning pronunciation, but the existence of moderate-to-high levels of anxiety could be viewed as a psychological impediment, hence the assumption of Hypothesis 1.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.732	.536	.528	0.482

ANOVA[a]

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	48.327	3	16.109	69.282	.000[b]
Residual	41.839	180	0.232		
Total	90.166	183			

[a] Dependent Variable: Pronunciation Learning
[b] Predictors: (Constant), Anxiety, Motivation, Attitude

Coefficients[a]

Model	Unstandardized Coefficients (B)	Std. Error	Standardized Coefficients (Beta)	t	Sig.
(Constant)	0.842	0.212	–	3.971	.000
Anxiety	-0.214	0.067	-0.221	-3.194	.002
Motivation	0.487	0.059	0.523	8.254	.000
Attitude	0.276	0.063	0.298	4.381	.000

[a] Dependent Variable: Pronunciation Learning

The finding of the multiple regression analysis proves that psychological variables play a significant role in learning pronunciation in non-native English learners. The omnibus model was significant $F(3,180) = 69.282$, $p=.001$), which accounted 53.6% of the variation in pronunciation learning ($R^2 =.536$). Motivation came out as the strongest positive predictor ($b = 0.523$, $p < .001$) which implies that learners who are more motivated post better pronunciation results. The attitude towards pronunciation learning was also significantly positively correlated ($b = 0.298$, $p < .001$), which means that positive attitude and willingness to practice positively influence the capability of the learners to improve their pronunciation. Conversely, anxiety had strong negative effect ($b = -0.221$, $p =.002$), which indicates that students with anxiety or fear of erring exhibit bad performance in pronunciation. Together, the findings support the hypothesis of the research (H 1) as they demonstrate that psychological factors (in this case, motivation, attitude, and anxiety) are crucial to the process of pronunciation learning among non-native speakers.

OVERALL CONCLUSION

This research finds that the psychological factors are decisive to the pronunciation learning results of non-native English speakers. The results of the regression analysis show that motivation and the attitude of learners have the positive and significant effect on pronunciation improvement, and anxiety has the negative and negative impact on the same that does not contribute to improvement in a learner. These findings support the fact that pronunciation acquisition is not only a technical or linguistic phenomenon but also it is always concerning the psychological preparedness and emotional condition of students. The high predictive value of motivation lays stress on the need to promote both intrinsic and extrinsic motivation factors that promote sustained practice and maintenance. Equally, the positive attitude towards the learning of pronunciation increases the openness of learners to the feedback and the readiness to explore new patterns of speech. On the other hand, the negative effect of anxiety demonstrates the necessity to achieve supportive learning conditions where there is the minimum fear of mistake and the establishment of psychological safety in oral practice. In general, the research confirms the research hypothesis and proves that the pronunciation learning can be efficiently improved with the help of the psychological awareness becoming a part of the pedagogy and technologies-driven tools, i.e., the use of contrastive learning-based computational models. Such insights not only contribute to the theory of psychological aspects of second language acquisition, but have practical implications as well to language teachers, curriculum designers, and developers of computer-assisted pronunciation training systems.

REFERENCES

- Gambari, A. I., Kutigi, A. U., & Fagbemi, P. O. (2014). Effectiveness of computer-assisted pronunciation teaching and verbal ability on the achievement of senior secondary school students in oral English. *Gist Education and Learning Research Journal, 8*, 11–28.
- Hassan, E. M. I. (2014). Pronunciation problems: A case study of English language students at Sudan University of Science and Technology. *English Language and Literature Studies, 4*(4), 31–44.
- Kotani, K., & Yoshimi, T. (2018). Machine learning classification of pronunciation difficulty for learners of English as a foreign language. *Research in Corpus Linguistics*, 1–8. https://doi.org/10.32714/ricl.01.01
- Lai, K.-W. K., & Chen, H.-J. H. (2022). An exploratory study on the accuracy of three speech recognition software programs for young Taiwanese EFL learners. *Interactive Learning Environments*, 1–15. https://doi.org/10.1080/10494820.2022.2092492
- Lee, A. (2016). *Language-independent methods for computer-assisted pronunciation training* (Doctoral dissertation). Massachusetts Institute of Technology.
- Li, W., Chen, N. F., Siniscalchi, S. M., & Lee, C.-H. (2017, August 20–24). Improving mispronunciation detection for non-native learners with multisource information and LSTM-based deep models. *Interspeech 2017*, Stockholm, Sweden.
- Lu, L., Ghoshal, A., & Renals, S. (2013, December 8–12). Acoustic data-driven pronunciation lexicon for large vocabulary speech recognition. *2013 IEEE Workshop on Automatic Speech Recognition and Understanding (ASRU)*, Olomouc, Czech Republic (pp. 374–379). IEEE.
- McGraw, I., Badr, I., & Glass, J. R. (2012). Learning lexicons from speech using a pronunciation mixture model. *IEEE Transactions on Audio, Speech, and Language Processing, 21*(2), 357–366. https://doi.org/10.1109/TASL.2012.2214215
- Molina, C., Yoma, N. B., Wuth, J., & Vivanco, H. (2009). ASR-based pronunciation evaluation with automatically generated competing vocabulary and classifier fusion. *Speech Communication, 51*(6), 485–498. https://doi.org/10.1016/j.specom.2008.12.001
- Nijhawan, T., Attigeri, G., & Ananthakrishna, T. (2022). Stress detection using natural language processing and machine learning over social interactions. *Journal of Big Data, 9*(1), 1–24. https://doi.org/10.1186/s40537-022-00589-4
- Paula, A. J., Ferreira, O. P., Souza Filho, A. G., Filho, F. N., Andrade, C. E., & Faria, A. F. (2022). Machine learning and natural language processing enable a data-oriented experimental design approach for producing biochar and hydrochar from biomass. *Chemistry of Materials, 34*(3), 979–990. https://doi.org/10.1021/acs.chemmater.1c03124
- Peabody, M. A. (2011). *Methods for pronunciation assessment in computer aided language learning* (Master's thesis). Massachusetts Institute of Technology.
- Poggensee, A. (2016). *The effects of globalization on English language learning: Perspectives from Senegal and the United States* (Master's thesis). Western Michigan University, Kalamazoo, MI.
- Rutherford, A., Peng, F., & Beaufays, F. (2014, September 14–18). Pronunciation learning for named-entities through crowdsourcing. *Interspeech 2014*, Singapore.
- Syafrizal, S., Wahyuni, S., & Syamsun, T. R. (2022). Pronunciation errors of the silent consonants of Pariskian junior high school students. *ELTICS: Journal of English Language Teaching and English Linguistics, 7*(2), 155–165. https://doi.org/10.31316/eltics.v7i2.1474

- Tepperman, J., Silva, J. F., Kazemzadeh, A., You, H., Lee, S., Alwan, A., & Narayanan, S. S. (2006, September). Pronunciation verification of children's speech for automatic literacy assessment. *Interspeech 2006*, Pittsburgh, PA, USA.
- Weinberger, S. H., & Kunath, S. A. (2011). The speech accent archive: Towards a typology of English accents. In E. Pawlak, M. Waniek-Klimczak, & J. Majer (Eds.), *Corpus-based studies in language use, language learning, and language documentation* (pp. 265–281). Brill.
- Zrekat, Y. (2021). The effectiveness of blended learning in EFL context: An experimental study at Arab Open University–KSA. *Turkish Online Journal of Qualitative Inquiry, 12*(7), 1234–1246.