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Report

Computer Use Changes Generalization of Movement Learning

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Summary

Over the past few decades, one of the most salient lifestyle changes for us has been the use of computers. For many of us, manual interaction with a computer occupies a large portion of our working time. Through neural plasticity, this extensive movement training should change our representation of movements (e.g., [1–3]), just like search engines affect memory [4]. However, how computer use affects motor learning is largely understudied. Additionally, as virtually all participants in studies of perception and actions are computer users, a legitimate question is whether insights from these studies bear the signature of computer-use experience. We compared non-computer users with age- and education-matched computer users in standard motor learning experiments. We found that people learned equally fast but that non-computer users generalized significantly less across space, a difference negated by two weeks of intensive computer training. Our findings suggest that computer-use experience shaped our basic sensorimotor behaviors, and this influence should be considered whenever computer users are recruited as study participants.

Results and Discussion

The average computer user produces 7,400 mouse clicks per week [5]. Computer use often involves globally linear transformations between the body movement and its screen representation, e.g., the mapping from hand movement to mouse cursor position. Hence, with long-term interaction with mice, computer users probably develop an expectation that visuomotor transformation between hand movement and its screen representation should remain consistent across work space. Hence, in line with recent findings that prior experience affects motor control [6–9], and motor generalization in particular [10, 11], our working hypothesis is that people without computer experience will generalize more locally in visuomotor learning and that this difference should be negated with computer-use training.

To assess how such movement behaviors are affected by computer use, we recruited 18 Chinese migrant workers, nine of them being regular computer users (*control* group, age 41.9 ± 8.9 years) and nine of them never having used a computer before (*non-computer-user* group, age 38.2 ± 10.1 years). We also assembled a control group made up of nine college students (*student* group, age 21.9 ± 2.4 years). All of these naive subjects were tested with a standard visuomotor gain adaptation experiment [12, 13] in which subjects learned to move a cursor while their hand was hidden from view (Figure 1A). The gain between the hand displacement and the cursor displacement was modified in the training direction (Figure 1B). Subjects adapted to this visuomotor gain change and were subsequently tested in other directions to assess their directional generalization.

So how does computer use affect movement behavior? It affected neither the speed of learning [$F(8,18) = 0.91$, $p = 0.53$, one-way ANOVA] nor the degree of learning [$F(8,18) = 0.77$, $p = 0.64$; Figure 2A]. However, the computer users, compared to the non-computer-user group, generalize much more into other directions [interaction effect $F(8, 96) = 6.9$, $p < 0.0001$; main effect on groups $F(2, 24) = 12.5$, $p < 0.0001$, two-way ANOVA; Figure 2B]. Interestingly, non-computer users still have a broad generalization as their generalization is significantly larger than zero even at the largest angular separation of 180° (30.0% ± 6.9%; $p < 0.001$, one-sample t test). There is no difference between the computer group and the student group, suggesting that subjects of different ages behave similarly as long as they are computer users.

To establish the causal relationship, we recruited another group of ten non-computer users and examined their generalization before and after intensive computer-use training. We realized that our movement interaction with computer is mostly via a computer mouse; this interaction involves a mapping between a movement space and a visual space, rather similar to experimental setting in our and others' studies. We thus chose to give subjects intensive training on using computer mouse. Before training, their generalization was again quite narrow and their generalization was not significant from that of the non-computer-user group in experiment 1 [Figure 3A; two-way mixed-design ANOVA, main effect on groups $F(1,17) = 0.24$, $p = 0.63$ and interaction effect $F(4,68) = 0.25$, $p = 0.92$]. In the following 2 weeks, participants were instructed to play computer games (e.g., Pong) that require intensive mouse use for 2 hr each day. We also tested their mouse-use ability by asking them to track a moving cursor with mouse cursor (Figure 3B, inset). This tracking task was performed before and after training on each day. The overall tracking error was reduced across days (Figure 3B). More importantly, participants exhibited significantly larger generalization when they were tested again after 14-day training (Figure 3A). Two-way repeated-measures ANOVA revealed significant main effect on timing [before versus after training, $F(1,9) = 13.08$, $p < 0.01$] and significant interaction effect [$F(4,36) = 9.48$, $p < 0.0001$]. The generalization was significantly higher at all but the 0 angular separations ($p < 0.01$ or $p < 0.005$ for simple main effect tests). Two weeks of computer training converted the generalization patterns into those of computer users.

