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Neuralink and Brain–Computer Interfaces: Engineering the Link Between the Human Brain and Machines

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Abstract

An implanted brain–computer interface (BCI) allows a person with a disability to Paralysis use a computer to read the activity of motor-cortex neurons. Its performance is largely dependent on two factors:It depends primarily on the number of how many and how long recording channels it can record from. keep working.

This paper takes an engineering perspective on the Neuralink N1 implant. point of view. It is made of flexible polymer threads that are able to bend. robots installed in the brain connected to electronic devices embedded in the robot. implant itself. We take the specifications that the company has. published or reported, use them to work out data-rate and insertion-time budgets, and build a synthetic motor cortex to see how The more the channels and to the loss, the better the decoding quality. of whole threads.

For our simulation, we achieved the best result with a decoder using a Kalman filter. $R^2 = 0.200 \pm 0.055$ with 16 channels, 0.866±0.004 with 1024 channels, and 0.917±0.006 with 3072 channels. After 85% of the Because the decoder that didn't change, it fell to, a negative R^2 (−0.096±0.146), even though its correlation was still 0.777. Reconfiguring decoder to the ones that still existed brought R^2 back up to 0.661±0.020.

It would take 1024 channels of raw samples to be streamed off the device. The data rate is approximately 205 Mb/s, which is approximately 1250 times the data rate required for binned spike. counts. The reason for compression is that gap. implant. All the simulated results are based on the assumed data and are stated assumptions, therefore they are only pointing in the direction – not necessarily. measurements of the real device.

Keywords : Brain–computer interface, intracortical recording, Neuralink, flexible electrodes, neural decoding, Kalman filter, channel scaling.

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I. INTRODUCTION

A spinal-cord injury, a brainstem stroke or motor-neuron disease can sever the link between the brain and the muscles it controls. An intracortical brain–computer interface goes around the break. It records the electrical activity of motorcortex neurons and turns that activity into commands for a cursor, a keyboard or a robotic limb [1], [2].

Research groups have already shown what this can achieve. Recorded neural activity has been used to drive a robotic arm, to produce text from attempted handwriting, and to convert attempted speech into written words and synthetic voice [3]– [6].

A single idea runs through most of BCI engineering: a decoder can only be as good as the signals it receives. Recording from more neurons at once generally reveals more about the movement the user intends [18], but the cost is heavier data processing and a longer list of engineering problems.

Older rigid silicon arrays carry roughly one hundred contacts [9]. Newer silicon probes offer hundreds or even thousands of recording sites, although whether they are suitable for chronic implantation depends on the use case [10]. Biology adds a further obstacle: the brain reacts to foreign material left inside it, and that reaction can slowly erode signal quality [13].

In 2019 Neuralink published a technical description of flexible electrode threads, a surgical robot and custom electronics for high-channel-count recording [7]. That research platform supported up to 3072 electrodes, while the human N1 implant has been reported to carry 1024 electrodes spread over 64 threads [8].

Accounts of the first human participant in 2024 described threads pulling out of position and fewer electrodes giving useful signals. Software changes made afterwards were reported to bring performance back up [22], [23]. These events raise two engineering questions:

1) How quickly does decoding accuracy rise as the number of channels grows?
2) How many channels can be lost before a decoder fails, and how much of the damage can retraining repair?

We address both with an openly specified simulation. We do not claim to measure how the real Neuralink implant performs. The paper makes four contributions:

1) A consolidated description of the N1 signal chain that keeps published specifications apart from company statements and press reports.
2) Data-rate and insertion-time budgets calculated from the reported specifications.
3) A reproducible synthetic motor-cortex simulation that compares ridge-regression and Kalman-filter decoders.
4) A thread-loss experiment that contrasts an unchanged decoder with one refitted to the surviving channels.

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II. PROBLEM STATEMENT AND RESEARCH GAP

A. Engineering Requirements

A usable implanted BCI has to satisfy several demands at once. It must record from many neurons over a long period, keep surgical risk low, digitize and transmit data without exceeding power and heat limits, decode intent in real time, and continue to work as the neural signals drift.

