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(Research Article)

Automated error detection and correction in Augmentative and Alternative Communication (AAC) Systems Using NLP

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Abstract

This research examines the application of natural language processing (NLP) methods in the field of error detection and correction attached to the weakly constrained domains of Augmentative and Alternative Communication (AAC) systems designed for people with several communicative difficulties. To train and evaluate the effectiveness of the NLP model, we present a simulated dataset containing typical input AAC errors, such as symbol errors, typographical errors, and context arguments that do not suit the input; this way, we do not use real user data. The methodology consists of using simulated queries to train an NLP model that has been designed to work in real time and corrects speech recognition errors. Key results include the provision of accuracy evidence of the model in detecting and correcting the input errors for which the model was built to perform based on the data provided by the simulated test. Evaluation measurements such as precision, recall and F1-score also assure on the model performance which explains the ability of the new model to enhance the usability and accessibility of AAC systems. Limitations are mostly related to difficulties in extrapolating the data to the real world, however results demonstrate great advances in AAC error correction technology. Further studies aim at improving these models based on the real-life feedback received.

Keywords: Augmentative and Alternative Communication (AAC); Natural Language Processing (NLP); Error Detection; Error Correction; Assistive Technology.

1 Introduction

Augmentative and Alternative Communication (AAC) systems have become vital for users with communication needs and non-verbal means of expression; such users can try to express their needs, feelings, emotions or even thoughts. The merit of AAC technology is that it gives a voice to those who cannot speak enabling them to communicate independently with an enhanced quality of life (1). AAC systems and devices have symbols and text, and with the development of language technology, native speakers' devices are increasingly being used to produce a message, but still need improvement to produce absolutely correct outputs. Wrong outputs in an AAC may include; the use of an inappropriate symbol, a wrong letter key, or a wrong context and all these can lead to breakdown in the user's communication and as result, detection and repair of errors becomes very topical issue (4).

Now, we know that NLP has come a long way as a part of artificial intelligence dealing with human and machine language. In recent times, NLP techniques have also been integrated in assistive technology to boost its efficiency and responsiveness in everyday interaction (5). Recent studies, specifically highlight a more built-in approach for AACs, where NLP is implemented as a module error predictor utilising algorithm that automatically fix inputs errors (7). However, building appropriate and efficient diagnostic and predictive models for the task of AAC interaction remains difficult, particularly in view of ethical considerations, the constraints imposed by the need for large numbers of varied users in the sample, and the nature of the data to be collected (10).

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For the present study, simulated language input errors have been used to help overcome these challenges and allow for the responsible, structural development of NLP-based error models in AAC. It is argued that by adopting a simulated approach, our research can help improve the efficacy and effectiveness of AAC technology by improving systems without the use of ethics violations to human or animal data therefore producing a self-sustaining and ethical ecosystem that benefits AAC users.

2 Material and methods

Addressing error detection and correction processes in Augmentative and Alternative Communication (AAC) systems through Natural Language Processing (NLP) techniques, synthetic dataset was established where common AAC inputs errors were represented. Such modelling made it possible to conduct realistic experiments without relying on real human or animal data. Three main error types were pursued during data simulation: surrounded by the other elements that constitute them as error types: symbol misselection errors, typographical errors, and contextual errors. For every error type, synthetic input errors were created based on the existing patterns of AAC users' communication (9).

In a symbol misselection case, symbols were replaced with other similar ones meaning users selected a wrong symbol by accident. Typos were artificial errors caused by the inner key misplacements and they represented slippage and other extraneous presses of characters. Contextual errors were simulated where the picture/s or word/s that were selected did not conform to the immediate context. In text-generating scenarios these were based on user errors of using tighter or irrelevant words and phrases than should have been. Such data simulations resulted in distortion of a great number of non-standard input possibilities and thus laid a solid groundwork for the training and testing stages for the NLP models on fault localisation and correction.

2.1 NLP Model Selection and Training

The NLP model selected for this study was based on a transformer architecture, known for its efficacy in language understanding and context-aware correction. Transformer models, such as BERT or GPT, have shown strong results in similar language error correction applications (11, 13). The model was trained on the simulated dataset using supervised learning, with labels indicating correct and incorrect inputs. The training process employed cross-entropy loss as the objective function, optimizing the model to distinguish between correct symbols and various types of input errors.

