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Brain–Computer Interfaces for Augmentative and Alternative Communication: Separating the Reality From the Hype

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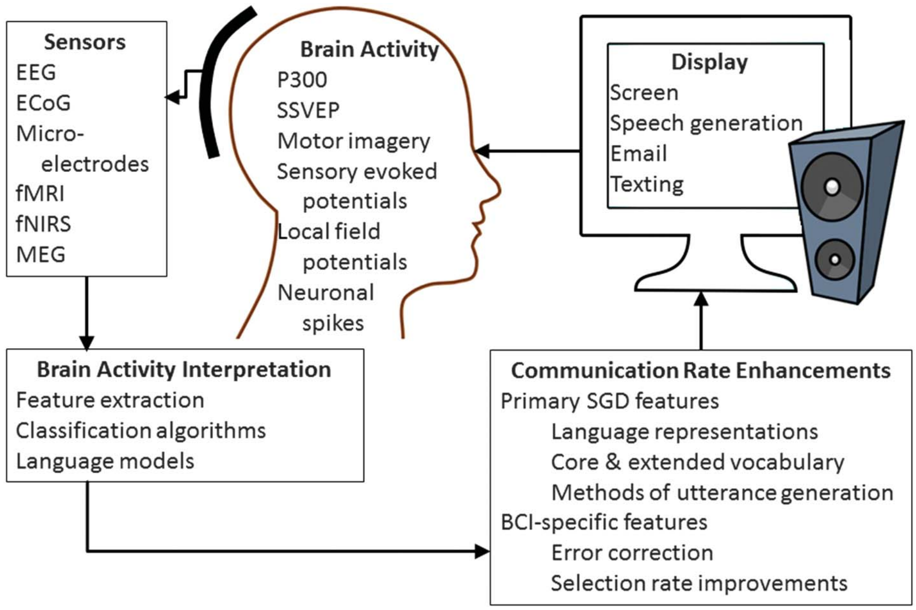
Brain–computer interfaces (BCIs) are topics of great interest to people who need augmentative and alternative communication. Although media reports focus on the promise of BCI to provide communication without physical movement, such reports often contain few details to critically evaluate whether BCIs are yet sufficiently developed for real-world communication. This article provides an introduction to the breadth of BCIs designed for communication. We examine the reasons for misconceptions about BCIs and discuss the functions BCIs can currently provide. Finally, we summarize important factors to consider when evaluating BCI as a communication element for individuals with complex communication needs.

Definition of a Brain–Computer Interface

Brain–computer interfaces (BCIs), sometimes referred to as *brain–machine interfaces*, are assistive technology interfaces that directly interpret brain activity to enable a person to control technology. In augmentative and alternative communication (AAC) applications, a BCI can be conceptualized as a system of four basic components (Figure 1): sensors to record brain activity, signal analysis methods to extract desired control signals from the brain activity, communication rate enhancement techniques to improve the efficiency of each selection, and the output that results from the process, often on a display. Most BCIs take advantage of the closed loop formed by these components by presenting stimuli on the BCI display and interpreting brain activity generated in response to the stimuli as command signals to operate technology.

Figure 1. Functional diagram of BCI for communication. EEG = electroencephalogram; ECoG = electrocorticogram; fMRI = functional magnetic resonance imagery; fNIRS = functional near-infrared spectroscopy; MEG = magnetoencephalography; SSVEP = steady-state visual evoked potential; SGD = speech-generating device; BCI = brain–computer interface.



The form that the output takes depends on the BCI application. Application areas include communication, mobility, environmental control, rehabilitation, and so forth. Indeed, if a BCI is constructed as a generic interface to other technology, the applications it can support are limited only by the appropriateness of the control signals produced. If these are sufficiently responsive, any technology could be operated by a BCI. However, BCIs are rarely constructed as generic interfaces to other technology. They are usually designed and optimized for specific purposes. Wolpaw and Wolpaw (2012) conceptualize BCIs in relation to the natural output channels of the brain through muscle activity. They propose that BCIs either replace, restore, enhance, supplement, or improve the natural output channels of the brain that drive muscle activity.

