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Article

Augmentative and Alternative Communication (AAC) Advances: A Review of Configurations for Speech Disabled Individuals

Yasmin Elsahar, Sijung Hu*, Kaddour Bouazza-Marouf, David Kerr, Annysa Mansor

Wolfson School of Mechanical, Electrical, and Manufacturing Engineering, Loughborough University, Loughborough, UK, LE11 3TU

* Correspondence: S.Hu@lboro.ac.uk; Tel.: +44-150-922-7058

Abstract: High-tech augmentative and alternative communication (AAC) methods are on a constant rise; however, the interaction between the user and the assistive technology is still challenged for an optimal user experience centered around the desired activity. This review presents a range of signal sensing and acquisition methods utilized in conjunction with the existing high-tech AAC platforms for speech disabled individuals, including imaging methods, touch-enabled systems, mechanical and electro-mechanical access, breath-activated methods, and brain computer interfaces (BCI). The listed AAC sensing modalities are compared in terms of ease of access, affordability, complexity, portability, and typical conversational speeds. A revelation of the associated AAC signal processing, encoding, and retrieval highlights the roles of machine learning (ML) and deep learning (DL) in the development of intelligent AAC solutions. The demands and the affordability of most systems were found to hinder the scale of usage of high-tech AAC. Further research is indeed needed for the development of intelligent AAC applications reducing the associated costs and enhancing the portability of the solutions for a real user's environment. The consolidation of natural language processing with current solutions also needs to be further explored for the amelioration of the conversational speeds. The recommendations for prospective advances in coming high-tech AAC are addressed in terms of developments to support mobile health communicative applications.

Keywords: augmentative and alternative communication; assistive technologies; sensing modalities; signal processing; voice communication; machine learning; mobile health; speech disability

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1. Introduction

Recent studies show that up to 1% of the world population suffers a degree of speech, language or communication need (SLCN) [1,2]. The loss of speech capabilities associated with extreme forms of paralysis and further medical complications has long been regarded as a barrier between the sufferers and the outside world. Augmentative and alternative communication (AAC) incorporates a wide range of processes that augment, complement, or replace speech of individuals with complex communication needs [3,4]. In the broad context of speech and language, *speech* is often associated with the motor movements responsible for the production of spoken words, whereas *language* is associated with the cognitive processing skills of communication.

AAC solutions are classified into three categories: no-tech, low-tech, and high-tech AAC [4]. No-tech AAC is considered the oldest of the three AAC categories, given its reliance on the interpretation of facial expressions and voluntary motor movements, such as sign language, to deliver non-verbal messages [5]. Low-tech AAC utilizes basic tools, such as books and display boards with extended lexicons of images and phrases to aid the communication process [6]. High-tech AAC

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encompasses the use of electronic devices to achieve an AAC target. Devices falling under this category, such as smart devices and dedicated AAC devices, integrate hardware and software to support a user's communication needs. A common attribute of modern day AAC solutions tends to rely on the translation of a user's intended meanings into speech via speech generating devices (SGDs) [4]. AAC communication is also often classified as either un-aided or aided, given the dependence of the solution on the human body solely or the interaction with an external communicative aid for communication respectively [4].

The potential of AAC intervention has hence been substantial over the last 30 years, with the provision of innovative solutions to a wide range of speech-impaired users [7]. However, although high-tech AAC systems are rapidly evolving, several considerations are yet pertinent to the provision of effective solutions efficiently serving AAC users [4,8]. Low-tech AAC solutions are usually the first techniques tried by speech and language therapists, as the use of simplistic display boards and communication books is both cost-effective and easy to obtain. Moreover, the high costs and complicated training a user requires to operate most high-tech AAC devices could hinder the access to high-tech AAC, and thus the usability of speech generating devices. In turn, an optimized use of high-tech AAC should be researched to provide a faster means of communication, in comparison to low-tech, by prioritizing the communicative needs of the users over the needs of the system. Studies also show that after testing several AAC systems, the potential of AAC might be limited by complex operational difficulties given the number of users who are simultaneously physically impaired and speech-disabled [8]. Predominantly, AAC users still use combinations of unaided low-tech methods together with an aided high-tech device as suitable for the context of usage and the person they are conversing with [9].

Due to the complex composition of the human body, speech and communication impairments requiring an AAC intervention could result from diverse medical conditions [10,11]. These commonly include Autistic Spectrum Disorders (ASD), strokes, learning disabilities, Locked-in-Syndrome (LIS), Dementia, head and neck cancers, and brain injuries. This also expands to include patients with progressive diseases, such as Parkinson's Disease and Amyotrophic Lateral Sclerosis (ALS) [10]. Other AAC users include patients in transient post-operative states where interventions and treatments, such as ventilator support, may render them unable to speak normally, or at all. In turn, the users benefiting from AAC intervention could be classified into three major groups based on their individual conditions and the intended target use of the AAC communicative aid [12]. These three classes comprise alternative-language users, augmentative-language users, and temporary AAC users. Alternative-language users have a well-established cognitive understanding of language and speech, but have difficulties in conversing. On the other hand, augmentative-language users have difficulties both in understanding speech and in conversing. To be able to use an AAC device, augmentative-language users need assistance in the re-categorization of their surroundings into labels and symbols they comprehend to form a communication language. Temporary AAC users require AAC intervention only for a limited duration of time. This category primarily includes children with developmental conditions, and adults who require transient speech assistance following surgical intervention [12].

Given the complexity of the user base, and the wide need for AAC solutions to serve diverse groups of speech disabled individuals, current research efforts are being redirected towards the establishment of assistive systems that are suited to respond to their personal users' needs and capabilities. The aim of this study is to review the access and processing techniques pertaining to predominant high-tech AAC methods, including the input signal sources, and the developments of machine learning (ML) and deep learning (DL) associated with AAC solutions for the provision of a personalized user experience.

