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Noninvasive decoding of typing-related brain activity opens a new route for communication brain-computer interfaces

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The Innovation Neurology

Dear Editor,

Language is the most direct channel through which humans express intention, emotion, and identity. For people with paralysis, anarthria, amyotrophic lateral sclerosis, brainstem stroke, or locked-in syndrome, the loss of speech or motor control can therefore mean more than impaired communication; it can sever a fundamental link to social participation and autonomy. Brain-computer interfaces (BCIs) offer a route to restore this link by translating neural activity into text or speech. Compared with noninvasive BCIs, invasive systems generally offer superior performance, but they also involve surgical risks and long-term stability challenges. Recently, however, a study by Lévy et al., which decoded typed sentences from noninvasive brain recordings (Figure 1A), marks an important step toward safer and more accessible communication BCIs.[1]

SPEECH- AND TYPING-BASED COMMUNICATION BCIs

For individuals who lose the ability to speak or move, communication often becomes slow, effortful, and dependent on caregivers or assistive devices. Eye-tracking systems, switch-based interfaces, and spelling boards can provide effective communication for some users, although their suitability varies according to residual motor control and clinical context. Language-centered BCIs aim to restore this missing link by translating neural activity associated with intended speech, imagined speech, handwriting, or typing into text or synthesized voice.[1-5]

Recent invasive neuroprostheses have demonstrated that this goal is technically achievable (Figure 1B).[3] Intracortical speech BCIs have decoded attempted speech into text at increasingly practical speeds, including large-vocabulary sentence decoding in people who can no longer speak intelligibly.[2] Other systems have moved beyond text by generating streaming synthesized voice from neural activity, thereby approaching the temporal dynamics of natural spoken interaction.[3] Meanwhile, attempted finger movements can support rapid and accurate QWERTY-style communication, taking advantage of a familiar interface that many users already understand.[4] It should be noted that although these approaches ultimately produce linguistic output, their immediate neural targets are different.

These advances reveal an important conceptual shift. Language BCIs are no longer limited to selecting letters one by one or classifying a small set of commands. They are becoming communication systems that combine neural decoding, sequence modeling, and language priors to reconstruct meaningful sentences. This matters because human communication is not only about transmitting information; it also depends on timing, agency, correction, and the ability to initiate interaction voluntarily. A clinically useful language BCI must therefore support more than accurate decoding. It should allow users to express open-ended thoughts, maintain conversational flow, and retain control over what is finally communicated.

Against this background, the study by Lévy et al. represents an important step toward safer communication BCIs. The authors introduced Brain2Qwerty, a deep learning architecture designed to decode typed sentences from noninvasive brain recordings. Brain2Qwerty was evaluated in healthy, right-handed, skilled typists who briefly memorized visually presented Spanish sentences and then physically typed them on a QWERTY keyboard while their brain activity was recorded using magnetoencephalography (MEG; specifically, superconducting quantum interference device [SQUID]) (Figure 1A) or electroencephalography (EEG). The model applied a convolutional neural feature extractor to 0.5-s neural windows aligned to known keystroke onsets, followed by sentence-level transformer modeling and a pretrained character-level language model. Several limitations should be noted: the transformer and language model operate at the sentence level and thus require the trial to conclude before an output can be produced; therefore, the system did not operate continuously or in real time. Attempted or imagined typing without overt movement was not tested.[1]

With MEG, Brain2Qwerty achieved an average character error rate of 29%, ranging from approximately 18% in the best-performing participant to 47% in the worst-performing participant. EEG performance remained substantially lower, with an average character error rate of approximately 65%. And words absent from the vocabulary had an error rate of approximately 70%. Some rare characters were not decoded above chance level. Some apparently correct sentences emerged only after sentence-level language-model correction, and no online communication speed or information-transfer rate was reported.[1] These results demonstrate that noninvasive recordings contain decodable information about overt typing, but they do not establish direct decoding of abstract language representations. Generalization was evaluated on held-out sentences rather than held-out participants or recording sessions. Because the architecture included a subject-specific linear layer, the study did not demonstrate zero-shot decoding in previously unseen individuals or leave-one-session-out robustness.[1]