In summary, computer use leaves learning speed unaffected but leads to enhanced generalization into untrained directions. A possible reason for this change is that the gain mapping between mouse movements and cursor movements is uniform across different directions. Thus, long-term exposure to this sensorimotor mapping leads to our prior expectation of consistent transformation between manual actions and screen representations across directions. This prior expectation, in turn, leads to broad generalization in similar task settings.

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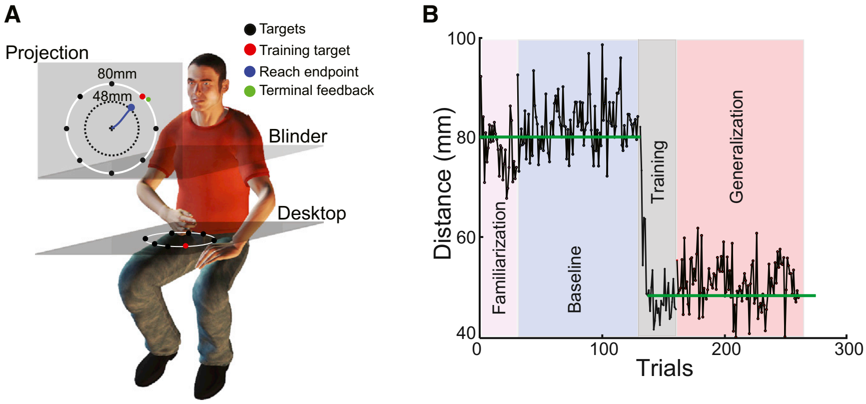

Figure 1. Experimental Setup and Data from a Typical Subject

(A) Illustration of experimental setup and movement targets arranged on the screen. With perturbed visuomotor gain, the terminal feedback is shown 1/0.6 further from the actual reach endpoint, i.e., people only need to move the unseen hand 48 mm to reach 80 mm targets. This terminal feedback is only shown for the training direction. Thus, subjects only learned this sensorimotor gain in one direction and were then asked to generalize to other directions.

(B) Movement distance of all the reaches to the training target from a typical subject. The gain is 1 during the familiarization and the baseline phases and is 0.6 during the training (with feedback) and the generalization phase (without feedback). The distances of reaches to other targets (not shown) reflect how subjects generalize.

We postulate that this enhanced generalization is specific for visuomotor learning since computer use extensively involves visuomotor transformation. Furthermore, it has been shown that altered motor generalization in some neuropathological population is also task specific [14].

It is interesting to note that normal participants (i.e., computer users) have a much broader generalization for visuomotor gain learning as compared to visuomotor rotation learning, another type of visumotor transformation (e.g., [15]). Can computer use explain this discrepancy? Our data show that non-computer users exhibit broader generalization in gain learning than computer users in rotation learning, i.e., their gain generalization is significant even at 180° angles, in which rotation generalization is supposed to be absent. This suggests that computer use alone cannot explain the discrepancy between these two types of motor generalization. This behavioral distinction is consistent to the neurophysiological findings that separate neural substrates supports these two types of visuomotor learning [16].

Similar to existing studies on visuomotor generalization [3, 12, 17–22], we have analyzed the generalization of rather artificial movements on a plane. It is well possible that computer use is more important for such artificial movements than it would be for natural movements. However, our study informs the interpretation of the work that has been done so far. Future work can reveal how important naturalness is for the effects of generalization [10] and the importance of computer use in such a context.

The way subjects learn and generalize is often viewed as a reflection of the fundamental neural representation of movement [23–29]. Particularly, people usually reported limited generalization in various motor learning tasks [3, 17–19, 21, 30–32], and these patterns have been quantified to probe neural representations of movement learning (e.g., [3, 11, 17–20, 26, 30–35]). Hence, our findings suggest that computer use, through neural plasticity, changes movement representations. Our results also suggest that in typical movement experiments, at least those involving visuomotor perturbations, computer use affects the results. It is thus important to be cautious in generalizing behavioral findings on computer users to the overall population, just as psychologists recently acknowledged that data from selected western subjects is not broadly representative across populations [36]. Computer use not only changes our lifestyle, but it also appears to fundamentally affect the neural representation of our movements.