Some of these demands work against each other. Every added electrode produces more data to handle. Thinner, more flexible threads may disturb less tissue, but they are harder to implant and harder to hold in position.

B. Research Gap

Most clinical BCI studies used arrays with far fewer channels than the thousand-channel systems now being proposed. What the public knows about the performance of Neuralink's human N1 implant comes mainly from company updates and news coverage, not from a full independent technical evaluation [8], [22], [23].

What is missing is a clear picture of how channel count, channel loss and decoder adaptation interact in a BCI with a very large number of channels.

The neural recordings are not public, so outside researchers cannot fully reproduce the reported human results. A simulation is no substitute for real data. It does, however, force the underlying assumptions into the open and lets us explore what different channel configurations would imply.

The gap we address is therefore the lack of a single transparent analysis that brings together channel-count scaling, threadloss scenarios, decoder retraining and data-rate estimates for an implant of the Neuralink type.

III. AIM AND OBJECTIVES

A. Aim

We aim to explain, using published sources and a transparent simulation, how channel count, thread design, onchip processing and decoder adaptation shape the engineering performance of the Neuralink N1 implant.

B. Objectives

1) Collect the platform specifications and judge how reliable each source is.
2) Calculate data-rate and insertion-time budgets from the reported figures.
3) Build a synthetic motor-cortex simulator whose assumptions are stated explicitly.
4) Measure decoding accuracy from 16 to 3072 channels with ridge regression and a Kalman filter.
5) Test the effect of losing 0–90% of threads, both with and without retraining the decoder.
6) Separate what the simulation supports from what cannot be concluded without real neural recordings.

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IV. LITERATURE REVIEW

A. Intracortical BCIs for Movement and Communication

Hochberg et al. showed that a person with tetraplegia could steer a computer cursor and a robotic hand using intracortical recordings [2]. Collinger et al. later reported high-performance neuroprosthetic control by another individual with tetraplegia

[3].

Pandarinath et al. examined how an intracortical BCI can support communication for people with paralysis [17], and Willett et al. then demonstrated fast brain-to-text communication based on attempted handwriting [4].

Two studies in 2023 turned attempted speech into usable communication outputs [5], [6]. Taken together, this body of work shows how much rests on recording quality and on decoders tuned to the individual participant.

B. Recording Hardware and Tissue Response

The Utah array became a standard tool for intracortical research [9]. High-density silicon probes later multiplied the number of recording sites that can be placed in neural tissue

[10].

Hong and Lieber surveyed electrode technologies for neural recording, including flexible and nanoscale designs [11]. Luan et al. studied ultraflexible nanoelectronic probes intended to blend into the surrounding tissue [12]. Polikov et al. reviewed how brain tissue responds to electrodes that stay in place for long periods [13].

Together, these papers give a reason to look at flexible electrode threads as a route to stable long-term recording.

C. Decoding Neural Activity

Georgopoulos et al. showed that populations of motorcortex neurons encode the direction of movement [14]. Wu et al. treated decoding as a state-space estimation problem and solved it with a Kalman filter [15], building on the classical filter of Kalman [20]. Gilja et al. found that careful design of the decoder and the control algorithm can raise neuralprosthesis performance considerably [16].

Trautmann et al. estimated neural population dynamics without conventional spike sorting [19]. Methods like this matter for systems that have to handle very many channels efficiently.

D. Diminishing Returns from Increasing Channel Count

Stevenson and Kording discussed how progress in recording technology changes the way neural data are analysed and how much information can be drawn from neural populations [18].

Extra channels can raise decoding accuracy, but nearby neurons often carry overlapping information about the same movement. Each new channel may therefore add less than the one before it.

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Shannon's framework supplies the mathematics for information rates [21]. We use an information-rate proxy only to compare simulated conditions with one another.

E. The Neuralink Platform

The Neuralink technical publication describes a research platform with up to 3072 electrodes on 96 threads. Threads were inserted at a reported six per minute, equal to 192 electrodes per minute. The publication also covers the onboard amplification and digitization electronics [7].