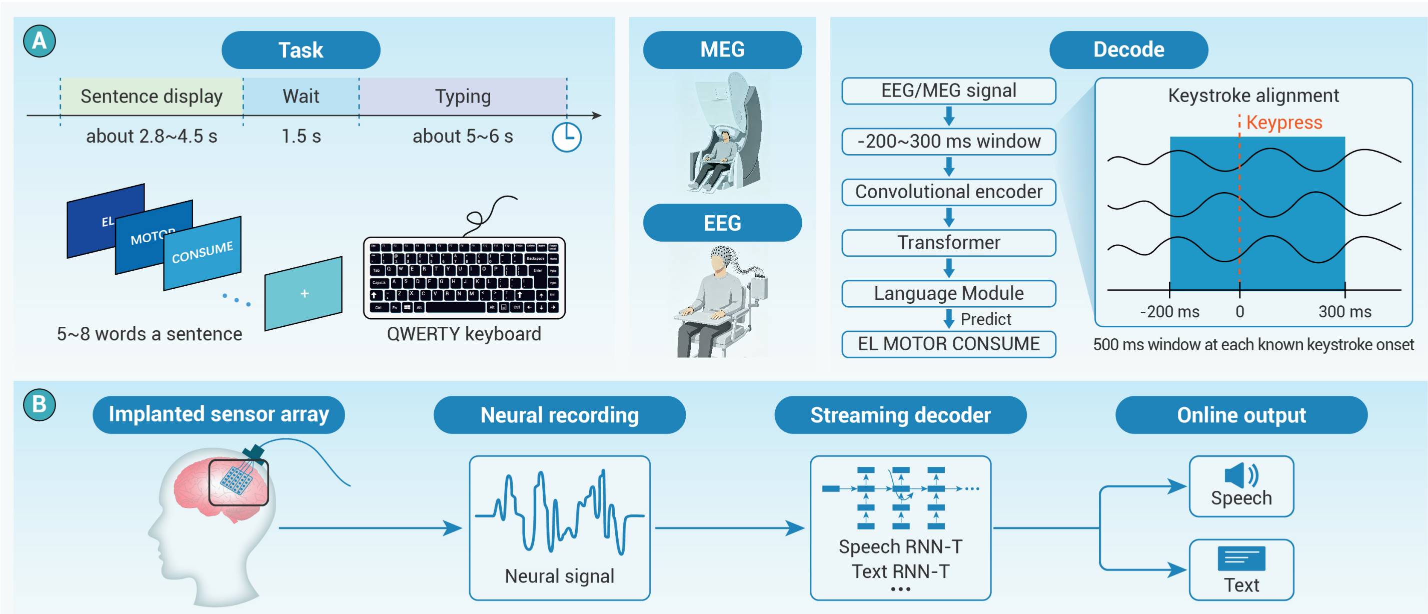
Brain2Qwerty and invasive streaming speech neuroprostheses occupy distinct positions within the broader landscape of language-centered BCIs: the former remains an offline proof of concept based on overt typing in healthy participants,[1] whereas the latter have demonstrated online communication in implanted participants.[2-3] Figure 1C extends this comparison to EEG, conventional SQUID-MEG, optically pumped magnetometer-based magnetoencephalography (OPM-MEG), electrocorticography (ECoG), and intracortical recording across multiple dimensions, including the immediate neural target, invasiveness, operation mode, validation population, and practical status.

These results show that overt typing-related neural activity recorded with MEG can support the offline reconstruction of prompted sentences. However, the experiment does not establish direct decoding of abstract or effector-independent language representations.

THE CURRENT BOTTLENECKS

Despite rapid progress, language-centered BCIs continue to face trade-offs among decoding performance, invasiveness, practical deployability, and communicative fidelity (Figure 1C). Performance values should also be interpreted cautiously across studies, because invasive and noninvasive systems differ substantially in their participants, neural targets, task constraints, vocabularies, output modalities, and evaluation metrics.[1-5]

Invasive systems currently provide the strongest demonstrations of high-throughput communication in implanted participants. Intracortical arrays have enabled large-vocabulary text decoding from attempted speech and rapid QWERTY communication from attempted finger movements, whereas high-density ECoG has supported online streaming voice synthesis from silently attempted speech.[2-4] However, they require neurosurgical implantation, carry risks of infection, hemorrhage, and hardware failure, and must remain stable over months or years. Their performance advantage is therefore constrained by a clinical and engineering burden that may limit broad adoption.



C **Multidimensional comparison of recording platforms and translational status**

Demension	EEG	SQUID-MEG	OPM-MEG	ECoG	Intracortical arrays
Signal and placement	Scalp electrical signals	Fixed-sensor magnetic recordings	On-scalp magnetic recordings	Cortical-surface field potentials	Intracortical neural activity
Immediate target in cited studies	Overt typing[1]; predefined speech imagery[5]	Overt typing and keystrokes[1]	Not evaluated in the five cited studies	Silently attempted speech[3]	Attempted speech[2]; attempted finger movements[4]
Operating mode	Offline sentence output[1]; constrained real-time classification[5]	Offline; output after trial[1]	Not evaluated in Brain2Qwerty	Online streaming text and voice[3]	Online speech text[2] or user-paced QWERTY typing[4]
Validation population	Healthy participants[1,5]	Healthy skilled typists[1]	No communication validation in the cited studies	One implanted participant with paralysis[3]	One speech participant[2]; two typing participants[4]
Practical status	Comparatively portable	Fixed 306-channel laboratory system	Emerging wearable possibility	Requires cortical-surface implantation	Requires intracortical implantation
Principal limitation	Limited open-ended accuracy and signal variability	Infrastructure, known keystroke timing, no patient transfer	Communication performance and deployability not established	Surgery, small sample and long-term stability	Surgery, small samples and long-term stability

