AI and Global AAC Symbol Communication

Chaohai Ding(✉), E. A. Draffan, and Mike Wald

Web and Internet Science Group, School of Electronics and Computer Science, University of Southampton, Southampton SO17 1BJ, UK
{c.ding,ead,mw}@ecs.soton.ac.uk

Abstract. Artificial Intelligence (AI) applications are usually built on large trained data models that can recognize and label images, provide speech output from text, process natural language for translation, and be of assistance to many individuals via the internet. For those who are non-verbal or have complex speech and language difficulties, AI has the potential to offer enhanced access to the wider world of communication that can be personalized to suit user needs. Examples include pictographic symbols to augment or provide an alternative to spoken language. However, when using AI models, data related to the use of freely available symbol sets is scarce. Moreover, the manipulation of the data available is difficult with limited annotation, making semantic and syntactic predictions and classification a challenge in multilingual situations. Harmonization between symbol sets has been hard to achieve; this paper aims to illustrate how AI can be used to improve the situation. The goal is to provide an improved automated mapping system between various symbol sets, with the potential to enhance access to more culturally sensitive multilingual symbols. Ultimately, it is hoped that the results can be used for better context sensitive symbol to text or text to symbol translations for speech generating devices and web content.

Keywords: Alternative and augmentative communication · Web accessibility · Complex communication needs · AI and inclusion

1 Introduction

According to the American Speech-Language-Hearing Association (ASHA), over 2 million people use alternative and augmentative methods of communication (AAC) in their daily lives. Generally, this is due to severe speech, language, reading and learning difficulties [6]. Depending on the type of difficulties encountered, different styled characters, images or pictographic symbols can be used to support other gestures or vocalizations. However, alternative forms of communication come with a learning curve that may be more challenging when compared to spoken language and literacy skills and yet they can leave the user without the range and variety of options for expression. Just choosing pictures often means users are restricted to simple forms of language and when they want to build...
phrases and sentences, the availability of pictographic representations may also lack linguistic complexity and cultural sensitivity. AAC users also face a wide variety of barriers to accessing current web content when they are using symbols as their primary means of communication for both consuming and producing information. One of the main challenges is a lack of standardized interoperability between different symbol sets, or a mechanism for translating the concept represented in one symbol set from another symbol set without a high degree of misrepresentation. This paper will discuss ideas about how to leverage Artificial Intelligence (AI) techniques to enhance the interoperability of AAC symbols across different symbol sets and improve the access to a global and inclusive symbol repository with more culturally sensitive multilingual symbols for AAC users.

2 AAC and AI

Symbols are widely used in AAC systems to represent objects, actions, concepts, and emotions, which can include drawings, photographs, objects, facial expressions, gestures, auditory symbols, or orthography\(^1\). There are three different types of symbols communications following three language presentation methods that are commonly used in AAC:

- Alphabet system methods use traditional orthographies and rate enhancement techniques such as word or phrase prediction.
- Single meaning methods use each pictographic symbol to represent one word or one meaning.
- Multiple meaning methods combine pictographic symbols in various semantic sequences to form words or phrases based on the concept of multiple-meaning iconic encoding.

![Fig. 1. Three different kinds of symbols: (a) Alphabet: a; (b) Single Meaning: 5 euro banknote; (c) Multiple Meaning: smile, happy, glad or happy to do something](https://www.asha.org/PRPSpecificTopic.aspx?folderid=8589942773&section=Key-Issues#AAC_Populations)

Multiple meaning methods sometimes known as ‘semantic compaction’, may be used to present more flexible and meaningful sentences for complex communication needs. The freely available ARASAAC pictographic symbol set\(^2\) has examples (see Fig. 1) that illustrate the three language presentation methods.

---

\(^1\) [https://www.asha.org/PRPSpecificTopic.aspx?folderid=8589942773&section=Key-Issues#AAC_Populations](https://www.asha.org/PRPSpecificTopic.aspx?folderid=8589942773&section=Key-Issues#AAC_Populations).