The human N1 implant has been reported to hold 1024 electrodes on 64 threads [8]. Coverage in 2024 described thread displacement in the first participant and later software changes meant to improve performance [22], [23].

Any reported human performance figure has to be read in light of its source. Company statements and press articles do not carry the weight of independently evaluated clinical-trial results.

F. Open Research Questions

Several questions remain open: how nominal channel count relates to usable information, how many surviving channels effective decoding needs, and how far retraining can make up for lost channels.

This study does not attempt to provide clinical performance. Its The purpose of these simulations is to give a clear one for a study of these. engineering relationships.

V. PROPOSED FRAMEWORK AND SYSTEM ARCHITECTURE

Activity in the motor cortex is the origin of the BCI signal chain. Electrodes on the flexible threads are able to detect the signals and electronics processes the data. The implant detects, amplifies and digitizes them. Signal processing then From the processed data, extracts useful features and the processed data is transmitted through a wireless link. Data Transfer to external device.

A decoder converts the data into an estimation of what was intended A mouse or other type of device that is compatible with movement to operate a cursor. The user watches the result on screen and can adjust to the system in response. Our analysis has three parts:

- Specification ledger: a record of each reported parameter together with its source.
- Budget calculator: estimates of data rates and electrode insertion time.
- Simulator and decoders: a generator of synthetic neural activity, used to test channel scaling and thread loss.

VI. SPECIFICATION DATA AND SOURCE PROFILE

A. Specification Ledger

Table I lists the platform specifications used throughout this study.

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B. Source Reliability and Interpretation

The 3072-electrode figure refers to the research platform for 2019, and the 3072-research-stations figure refers to the research stations for 2019. The human N1 reported implant has 1024 electrodes. The two The configuration should never be confused for the others.

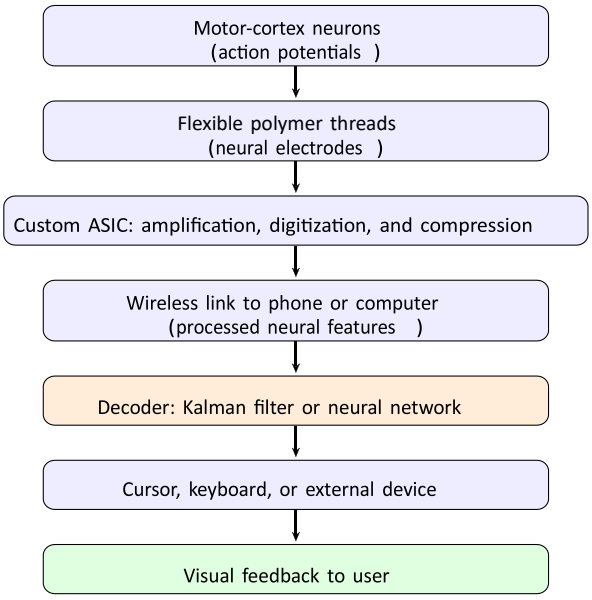


Fig. 1. Signal chain of an intracortical BCI as analysed in this study. The diagram represents a conceptual architecture, not a complete circuit design of the Neuralink N1 implant.

he human performance figures that are available to us, are from company. Statements, participation interviews and media coverage. As evidence, they rank below a complete, independently reviewed clinical-trial report.

Terminology needs care as well. Electrodes, channels, effective electrodes and recording yield are related but not identical quantities. Here, a usable channel means one that delivers a usable neural signal.

We treat the reported 85% thread displacement as a scenario for stress-testing the model. It is not an independently verified measurement.

C. Derived Insertion-Time Estimates

The reported insertion rate is six threads per minute. For the 96-thread research platform, this gives:

$$T_{96} = \frac{96}{6} = 16 \text{ minutes.} \qquad (1)$$

For the 64-thread N1 configuration:

$$T_{64} = \frac{64}{6} \approx 10.67 \text{ minutes.} \qquad (2)$$

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These are theoretical times at the stated rate. A real operation takes longer, because it also involves preparation, imaging, positioning and other clinical steps.