This article focuses on BCIs that replace lost natural output methods for communication purposes. Reviews of BCIs for other purposes can be found elsewhere (e.g., Blankertz et al., 2016; Riccio et al., 2016; Vidal, Rynes, Kelliher, & Goodwin, 2016). Ideally, saying that a BCI replaces lost natural output methods for communication would indicate that the BCI directly reads the intent to speak and replaces the muscle movements that generate speech with a speech-generating device (SGD). In reality, BCIs are used as computer access methods. With this approach, optimal performance would be expected if the BCI is used to operate AAC devices. However, BCIs are typically created as stand-alone systems that attempt to incorporate communication functions and not as general purpose replacements for physical input devices (see BCI Applications for AAC).

Components of a BCI

Brain Activity

Brain activity is arguably the most important part of the BCI. It should not be counted as a BCI component but as the user's input method. On most BCI systems, brain activity is monitored and used to control the selection of locations on a virtual keyboard. Many different types of brain activity can be used to operate a BCI.

It may seem natural to envision a BCI as reading thoughts. This challenging task has only been attempted in a few preliminary studies. Researchers have attempted to interpret intended speech from the speech areas of the brain using a variety of sensors. However, results remain extremely limited (for review, see Herff & Schultz, 2016).

The most common BCI systems for communication use the P300 BCI design (Farwell & Donchin, 1988). P300 BCIs support direct selection of locations on a virtual keyboard. Keyboards with four (Sellers & Donchin, 2006; Sellers, Krusienski, McFarland, Vaughan, & Wolpaw, 2006) to 84 (Jin, Sellers, & Wang, 2012) locations have been reported. The P300 brain signal is a positive change in brain activity that occurs approximately 300 ms after a somewhat rare and unexpected event that is important to a person. On a P300 BCI keyboard, locations "flash" in a seemingly random pattern so that the user cannot anticipate when the location they want to select will flash. Flashes can be short (e.g., 30 ms). However, P300 BCIs typically combine information from multiple flashes of each location to increase accuracy, which increases the time needed for each selection.

The term *P300 BCI* generally refers to BCIs that rely on any evoked potential that occurs in response to a stimulus. Some methods of "flashing" the locations on a keyboard are explicitly designed to harness evoked potentials other than the P300. For example, flashing a face over the top of different letters on a keyboard not only uses the P300 but also harnesses the N170 signal and the N400f, negative brain activity changes at 170 and 400 ms that are associated with visual processing of faces (Kaufmann, Schulz, Grunzinger, & Kubler, 2011). P300 BCIs can also work with auditory or tactile stimuli (Hill & Scholkopf, 2012; Kaufmann, Holz, & Kubler, 2013), potentially making these BCIs the best or the only option for those with the most severe physical impairments. However, BCIs with auditory or tactile stimuli typically limit users to select from two to four locations instead of the large keyboards of locations available on a visual P300 BCI.

Other types of brain activity may also be used to control a variety of different BCI technologies that could potentially be used to support expressive communication in future applications, but most have so far only been tested in highly controlled experiments:

- Steady-state visual evoked potential (SSVEP) BCIs use frequency analysis to monitor brain activity for the natural representation of a light or pattern that flickers at a known frequency (see review by Zhu, Bieger, Garcia Molina, & Aarts, 2010). This response is larger when a person is focusing on a flickering stimulus than when the person is ignoring it. SSVEP BCIs can only differentiate between responses to a limited set of stimuli and may be useful for controlling arrow keys or similar controls. While most SSVEP BCIs rely heavily on eye movement to enable a user to focus on stimuli of interest, users without eye movement could still potentially use SSVEP activity to operate BCIs by paying attention to stimuli in peripheral vision. One study even involved using an SSVEP BCI through closed eyelids (Hwang et al., 2015).
- Encoded sensory evoked potential BCIs monitor brain activity for an instantaneous pattern in response to a coded flicker that somewhat mimics binary information transmission. This method allows selections from keyboards with as many as 64 locations. Although this approach was used in one of the earliest communication BCIs (Sutter, 1992), the method was not repeated until recently (Thielen, van den Broek, Farquhar, & Desain, 2015).
- Another approach is to interpret spontaneous signals in the user's brain activity as commands at any time the user chooses. These signals typically result from motor programs (known in BCI research as motor imagery; for review, see Neuper, Müller-Putz, Scherer, & Pfurtscheller, 2006), but tasks like mental arithmetic have also

been used (e.g., Herff et al., 2013; Wang, Xu, Wang, Yang, & Yan, 2007). Such signals are generally used to move a computer cursor over a keyboard. Separate signals may be used to generate a mouse-click and make selections.