\(^2\) [http://www.arasaac.org/](http://www.arasaac.org/).
2.1 Related Works

AI-based techniques have the potential to improve digital accessibility and the capability to accelerate progress in serving individuals with complex communication needs. Computerized text-based AAC devices often include some form of word prediction or sentence generation using a language model [3,9]. D. Jeffery Higginbotham et al. [4] explored the development of AI and Natural Language Processing (NLP) techniques for AAC, particularly in the areas of interface design and word prediction. They also discussed the future direction of how AI and NLP-enabled AAC systems could benefit AAC users such as context and genre based word prediction. S. Dudy et al. also proposed a method to generate language models for corpus-less symbol sets, which could generate synthesizing training data for machine learning [2]. S.C. Sennott et al. [7] discussed the implications, promises, and precautions of each component of the various AI techniques and what they could bring to AAC, namely knowledge representation, reasoning, natural language processing, machine learning, computer vision, and robotics. Annalu Waller [10] has shared insights and stories of how the combination of user-centered design, interdisciplinary research and the application of intelligent computing could provide a vision for future generations of AAC technologies. All of these works have encouraged further research into the advantages of AI techniques to create more intelligent and personalized AAC applications.

2.2 Challenges and Limitations

Current AAC systems offer a range of symbols that are often found on a grid layout with several categories considered representative of a person’s spoken vocabulary and understanding. The choices may be based on the user’s age, cognitive and language abilities, environment, cultural needs and context. The way they are accessed, their layout and editing features vary depending on the particular AAC system, but they invariably need to be sensitive to change. This potential to be customized and modified throughout the lifetime of an AAC system’s use is essential [1]. There have been several attempts to support online social interactions with the harmonization of AAC symbol sets, so that users can communicate with other symbol users, each using their chosen symbol sets with text translations in various languages. In an effort to advance the situation, a Concept Coding Framework (CCF) was developed by Lundalv and Derbring [5] offering the mapping of different symbol sets. However, there were some limitations to the resulting output. The lack of freely available symbol sets made it difficult to provide personalized AAC at the time and even today it is felt that additional metadata is required to increase accuracy levels. Expense in terms of time is also a factor when designing personalized AAC symbol systems, so there is a need to develop methods that allow for the individualization of AAC symbol systems that are low cost and adaptable. The lack of interoperability between different symbol sets taking account of the range of cultures and languages around the world is also a real barrier for AAC users when text to symbol or symbol to text translation is required, not forgetting the need for text simplification and syntax changes.
3 Global Symbols

Global Symbols\(^3\) is a project that has been developed to create and link freely available AAC symbol sets with different linguistically and culturally localised symbols to provide worldwide access to appropriate pictographic based communication. There are five primary symbol sets that have already been linked all with open or Creative Commons licenses namely:

- ARASAAC offers more than 10,000 pictographic symbols for individuals who may have autism, intellectual disabilities, language impairment or other spoken language difficulties.
- Blissymbolics\(^4\) as a semantic graphical language made up of ideographic and pictographic symbols that can be combined to represent different meanings.
- Tawasol Symbols\(^5\) with 700 Arabic localised symbols that can be used alongside the ARASAAC symbols.
- Mulberry Symbols\(^6\) with scalable SVG graphic images designed for adults.
- Jellow Symbols\(^7\) which has more than 1,000 symbols in English, Marathi and Hindi.

In order to link the symbol sets, ConceptNet \([8]\) was used with additional metadata to provide descriptions and parts of speech. ConceptNet is a collection of interlinked descriptions of entities, objects or abstract concepts making up a ‘knowledge graph’ version of the Open Mind Common Sense project. ConceptNet, has been applied as the common knowledge base that semantically links to the symbol labels.

3.1 Key Results and Limitations

Initially, Global Symbols automatically linked the five aforementioned AAC symbol sets, providing a repository that can be searched or filtered using the available languages or a chosen symbol set. At present, the results of the mapping are approximately 77\% successful, but many of the parts of speech have been skipped or are inaccurate. There are issues around multiple representations of symbols that fail to resolve concerns regarding different meanings for the same symbols, where tense is involved or some labels or glosses producing very different symbol concepts, even antonyms, which can be seen when filtering takes place. At present, symbol searching are totally dependent on the accuracy of the labels with limited metadata. Many of the inappropriate search results are due to the different label methodologies used by symbol sets; time has to be spent on cleaning data. It is felt that by using concept linking with improved Natural Language Processing (NLP) techniques, plus data tagging and image recognition

\(^3\) https://globalsymbols.com/.
\(^4\) http://www.blissymbolics.org/index.php/about-blissymbolics.
\(^5\) http://madaportal.org/tawasol/en/home/.
\(^6\) https://mulberrysymbols.org/.
\(^7\) http://www.jellow.org/.
it would be possible to speed search processes, as well as provide more meaningful results across the symbol sets. This in turn, would provide those supporting AAC users with better access to a wider range of more appropriate symbols, as well as more accurate classification features.