Taking the reported maximum chronic spiking yield of 70%, a 3072-electrode array would in theory provide this many usable channels:

$$C_{\text{usable}} = 0.70 \times 3072 \approx 2150. \quad (3)$$

If 85% of the 64 threads in a 1024-electrode N1 implant were unavailable, about 10 threads would remain, which is 160 electrodes under the model's assumptions.

TABLE I SPECIFICATION LEDGER AND SOURCE RELIABILITY

Parameter	Reported Value	Source
Research-array electrodes	3072 on 96 threads	Neuralink technical publication [7]
Insertion rate	6 threads (192 electrodes) per minute	Neuralink technical publication [7]
Package dimensions	Less than 23×18.5×2 mm^3	Neuralink technical publication [7]
Chronic spiking yield	Up to 70%	Neuralink technical publication [7]
Human N1 electrodes	1024 on 64 threads; 16 electrodes per thread	Company and press reports [22], [23]
Threads reportedly displaced in first participant	Approximately 85%	Participant interview reported in the press [22]
Reported cursor-control rate	Approximately 8 bits/s	Company statement reported in the press [22]
Working electrodes in second participant	Approximately 400 reported by the company's CEO	Press report [24]

VII. RESEARCH METHODOLOGY

A. Synthetic Motor-Cortex Model

We represent the intended cursor velocity as a twodimensional autoregressive process:

$$\mathbf{v}_t = 0.95\mathbf{v}_{t-1} + 0.3\epsilon_t, (4)$$

and standardize it to unit variance on each axis.

Every channel i is assigned a preferred movement direction θ_i drawn uniformly around the circle, a baseline firing rate $b_i \sim U(5,15)$ Hz, and a tuning depth $m_i \sim U(0.3,2.0)$ Hz. The firing rate of a channel is modelled as:

$$\lambda_i(t) = \max\left\{0, \left[b_i + m_i \mathbf{d}_i^T \mathbf{v}_t\right] g(t) + \mathbf{w}_i^T \mathbf{l}(t)\right\}, \quad (5)$$

where $\mathbf{d}_i$ is the unit vector pointing in the preferred direction

of channel i.

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The shared gain $g(t)$ has a mean close to 1 and a standard deviation close to 0.1. The latent process $\mathbf{l}(t)$ stands for shared activity unrelated to movement. It has three dimensions, each following an autoregressive process with coefficient 0.97, and its loading vector is drawn from a normal distribution with standard deviation 1.2.

The spike count in each 50 ms bin is then sampled as:

$$n_i(t) \sim \text{Poisson}(\lambda_i(t)\Delta), \qquad \Delta = 0.05 \text{ s}. \qquad (6)$$

The model mimics multi-unit threshold-crossing counts. It is synthetic and leaves out much of the biological complexity of the human motor cortex.

B. Simulation Parameters C. Ridge Regression Decoder

The ridge-regression decoder takes a three-bin moving average of the neural counts and maps it to cursor velocity. The regularization penalty is chosen from the set:

$$\alpha \in \{1, 10, 10^2, 10^3, 10^4\}. \quad (7)$$

TABLE II

SIMULATION PARAMETERS

Parameter	Value
Bin width / session length	50 ms / 800 s
Total bins	16,000
Training / testing split	70% / 30%, contiguous
Baseline rate b	$U(5,15)$ Hz
Tuning depth m	$U(0.3,2.0)$ Hz per unit speed
Shared gain $g(t)$	Mean 1, SD about 0.1
Latent noise	3 dimensions, AR(1) coefficient 0.97
Noise loadings	$N(0,1.2^2)$
Channels per thread	16
Threads in the N1 configuration	64
Random seeds	0–5 (six runs)

The last fifth of the training data serves as a validation set for this choice. The test segment plays no part in model selection.

D. Kalman-Filter Decoder

The Kalman filter [20] describes the system through a statespace model:

$$\mathbf{x}_t = A\mathbf{x}_{t-1} + \mathbf{w}_t, \qquad (8)$$

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$$\mathbf{z}_t = H\mathbf{x}_t + \mathbf{q}_t, \qquad (9)$$

where $\mathbf{x}_t$ is the intended velocity and $\mathbf{z}_t$ holds the mean-

centred neural counts.