Sensors to Record Brain Activity

BCI sensors may be invasive or noninvasive. Most record electrical brain activity. Electroencephalogram (EEG) sensors record activity from the scalp. Electrocorticogram sensors record from the surface of the brain, under the skull. Local field potentials or neuronal spikes are recorded by electrodes penetrating the brain. Magnetic signals produced by the brain can be sensed with magnetoencephalography and used for BCI. Variations in the blood oxygenation levels of specific parts of the brain can be sensed with functional magnetic resonance imagery (fMRI) and used for BCI. Functional near-infrared spectroscopy (fNIRS), another method of sensing blood oxygen levels, uses optical sensors to pick up reflections of infrared light directed at the brain through the skull. Magnetoencephalography and functional magnetic resonance imagery equipment are too large and expensive for in-home use, but functional near-infrared spectroscopy is available for home use.

Brain Activity Interpretation

The signal analysis methods of the brain activity interpretation component are arguably the most extensively studied. BCI signal analysis methods are intended to extract relevant information from the brain activity and separate it into distinct control signals. These methods are often referred to as machine learning, signal processing, feature extraction, or classification algorithms or methods. Some methods may also incorporate language models to guide the classification of brain activity (Moghadamfalahi et al., 2015). In AAC-BCI research, accuracy and selection rates are typically reported for highly structured tasks using letter-by-letter spelling. These measures are taken before any rate enhancement features are applied and represent the accuracy of the control interface at its simplest.

Most BCIs use a fixed selection rate, unlike physical access, in which selection rates vary with the speed of a person's movements. The selection process for most BCIs follows a cycle controlled by the BCI that does not allow for variations. The stimuli are presented for a fixed amount of time in each cycle, then the BCI registers a selection.

Communication Rate Enhancement

Primary features of AAC systems, which relate to the ways in which language is represented and generated, should be considered among the critical components of AAC systems using BCI interfaces (Hill, Kovacs, & Shin, 2015). These features include language representation methods, access to core and extended vocabulary, and methods of utterance generation (i.e., spontaneous vs. preprogrammed utterances). Early BCI studies focused exclusively on spelling tasks and studied users generating output one letter/character at a time. Many current BCI studies still focus on spelling tasks. Other language representation methods may enhance communication rate relative to the rate obtained using spelling alone. Studies of BCI users using spelling and word prediction (e.g., Ruff, Wolpaw, & Bedlack, 2011) are becoming more common, especially in studies of BCI users with disabilities. Studies investigating the use of multimeaning icons and single meaning pictures to produce whole words with fewer keystrokes are also needed.

Language representation methods. Studies are just beginning to investigate the effects of language representation methods on communication rate and accuracy in people using BCI. With physical access methods, keystroke savings from word prediction do not necessarily translate into increased communication rates (Koester & Levine, 1997). The added time required to scan the list of predicted words may actually reduce communication rate unless the keystroke selection rate is extremely slow. With BCIs, there is also a question of the effect of additional mental workload. A study of word prediction use with BCI (Ryan et al., 2011) found that use of word prediction reduced the accuracy with which the BCI made selections, presumably due to the added mental workload associated with word prediction. However, the overall communication rate increased because the keystroke savings of using word prediction outweighed the reduction in speed created by the reduced accuracy. This also points out that, unlike most physical access methods, BCI selection rates are slow enough that word prediction can be beneficial.

Automatic error correction. BCIs also present a unique opportunity for automatic error correction. Most of us are familiar with auto-correct features in word processors in which common spelling errors are automatically fixed without user intervention. Whereas such features could also benefit BCI communication, BCIs present an additional opportunity for error correction by reacting to brain activity produced when the BCI user recognizes an error. So, if the BCI makes a selection that the user did not intend, the brain activity associated with recognizing the mistake can cue the BCI to reverse the erroneous selection (e.g., Buttfield, Ferrez, & Millan, 2006; Schmidt, Blankertz, & Treder, 2012). The reversed selection could then be replaced with another selection after the BCI automatically saves the user the task of deleting the error. Such error correction methods rely on accurate classification of the brain activity produced by recognizing an error. If that classification goes wrong, then correct selections made by the user will be reversed, causing great frustration for the BCI user. It is not clear if EEG-based error detection can be accurate enough in everyday use to improve overall communication rate.