4 Global Symbols 2.0

The next version of Global Symbols (GS2) aims to have a more inclusive and concept searchable series of AAC symbol sets compared with the first version. The proposal is to have advanced search and filtering approaches using AI techniques alongside the previous methods using ConceptNet. The present mapping strategies will not be discarded, but enhanced with the use of semantic embedding to find related symbols, using the pre-trained word-embedding model (ConceptNet Numberbatch [8]). In the future, this process will be combined with additional metadata and image recognition techniques to offer improved automatic clustering of AAC symbols.

4.1 Methodologies and Experiment

In both the first version of Global Symbols (GS1) and the second, label mapping has been the initial step to link symbols to concepts. In GS2 the proposed process integrates different strategies to improve the mapping of symbol labels to correct concepts in ConceptNet, which includes a label text preparation strategy, label-to-concept mapping strategy, and the Out-of-Vocabulary (OOV) strategy. It is a common issue that label text for individual symbols can contain various special characters, which affect the concept mapping process. Therefore, the proposed ‘label text preparation’ strategy will remove these characters and extract the text part to clean the label text.

The proposed OOV strategies for label-to-concept mapping process include: 1. find relevant concept entity matching the label text; 2. if no match and containing single word, delete last letter from the word with maximum twice; 3. if no match and containing multiple words, separate the words and go to step 1. After mapping the labels to the concept entities, word embedding model Numberbatch [8] is applied to find similar concept entities. Numberbatch provides a semantic embedding model that adjusts the values of existing word embeddings (GloVe, word2vec, OpenSubtitles 2016) by taking the ConceptNet knowledge graph into account. It also supports 78 languages, which will be helpful in the multilingual environment of the repository.

For this part of the experiment, 12,847 ARASAAC symbols were used, the special characters in the labels were removed using the strategies described above. Based on observation, some symbol labels could be divided into multiple concepts and OOV strategies were used to map symbol labels to concept entities that had been developed to solve this problem:

- Single Word Matching: (a) delete the last letter if OOV (b) if non-matched with maximum two letters deleted, then indicate non-matched.
Multiple Words Matching: (a) delete the last letter if OOV (b) if non-matched with maximum two letters deleted, then divide the multiple words into multiple single-word; (c) process single word matching strategy

4.2 Results and Evaluation

There were 362,891 concept entities for the label-to-concept mapping process in the pre-trained word embedding model, 150,875 being in English. Although, 12,847 ARASAAC symbols were used in the current experiment, 13,173 text labels were generated based on the proposed label cleaning strategies. Of these, 3,520 symbol labels were not matched with any concept entity. An evaluation study was conducted using a sample result from the mapping of the symbols in both GS1 and GS2 based on 100 high frequency core words used for AAC\textsuperscript{8}. The results were gathered via an online voting procedure sent out to 5 AAC experts and users with 1,172 symbols generated using the GS2 methodology and 784 symbols generated from the original system. GS1 resulted in a 45.4% exact match of symbol to core word, while, in new version of GS2, 48.03% matched the exact meaning. The pilot showed the symbols and the target core word with no labels, that made the exercise harder for the voters. In the second experiment using the 500 Core Words\textsuperscript{9} it was possible to see not only the label matches achieved for both versions of GS, but also the next best match of any other semantically linked labels in GS2. The results showed that 47.24% of the labels matched in GS1 whereas 57.86% matched in GS2 and when the top most similar labels (scoring above 70%, but not antonyms) were considered the score rose to 85.47% for GS2 compared to 69.8% for GS1. Table 1 presents the example of top 10 similar symbols related to a search for automobiles. The similarity score for each symbol has been generated based on the ranking of semantic relatedness, which is calculated from the concept embedding model.

Finally, another experiment used the K-mean clustering method for automatic symbol categorization. Different K values were applied to explore how different symbols with similar semantic relatedness could be grouped together. The preliminary result (K = 100) showed a 85% accuracy compared with other K values from 50 to 100. Therefore, although label-based clustering can be used to categorize symbols into different groups, some symbols with the same label still produced questionable results. For example, when searching for a ‘car’ where the label or gloss is used, the result using the ARASAAC symbol set produced the symbol of a ‘horse and cart’ as well as several different types of car. This highlights the need for additional AI based approaches, in order to discriminate the items represented in these symbols. There were also several instances where the opposite of a word would appear in the similarity list for example ‘she’ for ‘he’ or ‘her’ for ‘him’, which could be removed using additional metadata from ConceptNet and WordNet.