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2. Human Interaction

Several studies exist in the literature of modelling the user's interaction with assistive technologies (AT) [13]. A primary, well-established, AT framework is the Human Activity Assistive Technology (HAAT) model [4]. The HAAT model underpins a consolidated approach of the interactions between the activity, the human, the context, and the assistive technology. It links the process of selection of an assistive technology solution with the person carrying out an activity in a given context [14]. The four components constituting the HAAT model are shown in Figure 1. A particular attention is drawn to each component, detailing the importance of firstly considering the target activity (self-care, productivity, leisure), the human abilities of the person using the device (physical, cognitive, emotional, and expertise), the context the device is used in (physical, cultural, institutional), and in turn the consideration of the suitable AT device (interfaces, processor, output) [4]. The developers of the HAAT model emphasize on the concept of serving the needs of the users in order to optimize the usage of the technology, stating that the technology aspect should encompass the function it serves, the person who will be using the AT device, and the context of usage [4].

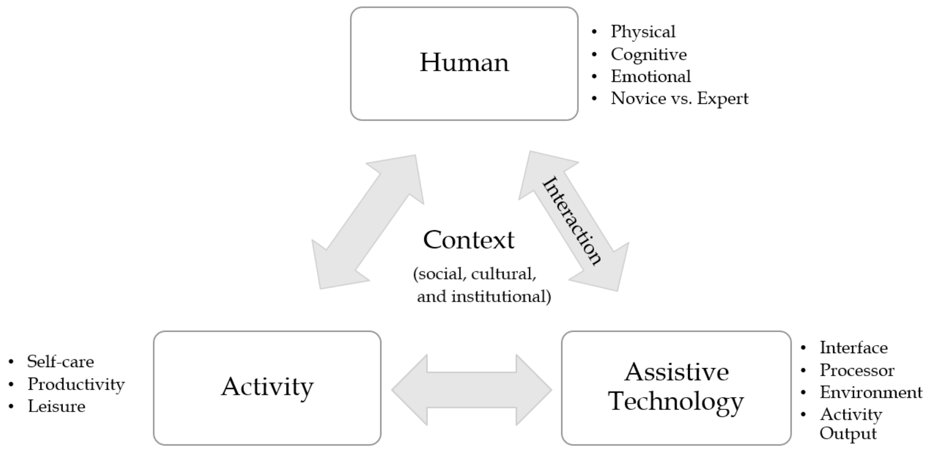

Figure 1. The four components of the Human Activity Assistive Technology (HAAT) model, from [4]. The interaction between the human and the assistive technology (AT) is emphasized to highlight the relationship between the needs of the AAC users and the elements of development of high-tech solutions discussed in this review.

In light of the HAAT model, AT could hence be used to aid the communication process of speech disabled individuals, given that the technology prioritizes the activities and abilities of the user. Basing high-tech AAC applications and platforms on the skills and communicative needs of the users, disabled persons could in turn be allowed to participate in a wider range of activities to communicate their individual needs [15]. From the societal perspective, smart devices have been promoting both the visibility and acceptance of AAC [16]. A number of factors also aids in increasing the access to high-tech AAC platforms, including the ease of operating and using the AAC device, its processing capabilities, the cost of the hardware, and the licensed software packages used to operate the devices [4]. Emphasis is also placed through several studies [4,17] on the importance of customizing AT solutions to address the needs of the users who might find difficulties in accessing the devices' interfaces. A survey study in [18] further highlighted the importance of the provision of technical support and the time taken by a device to communicate a message.

3. Sensing Modalities and their Functionalities

The integration of smart developments into daily life activities has widened the scope of dedicated and non-dedicated AAC applications [7,19]. A survey of high-tech AAC devices with regards to the signal acquisition, ML, and output generation is presented in this section.

3.1. AAC Signal Sources and Associated Processing

AAC interfaces are activated through an array of methods for the detection of human signals generated via body movements, respiration, phonation, or brain activities [4]. The acquisition of AAC signals is accomplished through several modalities. Table 1 outlines the AAC signal sensing categories discussed in this review together with their relevant activation methods. The listed AAC access methods could be used in a stand-alone format or in combination with one another. For example, imaging methods may be combined with touch-activated methods or mechanical switches to provide the users with a multi-modal access using the same device. A commercial example is Tobii Dynavox PCEye Plus, which combines several functionalities including eye tracking and switch access to use a computer screen [20].

Table 1. Sensing modalities of AAC signals

Signal sensing category	Activation method
Imaging methods	Eye gaze systems, head-pointing devices
Mechanical and Electromechanical methods	Mechanical keyboards, switch access
Touch-activated methods	Touchscreens, touch membrane keyboards
Breath-activated methods	Microphones, low-pressure sensors
Brain Computer Interface methods	Invasive and non-invasive

3.1.1. Imaging Methods

Imaging methods, such as eye gazing, eye tracking and head-pointing devices, have been widely reported in the literature [21–31]. Eye gaze technologies work using the principle of tracking the eye movements of a user for the determination of the eye gaze direction [24,27]. Several eye tracking methods are commonly used, including video-oculography [32], electro-oculography [33], contact lenses [34], and electromagnetic scleral coils [21,25,30,35,36]. Oculography is involved with the measurement and recording of a user's eye movements [35]. Video-oculography and electro-oculography use video-based tracking systems and skin surface elecrodes respectively to track the movements of the eye [25]. In the context of AAC, non-invasive eye tracking methods are better suited to address the daily needs of the users who lack motor abilities [27,29]. Practical methods involve the utilization of non-invasive cameras, an illumination source, image processing algorithms, and speech synthesizers to communicate a user's message [25,27]. Image data is obtained in video-oculography operated system using one or more cameras [23,27]. Typical video-oculography systems use glints produced on the surface of the eye through an illumination source, such as near-infrared (NIR) LEDs with typical wavelengths of 850 ± 30 nm, and in turn, gaze locations are estimated from the movement of the eye pupil in relation to the illuminated glint positions [34].

