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New Directions in Access to Augmentative & Alternative Communication Technologies for Persons with Minimal Movement

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Three innovative approaches to improve access to AAC

1. The RSVP Keyboard™: A brain-computer interface that uses the P300 brainwave as the selection method for spelling;
2. Multi-modality access options to control smart technologies;
3. SmartPredictor: an app that permits a familiar communication partner to provide language to an AAC user during message generation.

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Learning Objectives

- **1.** Describe challenges frequently encountered in providing access to communication technologies for persons with minimal movement.
- **2.** Describe potential benefits of the use of the RSVP Keyboard™ to provide access to communication technologies for persons with minimal movement
- **3.** Describe potential benefits of the use of the multimodal access approaches to provide access to communication technologies for persons with minimal movement
- 4. Describe potential benefits of the use of the SmartPredictor app to provide access to communication technologies for persons with minimal movement

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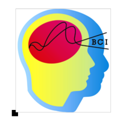

RSVP Keyboard™: A P300 brain-computer interface for spelling

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Clinical team
- Glory Noethe, Public health gerontology expert; research coordinator
- Aimee Mooney, SLP and senior research associate)
- Betts Peters, SLP and research associate
- Barry Oken, OHSU clinical neurophysiologist

NLP team
- Steven Bedrick, Assistant professor, computer science
- Andrew Fowler, PhD student
- Shiron Dudy, PhD student

Signal processing team (NEU)
- Deniz Erdogmus, Associate professor of electrical and computer engineering
- Paula Gonzalez-Navarro, PhD student

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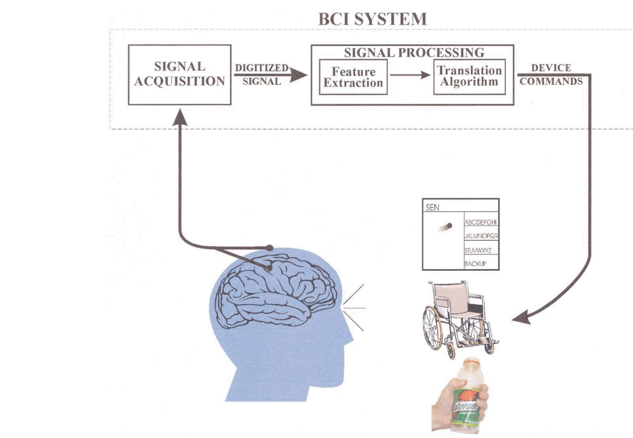

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Functions of BCI

1. Replace function (AAC; computer or wheelchair control)
2. Restore function (stimulate paralyzed muscle; bypass SCI)
3. Enhance (optimize performance for highly demanding attentional tasks such as driving)
4. Supplement (offer another modality such as gaming)
5. Improve (neurofeedback for ADHD or pain control)

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Obtaining a brain signal

- Non-invasive BCI
  - P300 brainwave for stimulus selection
  - SSVEP brainwave for stimulus selection
  - Sensorimotor rhythms for motor imagery
- Invasive BCI
  - ECoG: Placement of electrodes right on the cortext

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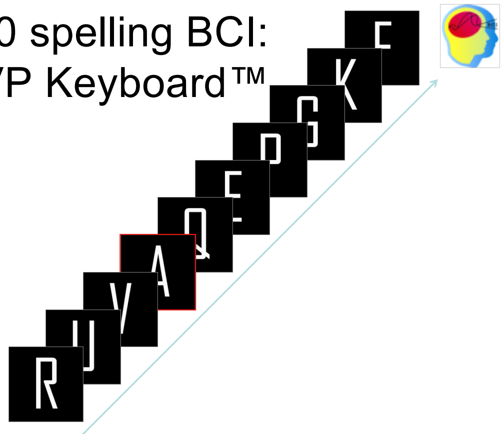
P300 spelling BCI: RSVP Keyboard™



- Oken, B., Orhan, U., Roark, B., Erdogmus, D., Fowler, A., Mooney, A., Peters, B., Miller, M., & Fried-Oken, M. (2014). Brain-computer interface with language model-EEG fusion for locked-in syndrome. Neurorehabilitation
- and Neural Repair, 28(4), 387-394. PMCID: PMC3989447.