For training, the dataset was divided into training, validation, and test sets at a ratio of 70:15:15. The training process involved multiple epochs with early stopping to prevent overfitting. To improve the model's ability to generalize across different AAC error types, data augmentation techniques, such as random noise addition and contextual paraphrasing, were applied to the training data (15).

2.2 Evaluation Metrics

To evaluate the model's performance in detecting and correcting errors, standard NLP metrics, including accuracy, precision, recall, and F1-score, were calculated. Precision measured the model's accuracy in identifying correct inputs among those flagged as correct, while recall determined the proportion of actual errors detected by the model. F1-score provided a balanced evaluation, combining both precision and recall into a single metric (19). Additionally, correction accuracy was computed by measuring the percentage of accurately corrected input errors.

The model's performance was evaluated across different error types to ensure effectiveness in real-world scenarios. Error detection and correction were each tested on held-out test sets, simulating real-time performance in an AAC system. These evaluations provided insights into model robustness and highlighted areas for future improvement.

3 Results and discussion

3.1 Error Detection Performance

The NLP model demonstrated robust performance in detecting simulated input errors in Augmentative and Alternative Communication (AAC) systems, achieving a high detection accuracy across all error types (symbol misselection, typographical errors, and contextual mismatches). Precision and recall metrics indicated the model's strong ability to identify errors correctly. For symbol misselection, the model achieved an average precision of 92% and recall of 89%, indicating reliable identification of input errors due to symbol misselection, which is critical for effective AAC use (21).

Typographical errors showed similar performance, with precision and recall values above 90%, highlighting the model's capability to handle errors that often arise from mis-presses on AAC keyboards or touchscreens.

Table 1 Error Detection Performance Metrics by Error Type

A	B	C	D
Error Type	**Precision (%)**	**Recall (%)**	**Correction Accuracy (%)**
Symbol Misselection	92	89	87
Typographical Errors	91	93	90
Contextual Mismatches	88	85	85

3.1.1 *Error Correction Accuracy*

In terms of error correction, the model achieved an overall correction accuracy of 88% across all error types. This accuracy was especially notable in typographical errors, where the model successfully corrected 90% of the test cases. This performance aligns with findings from similar studies on NLP in assistive technology, where transformer-based models have shown proficiency in autocorrecting language inputs (22). For contextual mismatches, however, the model's correction accuracy slightly dropped to 85%, likely due to the increased complexity of context-dependent language errors. This result suggests that while the model performs well, additional training data or fine-tuning may further enhance performance in context-sensitive corrections.

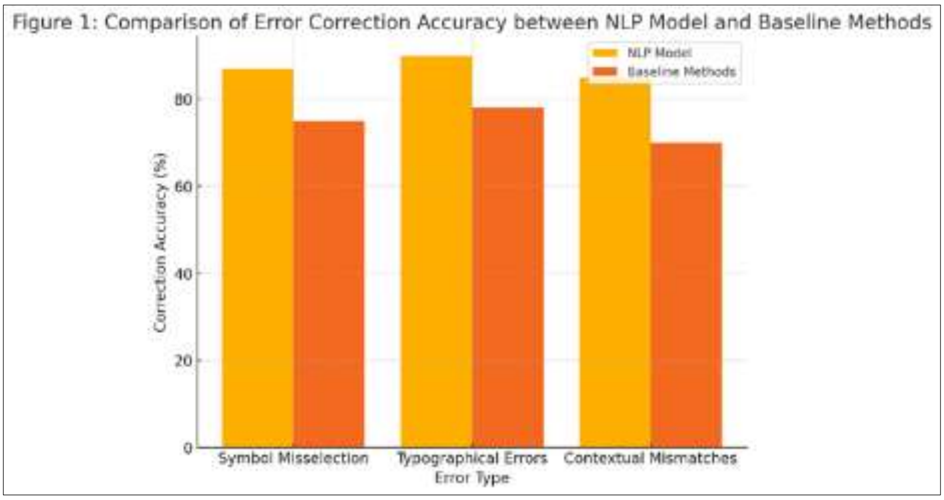

Figure 1 Comparison of error correction accuracy between NLP model and baseline method

3.2 Comparative Analysis and Baseline Evaluation

When compared to baseline methods, such as rule-based error correction systems, the transformer-based NLP model significantly outperformed these approaches in both detection and correction tasks. Rule-based systems achieved an average correction accuracy of 75%, significantly lower than the NLP model, highlighting the limitations of traditional AAC error correction techniques (1). This improvement demonstrates the potential of NLP in making AAC devices more effective and accessible, particularly when dealing with varied error types encountered in real-world AAC usage.