The components of a typical video-based tracking system are shown in Figure 2. Different approaches are present in the literature of calculating the accuracy of an eye tracking system, including the distance accuracy (in cm or in pixels) and the angular accuracy (in degrees) [22]. The pixel accuracy can be given by

$$P_{acc} = \sqrt{(X_{target}PX)^2 + (Y_{target}PY)^2} \tag{1}$$

where X_{target} and Y_{target} are the coordinates of the target points, and PX and PY are the gaze point coordinates given by

$$PX = mean\left(\frac{PX_{left} + PX_{right}}{2}\right) \tag{2}$$

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and

$$PY = mean\left(\frac{PY_{left} + PY_{right}}{2}\right) \tag{3}$$

respectively, with the subscripts $left$ and $right$ referring to the coordinates of gaze points of the left and the right eye. The on-screen distance accuracy (DA) is similarly given by

$$DA = p_{size}\sqrt{\left(PX - \frac{x_{pixels}}{2}\right)^2 + \left(y_{pixels} - PY + \frac{offset}{pixelsize}\right)^2} \tag{4}$$

where p_{size} is calculated based on the resolution, height, and width of the screen, x_{pixels} and y_{pixels} are the pixel shifts in the directions of x and y respectively, and the $offset$ is the distance between the eye tracking unit and the lower edge of the screen [22,37]. The angular accuracy (AA) can be also computed via

$$AA = \frac{p_{size} \times P_{acc} \times cos(mean(\theta))^2}{meandist} \tag{5}$$

where the gaze angle θ is given by

$$\theta = tan^{-1}\left(\frac{DA}{dist}\right) \tag{6}$$

and $dist$ and $meandist$ are the distances from the eye to the screen and from the eye to the tracker respectively [22,37].

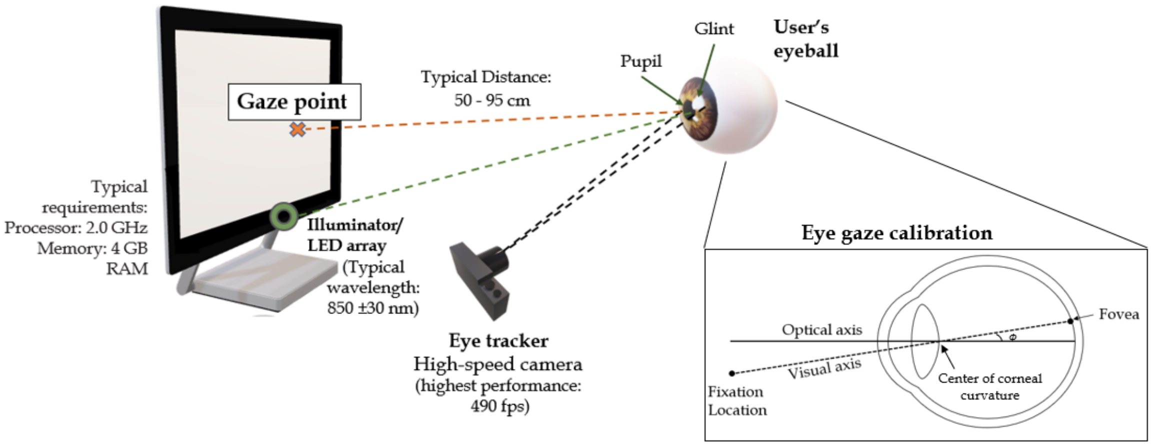

Figure 2. Components of a typical eye gaze system, adapted from [22,38]. The optical and the visual axes are used for the calibration process commonly required to set up the eye gaze system [22,39].

Fixations and saccades are commonly used to analyze eye movements [40]. Fixations are the pauses a user intently inputs by fixing his eye movements at the target gaze point, whereas saccades are the eye movements rapidly occurring following and in between the fixations. Metrics of eye gaze estimations include fixation durations, fixation rates, fixation sequences, saccadic amplitudes and velocities [22,40]. Although electro-oculography is a cost-effective eye tracking method, Infrared pupil corneal reflection (IR-PCR) video-based systems are most commonly used by speech and language practitioners due to their non-invasive nature [25,27]. A calibration operation is essential in video-based trackers to fine-tune the system with a user's eye movements [41]. As seen in Figure 2, a user's visual axis deviates from the optical axis upon the usage of a gaze system. Calibration is expressed as the process of finding the visual axis pertinent to each user by calculating the angle between the line joining the fovea (the highest point of sensitivity in the eye retina) with the center of corneal curvature, and the optical axis [22].

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The estimation of the visual axis is usually not feasible, and as such, the calibration process enables the tracker to capture and learn the difference between the user's eye positions when gazing at a specific target in comparison to the actual coordinates of the gaze target. The user's head orientation should be also considered in IR-PCR systems, as the movements of the user's head can adversely impact the calculations of the glint vectors [22]. Studies are however addressing advances in eye tracking methods to overcome the related constraints, providing the forthcoming possibilities of free IR eye tracking and robust algorithms for head movements compensation [42].

3.1.2. Mechanical and Electro-mechanical Methods

Mechanical and electro-mechanical AAC devices have applications for both direct and indirect selection access methods. Direct selections offer the users sets of choices, and require a voluntary input selection of the intended messages from the user's side. This usually involves the coordination of voluntary controls using a body part, such as the hand or fingers, or a pointing device, to select a message [19]. Mechanically activated direct-selection methods include mechanical keyboards, which utilize the physical mechanical depression of the pressed keys to activate a user selection. Keyboard layouts maybe reconfigured for individuals who find the use of a standard keyboard difficult due to the required coordination between the two hands [4].

For individuals lacking voluntary controls, communication via direct selections is often cumbersome, and consequently, indirect selection methods are best-suited for this group of users [19]. Scanning methods are predominantly in use with indirect selections, involving a systematic representation of options appearing in timed intervals for the users to select from [19,43]. Mechanical scanning methods include single switches, arrays of switches, or other variations of methods activated via the application of a force [4]. Switches are generally considered a form of low-tech AAC due to their minimal hardware requirements; however, switching applications have recently expanded to allow users the access of several high-tech AAC platforms, including computers, tablets, or smart devices via scanning. Scanning techniques range across three levels, each suited to accommodate users with specific motor abilities: Automatic scanning is used to present items in adjustable time intervals, based on the user's skills, until a selection is made; step scanning allows the users to control the presentation of selections, in turn controlling the rate of advancement; and inverse scanning involves holding down a control interface and releasing it upon the desired selection [4]. Figure 3 shows a visual scanning interface together with typical activation switches.

(a) (b)

Figure 3. (a) A sample visual scanning interface activated via switch scanning. The yellow box moves vertically across the lines until a selection is made, followed by a gliding green box moving horizontally across the highlighted line until a letter is also selected. In (b), two scanning button switches are displayed.