Recognizing intended control. The communication rate enhancement module may also include signal analysis to determine whether the selection about to be made was intentionally produced by the BCI user. This function, referred to as a no-control or idle function, will be important for acceptance of the BCI. We are used to devices, such as keyboards, that reliably remain inactive when we are not using them. For a keyboard, *not using* is easily defined as whenever the user is not touching the keyboard. A BCI must determine when a person is actively using the BCI by interpreting brain activity because the person must be "touching" the BCI in order for it to be available for use. If the BCI determines that the selection about to be made was not intended, it will abstain from any selection. The ability to make determinations of this type on a selection-by-selection basis can support natural use of the interface by allowing the user to make brief pauses for thought or to accommodate short lapses in attention. It can also support pauses while a communication partner is speaking.

BCI Display

The BCI Display is the component that completes the loop, presenting any stimuli used to elicit or guide the user's brain activity and providing feedback to the user as selections are made. For AAC applications, the display is usually a screen showing stimuli and selections made with the BCI. A speaker to output the speech generated by the device would also be considered part of the display. For SSVEP and P300 BCIs, the display may incorporate flickering or flashing elements to elicit the SSVEP or P300 brain activity.

Why We Care About Reality Versus Hype

BCIs are of great interest to both the general public and people with disabilities. They are a popular topic for the news media, and it seems that every week brings a new announcement on BCI research and development. Someone paying careful attention to the media reports will notice that the same claims are repeated frequently. This persistent and generally uncritical media attention raises the expectations of patients and families. These stakeholders often form unrealistic expectations of what BCIs can deliver or unrealistic concerns about invasion of privacy. It is important for clinicians to be able to separate the media hype from the reality of current BCIs so that they can educate their patients and ensure that patients have realistic expectations when they try a BCI. Otherwise, when BCIs fail to meet expectations, the stakeholders will be dissatisfied and disappointed. Often, media reports lead people to expect BCIs to be accurate, easy, fast, and a natural replacement for spoken language. In reality, most of the functionality that we would like to see from BCIs is still in the realm of the unknown. Current BCIs are slow, inaccurate, and somewhat awkward to learn. Many challenges remain for independent use in a home environment for everyday applications (Kathner et al., 2017; McFarland & Vaughan, 2016).

They do not read thoughts or replace natural speech. They have the function of a switch, keyboard, or mouse. While BCI functions may mimic those of standard computer input devices, BCIs may not interface with other technology, and may only function within an isolated software environment. We need to critically evaluate reports of BCI capabilities in the mass media and compare these reports to the current best evidence to correctly frame expectations and lay the groundwork for effective integration of BCIs into disability management plans.

BCI Hype Versus Reality

BCI Hype

Some hype from companies, researchers, and developers comes from a desire to set lofty goals and work for rapid advancement, an approach sometimes known as *the moonshot philosophy* (Chokshi, 2013). The thought is that, if you pick a large problem and an ideal solution and you have some evidence of scientific progress that can make that solution a reality, you can make rapid advancements. However, this approach makes it difficult to determine whether the proposed project is science advancement or science fiction. Many media announcements, especially those describing the goals of just-established projects, report timelines that make them science fiction for the practical purposes of patients. Even if these ambitious goals could be met in the proposed timeline, the result may be a demonstration of an improved prototype with much more room for improvement, not a commercial product that can immediately benefit patients.

Even when media reports make every effort to provide an objective and factual report of BCI performance, people often come away with unrealistic expectations. For example, a 60 Minutes report on BCI (Schrier Cetta, 2009) took great pains to show the long setup time required and to emphasize the slow communication rate that the BCI provided. The slow communication rate caused the 60 Minutes producers to, for the first time ever, provide questions to an interviewee before the interview so the BCI user could preprogram his responses. However, many viewers still had unrealistic expectations of communication rate and setup time.

BCI Reality

When discussing the reality of the current state of BCI research and development, it is important to remember that few aspects of BCIs have been finalized. There are still many unanswered questions and many poorly understood factors. As a cutting-edge technology, BCI functionality and usability should improve as the technology matures and testing in real-world scenarios increases.