We estimate A and H from the training data. The noise covariances come from the residuals, and the observation covariance matrix Q is assumed to be diagonal.

To keep the computation tractable at large channel counts, the implementation applies the update in information form.

E. Experiment 1: Channel Scaling

This experiment covers the following channel counts:

$$C \in \{16,32,64,128,256,512,1024,2048,3072\}. \quad (10)$$

For each setting we take the first C channels of the same synthetic population and use them to train and test both decoders.

F. Experiment 2: Thread Loss

Here the 1024 channels are arranged as 64 threads of 16 channels each.

The decoder is trained on the full array. During the test segment, randomly chosen threads are then removed. The loss levels simulated are:

$$L \in \{0,25,50,75,85,90\}\%. \qquad (11)$$

We compare two conditions:

1) Stale decoder: the original decoder keeps being used, and the missing channels simply report zero counts.
2) Retrained decoder: a new decoder is fitted to the channels that survive.

Retraining is meant to stand in for a recalibration session after channels are lost. It does not capture every detail of the clinical software changes reported for Neuralink.

G. Information-Rate Proxy

When two variables are jointly Gaussian, the correlation ρ between true and decoded velocity can be converted into an information proxy:

$$I = -\frac{1}{2}\log_2(1-\rho^2). \qquad (12)$$

With two velocity axes and a bin width Δ, the rate becomes:

$$I_{\text{rate}} = \frac{2\left[-\frac{1}{2}\log_2(1-\rho^2)\right]}{\Delta}. \qquad (13)$$

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This is an idealized proxy for continuous velocity. It is not a measured communication rate from a real task, and we use it only to rank the simulated conditions against each other.

H. Data-Rate Estimation

The raw data rate is computed as:

$$R_{\text{raw}} = Cf_s b, \qquad (14)$$

where C is the channel count, f_s the sampling rate and b

the number of bits per sample.

For binned features the rate is:

$$R\text{feat} = Cf\text{bin}bc, \quad (15)$$ where f_{bin} is the bin rate and b_c the number of bits used

for each count.

For illustration we assume raw sampling at 20 kS/s with 10 bits per sample, and binning at 20 bins/s with 8 bits per count. These values are illustrative and are not published N1 operating specifications.

VIII. IMPLEMENTATION AND TECHNOLOGY STACK

The simulation is written in Python 3. NumPy [26] generates the synthetic neural activity and handles the numerical work, scikit-learn [25] provides the ridge regression, and Matplotlib produces the plots.

Fixed random seeds from 0 to 5 make the experiments reproducible. On an ordinary CPU, the reported implementation needed about 220 seconds to run all six seeds. The software stack is:

- Python 3 as the implementation language.
- NumPy for simulation and linear algebra.
- Scikit-learn for ridge regression.
- Matplotlib for plotting the results.

IX. EXPERIMENTAL SETUP AND EVALUATION METRICS

One 800 second synthetic session per random seed is generated. The first 70% is used for training and the last 30% is held out for testing.

There are 4800 bins in the test segment, equivalent to 240 seconds. The test data is not used to tune any model parameter.

Standard deviation σ for every pair of variables.For each pair of variables, we report the Pearson correlation coefficient ρ and the To obtain the coefficient of determination R^2 for each, the data must be averaged over the two runs. velocity axes.

Data are reported as means and standard deviations for the data sets. six random seeds.

R^2 is especially informative here, because correlation by itself can hide errors in scale and offset.

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X. RESULTS AND DISCUSSION

A. Channel Scaling

Table III shows how decoding performance changes as the number of usable channels increases.

Here, R^2 is particularly useful, since the correlation alone Can mask scale and offset errors. The Kalman decoder used 16 channels, which covered about 20%. the velocity variance. This increased to 87% at 1024 channels. 92% at 3072 channels.

Moving from 1024 to 3072 channels raised R^2 by only about 0.051, It increased by around 0.135 when the number of channels was increased from 256 to 1024.