In addition to letters, scanning interfaces expand to include a variety of access options, including icons, pre-stored messages, and auditory messages. Some operating systems also provide the option

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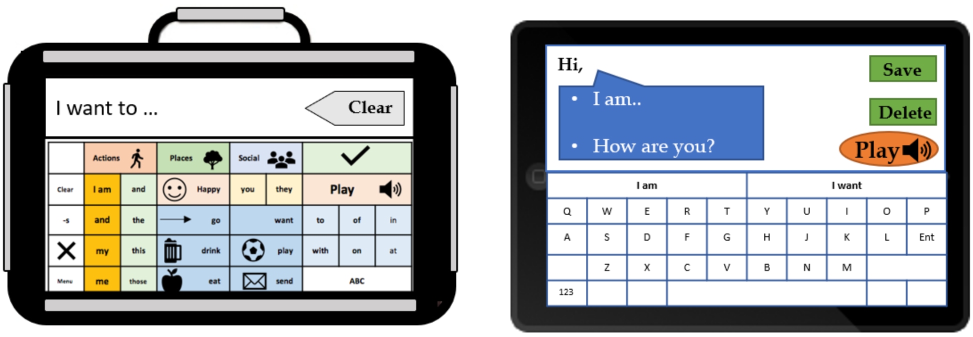
of device navigation via an external switch. The position and access methods of switches are user dependent. They can be adjusted to be in close proximity to the hands or the feet for the ease of activation. Mechanical switches can be also mounted on wheel chairs to allow access using head movements. Different variations of switches are available in terms of shapes and types to suit the user's requirements. In general, mechanical switch scanning requires minimal motor movements; however, the communicative rates could be slowed down by the delay required to make a selection.

3.1.3. Touch-activated Systems

With the escalation of the touchscreen developments, touch-activated AAC applications are commonly in use with AAC direct selection activation. Touchscreen technologies comprise various types, including resistive, capacitive, Surface Acoustic Wave, and optical/infrared touchscreens [44]. Resistive and capacitive touchscreens are predominantly used with smart devices [45]. Resistive touchscreens are dependent on the production of a force or pressure using the user's fingers, whereas capacitive touchscreens are activated using the electrical charge present on the user's finger [46]. Although resistive touchscreens are cost efficient, capacitive touchscreens are often known to present a better visual clarity, presenting an added benefit for AAC users suffering a degree of visual impairments. Touch membrane keyboards are also in use by AAC users. They are built using non-conductive spacers separating conductive flat surfaces; and acquire electronic signals through the pressure resulting from holding down a key, generating an input signal to the AAC device [19].

AAC users utilize touchscreens and touch activated systems to make selections via swiping and tapping; however, such actions could be restrictive for the users who are physically impaired [4]. Nonetheless, the accuracy can be augmented using pointers, as the icons presented on a touchscreen often have the advantage of being cognitively easy to select, and less demanding in comparison to the operation of a regular computer [4].

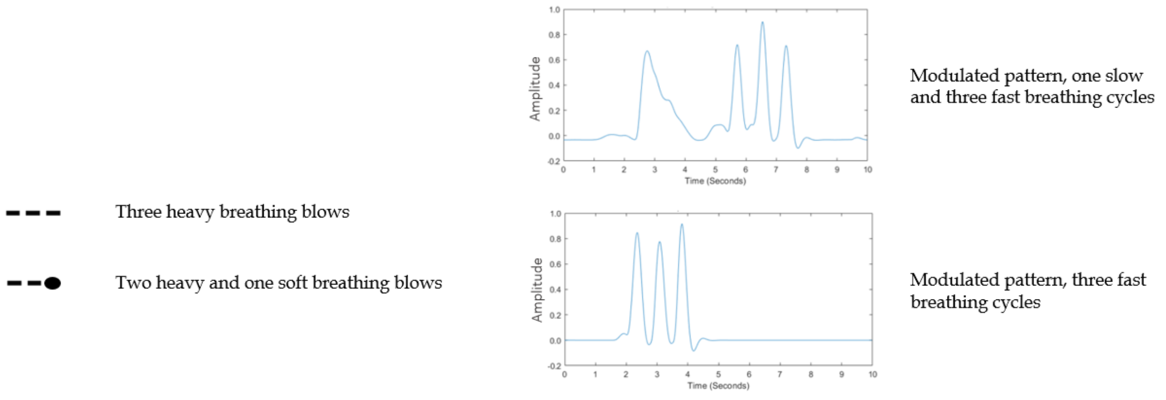


(a) (b)

Figure 4. Examples of (a) a dedicated touch-based device and (b) a non-dedicated smart device running an AAC APP, usually with predictive language model and speech generation capabilities.

3.1.4. Breath-activated Systems

The wide availability of sensing modalities expands the scope of AAC control interfaces to include the detection of respiratory signals in addition to the regular voluntary body movements [4]. Voluntary body movements are commonly detected through the integration of sensors with imaging, and/or optical, mechanical, and electro-mechanical devices. Respiration signals are recorded via a wide range of modalities, including fibre optic sensors [47], pressure and thermal sensors [48], photoplethysmogram (PPG) measurements [49], electroencephalogram (EEG) signals [50], and the examination of airflow [50,51]. Discrete and continuous breathing signals can be used to encode messaged, as shown in figure 5. Discrete breath encoding involves the generation of soft and heavy breathing blows encoded as binary combinations of zeros and ones, or Morse codes to represent the user's intended messages or the International Morse code's letters respectively. On the other hand, continuous breath encoding uses the modulation of the speed, amplitude, and phase of breathing signals to create patterns representing the intended message. The modulation of the continuous breathing patterns encoded to represent user selected phrases, including the training and retrieval modes, is shown in Figure 6 for a mobile based APP.



(a) Discrete breath-encoding (b) Continuous/Analogue breath-encoding

Figure 5. Examples of (a) discrete breath encoding, where soft and heavy breathing blows are recorded to encode combinations of zeros and ones, or Morse codes, representing the intended messages, and (b) continuous breath encoding, where the speed, amplitude, and phase of breathing are modulated to create patterns representing the intended message.

(a) (b)

Figure 6. Examples of (a) training mode, and (b) live mode of continuous breath encoding for the storage and the retrieval of breathing patterns linked to a user phrase using a mobile APP.