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Non-invasive, wet electrode BCI

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RSVP

- **R**apid
- **S**erial
- **V**isual
- **P**resentation

- One symbol presented at 400 ms;
- A series of letters (epoch) presented repeatedly for P300 signal acquisition.

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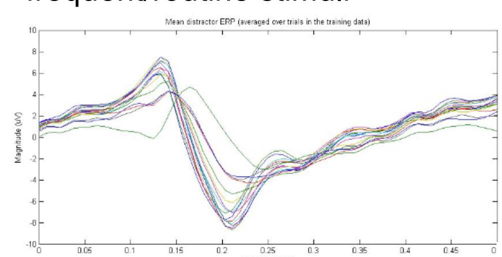
P300 Response

- Involuntary spike in EEG activity over the parietal cortex
- Indicates a salient, infrequent event following frequent/routine stimuli



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A	+
Q	E

C

M

H

A

Y	R
L	T

RSVP Keyboard™: Fusing Language Model & EEG Evidence

- RSVP Keyboard makes letter selections based on *joint evidence* from an n-gram language model and EEG signals.
- Language model is trained using large language databases:
  - *Wall Street Journal* and *New York Times* databases
  - Enron e-mails
  - User-provided previous conversations and vocabulary lists

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Vision and project goals

Vision: To make BCI available for independent use so that individuals with the most severe disabilities can return to their families, live in the community, and contribute to decision-making and medical management.

Project Objectives:

1. To improve the language model in the RSVP Keyboard™ to increase its usability for communication; and
2. To identify training interventions to improve learning and performance with the RSVP Keyboard™.

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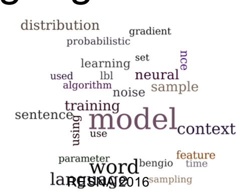
Investigating use of a BCI with enhanced language modeling



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Language Modeling

- A Language Model (LM) is a way of assigning *probability* to strings of symbols (words, letters, etc.)
- Using a large collection of real-world text, an LM learns patterns of language
- "President of the United ______"
- "FRED WAS Q_"
- Often we think of an LM in terms of conditional probability (Given X, what is the probability of Y)

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Language Models in Practice

- LMs are useful in any application where "how likely is this word/character" is a good question
  - Machine Translation
  - Smartphone Autocorrect
  - Speech Recognition
  - Spellcheck
- They are especially helpful when we want to construct text from noisy inputs

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Language Models for BCI

BCI is a very good place to use LMs
- Communication is often text-based
- Speed is essential
- Brain signal measured by scalp EEG sensors is noisy and relatively weak, often not enough on its own

- A language model can not only make a BCI typing system faster, it can make it usable

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RSVP Keyboard™

- RSVP Keyboard™ is a BCI typing system
  - Letters are typed one at a time
  - A rapid sequence of individual letters is shown to the user
  - EEG measurements are made and processed
  - This evidence is *combined* with a character-based language model
- This combination is called fusion
- When the EEG/LM evidence points strongly to a specific letter, we type it and begin again

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RSVP Keyboard™ Fusion Example

- Suppose you are typing this phrase:

  `my_respirator_is_loud`

- This is what you have so far:

  `my_respirator_is_`

- This is your target letter:

  `l`

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Symbol	LM Prob					Final Prob
a	0.207					0.207
b	0.015					0.015
c	0.018					0.018
d	0.013					0.013
e	0.145					0.145
f	0.010					0.010
g	0.012					0.012
h	0.011					0.011
i	0.021					0.021
j	0.003					0.003
k	0.002					0.002
l	0.013					0.013
m	0.283					0.283
n	0.030					0.030
o	0.015					0.015
p	0.015					0.015
q	0.001					0.001
r	0.011					0.011
s	0.033					0.033
t	0.066					0.066
u	0.006					0.006
v	0.004					0.004
w	0.011					0.011
x	0.000					0.000
y	0.003					0.003
z	0.000					0.000
[space]	0.000					0.000
[back]	0.050					0.050

