An Experimental Investigation on Learning Activities Inhibition Hypothesis in Cognitive Disuse Atrophy

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Abstract—The term "disuse atrophy" is generally used for physical atrophy such as muscle wasting. When muscles are no longer used, they slowly weaken. This weakening, or atrophy, can also occur from continuous physical support that leads to a minimal use of the body. We advance the idea that disuse atrophy occurs not only in the physical realm but also in cognitive ability. We investigate why cognitive disuse atrophy occurs. Specifically, we examine the learning activities inhibition hypothesis, which posits that cognitive disuse atrophy occurs because continuous use of support systems provides cognitive shortcuts for performing activities and inhibits learning-oriented activities. To investigate this hypothesis, two experiments were performed in which the participants played Reversi games. Both Experiments 1 and 2 indicated that the participants' winning rates were highest when they were given a higher level of support, and their decision times for determining each move were shortest in the training phase. Experiment 2 also indicated that participants' post-test scores (measured as learning gains) were lower when they were given higher levels of support. These results confirmed that a higher level of support promotes performance-oriented activities, but inhibits learning-oriented activities when engaging in training, supporting the learning activities inhibition hypothesis.

Keywords–cognitive disuse atrophy; performance-orienged activities; learning-orienged activities

I. INTRODUCTION

A variety of human support systems based on advanced technologies, such as automation systems, operate in our daily lives. These systems have contributed to the increase of human abilities to perform tasks. However, we often recognize negative secondary effects of the overuse of such systems (e.g., difficulty in memorizing maps due to daily usage of car navigation systems, or difficulty remembering the accurate spelling of words because of using a word processor with spell checker software). Human factor studies have reported that the continuous use of automated systems decreases users' manipulation abilities [1][2], and more seriously, complacency on this front causes aircraft accidents [3]. This happens because long-term continuous supports decrease human cognitive activity, weakening the ability to performing tasks.

Miwa and Terai proposed the concept of cognitive ability disuse atrophy, the loss of cognitive ability due to the disuse of cognitive activities [4]. We see this as a key issue underlying some human factor problems that emerge when people engage in cognitive tasks aided by computers. The term "disuse atrophy" is generally used for physical atrophy, such as muscle wasting [5]. We advance the idea that disuse atrophy occurs not only in the physical realm but also in cognitive ability.

In this paper, we investigate why cognitive disuse atrophy occurs. Specifically, we propose the learning activities inhibition hypothesis to explain this psychological phenomenon. In explaining this hypothesis, we first note the duality of cognitive processing when engaging in a task [6]. Generally, there are two objectives for performing a task. One ordinary objective is to perform and complete the task. However, there is another important objective: for performers to develop proficiency and knowledge by performing the task. Performance and mastery are the prime reasons to engage in a task. We contend that cognitive disuse atrophy emerges when the mastery factor is lost.

For example, consider car navigation systems. When people search for a route from a current location to a new destination, they usually try to remember a mental map, a configuration of the possible pathways, select candidate pathways related to the target route, and decide on the best route from multiple candidates while considering current traffic and construction. These cognitive information processing efforts develop a mastery of memorizing maps and the acquisition of the skills to search for a route. However, when we use navigation systems, we do not need to perform any such mental activities. All one has to do is to enter the destination and press the confirmation button. From the perspective of performance, this is all it takes to achieve the goal. But for mastery, the mental activities of memorizing a map and finding a route with a printed map are also important. Since car navigation systems deprive users of opportunities for such efforts toward mastery, they cause mental disuse atrophy.

We define performance-oriented activities as those for performing tasks and learning-oriented activities as those for mastery. The learning activities inhibition hypothesis proposes that cognitive disuse atrophy occurs because the continuous use of support systems provides cognitive shortcuts for performing activities and thus inhibits the learning-oriented activities.