Experimental Procedures

All subjects were naive to our research purpose and they provided written consent before experiments. All procedures were approved by the institutional review board of Peking University. Experiment 1 was a cross-sectional experiment with a *non-computer-user* group (eight females and one male; age 38.2 ± 10.1 years; education 4.9 ± 2.1 years), an age- and education-matched *control* group (eight females and one male, age 41.9 ± 8.9 years; education 6.6 ± 2.5 years), and a *student* group (seven females and two males; age 21.9 ± 2.4 years; education 15.3 ± 1.9 years). Experiment 2 was a longitudinal experiment in which ten non-computer users were recruited (ten females; age 38.7 ± 7.9 years; education 7.9 ± 3.1 years). Their motor generalization was accessed before and after 14 days of computer training. All subjects were screened for their computer use experience. Non-computer users were determined by one-on-one interview, and they were required to use a computer mouse to open a file folder placed on the desktop of a Windows PC. They usually had trouble maneuvering the mouse to move the cursor, a hallmark of no experience of

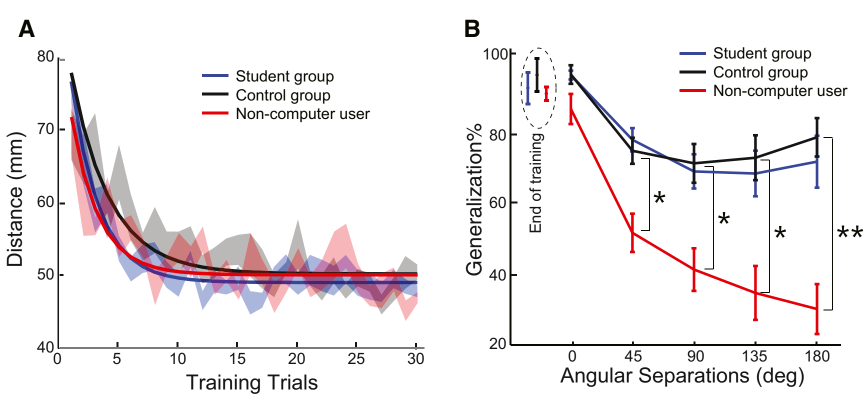

Figure 2. Same Learning Speeds but Different Generalization

(A) Average learning data during the training phase. The error bars indicate the SEM across subjects. Solid lines are fitted exponential learning curves.

(B) The generalization as a function of difference in direction is assessed. The difference between computer-user groups and the non-computer-user group was significant at distant angles (*$p < 0.005$, **$p < 0.001$, simple main effect with Bonferroni correction).

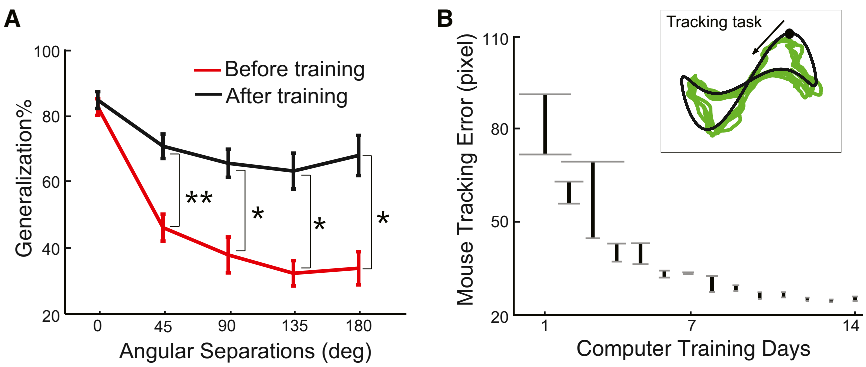

Figure 3. Two Weeks of Computer Use Produces Broad Generalization Curves

(A) The generalization as a function of difference in direction before and after computer-use training. The difference induced by computer-use training was significant at distant angles (*p < 0.01, **p < 0.005, simple main effect).