Symbol	LM Prob	EEG				Final Prob
a	0.207	0.049				0.253
b	0.015	0.032				0.012
c	0.018	0.042				0.019
d	0.013	0.038				0.012
e	0.145	0.034				0.122
f	0.010	0.004				0.001
g	0.012	0.041				0.013
h	0.011	0.022				0.006
i	0.021	0.019				0.010
j	0.003	0.029				0.002
k	0.002	0.007				0.000
l	0.013	0.133				0.043
m	0.283	0.034				0.238
n	0.030	0.043				0.032
o	0.015	0.033				0.013
p	0.015	0.017				0.006
q	0.001	0.006				0.000
r	0.011	0.049				0.013
s	0.033	0.048				0.040
t	0.066	0.048				0.079
u	0.006	0.034				0.005
v	0.004	0.039				0.004
w	0.011	0.052				0.014
x	0.000	0.001				0.000
y	0.003	0.042				0.003
z	0.000	0.013				0.000
[space]	0.000	0.048				0.000
[back]	0.050	0.046				0.058

Symbol	LM Prob	EEG 1	EEG 2			Final Prob
a	0.207	0.049	0.049			0.293
b	0.015	0.032	0.015			0.004
c	0.018	0.042	0.061			0.027
d	0.013	0.038	0.050			0.015
e	0.145	0.034	0.013			0.037
f	0.010	0.004	0.029			0.001
g	0.012	0.041	0.004			0.001
h	0.011	0.022	0.001			0.000
i	0.021	0.019	0.010			0.002
j	0.003	0.029	0.022			0.001
k	0.002	0.007	0.036			0.000
l	0.013	0.133	0.160			0.163
m	0.283	0.034	0.056			0.314
n	0.030	0.043	0.053			0.039
o	0.015	0.033	0.003			0.001
p	0.015	0.017	0.060			0.009
q	0.001	0.006	0.045			0.000
r	0.011	0.049	0.008			0.003
s	0.033	0.048	0.027			0.025
t	0.066	0.048	0.010			0.018
u	0.006	0.034	0.027			0.003
v	0.004	0.039	0.025			0.002
w	0.011	0.052	0.038			0.013
x	0.000	0.001	0.061			0.000
y	0.003	0.042	0.023			0.002
z	0.000	0.013	0.052			0.000
[space]	0.000	0.048	0.042			0.000
[back]	0.050	0.046	0.019			0.026

Symbol	LM Prob	EEG 1	EEG 2	EEG 3		Final Prob
a	0.207	0.049	0.049	0.016		0.093
b	0.015	0.032	0.015	0.051		0.004
c	0.018	0.042	0.061	0.044		0.025
d	0.013	0.038	0.050	0.049		0.015
e	0.145	0.034	0.013	0.016		0.012
f	0.010	0.004	0.029	0.003		0.000
g	0.012	0.041	0.004	0.046		0.001
h	0.011	0.022	0.001	0.009		0.000
i	0.021	0.019	0.010	0.038		0.002
j	0.003	0.029	0.022	0.042		0.001
k	0.002	0.007	0.036	0.059		0.000
l	0.013	0.133	0.160	0.154		0.512
m	0.283	0.034	0.056	0.040		0.258
n	0.030	0.043	0.053	0.013		0.011
o	0.015	0.033	0.003	0.034		0.001
p	0.015	0.017	0.060	0.000		0.000
q	0.001	0.006	0.045	0.040		0.000
r	0.011	0.049	0.008	0.017		0.001
s	0.033	0.048	0.027	0.058		0.030
t	0.066	0.048	0.010	0.014		0.005
u	0.006	0.034	0.027	0.010		0.001
v	0.004	0.039	0.025	0.051		0.002
w	0.011	0.052	0.038	0.010		0.003
x	0.000	0.001	0.061	0.027		0.000
y	0.003	0.042	0.023	0.032		0.001
z	0.000	0.013	0.052	0.059		0.000
[space]	0.000	0.048	0.042	0.024		0.000
[back]	0.050	0.046	0.019	0.042		0.022