BCI and disability. A key real-world factor is that BCI methods often do not work as well for people with physical impairments as they do for individuals from the general population (e.g., Kathner et al., 2017; Ortner et al., 2011). The conditions that cause disability and the need for a BCI may change brain activity in ways that BCIs are not yet well-designed to handle. Further, although BCIs are intended to provide access to technology without eye movements, most BCI experiments do not prevent or control eye movements. Thus, the BCI performance may depend to some degree on whether the eyes are focused on the stimuli of interest. Uncontrolled eye movements and visual impairments can interfere with BCI operation (McCane et al., 2014). This is true both for P300 and SSVEP BCIs, although both types of brain signals have been shown to be usable in BCIs without eye movement. However, to be truly useable without eye movement, the arrangement of the stimuli on the BCI display should be explicitly designed so that eye movements are not necessary. This can be done either by arranging the stimuli so closely that they can all be seen at once or by distributing them to equalize the availability of all stimuli. Riccio, Mattia, Simione, Olivetti, and Cincotti (2012) review eye gaze–independent BCIs for communication. Alternatively, visual stimuli can be replaced by either audio (Hill & Scholkopf, 2012) or tactile stimuli (Kaufmann et al., 2013), though this often comes with a reduced number of locations available for selection.

BCIs and privacy. BCIs do not read minds. They interpret brain activity in response to stimuli or, sometimes, motor programs. This should comfort people who are concerned about privacy issues. A BCI can obtain relatively little information without the voluntary participation of the user. Of course, the inability of BCIs to read thoughts can also be considered a disadvantage because it means that real-world BCI operation does not come close to the speed that we dream a brain interface should provide.

BCIs are slow. P300 BCIs provide selection rates around five to 10 selections per minute. A theoretical maximum selection rate for P300 BCIs can be determined on the basis of how long it takes to present all options. For example, with a 36 location grid and flashes of 31.25 ms separated by 125 ms, the BCI would take 1.875 s to present all options. If the BCI could make a selection immediately after all locations have flashed once, that would give a maximum selection rate of 32 selections per minute. This assumes that only one flash of each location is necessary for accurate selections and that the user does not need any time to identify the next target location. A more realistic maximum selection rate is 20 selections per minute (about four words per minute), with 1 second between selections to allow the user to verify correctness and choose the next selection. The speed record for BCI communication (done with implanted electrodes) is nearly eight words per minute (Pandarinath et al., 2017). Current BCIs operate well below this theoretical maximum, with selection rates of less than one word per minute (Hill, Kovacs, & Shin, 2014; Thompson, Gruis, & Huggins, 2014).

BCI applications for AAC. Historically, a gap has existed between BCI researchers and developers and AAC providers. As a result, commercial BCIs do not have strong AAC applications. BCIs tend to be stand-alone systems that are designed to interpret brain activity as commands and to use those commands within their own applications. This creates BCI systems whose features are limited to those envisioned by the BCI developers. Updates to such stand-alone systems must be implemented within the BCI itself, which often represents a duplication of features available on other devices and poses potential difficulties with intellectual property. Alternatively, a BCI could be implemented as a general purpose replacement for a physical input device. A BCI designed to operate as a plug-and-play USB keyboard was successfully used as an interface to other technology, namely, a laptop computer and a DynaWrite communication system (Dynavox Systems, LLC; Thompson et al., 2014). However, this use of BCI as an interface to other technology is not widely available. To support the most effective communication possible, future development is needed to either integrate the primary features of AAC systems and other potential communication rate enhancements into the design of BCIs or to streamline the use of BCIs as interfaces to existing AAC. Studies measuring the language performance of users communicating spontaneously in real-world settings are needed to evaluate the effectiveness of new developments as systems improve.

To date, most BCI research has focused on a category of elicited imitation tasks referred to in the BCI literature as copy-spelling. In elicited imitation tasks, a patient produces a target word, phrase, or sentence after an examiner gives explicit directions to repeat a stimulus as accurately as possible (Prutting & Connolly, 1976; Vinther, 2002). Speech-language pathologists (SLPs) routinely elicit spoken productions to assess the speech or language skills of individual patients in clinical settings. Elicited imitation tasks are used in a wide range of speech and language assessment tools (e.g., Carrow, 1974; Goldman & Fristoe, 2015; Kertesz, 2006; Semel, Wiig, & Secord, 2013).