\textsuperscript{8}https://aaclanguagelab.com/resources/100-high-frequency-core-word-list.
\textsuperscript{9}https://studylib.net/doc/6811573/core-word-comparison-for-language-building.
Table 1. Top 10 similar symbols related to automobiles in GS2

| Score | Label       | Concept     | Symbol       | Score | Label       | Concept     | Symbol       |
|-------|-------------|-------------|--------------|-------|-------------|-------------|--------------|
| 1.00  | automobiles | /c/en/automobiles | 🚗 | 0.74 | vehicles    | /c/en/vehicles | 🚗 |
| 1.00  | automobiles | /c/en/automobiles | 🚗 | 0.74 | vehicles    | /c/en/vehicles | 🚗 |
| 0.81  | cars        | /c/en/cars   | 🚗 | 0.74 | vehicles    | /c/en/vehicles | 🚗 |
| 0.81  | cars_1      | /c/en/cars   | 🚗 | 0.74 | vehicles    | /c/en/vehicles | 🚗 |
| 0.81  | cars_2      | /c/en/cars   | 🚗 | 0.74 | vehicles    | /c/en/vehicles | 🚗 |

5 Conclusion

Most speakers will have access to spoken and written language that fits their cultural, social and linguistic environment. This is rarely a reality for AAC symbol users and yet the use of machine learning using large amounts of data with NLP has allowed companies such as Google to provide automatic translations for over 104 languages despite their often complex linguistic and orthographic differences. These processes have provided text to speech, speech to text and captions to support understanding between communities. A multilingual standardized global symbols model could offer improved interoperability between symbols from different sets and has the potential to enhance communication and literacy skills for those with complex communication needs.

However, without the support of harmonisation across all AAC symbol sets there will always be a challenge for AAC users who wish to use their personalized language system when they collaborate and communicate with other symbol users online. The work of the W3C ‘Personalization Semantic Explainer’\textsuperscript{10} and Easy Reading EU project\textsuperscript{11} teams have explored these technologies in order to support text to symbol representations of web-based content. So it is clear this is an important area of work, but the results of this recent use of AI models only produced a limited increase in successful symbol to concept matching. It was still not sufficiently accurate be considered a successful way of offering symbol set harmonisation. Therefore, the next step in this research will focus on how to combine semantic relatedness with an increase in linked metadata and image recognition to improve symbol mapping outcomes.

\textsuperscript{10} https://www.w3.org/TR/personalization-semantics-1.0/.
\textsuperscript{11} https://www.easyreading.eu/.
References

1. Beukelman, D.R., Mirenda, P.: Augmentative & Alternative Communication: Supporting Children and Adults with Complex Communication Needs. Paul H. Brookes Publishing, Baltimore (2013)

2. Dudy, S., Bedrick, S.: Compositional language modeling for icon-based augmentative and alternative communication. In: Proceedings of the Workshop on Deep Learning Approaches for Low-Resource NLP, pp. 25–32 (2018)

3. Garay-Vitoria, N., Abascal, J.: Text prediction systems: a survey. Univ. Access Inf. Soc. 4(3), 188–203 (2006)

4. Higginbotham, D.J., Lesher, G.W., Moulton, B.J., Roark, B.: The application of natural language processing to augmentative and alternative communication. Assistive Technol. 24(1), 14–24 (2012)

5. Lundälv, M., Derbring, S.: AAC vocabulary standardisation and harmonisation. In: Miesenberger, K., Karshmer, A., Penaz, P., Zagler, W. (eds.) ICCHP 2012. LNCS, vol. 7383, pp. 303–310. Springer, Heidelberg (2012). https://doi.org/10.1007/978-3-642-31534-3_46

6. Odom, S.L., Horner, R.H., Snell, M.E.: Handbook of Developmental Disabilities. Guilford press, New York (2009)

7. Sennott, S.C., Akagi, L., Lee, M., Rhodes, A.: AAC and artificial intelligence (AI). Top. Lang. Disord. 39(4), 389–403 (2019)

8. Speer, R., Chin, J., Havasi, C.: Conceptnet 5.5: an open multilingual graph of general knowledge. In: Thirty-First AAAI Conference on Artificial Intelligence (2017)

9. Vertanen, K., Kristensson, P.O.: The imagination of crowds: conversational AAC language modeling using crowdsourcing and large data sources. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing, pp. 700–711. Association for Computational Linguistics (2011)

10. Waller, A.: Telling tales: unlocking the potential of AAC technologies. Int. J. Lang. Commun. Disord. 54(2), 159–169 (2019)