In this paper, we empirically investigate the learning activities inhibition hypothesis in the following research paradigm. We had participants engage in a task. In the training phase, participants performed the task with help from a task-supporting system. Task performance was measured and used as an index
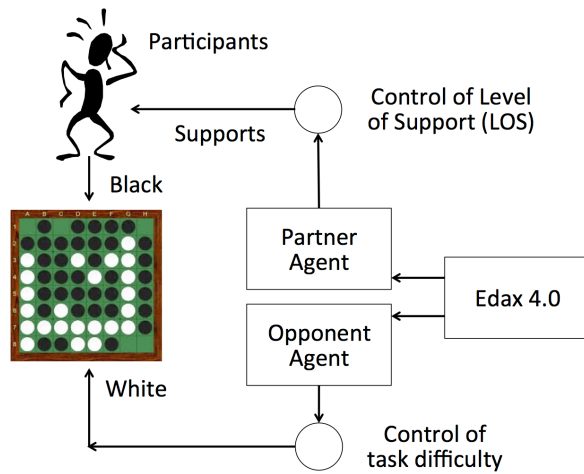
Figure 1. Overall configuration of the Reversi-based learning environment.

Figure 2. An example screenshot of the experimental system.

Figure 3. Winning rate of the simulated participants against an opponent agent.

for their performance-oriented activities. After the training phase, a post-test was performed without any supports available. Post-test scores were measured and used as an index of their learning-oriented activities in the training phase. We then evaluated the two indexes as a function of the level of support (LOS) in the training phase.

The learning activities inhibition hypothesis predicts the following:

- As LOS increases, task performance in the training phase would increase because the performance-oriented activities would increase due to high-level supports.

- However, post-test scores would decrease because high-level assistance inhibits the learning-oriented activities in the training phase.

In Section 2, we explain an experimental system developed for this study, and Experiment 1 in Sections 3 and 4 and Experiment 2 in Sections 5 and 6 are reported, followed by discussion and conclusions in Section 7.

II. EXPERIMENTAL SYSTEM

A. Reversi-based learning environment

We developed a Reversi-based learning environment as a workbench to investigate the learning activities inhibition hypothesis. Figure 1 shows the overall configuration of the experimental system. In our experimental environment, a participant plays 8 by 8 Reversi games against a virtual opponent (i.e., opponent agent) on a computer. A virtual partner (i.e., partner agent) assists the participant in selecting winning moves. Both agents, opponent and partner, are controlled by a Reversi engine, Edax, which suggests the best moves by assessing future states in the game. The opponent's competence can be controlled by setting the maximum depth to which Edax searches for future game states. The partner agent recommends candidate moves among valid squares before the participant makes a move.

The Edax-generated opponents are exceptionally competent Reversi players that cannot be defeated by human participants.
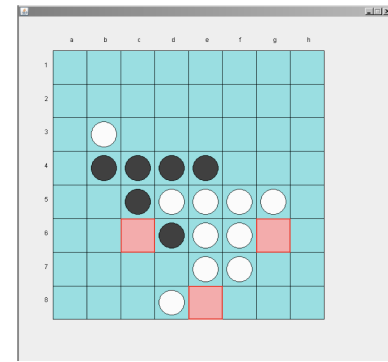
To reduce the strength of the opponent agent to a level compatible with human participants, the agents were set to randomly miss the best move twice in the initial and middle stages. Support levels (LOSs) from the partner agent were controlled by presenting the candidate with the best or multiple moves, or no candidates (i.e., no supports). Figure 2 shows an example screenshot of the experimental system where three candidate moves are presented.

B. Preliminary simulations

To predict the degree of winning by human participants in the environment, we conducted preliminary simulations. The simulated participant randomly selected one of the candidate moves. In the no-support condition, it randomly selected one of the possible moves.

Figure 3 shows the ratio of wins by the simulated participant against the opponent agent in 20 simulated games. This figure implies that the winning ratio of human novices increases as the support level increases. However, the learning activities inhibition hypothesis predicts that consistently presenting the best move to participants would inhibit their skill mastery. Therefore, post-test scores in the best-move presentation condition would be lower than those in the multiple-candidate-moves presentation condition and the no-supports condition.