(B) The mouse tracking error was reduced over 14 training days. The upper end of each vertical line denotes the error before training on each day and the lower end the error after the training. The width of gray horizontal lines denotes intersubject variance (SEM). The trajectory of the moving target (black) and the mouse cursor trajectory of an exemplary trial (green) are shown in the inset.

interacting with computers. All experiment sessions were scheduled during the day. For quantifying generalization, subjects sat behind a desk and moved their right, dominant hand on the desktop. Their vision of the hand was blocked by a mirror placed horizontally at chest level. The movement of the index finger tip was measured at a frequency of 200 Hz (Codamotion, Charnwood Dynamics). Visual feedback was projected on a vertically placed back-projection screen about 100 cm in front of the subject. On the screen, eight visual targets were arranged on an 80-mm-radius circle and separated 45° apart (Figure 1A). At the beginning of each trial, subjects rested their index finger on a 4-mm-thin, smooth plastic disc glued on the desktop. This disc facilitated subjects returning to the center of the target circle without visual guidance. Once the finger was still for 100 ms, one of the targets was highlighted to signal subjects to move their hand from the center to the target. A cursor, representing the finger position, was only visible within 1 cm around the circle center. On selected trials (see below), the cursor would reappear when the reach stopped, and this terminal feedback indicated the distance traveled by the finger/cursor. A beep, played at the trial end, signaled the subject to bring the finger back to the starting position for the next trial.

The assessment of generalization was conducted with four phases of trials (Figure 1B). In the familiarization phase, subjects moved to each target six times in a random sequence with terminal feedback. In the baseline phase, trials were organized in 50 blocks of nine trials: every target was shown once, with the exception of the training target (the upper-left target), which was shown twice. The terminal feedback was presented only for the reaches to the training target. For both familiarization and baseline phases, the gain between the hand movement and the cursor movement was 1, i.e., the terminal feedback was veridical. In the training phase, subjects reached to the training target with terminal feedback for 30 consecutive trials. Importantly, the gain was modified from 1 to 0.6, creating a visuomotor perturbation. With this perturbation, subjects only needed to move 48 mm to reach the target. The last generalization phase was identical to the baseline phase except that the gain was kept at 0.6. As subjects never received visual feedback for reaches to targets other than the training target, we could assess their transfer of learning from the training direction to other directions. The amount of generalization is quantified as

$$Generalization\% = \frac{D_{generalization} - D_{baseline}}{D_{baseline} \times (1 - 0.6)} \times 100\%,$$

where $D_{generalization}$ and $D_{baseline}$ are average movement distances in the generalization phase and in the baseline phase, respectively. This generalization percentage was calculated for each direction separately and expressed as a function of angular separation from the training direction (Figure 2B). Subjects exhibited typical exponential learning during the training phase (Figure 2A). We fitted the learning data with an exponential function $y = a \times e^{-(t/\tau)} + b$, where τ denotes the learning rate and b denotes the achieved learning level. When fitting parameters for each subject, we set the initial value of b at the learning achieved at the end of the training session (average error of the last three training trials). a was not a free parameter, but rather the actual learning achieved during training; it was calculated for each participant as the average error before training (average of the last three baseline trials) minus the average error after training (average of the last three training trials).

The computer training in experiment 2 involved subjects playing simple flash-based computer games that require frequent and precise mouse cursor movements, 2 hr each day for 14 consecutive days. Subjects were allowed to switch between eight types of games and to take a break at their convenience. For quantification of their improvement in using computer mouse, on each training day subjects also performed a modified pursuit rotor task, which required them to use mouse cursor to track a moving target on the computer monitor. The movement of the target followed a predefined trajectory whose horizontal position was a sine function (0.3 Hz; 261 pixels in amplitude) and vertical position a sum of three sine functions (0.3, 0.6, and 0.9 Hz; 150 pixels in amplitude). On the screen, this tracking target spanned 522 and 750 pixels horizontally and vertically, respectively. Importantly, it moved with unpredictable and varying speeds (mean ± SD: 545 ± 293 pixels/s) and thus discouraged subjects to improve the performance by simply remembering the trajectory. This task was organized as 20 s trials, five trials before and after the training on each day. The average, absolute distance between the target and the mouse cursor was computed as tracking error. The training was conducted in a lab setting under supervision of the experimenters.