Symbol	LM Prob	EEG 1	EEG 2	EEG 3	EEG 4	Final Prob
a	0.207	0.049	0.049	0.016	0.037	0.032
b	0.015	0.032	0.015	0.051	0.038	0.002
c	0.018	0.042	0.061	0.044	0.042	0.010
d	0.013	0.038	0.050	0.049	0.010	0.001
e	0.145	0.034	0.013	0.016	0.029	0.003
f	0.010	0.004	0.029	0.003	0.025	0.000
g	0.012	0.041	0.004	0.046	0.040	0.000
h	0.011	0.022	0.001	0.009	0.014	0.000
i	0.021	0.019	0.010	0.038	0.036	0.001
j	0.003	0.029	0.022	0.042	0.006	0.000
k	0.002	0.007	0.036	0.059	0.042	0.000
l	0.013	0.133	0.160	0.154	0.177	**0.847**
m	0.283	0.034	0.056	0.040	0.035	0.085
n	0.030	0.043	0.053	0.013	0.036	0.004
o	0.015	0.033	0.003	0.034	0.045	0.000
p	0.015	0.017	0.060	0.000	0.041	0.000
q	0.001	0.006	0.045	0.040	0.040	0.000
r	0.011	0.049	0.008	0.017	0.033	0.000
s	0.033	0.048	0.027	0.058	0.034	0.010
t	0.066	0.048	0.010	0.014	0.032	0.002
u	0.006	0.034	0.027	0.010	0.025	0.000
v	0.004	0.039	0.025	0.051	0.049	0.001
w	0.011	0.052	0.038	0.010	0.040	0.001
x	0.000	0.001	0.061	0.027	0.019	0.000
y	0.003	0.042	0.023	0.032	0.022	0.000
z	0.000	0.013	0.052	0.059	0.032	0.000
[space]	0.000	0.048	0.042	0.024	0.017	0.000
[back]	0.050	0.046	0.019	0.042	0.002	0.000

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Symbol	LM Prob					Final Prob
a	0.053					0.053
b	0.000					0.000
c	0.000					0.000
d	0.000					0.000
e	0.144					0.144
f	0.000					0.000
g	0.000					0.000
h	0.000					0.000
i	0.277					0.277
j	0.000					0.000
k	0.000					0.000
l	0.000					0.000
m	0.000					0.000
n	0.000					0.000
o	0.466					0.466
p	0.000					0.000
q	0.000					0.000
r	0.000					0.000
s	0.000					0.000
t	0.000					0.000
u	0.006					0.006
v	0.000					0.000
w	0.000					0.000
x	0.000					0.000
y	0.003					0.003
z	0.000					0.000
[space]	0.000					0.000
[back]	0.050					0.050

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RSVP Keyboard™ Has Some Weaknesses

- We discard EEG observations after advancing/deleting a letter
  - Sometimes we get stuck
  - System doesn't "remember" that a letter was just deleted
- Backspace is hard to do properly
  - Backspace never shows up in the LM training data
  - Assigning it probability is complex

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Full History Fusion

- Idea: What if we remember all EEG observations?
  - Combine this "full history" into a more robust, principled prediction in each context
  - Requires that we use the language model a little differently
  - Computation of backspace is more involved, but now can be dynamic and more principled
  - In theory, allows for better predictions and faster typing

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String	LM Prob	EEG 1	EEG 2	EEG 3	EEG 4	Final Prob
a	0.150	0.020	0.200	0.100	0.060	0.002
e	0.100	0.050	0.200	0.100	0.060	0.004
h	0.069	0.010	0.200	0.100	0.060	0.000
i	0.080	0.030	0.200	0.100	0.060	0.002
r	0.100	0.020	0.200	0.100	0.060	0.001
s	0.200	0.050	0.200	0.100	0.060	0.007
ta	0.030	0.800	0.001	0.030	0.060	0.000
te	0.030	0.800	0.020	0.010	0.060	0.000
tha	0.027	0.800	0.200	0.300	0.100	0.078
the	0.108	0.800	0.200	0.300	0.200	0.626
thh	0.000	0.800	0.200	0.300	0.100	0.001
thi	0.018	0.800	0.200	0.300	0.050	0.026
thr	0.025	0.800	0.200	0.300	0.300	0.221
ths	0.000	0.800	0.200	0.300	0.100	0.003
tht	0.000	0.800	0.200	0.300	0.080	0.001
th_	0.000	0.800	0.200	0.300	0.010	0.000
ti	0.015	0.800	0.200	0.200	0.060	0.017
tr	0.030	0.800	0.100	0.100	0.060	0.009
ts	0.009	0.800	0.100	0.020	0.060	0.001
tt	0.003	0.800	0.100	0.040	0.060	0.000
t_	0.003	0.800	0.079	0.200	0.060	0.001
_	0.001	0.020	0.200	0.100	0.060	0.000