Researchers investigating use of BCI for communication frequently elicit written imitations from their subjects using copy-spelling tasks as a primary component of research protocols. Copy-spelling tasks have been used in many studies in an effort to refine technology features in a way that improves the speed and accuracy of BCI communication control (e.g., Sheikh, McFarland, Sarnacki, & Wolpaw, 2003). Both SLPs and BCI researchers hope to help patients who need BCI systems for communication use systems in real-world settings and generate spontaneous novel utterances (K. Hill et al., 2015; Huggins, Alcaide-Aguirre, & Hill, 2016).

Researchers are beginning to study spontaneous novel utterance generation in BCI users and extend BCI use to real-world settings. These studies provide some evidence that novel utterance generation can reduce the accuracy of the BCI as a selection interface (Huggins et al., 2016), though the reduction is minimal. However, more research is needed to improve the performance of these early systems in unscripted conversational contexts.

Costs of a BCI. Cost is typically evaluated in terms of monetary expense. In this realm, a quality BCI that can be shown to rely on brain activity (instead of muscle movement) and includes dedicated letter-by-letter communication software can cost at least $20,000. Although some devices costing around $500 can be found when using *BCI* as a search term, they often include even fewer communication features, and it may not be clear whether performance relies on brain activity or muscle activity. BCI prices may drop, and BCI features may improve as technology advances. Although BCI access has not yet been shown to be reimbursable by insurance, future success in BCI for AAC will hopefully justify coverage for those with a documented need for BCI access.

Nonmonetary costs are also associated with BCI use. These include setup and maintenance time, often as an everyday investment. This time investment is required, not only of the user but also from a reliable system operator on the patient's support team. Some tasks of the system operator would be required for any AAC device. However, the system operator also must perform essential setup and maintenance tasks every time the BCI is used.

System operator support for setup and maintenance. The setup time and technical expertise required for the system operator vary according to electrode type. EEG gel electrodes require the most setup and maintenance. Setup involves adding gel under each electrode and ensuring good recording by ensuring that the gel builds a connection from the skin to each electrode. This can involve repeatedly adding gel or scrubbing the skin under the electrode. The BCI can then be used for many hours, but the quality of the initial setup is vital. Cleaning the electrodes is essential to prevent deposits on the electrodes from interfering with recording quality and degrading BCI function. Finally, the user's hair should be washed to remove electrode gel after each use. These setup and maintenance tasks can be expected to take at least 45 min per BCI use.

Active EEG electrodes, which have tiny amplifiers mounted on the head at the location of each electrode, report quicker setup times and use a different gel formula that may not have to be washed out after each use. These electrodes are more expensive and not quite as well studied, but their use can be advantageous.

Dry EEG electrodes contact the scalp directly and do not require gel. Dry electrodes can be setup quickly and require little maintenance. This setup involves appropriately positioning the electrodes for good contact with the skin and ensuring that the electrodes do not put uncomfortable pressure on the person's scalp. Electrodes must be adjusted to ensure good quality recording.

Sensors on the head make noninvasive BCIs obvious. An EEG gel cap looks like a swim cap studded with white buttons. A dry EEG headset looks more like a large set of headphones. Invasive BCI systems have the potential to be fully implanted and provide the best aesthetics. However, such systems are not generally available yet and currently use external ports and through-skin connections.

Strong SLP support. Strong SLP support is central to meeting the needs of people who use BCIs for communication. SLPs can assess language and literacy, use evidence-based practice to train users and system operators, monitor language performance, and help optimize communication rate. SLPs can also make adjustments to support continued access when users' needs change.

Conclusion

BCIs are emerging as a potential access method for people who need SGDs to communicate. SLPs should think critically about the possibility of using BCI technologies to help a patient access an SGD. SLPs should differentiate between the hype surrounding these technologies and the reality of implementing these technologies in clinical settings. When making decisions about BCI technologies, SLPs should ask whether or not a given interface supports the most effective communication possible for the patient and consider several related questions:

- What primary features of AAC systems (language representation methods, vocabulary, and methods of utterance generation) do the BCI help the user access? Are other communication rate enhancement strategies in place?
- Will the BCI support faster and more effective communication than other interface technologies on devices with similar primary features?
- Does the patient's prognosis indicate that a BCI will be necessary to support continued access to communication in the future?
- Can one or more system operators be trained to help with setup and maintenance?

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