An early respiration activated AAC development involving a breath-to-text application was initiated at the Cavendish Laboratory at Cambridge University [52]. The study presented the use of fine breath tuning to use Dasher to support the communicative requirements of AAC users. Dasher is a text-entry system with a predictive language model available on several operating systems, and uses single and two-dimensional inputs from pointing devices to access an on-screen cursor. The fine breath tuning system encodes letters using Dasher's interface and a specially designed thoracic belt worn around the chest. Two inches of the belt are replaced by an elastic material, with a sensor measuring the changes of a user's waist circumference resulting from breathing variations. The study reports an expert user conversational rate of 15 words per minute using this system. The usage of sniffing signals was also established in the scope of AAC in [53]. A device was developed for the measurement of human nasal pressure via a nasal cannula and a pressure transducer. The device was tested with individuals in LIS, and quadriplegic users. To write text, the captured nasal pressure changes are converted into electrical signals, and passed to a computer. The device comprises two associated

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interfaces for the user's selection of letters, including a letter-board interface, and a cursor-based interface. The system aided the users in LIS, with reported rates of three letters per minute.

Microphones could be also used in combination of an AAC interface. The loss of speech abilities associated with SLCN centralizes the usage of microphones around two AAC areas, including speech augmentation of individuals suffering partial loss of speech [54] and breath encoding for individuals with speech disabilities [51,55]. Encoding distinct inhalation and exhalation signals was presented in [55] to produce synthesized machine spoken words (SMSW) through soft and heavy blows represented through four bit combinations of zeros and ones. The classification is achieved based on the threshold values of the generated blows. A micro-controller unit together with an MP3 voice module are appended to the microphone for the execution of the pattern classification and the playback of SMSW. The 16 discrete combinations were linked to predefined phrases selected with the aid of medical practitioners. "TALK" is also a solution involving a micro-electro-mechanical-system (MEMS) microphone together with two low-cost micro-controllers, and is similarly in use with distinct inhalation and exhalation signals to encode letters through the International Morse Code to produce SMSW [2]. A study has also reported the use of analogue breath encoding for AAC purposes by utilizing the recognition of continuous breathing modulations [51]. Analogue encoding of the acquired breathing signals was reported to provide an increased bandwidth at the low breathing frequencies, as it utilizes the signal's amplitude, frequency and phase changes to encode a user's intended meanings. The classification is achieved based on the dynamic time warped distances between the tested breathing patterns. A systematic reliability of 89% was reported with increased familiarity with the system.

3.1.5. Brain Computer Interface Methods

In the scope of AAC, Brain Computer Interface (BCI) solutions are being widely researched to allow AAC users to control external devices by modulating their brain signals [56–58]. Brain interfaces are either invasive or non-invasive. Invasive interfaces involve the usage of implanted electrodes and the interconnections of the brain with the peripheral nerves [57]. Non-invasive BCIs comprise the usage of external devices to monitor a user's brain activities through EEG [54,57], magnetoencephalography (MEG) [56], functional magnetic resonance imaging (fMRI) [56,57] or near-infrared spectroscopy (NIRS) [56,57]. The components and flow diagram of a typical BCI system are shown in Figure 7.

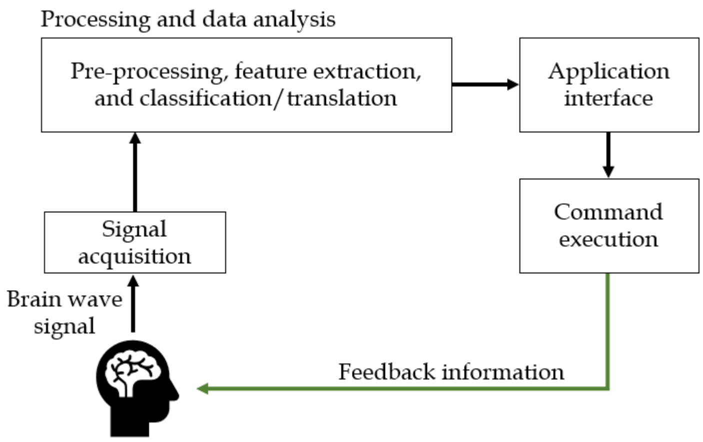

Figure 7. The components and flow diagram of a Brain Computer Interface (BCI) system, adapted from [59,60].

EEG is a popular BCI recording method, given its non-invasive nature and its relatively lower cost [61,62]. In electrical BCI systems, the brain produces a set of electrical signals when triggered by a stimulus, known as the evoked potential [63]. EEG signals are acquired through two to 64 sensors placed on the scalp of the user to record the brain activity [64]. Amplifiers and filters are typically utilized, with an output fed back to the user to accordingly modulate the brain activity [57]. To translate a brain activity into a computer command, regression and classification algorithms could be used [65]. An adaptive auto-regressive (AR) parameter estimation model used with EEG BCI describes a time series signal x(t) as

$$x(t) = \sum_{i=1}^{p} \phi_i x(t-i) + \epsilon_t \tag{7}$$

$$x(t) = \phi_1 x(t-1) + ... + \phi_p x(t-p) + \epsilon_t, \tag{8}$$

where ϕ_i and p are the AR coefficients and the order of the model respectively, and ϵ_t is white noise [66,67]. A review study [65] demonstrates that the use of classification algorithms is an increasingly popular approach with BCI interfaces, as they are commonly used to identify the acquired brain patterns. Classification is the process of using a mapping f to predict the correct label y corresponding to a feature vector x. A training set T is used with the classification model to find the best mapping f^* [65]. The classification accuracy of a model is dependent on a variety of factors. A study [65] demonstrates that using the mean square error (MSE), three sources are identified to be the cause of classification errors, given that

$$MSE = E[(y - f(x))^2] \tag{9}$$

could be decomposed into

$$MSE = Var(f(x)) + Bias(f(x))^2 + \sigma^2, \tag{10}$$

where the variance *(Var)* represents the model's sensitivity to T, the *Bias* represents the accuracy of the mapping f, and the noise σ^2 is the irreducible error present in the system. Common ML algorithms used with BCI include linear classifiers (such as linear support vector machines), neural networks, non-linear bayesian classifiers, nearest neighbors, and combinations of classifiers [64,65]. Signal processing techniques pertient to BCI methods include both time-frequency analysis, such as AR models, wavlets, and Kalman filtering, and spatiotemporal analysis, such as the Laplacian filter [68]. Hybrid BCI is a different approach to brain signals processing, combining a variety of brain and body signals in sequential and parallel processing operations with the aim of improving the accuracy of BCI systems [69].

