How to navigate everyday distractions: Leveraging optimal feedback to train attention control

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Introduction

- Information overload in everyday life diminishes progress toward goals [1]
- Coping ability is moderated by individual attention control skills [2]
- Research on cognitive plasticity suggests that attention control skills can be strengthened by training [3]
- Problem: lack of transferability of existing training paradigms to people's everyday lives [4]
- Solution: training in regular work and study situations with everyday life tasks

Modeling attention control

- Exerting attention control in the face of distractions can be formalized as finite-horizon Markov Decision Process (MDP) [5]

$$M = \left(\{s_f, s_d\}, [0,1], T, r, h\right).$$

  - $\{s_f, s_d\}$: focused vs. distracted states
  - $c \in [0,1]$: control signal intensities (ranging from 0% to 100%)
  - T : probabilities of state transitions depending on control signal intensity
  - r : value generated minus cost of control
  - h : length of the task in time steps

- Attention control skills can improve through reinforcement learning, which can be accelerated by giving elaborative feedback with metacognitive components [6]

Optimal feedback

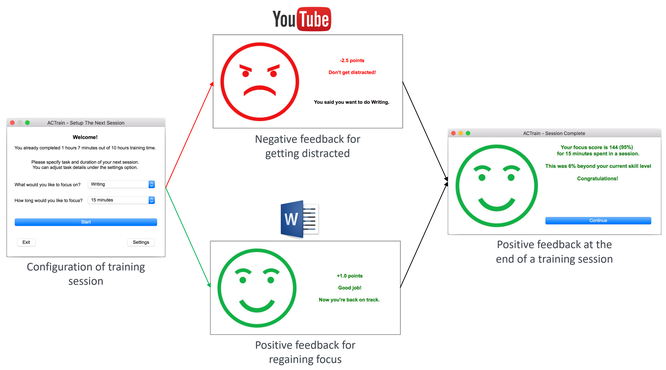
- Building on Expected Value of Control (EVC) theory [7], optimal feedback can accurately communicate long-term value of staying focused and inhibiting distractions

$$\mathrm{FB}(s_t, c_t) = \mathrm{EVC}(s_t, c_t) - \max_c \mathrm{EVC}(s_t, c)\,.$$

  - Feedback signal takes into account current state s_t and control signal strength c_t
  - Communicates the value of invested attention control compared to the value of the best possible attention control signal that a person could have chosen
  - Control signal strength c needs to be inferred from people's behavior by Bayesian inference

- Learned Value of Control (LVOC) model [8] predicts that training with optimal feedback improves people's attention control skills

Software characteristics



- Users can define their own tasks in the beginning (e.g., writing a paper) and select related programs and/or websites to use for that
- App tracks if the program in focus matches their goals (s_f) and reminds users of these goals if their focus derails (s_d).
- Formative metacognitive feedback includes visual cues (color, facial expression), auditory social cues ("boo" vs. cheer sounds) and point-based reward system
- Point score calculated from time spent focused minus time spent distracted indicates focus performance (*focus score*)
- Kalman filter used to estimate underlying attention control skills based on focus performance in prior sessions (part of summative feedback)

Field experiment

Sample

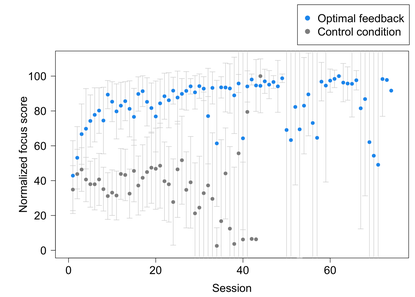
- 99 participants (*M* = 25.77 years, *SD* = 4.94, range: 18-43, 59% female)
- Enrolled in bachelor studies or with academic degree
- Average daily computer use of 6.14 hours (*SD* = 2.80, range: 0.5-13)
- All operating systems represented (59% Windows, 20% MacOS, 9% Linux)

Design

- Randomized controlled field experiment over eight days (pretest, six days of app use, posttest)
- App with optimal feedback (experimental condition) vs. placebo version without feedback (control condition)
- Pre-post design inspects a set of outcome variables
  - Focus performance (normalized focus score)
  - Productivity (commercial time tracking software RescueTime, subjective ratings)
  - Sustained attention (vigilance task)
  - Self-control (subjective ratings)

Results

- Higher focus scores resulted with optimal feedback, $t(447.75) = 28.12$, $p < .001$, $\xi = .74$
- Focus scores increased over time with optimal feedback, $r(775) = .22$, $t = 6.11$, $p < .001$



- Participants spent longer overall training times when receiving optimal feedback, $t(18.35) = 3.84$, $p = .001$, $\xi = .82$
- More training sessions were conducted when participants received optimal feedback, $t(768.49) = 10.10$, $p < .001$, $\xi = .41$
- Productivity rating: weighted sum of proportional time spent very distracted (-2), distracted (-1), neutral (0), productive (+1) and very productive (+2)
- Significantly increased productivity was observed during training with optimal feedback (controlled for pre-test differences), $F(1, 259) = 9.17$, $p < .01$, $f = .19$

Discussion

- Results support predictions of LVOC model [8] that optimal feedback accelerates acquisition of attention control skills
- Limitation in rather high and asymmetric attrition rates (41% control group vs. 53% experimental group)
- Feedback might be too intrusive → need for more personalized, empathetic design
- Potential of our approach to support millions of people all around the globe in achieving their goals more effectively

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