III.   EXPERIMENT 1

A.   Participants

A total of 71 undergraduate students in the school of informatics and sciences at Nagoya University participated in Experiment 1. They were paid 4000 Japanese Yen as baseline, and were additionally paid to a maximum of 3000 Yen based on their performance measured as post-test scores.

B.   Experimental conditions

We manipulated the LOS in participants' training by setting up three experimental conditions: (1) the Best Move condition, where the partner agent suggested the best move to the participants, (2) the Three Candidates condition, where three candidate moves were suggested, including the best move, and (3) the No Support condition, where no suggestions were given.

Twenty-three, twenty-four, and twenty-four participants were assigned to the Best Move, Three Candidates, and No Support conditions, respectively.

C.   Experimental procedure

In the initial stage, participants were instructed on how to operate the experimental system. In the Best Move and Three Candidates conditions, participants were taught that a virtual partner would present candidate moves in each trial, but they are not required to follow the suggestions. After the instruction phase, a pre-test was performed. The participants played a game against the virtual opponent without the partner agent's supports.

In the training phase, participants were divided into three groups and played twelve games in which the LOS was controlled. After the training phase, a post-test was performed in which the experimental setting was identical to that of the pre-test phase. After the post-test was performed, the participants played four additional games in each of the experimental settings, and then performed the second round of post-test. We evaluated their learning gains based on the first and second rounds of post-tests.

IV.   RESULTS

A.   Winning Rate

First, we evaluated the participants' performance in the training phase. Figure 4 shows the winning rate (the ratio of the obtained pieces (black pieces) to the total number of pieces (i.e., black and white pieces)) in the pre-test, the training phase, and the first and second rounds of post-tests.

A three (Condition: No Support, Three Candidates, and Best Move) × four (Trials: Pre, Training, Post 1, and Post 2) ANOVA revealed a significant interaction ($F(6, 204) = 13.11$, $p < 0.01$). The simple main effect of the Condition factor did not reach a significant level at Pre, Post 1, and Post 2 ($F(2, 68) = 3.12$, n.s.; $F(2, 68) < 1$, n.s.; $F(2, 68) = 1.94$, n.s.), but revealed significance at Training ($F(2, 68) = 184.74$, $p < 0.01$). The LSD analysis indicated that the winning rate was significantly higher in the Best Move condition than those in the Three Candidates and No Support conditions ($p < 0.05$; $p < 0.05$).
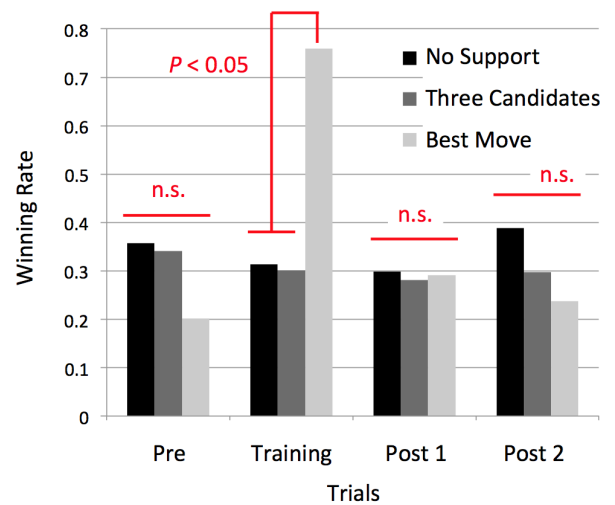