Typed So Far:
th

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String	LM Prob	EEG 1	EEG 2	EEG 3	EEG 4	Final Prob
a	0.150	0.020	0.200	0.100	0.060	0.002
e	0.100	0.050	0.200	0.100	0.060	0.004
h	0.069	0.010	0.200	0.100	0.060	0.000
i	0.080	0.030	0.200	0.100	0.060	0.002
r	0.100	0.020	0.200	0.100	0.060	0.001
s	0.200	0.050	0.200	0.100	0.060	0.007
ta	0.030	0.800	0.001	0.030	0.060	0.000
te	0.030	0.800	0.020	0.010	0.060	0.000
tha	0.027	0.800	0.200	0.300	0.100	0.078
the	0.108	0.800	0.200	0.300	0.200	0.626
thh	0.000	0.800	0.200	0.300	0.100	0.001
thi	0.018	0.800	0.200	0.300	0.050	0.026
thr	0.025	0.800	0.200	0.300	0.300	0.221
ths	0.000	0.800	0.200	0.300	0.100	0.003
tht	0.000	0.800	0.200	0.300	0.080	0.001
th_	0.000	0.800	0.200	0.300	0.010	0.000
ti	0.015	0.800	0.200	0.200	0.060	0.017
tr	0.030	0.800	0.100	0.100	0.060	0.009
ts	0.009	0.800	0.100	0.020	0.060	0.001
tt	0.003	0.800	0.100	0.040	0.060	0.000
t_	0.003	0.800	0.079	0.200	0.060	0.001
_	0.001	0.020	0.200	0.100	0.060	0.000

Typed So Far:
th

Backspace Probability
0.045

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Discussion

- In simulated tests, Full History Fusion results in faster typing across a range of brain signal strengths
- RERC on AAC goal:
  - Test Full History Fusion with individuals who have no impairments as proof-of-concept
  - Test Full History Fusion with individuals who have minimal movement and require BCI for spelling.

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Multi-Modal Access

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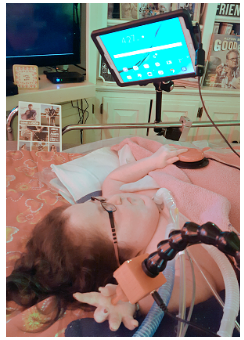
Developing multimodal access technologies

- Team
  - InvoTek, Inc., Madonna, Penn State, Saltillo
- The problem
- Focus has remained on single access methods despite advances in access technologies (eye/head tracking, touch interfaces, specialty switches).
- Single access method challenges:
  - Fatigue due to over-use
  - Inefficiency
  - Heavy reliance/focus on methods such as dwell that require vigilance and precise motor execution



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Developing multimodal access technologies

- Goals of the project
- Design multi-modal technology so that th best access method is always available.
  - E.g., Use a head tracker with dwell for accessing an onscreen keyboard; use an eye-blink for desktop selections.
- Min. the shortcomings of an access method.
  - E.g., Use an eye tracking for large cursor movements and head tracking for small, corrective cursor movements.
- Unintentional movements don't cause errors.
  - E.g., Thumb movement causes a switch closure only when the hand is still.