Figure 1. Representative communication brain-computer interface approaches and their translational limitations (A) Schematic overview of the Brain2Qwerty experimental task and decoding pipeline.[1] (B) Schematic overview of an invasive speech neuroprosthesis. (C) Multidimensional comparison of EEG, conventional SQUID-MEG, OPM-MEG, ECoG and intracortical recording platforms. The approaches differ in signal type, immediate neural target, operating mode, deployment requirements and current validation status. OPM-MEG is presented separately as an emerging wearable recording approach and was not evaluated in Brain2Qwerty.[1-5] Panels A and B were created by the authors based on the experimental paradigms and system architectures described by Lévy et al. and Littlejohn et al. respectively.[1,3]

Brain2Qwerty illustrates both the promise and the present limitations of noninvasive decoding. In healthy skilled typists performing overt finger movements, offline MEG decoding achieved an average character error rate of 29%, compared with 65% for EEG. However, the neural windows were aligned to known keystroke onsets, and each sentence-typing trial had to conclude before an output could be produced. The study therefore demonstrates offline reconstruction of overt typing-related activity, rather than self-paced online communication or decoding in people unable to move.[1] Importantly, the experiment used a conventional 306-channel fixed-sensor system—that is, conventional SQUID-MEG—not OPM-MEG. Although Lévy et al. identify OPM as a possible route toward wearable MEG, no OPM-MEG data were collected or evaluated in Brain2Qwerty.[1]

The form of communication is another bottleneck. Speech-based BCIs decode rapidly evolving articulatory, phonemic, or acoustic sequences and may support low-latency synthesized voice, whereas typing-based BCIs decode finger- or keystroke-related sequences into characters, which offer clearer discrete units, easier correction, and compatibility with existing digital interfaces.[1-4] Their reported speeds and error rates are not directly comparable because the underlying neural signals, participants, task constraints, vocabularies, and output metrics differ substantially. A central challenge is therefore to determine whether these modality-specific decoders can operate continuously and voluntarily, remain stable across sessions and users, and transfer to individuals with little or no residual movement.

FUTURE DIRECTIONS

Toward natural, context-aware communication

The next generation of language BCIs should no longer be evaluated solely by decoding accuracy, but by their ability to support natural, context-aware, and fluent communication. A practical system will need to infer when a user intends to communicate, decode language incrementally, and provide rapid feedback for correction. Accordingly, net communication rate, real-time throughput, and asynchronous intention detection should be treated as explicit evaluation criteria; these measures are discussed further below in relation to patient-centered evaluation.

Clinical validation in target populations

Future studies must validate language decoding in the populations who need these systems most. Many noninvasive studies still mainly rely on healthy participants, whereas invasive clinical studies often involve only a very limited number of patients with specific conditions. Future work should therefore place greater emphasis on clinical populations, expanding both the sample sizes and the diversity of diseases represented, and should also include leave-one-participant-out and leave-one-session-out evaluations, quantify the calibration required for each new user and recording session, and test transfer from healthy overt typing to attempted or imagined typing in target populations.

Recording platforms and multimodal interfaces that balance safety and performance

The field needs recording platforms that balance signal quality, procedural safety, and practical deployability. In Brain2Qwerty, conventional SQUID-MEG achieved a lower average character error rate, but the study did not evaluate OPM-MEG, which, although considered a possible future route toward wearable MEG, faces challenges involving magnetic shielding or active field compensation, sensor calibration, movement artifacts, setup complexity and cost; OPM-MEG should therefore be regarded as an emerging platform rather than an established communication technology.[1] Future studies should compare EEG, SQUID-MEG, and OPM-MEG in matched tasks and participants, assessing not only decoding performance but also calibration burden, repeated-use feasibility, real-time throughput, and clinical usability. Improvements in sensors and decoding models may make the trade-offs among signal quality, safety, and deployability more manageable, although invasive and noninvasive systems remain at substantially different stages of clinical validation. No single recording modality is likely to meet the needs of all users. Depending on the user's residual abilities, clinical condition, communication goals, and acceptable risk, neural decoding could be combined with residual motor or electromyographic signals, eye gaze, switch-based input, or explicit confirmation signals. These complementary channels may support asynchronous intention detection, error correction, and fallback communication when the neural decoder is uncertain.

Patient-centered metrics, language-model transparency, and user agency

Communication BCIs should be evaluated using patient-centered metrics. Decoding accuracy or error rate is important, but output latency, communication rate, calibration time, performance across sessions, false activations during periods of intended silence, correction burden, fatigue, and long-term reliability are equally critical.[1-4] As language models become more deeply integrated into neural decoding, studies should report performance both before and after language-model integration. The system should also indicate when a prediction is uncertain or has been substantially altered by the language model. In such cases, users should be able to reject the proposed output, select among alternative candidates, correct individual characters or words, or explicitly confirm the complete message before it is transmitted. The time required for these correction and confirmation procedures should be included when calculating net communication rate.

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AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

ETHICAL STATEMENT AND PATIENT CONSENT

Not applicable.

DATA AND CODE AVAILABILITY

Data are available from the corresponding author upon reasonable request.