The curve thus levels off when the number of channels is high. The Kalman filter outperformed ridge regression during the whole simulation, The margin was slightly reduced at higher channel counts, though. As more channels went down, the stale decoder steadily degraded. Its R^2 dropped below 0 when it lost 85Were not as accurate as just taking the average of the target.

B. Effect of Thread Loss

Table IV contrasts the stale decoder with the decoder retrained on the surviving channels.

Regardless of this, its correlation remained at 0.777. This demonstrates how correlation. Can make a broken decoder better looking than it is alone.

TABLE III

DECODING ACCURACY VERSUS CHANNEL COUNT (MEAN ± SD OVER SIX SEEDS)

Channels	Ridge R^2	Kalman ρ	Kalman R^2	Proxy (bits/s)
16	0.132±0.031	0.487	0.200±0.055	7.9
32	0.230±0.036	0.603	0.345±0.053	13.1
64	0.373±0.040	0.707	0.494±0.035	20.0
128	0.537±0.031	0.791	0.622±0.031	28.5
256	0.690±0.015	0.856	0.731±0.018	38.1
512	0.786±0.009	0.900	0.809±0.009	48.0
1024	0.853±0.005	0.932	0.866±0.004	58.6
2048	0.884±0.004	0.951	0.902±0.007	67.8
3072	0.895±0.004	0.959	0.917±0.006	72.9

TABLE IV

THREAD LOSS WITH 1024 CHANNELS (MEAN ± SD OVER SIX SEEDS)

Threads Lost	Stale ρ	Stale R^2	Retrained ρ	Retrained R^2
0% (1024 channels)	0.932	0.866±0.004	0.932	0.866±0.004

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25% (768 channels)	0.917	0.750±0.048	0.918	0.840±0.010
50% (512 channels)	0.896	0.457±0.110	0.900	0.808±0.006
75% (256 channels)	0.839	0.031±0.180	0.860	0.738±0.014
85% (160 channels)	0.777	−0.096±0.146	0.815	0.661±0.020
90% (96 channels)	0.700	−0.231±0.197	0.769	0.587±0.026

Retraining on the remaining channels gained a significant proportion of the lost performance. The retrained decoder achieved $85R^2 = 0.661 \pm 0.020$.

Under the assumptions of the simulation, this suggests that adapting the decoder can offset a good part of the damage from channel loss.

C. Data-Rate and Insertion Budgets

Table V gives the illustrative data-rate estimates.

TABLE V

ILLUSTRATIVE DATA-RATE BUDGET

Array	Raw Mb/s	Counts kb/s	Ratio
1024 channels (N1)	204.8	163.8	1250×
3072 channels (2019)	614.4	491.5	1250×

According to the assumptions of the simulation, the adaptation of The decoder is able to mitigate much of the impact of channel loss. The raw data for 1024 channels would be assumed in the following way: The stream of binned counts would require about 204.8 Mb/s, but. only about 163.8 kb/s.

A gap this big is reason enough for wireless implants to have to process and compress data locally. The figures are based on the data obtained from sampling. and the encoding parameters which we assumed, must not be read as measured

Neuralink specifications.

D. Engineering Implications

The experiments give rise to three conclusions.

More channels assist in decoding, but each one does a little to help less. than the last. Keeping channels alive over the long term may The names of the array are therefore as important as the size of the array. The thread displacement episode is a reminder that outcomes in the media are not necessarily an accurate representation of reality. Individuals are able to deviate from engineering expectations. Company statements, interviews with participants and journalism provide helpful background, They are not comparable to the independent clinical assessment.

Second, once a system is impaired, the number of surviving channels counts for more than the number the device started with. In our simulation, a retrained 1024-channel decoder with 50% of its threads lost reached an R^2 close to that of an intact 512-channel array.

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Third, a larger nominal array may act as a cushion against channel loss. This depends on the assumptions of the synthetic model and says nothing definite about how a real implant would perform in a patient.

E. Limitations of the Evaluation

The simulation runs on synthetic neural data, not on real Neuralink recordings. It assumes cosine-like tuning, tuning that stays fixed within a session, and channels that are independent of each other apart from three shared latent factors.