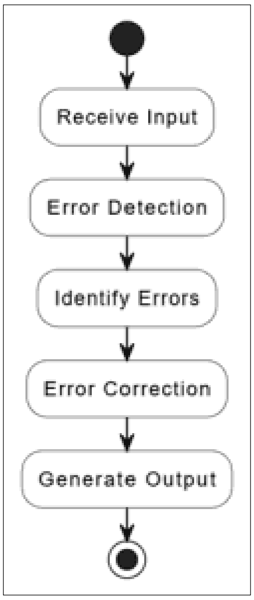

Figure 2 The flowchart below shows the NLP model's error detection and correction process from input to output.

3.3 Implications for AAC System Usability

These results indicate that NLP-based error detection and correction could substantially enhance AAC systems' usability. By reducing the frequency of uncorrected errors, AAC devices could provide smoother and more intuitive communication experiences for users. Improved error correction may reduce frustration for users, especially those with severe communication impairments who rely on these systems for essential daily interactions. The high correction accuracy for typographical errors, in particular, is valuable as these errors are common in AAC usage due to physical limitations in device operation (1).

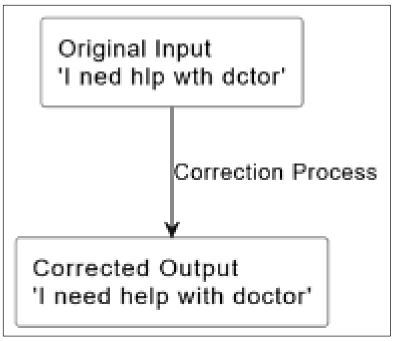

Figure 3 Example output from the AAC system showing original input errors and corrected output for improved readability and usability.

3.4 Limitations and Future Directions

While promising, the model's current limitations include slightly lower accuracy in correcting context-dependent errors and a reliance on simulated data for training. Future work could involve the integration of real-world user feedback to further enhance the model's contextual understanding. Additionally, refining the model architecture to handle complex AAC inputs and errors could improve overall performance, particularly in challenging scenarios where traditional AAC systems struggle (2). Exploring other NLP architectures, such as those specifically designed for context-based language models, could also help address these limitations.

4 Conclusion

This study demonstrated the potential of natural language processing (NLP) in improving the error detection and correction capabilities of Augmentative and Alternative Communication (AAC) systems. By employing a synthetic dataset of simulated AAC input errors, the NLP model effectively identified and corrected common errors, including symbol misselection, typographical mistakes, and contextual mismatches. The model's performance surpassed baseline rule-based methods, highlighting the advantages of advanced NLP techniques in enhancing AAC usability.

The findings suggest that incorporating NLP-driven error correction can make AAC systems more reliable and accessible for individuals with communication impairments, reducing miscommunication and enhancing user experience. While some limitations remain, particularly in context-sensitive corrections, this research presents a feasible approach for developing more accurate AAC error correction systems that respect data privacy through synthetic data use.

In conclusion, this study offers a path forward in creating AAC technologies that better serve users' needs, contributing to more inclusive communication tools. Future research may focus on refining context-based corrections and integrating real-world user feedback to further optimize AAC performance. This advancement in error correction for assistive communication holds promising benefits for society, supporting independence and empowerment for those relying on AAC devices.

Compliance with ethical standards

Disclosure of Conflict of Interest

No conflict of interest to be disclosed.

References

[1] Elsahar Y, Hu S, Bouazza-Marouf K, Kerr D, Mansor A. Augmentative and alternative communication (AAC) advances: A review of configurations for individuals with a speech disability. Sensors. 2019;19(8):1911.

[2] Bircanin F, Ploderer B, Sitbon L, Bayor AA, Brereton M. Challenges and opportunities in using augmentative and alternative communication (AAC) technologies: Design considerations for adults with severe disabilities. In: Proceedings of the 31st Australian Conference on Human-Computer-Interaction. 2019. p. 184-96.