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Developing multimodal access technologies

- Engineering solution
  - Develop multi-modal solutions specific to individual with SSPI
  - Develop 3-D movement tracking system capable of measuring eye, head, and gestures (e.g., jaw or finger movement)
    - Proposed system will provide universal access to wide range of computer and smart/mobile technologies
    - SDK (Software Development Kit) to integrate this technology into AAC devices

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Developing multimodal access technologies – Clinical Evaluation

- **Preliminary Investigations:**
  - Document current multi-modal use by persons with CCN (what technology is used, why, challenges associated, impact on participation)
  - Evaluate custom solutions through case study series

- **Systematic evaluation of movement tracking system**
- 45 participants (15 children with CP, 15 adults with CP, 15 adults with cervical SCI)
- Alternating treatment design (5 single access and 5 multimodal access counterbalanced sessions)
  - Target acquisition task
  - Dependent measures- accuracy, rate and movement across tasks
  - Individual feedback and personal preference/potential benefit of 3-D multimodal system

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Developing multimodal access technologies

- Progress to date
  - Survey of multi-modal use by individuals with CCN (currently data collected on 5 with SCI, 2 with ALS, and 3 with CP)
  - Case study illustrations:
    - Alison, Tiffany
  - Two 3-D tracking systems in design
    - 1st gen 9-axis sensor system completed. Seeking funding to create robust movement learning system
    - 1st gen camera-based hardware design completed. Firmware and software underway.
  - Expected outcome: New genre of access technology

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Smart Predict-AAC app

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INTRODUCTION

Challenge: Using an AAC spelling device to type out messages during spontaneous conversation is *very* slow. The rate of message production violates verbal interaction rules, leading to isolation or impoverished communication of AAC users.

Goal: To increase the speed of message generation in an AAC spelling device by relying on the knowledge of a familiar partner during conversation.

Research Question: Can we develop a novel dual-app AAC system that enables a person with severe speech and physical impairments to produce messages faster while still maintaining control over expression?

Targeted Users: Literate individuals with severe speech and physical impairments who use AAC devices, and their care or communication partners.

Current Efforts: Development of Smart Predict-AAC app.

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Smart Predict-AAC APP

Materials:
2 Samsung Galaxy tablets connected by Bluetooth®
- Smart Predict-AAC app for the AAC user
- Partner app for the familiar partner

Smart Predict-AAC app interface:
QWERTY keyboard with two lines above the keyboard:
- Message line
- Word prediction from language model system

Partner app interface:
QWERTY keyboard and 2 lines:
- Message line
- Word prediction line from Smart Predict-AAC app

Janis Joplin and partner with apps

Smart Predict-AAC app functionality:
- As an AAC user types with the Smart Predict-AAC app, the text appears in the message line AND in the partner's tablet message line.
- The partner can suggest a word or phrase started by the AAC user by typing in the partner app. The suggestions are sent to the word prediction line of the Smart Predict-AAC app.
- The AAC user does not know which words are from the Smart Predict-AAC word prediction system and which are from the partner suggestions to maintain user autonomy.

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METHODS

•**Design:** AB Brief Experimental Design (Gast & Ledford, 2014)

•**Subjects:** Three literate adult females with severe speech and physical impairments secondary to spastic cerebral palsy, who use AAC with direct selection access, and their personal assistants.

Janis Joplin: 54 years old; uses ECO and computer; completed AA; employed as researcher

Tina Turner: 25 years old; uses ECO and computer; at 3rd grade level academically; lives at home with father and care provider

Patti LaBelle: 59 years old; uses Lightwriter SL40 and computer; completed GED.

•**Task:**

- Describe two pictures:
  - Western Aphasia Battery **Picnic Picture**
  - Boston Diagnostic Aphasia Exam **Cookie Theft Picture**
- Pictures are described twice:
  - Typing with language model word prediction only (Smart Predict-AAC app only)
  - Addition of partner-assisted word prediction (Partner app)
- All conditions were counterbalanced

•**Dependent variables:**

- Words per minute in 10 minute typing task
- Selections per minute in 10 minute typing task
- Content Information Units (CIU) in the picture description

•**Independent variables:**

- Text generation with and without Smart Predict Partner App.

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Data for 4 conditions: Tina Turner

Condition	Picture	CIUs: Content Information Units	Words	WPM: Words per minute	Selections	SPM: Selections per minute
AAC User Alone	Cookie Theft		18	1.8	97	9.7
AAC User with Smart Predict Partner App	Cookie Theft		31	3.1	132	13.2
AAC User Alone	Picnic		20	2.0	150	15.0
AAC User with Smart Predict Partner App	Picnic		28	2.8	142	14.2

- More words per minute with Smart Predict-AAC Partner app.
- Fewer selections per minute needed with Smart Predict-AAC Partner app while describing the Picnic picture.
- More selections per minute made with Smart Predict-AAC Partner app while describing the Cookie Theft picture.