For experiment 1, between-group comparisons of generalization was performed with a two-way mixed-design ANOVA (three groups × five angular separations). Comparisons of learning rate and learning extent were performed with one-way ANOVA. For experiment 2, within-group comparisons between before- and after-training generalization was performed with a similar but repeated-measures ANOVA (two timing × five angular separations). Across-experiment comparisons between two non-computer-user groups were conducted via a two-way mixed-design ANOVA (two groups × five angular separations). For both experiments, comparisons of generalizations between groups (experiment 1) and between times (pre- and posttraining) at specific angular separations were performed using simple main effects with Bonferroni correction. Data entering two-way ANOVA tests were checked for normality. The significance level was set at $\alpha = 0.05$.

Author Contributions

K.W. and K.P.K designed experiments, X.Y., F.Z., G.K., C.Y., and Q.W. performed experiments, K.W., X.Y., and Q.W. analyzed data, and K.P.K. and K.W. wrote the paper.

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References

1. Karni, A., Meyer, G., Rey-Hipolito, C., Jezzard, P., Adams, M.M., Turner, R., and Ungerleider, L.G. (1998). The acquisition of skilled motor performance: fast and slow experience-driven changes in primary motor cortex. Proc. Natl. Acad. Sci. USA *95*, 861–868.

2. Draganski, B., and May, A. (2008). Training-induced structural changes in the adult human brain. Behav. Brain Res. *192*, 137–142.
3. Paz, R., Boraud, T., Natan, C., Bergman, H., and Vaadia, E. (2003). Preparatory activity in motor cortex reflects learning of local visuomotor skills. Nat. Neurosci. *6*, 882–890.
4. Sparrow, B., Liu, J., and Wegner, D.M. (2011). Google effects on memory: cognitive consequences of having information at our fingertips. Science *333*, 776–778.
5. Taylor, K. (2007). An Analysis of Computer Use across 95 Organisations in Europe, North America and Australasia. A White Paper from Wellnomics Limited. http://www.wellnomics.com/assets/Uploads/WorkPace/News/Wellnomics-white-paper-Comparison-of-Computer-Use-across-different-Countries.pdf.
6. Liu, X., Mosier, K.M., Mussa-Ivaldi, F.A., Casadio, M., and Scheidt, R.A. (2011). Reorganization of finger coordination patterns during adaptation to rotation and scaling of a newly learned sensorimotor transformation. J. Neurophysiol. *105*, 454–473.
7. Diedrichsen, J., White, O., Newman, D., and Lally, N. (2010). Use-dependent and error-based learning of motor behaviors. J. Neurosci. *30*, 5159–5166.
8. Huang, V.S., Haith, A., Mazzoni, P., and Krakauer, J.W. (2011). Rethinking motor learning and savings in adaptation paradigms: model-free memory for successful actions combines with internal models. Neuron *70*, 787–801.
9. Slijper, H., Richter, J., Over, E., Smeets, J., and Frens, M. (2009). Statistics predict kinematics of hand movements during everyday activity. J. Mot. Behav. *41*, 3–9.
10. Yan, X., Wang, Q., Lu, Z., Stevenson, I.H., Körding, K., and Wei, K. (2013). Generalization of unconstrained reaching with hand-weight changes. J. Neurophysiol. *109*, 137–146.
11. Krakauer, J.W., Mazzoni, P., Ghazizadeh, A., Ravindran, R., and Shadmehr, R. (2006). Generalization of motor learning depends on the history of prior action. PLoS Biol. *4*, e316.
12. Krakauer, J.W., Pine, Z.M., Ghilardi, M.F., and Ghez, C. (2000). Learning of visuomotor transformations for vectorial planning of reaching trajectories. J. Neurosci. *20*, 8916–8924.
13. Vindras, P., and Viviani, P. (2002). Altering the visuomotor gain. Evidence that motor plans deal with vector quantities. Exp. Brain Res. *147*, 280–295.