Thread loss in the simulation is random. In practice, which channels fail may depend on surgical placement, anatomy or other factors the model does not include.

The retrained condition is on the optimistic side, because it takes for granted that a suitable recalibration procedure exists after channels are lost. Real users also adapt to their decoder, and that adaptation is not modelled here.

Finally, the information-rate proxy is not a measured tasklevel communication rate, and small differences between decoders should not be read too heavily.

XI. ETHICAL CONSIDERATIONS AND LIMITATIONS

A. Neural Data Privacy

Recordings from the motor cortex hold information about movement intent and may expose other sensitive details as well. In India, the Digital Personal Data Protection Act, 2023 bears on the wider question of protecting personal data [27]. Neurotechnology also raises issues of mental privacy, personal autonomy and responsible handling of data [28].

B. Safety and Clinical Claims

The thread displacement episode is a reminder that outcomes in people can depart from engineering expectations. Company statements, participant interviews and journalism give useful background, but they are not equal to independent clinical evaluation.

C. Long-Term Responsibility

It is necessary to make long term maintenance arrangements for an implanted system, Technical assistance/support, software updates and, if applicable, removal. of the device. A clear statement should be made to participants who have these. responsibilities.

D. Access and Fairness

Only a fraction of the population will be able to afford a neural implant: it is complex and expensive. They might be able to be used by a small group of people. Wider adoption would depend on affordability, clinical capacity, training and fair access.

E. Scope of This Paper

This paper analyses a synthetic model of an implant of the Neuralink type. It makes no assessment of the real clinical safety or efficacy of the N1 device.

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XII. FUTURE SCOPE

This study could be extended in several directions:

- Real recordings: rerun the experiments on public intracortical datasets such as the Neural Latents Benchmark

  [29].

- Closed-loop users: add a simulated user who adapts to how well the decoder performs.
- Tuning drift and correlated loss: model slow changes in neural tuning and loss patterns tied to electrode position.
- Power and thermal limits: link the data-rate budget to an energy model of the implant electronics.
- Richer decoders: compare recurrent neural networks and adaptive Kalman-filter variants against the decoders used here.
- Task-level communication rates: convert decoded velocity into a selection-task rate, which would allow a more meaningful comparison with reported performance.

XIII. CONCLUSION

We researched the Neuralink N1 implant with sources that were published. transparent simulation.

The source review demonstrates that a technical design is documented in the source review. Several of the reported human results, however, were published in company journals, while the others were published in other journals. Leave it up to the company to keep you updated and informed via press releases.

In the simulation, decoding accuracy climbs quickly as channels are added and then gains less and less at higher channel counts. Heavy thread loss badly damages a decoder that is not retrained, and retraining restores part of the lost performance as long as enough channels remain.

The data-rate calculations also show that raw sampling needs far more bandwidth than a stream of binned neural features, which supports doing processing and compression on the device itself.

These conclusions are qualitative and depend on synthetic data and stated assumptions. Later work should test them on real neural recordings and on independently reported human trials.

REFERENCES

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, “Brain–computer interfaces for communication and control,” *Clinical Neurophysiology*, vol. 113, no. 6, pp. 767–791, 2002.
[2] L. R. Hochberg et al., “Neuronal ensemble control of prosthetic devices by a human with tetraplegia,” *Nature*, vol. 442, pp. 164–171, 2006.
[3] J. L. Collinger et al., “High-performance neuroprosthetic control by an individual with tetraplegia,” *The Lancet*, vol. 381, no. 9866, pp. 557– 564, 2013.