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Data for 2 conditions: Patti LaBelle

Condition	Picture	CIUs: Content Information Units	Words	Words per Minute	Selections	Selections per Minute
AAC user Alone	Picnic	8	8	0.8	121	12.1
AAC User with Smart Predictor	Picnic	17	17	1.7	139	13.9

•More Content Information Units with Smart Predict-AAC Partner app

•More words per minute with Smart Predict-AAC Partner app.

•More selections per minute with Smart Predict-AAC Partner app while describing the Picnic picture.

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INITIAL DESIGN TRIAL: Janis Joplin

Condition	Picture	CIUs: Content Information Unit	Words	WPM: Words per minute	Selections	SPM: Selections per minute
AAC User Alone	Cookie Theft	39	40	4.0	151	15.1
AAC User with CoConstruct Partner app	Cookie Theft	54	55	5.5	149	14.9
AAC User Alone	Picnic	38	39	3.9	135	13.5
AAC User with CoConstruct Partner app	Picnic	51	52	5.2	156	15.6

- More Content Information Units with Smart Predict-AAC Partner app
- More words per minute with Smart Predict-AAC Partner app.
- Fewer selections per minute needed with Smart Predict-AAC Partner app while describing the Cookie Theft picture.
- More selections per minute made with Smart Predict-AAC Partner app while describing the Picnic picture.

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IMPLICATIONS AND FUTURE DIRECTIONS

- The Smart Predict-AAC app and words provided by a knowledgeable partner *improves speed of message production* by:
  - Increasing rate of word production in 10 minute period.
  - Increasing number of CIUs and amount of information produced in a 10 minute period.
  - Changing number of selections needed in a 10 minute period for one picture.

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Challenges from the field

- Motor access is different for every user; touch tablet not ideal platform for people with CP.
  - Added a stylus
  - Added a customized keyguard
  - Switched tablets so smaller version for AAC user.
- Literacy is a challenge for many people with developmental disabilities. While Tina Turner could use the app, she often had literacy problems.
- Currently, no numbers option

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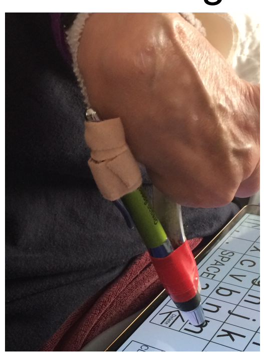
Touch tablet challenge

- We needed to add moleskin around thick stylus attached to her hand orthosis.
- Does this affect conductivity?
- What stylus works best given the force that Patti LaBelle exerts for each selection?



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User Feedback

- All three users report that they prefer to use Smart Predict-AAC with a partner because it allows them to communicate faster.

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Partner Feedback

- Patti LaBelle: “I feel that any way I can make it easier, I’m all for it!”
- Tina Turner: “I felt great about being able to provide written support for her.”
- Janis Joplin: “I am still giving words and advice to her without the focus being on me.”

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Next steps for technology

- Integrate SmartPredict into a scanning on screen keyboard Investigate the impact of
  - Larger English corpus (COCA)
  - Trigrams on prediction
- Investigate more sophisticated methods for integrating LMs into SmartPredict and measure their performance
  - SMS or spelling error options
  - Lessening the demands on the user’s spelling

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QUESTIONS?

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- The contents of this presentation were developed under a grant from the National Institute on Disability, Independent Living, and Rehabilitation Research (NIDILRR grant number **#90RE5017)** to the Rehabilitation Engineering Research Center on Augmentative and Alternative Communication (RERC on AAC).
- NIDILRR is a Center within the Administration for Community Living (ACL), Department of Health and Human Services (HHS). The contents of this presentation do not necessarily represent the policy of NIDILRR, ACL, HHS, and you should not assume endorsement by the Federal Government.
- Proof of concept for Smart Predictor was accomplished through an SBIR grant from **NIDCD grant #1R43DC014294.**

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