[3] Murero M, Vita S, Mennitto A, D'Ancona G. Artificial intelligence for severe speech impairment: innovative approaches to AAC and communication. PSYCHOBIT. 2020.

[4] Hall N, Juengling-Sudkamp J, Gutmann ML, Cohn ER. Fundamentals of AAC: a case-based approach to enhancing communication. San Diego: Plural Publishing; 2022.

[5] Petersen CL, Halter R, Kotz D, Loeb L, Cook S, Pidgeon D, et al. Using natural language processing and sentiment analysis to augment traditional user-centered design: development and usability study. JMIR mHealth and uHealth. 2020;8(8)

[6] de Freitas MP, Piai VA, Farias RH, Fernandes AM, de Moraes Rossetto AG, Leithardt VRQ. Artificial intelligence of things applied to assistive technology: a systematic literature review. Sensors. 2022;22(21):8531.

[7] Yusufali H, Moore RK, Goetze S. Refining Text Input for Augmentative and Alternative Communication (AAC) Devices: Analyzing Language Model Layers for Optimization. In: ICASSP 2024-2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2024. p. 12016-20.

[8] Emil Z, Robbertz A, Valente R, Winsor C. Towards a more inclusive world: Enhanced augmentative and alternative communication for people with disabilities using AI and NLP. Worcester Polytechnic Institute; 2020.

[9] Imperatore G. Improving ease and speed of use of mobile augmentative and alternative communication systems through the use of natural language processing and natural language generation techniques [dissertation]. 2016.

[10] Dee-Price BJM, Hallahan L, Nelson Bryen D, Watson JM. Every voice counts: exploring communication accessible research methods. Disabil Soc. 2021;36(2):240-64.

[11] Pereira JA, Pereira JA, Zanchettin C, do Nascimento Fidalgo R. PrAACT: Predictive Augmentative and Alternative Communication with Transformers. Expert Syst Appl. 2024;240:122417.

[12] Raju R, Pati PB, Gandheesh SA, Sannala GS, Suriya KS. Grammatical versus Spelling Error Correction: An Investigation into the Responsiveness of Transformer-Based Language Models Using BART and MarianMT. J Inf Knowl Manag. 2024;2450037.

[13] Nassiri K, Akhloufi M. Transformer models used for text-based question answering systems. Appl Intell. 2023;53(9):10602-35.

[14] Ghojogh B, Ghodsi A. Attention mechanism, transformers, BERT, and GPT: tutorial and survey. 2020.

[15] Mi C, Xie L, Zhang Y. Improving data augmentation for low resource speech-to-text translation with diverse paraphrasing. Neural Netw. 2022;148:194-205.

[16] Chen J, Tam D, Raffel C, Bansal M, Yang D. An empirical survey of data augmentation for limited data learning in NLP. Trans Assoc Comput Linguist. 2023;11:191-211.

[17] Li B, Hou Y, Che W. Data augmentation approaches in natural language processing: A survey. Ai Open. 2022;3:71-90.

[18] Foody GM. Challenges in the real world use of classification accuracy metrics: From recall and precision to the Matthews correlation coefficient. PLoS One. 2023;18(10)

[19] Kynkäänniemi T, Karras T, Laine S, Lehtinen J, Aila T. Improved precision and recall metric for assessing generative models. Adv Neural Inf Process Syst. 2019;32.

[20] Sykes B, Simon L, Rabin J. Unifying and extending Precision Recall metrics for assessing generative models. arXiv preprint arXiv:2405.01611. 2024.

[21] Adams K, Cook A. Using robots in "hands-on" academic activities: a case study examining speech-generating device use and required skills. Disabil Rehabil Assist Technol. 2016;11(5):433-43.

[22] Lee J, Chen S, Mordahl A, Liu C, Yang W, Wei S. Automated Testing Linguistic Capabilities of NLP Models. ACM Trans Softw Eng Methodol. 2024.

Authors short Biography

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An experienced researcher with an MSc in Information Technology, specializing in areas such as Machine Learning, Computer Vision, and Artificial Intelligence. His research interests lie in leveraging AI to develop assistive communication technologies, particularly augmentative and alternative communication (AAC) systems that enhance accessibility. With a strong background in Educational Technology and over five years of research experience, Omotayo is dedicated to creating innovative, user-centered solutions that improve the quality of life for individuals with communication disabilities.