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[4] F. R. Willett, D. T. Avansino, L. R. Hochberg, J. M. Henderson, and K. V. Shenoy, "High-performance brain-to-text communication via handwriting," *Nature*, vol. 593, pp. 249–254, 2021.
[5] F. R. Willett et al., "A high-performance speech neuroprosthesis," *Nature*, vol. 620, pp. 1031–1036, 2023.
[6] S. L. Metzger et al., "A high-performance neuroprosthesis for speech decoding and avatar control," *Nature*, vol. 620, pp. 1037–1046, 2023.
[7] E. Musk and Neuralink, "An integrated brain-machine interface platform with thousands of channels," *Journal of Medical Internet Research*, vol. 21, no. 10, Art. no. e16194, 2019. doi: 10.2196/16194.
[8] Neuralink, "PRIME Study Progress Update," May 2024. [Online]. Available: https://neuralink.com/updates/prime-study-progress-update/
[9] E. M. Maynard, C. T. Nordhausen, and R. A. Normann, "The Utah intracortical electrode array: A recording structure for potential braincomputer interfaces," *Electroencephalography and Clinical Neurophysiology*, vol. 102, no. 3, pp. 228–239, 1997.
[10] J. J. Jun et al., "Fully integrated silicon probes for high-density recording of neural activity," *Nature*, vol. 551, pp. 232–236, 2017.
[11] G. Hong and C. M. Lieber, "Novel electrode technologies for neural recordings," *Nature Reviews Neuroscience*, vol. 20, pp. 330–345, 2019.
[12] L. Luan et al., "Ultraflexible nanoelectronic probes form reliable, glial scar-free neural integration," *Science Advances*, vol. 3, no. 2, Art. no. e1601966, 2017.
[13] V. S. Polikov, P. A. Tresco, and W. M. Reichert, "Response of brain tissue to chronically implanted neural electrodes," *Journal of Neuroscience Methods*, vol. 148, no. 1, pp. 1–18, 2005.
[14] A. P. Georgopoulos, A. B. Schwartz, and R. A. Kettner, "Neuronal population coding of movement direction," *Science*, vol. 233, no. 4771, pp. 1416–1419, 1986.
[15] W. Wu, Y. Gao, E. Bienenstock, J. P. Donoghue, and M. J. Black, "Bayesian population decoding of motor cortical activity using a Kalman filter," *Neural Computation*, vol. 18, no. 1, pp. 80–118, 2006.
[16] V. Gilja et al., "A high-performance neural prosthesis enabled by control algorithm design," *Nature Neuroscience*, vol. 15, pp. 1752–1757, 2012.
[17] C. Pandarinath et al., "High performance communication by people with paralysis using an intracortical brain-computer interface," *eLife*, vol. 6, Art. no. e18554, 2017.
[18] I. H. Stevenson and K. P. Kording, "How advances in neural recording affect data analysis," *Nature Neuroscience*, vol. 14, pp. 139–142, 2011.
[19] E. Trautmann et al., "Accurate estimation of neural population dynamics without spike sorting," *Neuron*, vol. 103, no. 2, pp. 292–308, 2019.
[20] R. E. Kalman, "A new approach to linear filtering and prediction problems," *Journal of Basic Engineering*, vol. 82, no. 1, pp. 35–45, 1960.
[21] C. E. Shannon, "A mathematical theory of communication," *Bell System Technical Journal*, vol. 27, pp. 379–423, 1948.
[22] "What it's like to live with a brain chip, according to Neuralink's first user," *Scientific American*, 2024. [Online]. Available: https://www.scientificamerican.com/article/ neuralinks-first-user-describes-life-with-elon-musks-brain-chip/
[23] "Brain-sensing threads slip from gray matter in first human Neuralink trial," *The Register*, May 9, 2024. [Online]. Available: https://www.

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theregister.com/2024/05/09/neuralink trial update
[24] "Second patient receives the Neuralink implant," *The Register*, Aug. 5, 2024. [Online]. Available: https://www.theregister.com/2024/08/05/ second patient receives the neuralink/
[25] F. Pedregosa et al., "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
[26] C. R. Harris et al., "Array programming with NumPy," *Nature*, vol. 585, pp. 357–362, 2020.
[27] Government of India, "The Digital Personal Data Protection Act, 2023," Act No. 22 of 2023.
[28] R. Yuste et al., "Four ethical priorities for neurotechnologies and AI," *Nature*, vol. 551, pp. 159–163, 2017.
[29] F. Pei et al., "Neural Latents Benchmark '21: Evaluating latent variable models of neural population activity," in *Proceedings of the NeurIPS Datasets and Benchmarks Track*, 2021.