BCIs are under continuous research to aid the communication of individuals suffering from motor strokes [56], ALS, and LIS, and spinal cord injuries [70]. BCI systems involve three basic pillars, including the user training, the associated ML, and the application in use [71,72]. Research in the area of BCIs is currently evolving [56], with promising results in recent state-of-the-art projects. A study by Stanford University [73] confirmed the usability of BCIs to control an unmodified smart device for quadriplegic users. BCIs have been also in use to surf the internet [74], with an EEG BCI based application tested with LIS and ALS conditions [75]. It is also reported that BCIs could aid users control spelling and play games [73].

3.2. Machine and Deep Learning

Typical signal processing of the acquired AAC signals encompasses three primary operations: encoding, prediction, and retrieval [10]. Encoding involves the conversion of the acquired signal into a pre-defined format accepted by the system for the production of a specified output, whereas prediction is concerned with building the algorithms used to select the desired output [10]. Prediction encompasses several operational contexts, including word [76], message, and icon prediction [10]. In general, an ideal AAC system should integrate self-learning capabilities to respond to its users' individual needs [2,8]. Demographic data shows that current AAC users belong to numerous cultural and linguistic backgrounds [7]. In turn, the design of systems tailored to address specific users' requirements is vital. High-tech AAC is hence becoming a highly interdisciplinary area of research, combining rehabilitation engineering with clinical and psychological studies, signal processing, and ML [77].

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ML has been widely evolving over the last decade, with a number of applications aimed at aiding the provision of intelligent AAC solutions to address the users' needs. The automation of algorithms, prediction, and classification capabilities presented by ML solutions could be of great benefit to the users. Technologies such as natural language processing (NLP) are highly dependent on artificial intelligence (AI). The operation of NLP is centered around the analysis, augmentation, and generation of language, including the computation of probabilities of incoming words and phrases, and complete sentence transformations [78]. NLP has various applications in AAC, utilizing ML and statistical language models to process and generate outputs by optimizing word prediction models, topic models [79], speech recognition algorithms, and processing of the context of usage [78]. BCI is also highly dependent on ML, as users learn to encode the desired intended messages through dedicated brain signal features captured by the BCI for the translation to the intended meaning or the desired control [71,77,80,81]. Recent studies also show that advances with DL algorithms, such as conventional and recurrent neural networks, could have a potential superior performance in comparison with conventional classification methods [63].

3.3. Outputs and Speech generating Devices

High-tech AAC systems can produce outputs in a variety of formats, including symbols, icons, and electronic digitized or synthesized speech [10]. SGDs, or voice output communication aids (VOCAs), are devices with the ability to produce digitized or synthesized speech [9,82]. Digitized speech is pre-stored speech acquired via a microphone and stored in electronic format for retrieval upon a user action [83]; whereas synthesized speech is generated based on mathematical algorithms and played as natural voice [10]. The wide availability of smart devices facilitates the access to VOCA applications. Synthesized speech includes the production of output messages via text to speech synthesis, and is therefore commonly researched to assist the communication and free personal expression of speech impaired individuals. This is primarily due to the benefit of providing a greater flexibility in contrast with digitized speech. Studies show that AAC devices with SGD capabilities contribute to significant developments in terms of AAC solutions [10,82]. However, the efficiency and effectiveness of using a VOCA with an AAC user remains dependent on the user's abilities, their medical condition, and the communication partners they are conversing with [9].

4. Comparison of Existing AAC Signal Sensing Methods

With respect to the discussed HAAT model and the listed AAC access methods, the integration of state-of-the-art AAC systems with AI applications could help in the improvement and the ease of use of common AAC devices and their associated user interfaces. The focus on the user activity to be carried out needs to be at the core of the implementation. Table 2 provides a comparison of the input signal sources, the requirements for operation, the areas of strength, and the areas of limitation of the listed AAC sensing methods. A summary of each of the listed access categories is demonstrated below in terms of the ease of access, affordability, ease of programming and maintaining, portability, and conversational rates.

4.1. Ease of Access

Imaging methods, including eye gaze and eye tracking methods, are generally utilized as non-invasive means of communication for the individuals with minimal voluntary controls and motor movements. The natural eye gazing process is a an advantageous trait for accessing devices [26]. However, typical imaging methods were shown to require a learning curve for both the users and the systems, as a calibration step is usually required for the customization of an imaging device to each individual user [84]. The accuracy of the system is also dependent on many variants, including the gaze angle, the pixel accuracy, and the distance between the eye and the screen, as demonstrated in equations (1), (4), and (5), rendering eye gaze difficult when selecting small items on the screen [26]. The movements of the head and the direction of the gaze might impact the usability of the acquired

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signals, usually with algorithms implemented to cancel out the effects of such movements [22]. Recent eye gaze systems are better proofed against head movements, and in turn need to be calibrated less frequently [54]. Calibration models are also in use to facilitate the process of gaze calibration [85]. Recent studies are beginning to address the current constraints to create forthcoming robust imaging systems that are easy to use [84]. Mechanical and electro-mechanical activated switches and keyboards are usually easier to operate due to their simplistic nature. Mechanical switches are predominantly used with individuals requiring minimal motor movements to access a computer or a smart device via indirect selection [4]. Touch-activated methods require voluntary muscle controls, however with a minimal activation pressure, as discussed in Table 2. Touchscreens could be also used in combination with mechanical switches for individuals lacking motor controls to access the devices for indirect selections enablement. This multi-modal access can in turn be advantageous, as users will have a choice to access the device using more than one modality. Breath-activated methods are similarly used with individuals with minimal voluntary controls; however, they require a training step to recognize the selected patterns [51,55]. With regards to BCI access, non-invasive methods, such as EEG, are used due to their non-intrusive nature. BCI systems provide a natural means of access, aiding the users to gain independence [86]. However, the signal acquisition from the brain is at times cumbersome for the users, especially with EEG applications requiring the use of electrolytic gel to facilitate the acquisition of the brain signals from the scalp [87]. The length of the training process required to use a BCI system could also present a challenge for usage [88].