14. Haswell, C.C., Izawa, J., Dowell, L.R., Mostofsky, S.H., and Shadmehr, R. (2009). Representation of internal models of action in the autistic brain. Nat. Neurosci. *12*, 970–972.
15. Pine, Z.M., Krakauer, J.W., Gordon, J., and Ghez, C. (1996). Learning of scaling factors and reference axes for reaching movements. Neuroreport *7*, 2357–2361.
16. Krakauer, J.W., Ghilardi, M.-F., Mentis, M., Barnes, A., Veytsman, M., Eidelberg, D., and Ghez, C. (2004). Differential cortical and subcortical activations in learning rotations and gains for reaching: a PET study. J. Neurophysiol. *91*, 924–933.
17. Ghahramani, Z., Wolpert, D.M., and Jordan, M.I. (1996). Generalization to local remappings of the visuomotor coordinate transformation. J. Neurosci. *16*, 7085–7096.
18. Imamizu, H., Uno, Y., and Kawato, M. (1995). Internal representations of the motor apparatus: implications from generalization in visuomotor learning. J. Exp. Psychol. Hum. Percept. Perform. *21*, 1174–1198.
19. Mattar, A.A., and Ostry, D.J. (2007). Modifiability of generalization in dynamics learning. J. Neurophysiol. *98*, 3321–3329.
20. Thoroughman, K.A., and Taylor, J.A. (2005). Rapid reshaping of human motor generalization. J. Neurosci. *25*, 8948–8953.
21. Taylor, J.A., Hieber, L.L., and Ivry, R.B. (2013). Feedback-dependent generalization. J. Neurophysiol. *109*, 202–215.
22. Izawa, J., and Shadmehr, R. (2011). Learning from sensory and reward prediction errors during motor adaptation. PLoS Comput. Biol. *7*, e1002012.
23. Singh, K., and Scott, S.H. (2003). A motor learning strategy reflects neural circuitry for limb control. Nat. Neurosci. *6*, 399–403.
24. Mattar, A.A.G., and Gribble, P.L. (2005). Motor learning by observing. Neuron *46*, 153–160.
25. Berniker, M., and Körding, K. (2008). Estimating the sources of motor errors for adaptation and generalization. Nat. Neurosci. *11*, 1454–1461.
26. Poggio, T., and Bizzi, E. (2004). Generalization in vision and motor control. Nature *431*, 768–774.
27. Thoroughman, K.A., and Shadmehr, R. (2000). Learning of action through adaptive combination of motor primitives. Nature *407*, 742–747.
28. Houde, J.F., and Jordan, M.I. (1998). Sensorimotor adaptation in speech production. Science *279*, 1213–1216.
29. Ghahramani, Z., and Wolpert, D.M. (1997). Modular decomposition in visuomotor learning. Nature *386*, 392–395.
30. Hwang, E.J., Donchin, O., Smith, M.A., and Shadmehr, R. (2003). A gain-field encoding of limb position and velocity in the internal model of arm dynamics. PLoS Biol. *1*, E25.
31. Shabbott, B.A., and Sainburg, R.L. (2010). Learning a visuomotor rotation: simultaneous visual and proprioceptive information is crucial for visuomotor remapping. Exp. Brain Res. *203*, 75–87.
32. Wu, H.G., and Smith, M.A. (2013). The generalization of visuomotor learning to untrained movements and movement sequences based on movement vector and goal location remapping. J. Neurosci. *33*, 10772–10789.
33. Donchin, O., Francis, J.T., and Shadmehr, R. (2003). Quantifying generalization from trial-by-trial behavior of adaptive systems that learn with basis functions: theory and experiments in human motor control. J. Neurosci. *23*, 9032–9045.
34. Shadmehr, R., and Mussa-Ivaldi, F.A. (1994). Adaptive representation of dynamics during learning of a motor task. J. Neurosci. *14*, 3208–3224.
35. Gandolfo, F., Mussa-Ivaldi, F.A., and Bizzi, E. (1996). Motor learning by field approximation. Proc. Natl. Acad. Sci. USA *93*, 3843–3846.
36. Henrich, J., Heine, S.J., and Norenzayan, A. (2010). Most people are not WEIRD. Nature *466*, 29.