4.2. Affordability

In terms of costs, the expenses associated with the hardware and software requirements of the utilized platforms directly impact the expenses related to the systems. Imaging methods, including eye gazing and tracking, are relatively expensive in comparison to switch access, touch based methods, and breath-activated methods. This is mainly due to the high-costs associated with the systems' hardware requirements, which are listed in Table 2, together with the costs of research, programming and maintaining the devices [89]. Depending on a solution's capabilities, the price of a typical eye tracker ranges between hundreds to thousands of dollars [84]. Some solutions are emerging to reduce the costs of imaging AAC devices [27,84]; however, more research is still needed to widen the scope of usage of highly performing, low-cost eye trackers. On the other hand, mechanical keyboards and access switches are commonly simple to design and thus they are usually more affordable. The reliance of switch access or touch-based methods on a smart or a high-tech dedicated device could increase the costs of the provided solutions; however, with the prevalence of smart devices, several AAC communicative applications (APPs) are now available on various operating systems, widening the usability of AAC in contrast with traditional SGDs [16]. As listed in Table 2, breath-activated methods are usually accessed using pressure sensors or microphones together with micro-controller boards or a computer. The hardware requirements could increase the costs of the solutions; however, the escalating prevalence of smart devices might aid in the provision of cost-effective breath-activated APPs. BCI methods are also being researched to reduce the costs associated with the systems [69]; however, low-cost BCI systems were reported to require further research to improve the accuracy and quality of the acquisition in comparison with advanced BCI systems.

4.3. Ease of Programming and Maintaining

Programming an AAC access modality is dependent on the acquired signals, together with the research and skills required to set up and maintain the systems. Typical imaging devices are associated with increased complexities in terms of algorithm writing, data processing, and data parsing [90,91]. This in turn requires extensive programming and coding skills to set up the gaze detection algorithms, calibrate the sensors to individual users, and accurately respond to the needs of the users. The resulting amount of data also needs to be addressed, with specific considerations to

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sample sizes and data resolution [91]. Mechanical switch access of smart devices, and the programming of touch-activated APPs is in turn less variant in terms of calibration and set up. The APPs however need to be carefully designed and tested to respond to the user's input generated via a switch, a keyboard, or a touchscreen. Touch activated methods also need to incorporate a visual or auditory feedback mechanism to confirm the user's selection, as demonstrated in Table 2 [19]. Breath-activated methods are similarly programmed based on breath thresholds [55], and classification algorithms [51]. The complexities are in turn dependent on the requirements of the APP design together with the selected classification algorithms required for the system operation. Concerning BCI methods, the challenges related to managing and programming the systems are centred around the information transfer rates, the non-linearity of the systems, and the complexities associated with the high signals' dimensionalities [88].

4.4. Portability

In terms of portability, the typical requirements of the systems dictate the ease of moving the device for usage in a different setting. Commercial solutions of the AAC imaging methods are starting to address this constraint to increase the usability of the devices [42,84]; however, most typical system requirements still restrict eye-tracking systems to be used indoors [23] or together with a monitor. On a similar note, the portability of mechanically activated switches is variant depending on the context of usage; however, the integration of switch access with mobile and smart devices increases the ease of portability. Touch-activated methods are similarly highly portable, given the typical sizes of the smart devices used in coordination with the method. On the other hand, the portability of breath-activated systems is application dependent, as the solutions requiring the need of a computer interface still need to be developed to address this constraint. BCI methods are still challenged in terms of the communicative interfaces [88]; however, some advances in BCI have been reported for the potential possibility of home usage [86] and increased portability [92].

4.5. Conversational Rates

Natural speech has a rate of 125 to 185 words per minute (WPM) [93]. Speech rates of less than 100 WPM are identified as slow [94]. Direct selection techniques, including eye gaze systems, are found to provide conversational rates of about 8–10 WPM [93]. Likewise, mechanically activated AAC switches and keyboards also affect the conversational rates. The automatic, step, and inverse activation of switches often requires the users to wait until the desired selection is displayed, introducing conversational delays. Scanning methods were reported to allow communicative rates of around two WPM [93]. Selecting letters to form words may also impact the user's communication rate. This is apparent in touch-activated methods, where users are required to spell words or select icons to form sentences or to write text. The conversational rates of breath-activated systems are further dependent on the encoding method, as systems where breathing variations are used to select letters to write words could negatively impact the conversational rates. A recent study [87] similarly reported that most BCI technologies still offer conversational rates of less than 20 letters per minute. Generally, the rates of conversation using AAC systems, including word prediction and letter abbreviation, were found to be between 12-18 WPM, highly contrasting with the rates of natural speech [93].

Table 2. Signal sources, areas of strength and areas of limitation of current commercial AAC devices

Signal Source	Mode	Typical Hardware Requirements	Areas of Strength	Limitations and Areas of Improvement
Imaging methods	Eye gazing	• IR/NIR illumination source (commonly: 850+/- 30 nm) • Monitor • Camera	• Non-invasive • Minimal voluntary control of muscles • Can be used with patients requiring mechanical ventilation [26] • IR is invisible to the user's eyes[23] • IR can stabilize gaze estimation [23]	• High Temporal resolution = high volume of data as patterns are averaged over long time spans [90]; Consequence: sample sizes are often small [91] • Eye tracking data processing [91] and parsing is complex [90] • Need for calibration algorithms • IR signals are not reliable for outdoor use [23] • Generally, high cost [27]
	Head-pointing	• Head-mounted visors in addition to a monitor and a camera [95] • Light/optical pointers [4,19]	Less expensive compared to typical eye-gaze systems	• Need fine user precision and controls [95] • In direct contact with the user's head
Mechanical/Electro-mechanical methods	Automatic, step, or inverse activation	Single switch, array of switches	Requires minimal motor control [4]	Generally slow
	Typing/icon selection	Mechanical keyboards	Instant feedback to user whenever a key is pressed [4,19]	Voluntary muscle control is a requirement for activation [4,19]
Touch-activated methods	Force production through: • Hand/arm/ body part control • control extender [96]	• Resistive/Capacitive touch screen circuitry • Membrane keyboards: Non-conductive spacers separating conductive flat surfaces [4,19]	Minimal activation pressure	• No direct feedback upon activation • Requires appended feedback mechanisms (auditory/sensory) [4,19]

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Table 2 (Continued). Signal sources, areas of strength and areas of limitation of current commercial AAC devices

Signal Source	Mode	Typical Hardware Requirements	Areas of Strength	Limitations and Areas of Improvement
Breath-activated methods	Fine breath tuning [52]	• Thoracic belt • Sensor measuring the changes of waist circumference	Integration with a predictive language model	• Physical control of movements: restricted for paralysed users. • Portability constraints • Slow conversational rate
	Sniff control [53]	Control sensors for the acquisition of nasal pressure.	Confirmed usability with patients in LIS	Slowness: rate of three characters per minute.
	Discrete breath encoding [55,97]	• Microphones/MEMS sensors • Microcontroller boards	Wearable configuration	• Digitized inputs • Predefined words and sentences (not user-selected) • Confinement to limited patterns.
	Analogue breath encoding [51]	• Microphone • PC	Continuous/analogue breath encoding	• The processing of warped distances is computationally complex • Portability constraints
BCI methods	Invasive	Implantable electrodes	Communication and control of environment without the need for body movements [57]	• Prone to classification errors [22] • Low transfer rates of ECG-based BCI due to the low signal to noise ratio [61] • Most platforms are not yet suitable for everyday usage/ in-home usage • BCI devices often require extensive assistance from caregivers [98]
	Non-invasive	External monitoring: EEG, MEG, fMRI, NIRS. [56]		

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5. Prospective Advances in Future AAC

Studies are currently directed towards the establishment of intelligent AAC systems that are suited to respond to personal users' needs, intended activities, and individual capabilities [2,51,55]. The development of robust future AAC solutions should hence take into consideration some of the shortfalls of the current technologies. The conversational rates of most available AAC solutions are still slow, offering a rate of around 12-18 WPM in contrast with that of natural speech (125-185 WPM). [76,93]. In turn, AAC users still communicate at a rate that is approximately 10% the rate of natural speech [99]. This is most apparent in text-based communication involving complex navigation to search or select specific messages or to type full sentences to convey a meaning. On a similar note, the users are sometimes unable to solely rely on the devices due to the limited range of available words/phrases, in turn only engaging in "routinized conversations" using their AAC equipment [8]. As implied from Table 2, such conditions are further complicated with the increased complexities of some AAC systems, which might require special support from the user's carers to set up and operate the systems. The access and operation of AAC devices with minimal user movements is also vital, as the generation of voluntary movements may be cumbersome for users suffering extreme forms of paralysis.

In light of the discussed AAC sensing and acquisition modalities and the AT requirements reviewed using the HAAT model, the following implications can be drawn:

(A) **Affordability**

One of the barriers to the realization of the full-potential of high-tech AAC systems is related to the affordability of the devices. The expenses associated with speech generation, together with the hardware and processing requirements of most high-tech AAC sensing modalities, hinder the scale at which high-tech AAC systems are used, and in consequence, negatively impacting the scale at which high-tech AAC is expanding. In turn, low-technology AAC remains widely utilized by speech and language therapists, given its affordability and wide abundance. Therefore, addressing the affordability of high-tech AAC platforms is a necessity for high-tech AAC systems to become prevalent.

(B) **Mobile APP integration**

The development of AAC APPs utilizing the capabilities of smart phones and tablets can be further explored to assist the communication of speech impaired individuals, in turn reducing cost and enhancing portability. As demonstrated, the usage of VOCAs is of a potential benefit for users of different age ranges suffering a variety of medical conditions [100]. However, it is shown that the variability in terms of operational principles, user groups, and the complexity of a real and complicated user's environment still need to be tackled. The integration of smart devices and VOCA APPs could be researched to expand the scope of high-tech assisted voice communication.

(C) **DL functionalities**

AAC methods incorporating analogue encoded signals via the acquisition of continuous user inputs are generally less cumbersome to generate in comparison with discrete encoding. For example, the discretization process of inputting letters to form sentences via imaging, touch-activated, or breath-activated methods may slow down a user's conversational rate due to the efforts required to navigate the boards of letters to construct the intended phrases. The integration of state-of-the-art AAC systems with AI and DL applications can be researched to improve the access to high-tech devices, the speed of the output generation and the customization of the AAC interface to suit each individual user.

(D) **NLP and intelligent AAC**

By comparing the listed high-tech AAC sensing modalities, a trade-off is apparent between the speed of conversing, and the free expression of the user. Pre-programmed phrases restrict the dynamicity of the user's conversations; whereas spelling based communication is generally slow. Further research

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with regards to NLP and DL functionalities is needed for the provision of innovative activity-oriented AAC methods to support the user, the facilitator, and the communication partner [93].

(E) **Forthcoming development of mobile health applications**

The implications for future research could expand beyond the usage of the AAC devices for simple communication, as the integration of high-tech AAC with accessible smart devices paves the way for state-of-the-art developments, such as mobile health (m-Health) communicative applications, to exist. The development of smart mobile platforms would in turn aid the remote communication between users and their medical practitioners. This will expand the scope of AAC beyond physical communications, increasing the usability and the context of usage of future AAC solutions.

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Abbreviations

The following abbreviations are used in this manuscript:

AAC	augmentative and alternative communication
AI	artificial intelligence
ALS	Amyotrophic Lateral Sclerosis
APP	applications
AR	auto-regressive
ASD	Autistic Spectrum Disorders
AT	assistive technology
BCI	brain computer interface
DL	deep learning
EEG	electroencephalogram
fMRI	functional magnetic resonance imaging
HAAT	Human Activity Assistive Technology
IR	Infrared
IR-PCR	Infrared pupil corneal reflection
LIS	Locked-in-Syndrome
MEG	magnetoencephalography
MEMS	micro-electro-mechanical systems
ML	machine learning
MSE	mean square error
NIR	near-infrared
NIRS	near-infrared spectroscopy
NLP	natural language processing
PPG	photoplethysmogram
SGD	speech generating device
SLCN	speech, language or communication need
SMSW	synthesized machine spoken words
VOCA	voice output communication aid
WPM	words per minute

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