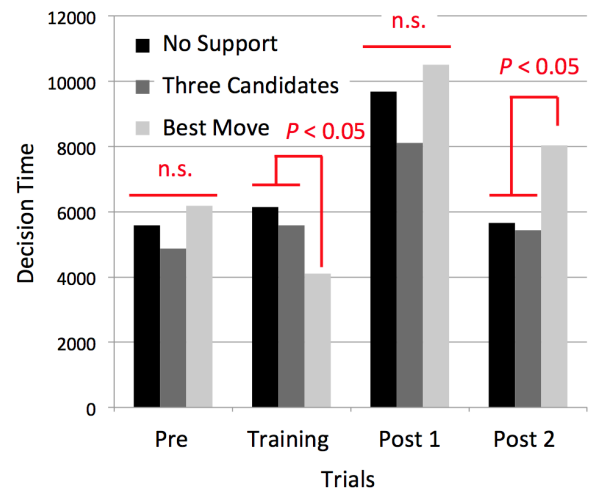Figure 4. Winning rate as a function of experimental conditions.

Figure 5. Decision time as a function of experimental conditions.

B.   Decision Time

Second, we evaluated the participants' behavior based on the average time for determining one move in their turn. First, we calculated the average time to decide one move in a game; then we averaged the decision times over the twelve games. Figure 5 shows the result.

Again, a three (Condition: No Support, Three Candidates, and Best Move) × four (Trials: Pre, Training, Post 1, and Post 2) ANOVA revealed a significant interaction ($F(6, 204) = 4.36$, $p < 0.01$). The simple main effect of the Condition factor did not reach a significant level at Pre and Post 1 ($F(2, 68) = 1.63$, n.s.; $F(2, 68) = 2.27$, n.s.), but revealed significance at Training and Post 2 ($F(2, 68) = 5.13$, $p < 0.01$; $F(2, 68) = 3.44$, $p < 0.05$). At Training, the LSD analysis indicated that the decision times in the No Support and Three Candidates conditions were longer than that in the Best Move condition ($p < 0.05$; $p < 0.05$). In contrast, at Post 2, the decision times in

the No Support and Three Candidates conditions were shorter than that in the Best Move condition ($p < 0.05$; $p < 0.05$).

C. Discussion

The learning activities inhibition hypothesis predicted that the winning rate in the training phase would increase with higher support conditions. This prediction was partially confirmed because the rate was highest in the Best Move condition, but no difference was found between the No Support and Three Candidates conditions.

The hypothesis also predicted that post-test scores would be higher in lower support conditions; but this prediction was not confirmed. There were no significant differences in the winning rates in the post-test among the three conditions. However, note that for Post 2, decision times were longer in the Best Move condition than in the other two lower support conditions. This implies that training with such a high level of support, where participants were continuously given the best move, may have inhibited learning gains, resulting in longer decision times in the post-test phase where no such computer supports were available. This speculation is consistent with the shorter decision times for Training in the Best Move condition, implying that shorter decision times reflect superficial thinking without deliberate consideration during training.

V. EXPERIMENT 2

The overall results in Experiment 1 confirmed that the performance-oriented activities are raised in higher-supported situations, but not that the learning-oriented activities increase in less-supported situations. In terms of learning gains, shorter decision times in lower supported conditions were found only in Post 2 after additional four training trials, but not in Post 1. This may imply that learning effects may emerge after longer training times. Based on this insight, we conducted Experiment 2.

A. Participants

Initially, 27 undergraduate students in the school of informatics and sciences at Nagoya University participated in Experiment 2. They were not paid because the experiment was performed as a part of the class curricula for cognitive science. Twenty-one participants were analyzed since six of the initial participants withdrew from the experiment after the pre-test.

B. Experimental conditions

In Experiment 1, we could not confirm any differences between the Three Candidates and No Support Conditions. Therefore, in Experiment 2, we set up only two experimental conditions: the Best Move and No Support conditions. The initial 27 participants were ordered according to their pre-test scores and were divided into two groups. Specifically, odd-numbered (i. e., top, third, fifth, etc.) participants were assigned to one of the two conditions, and even-numbered participants were assigned to the other condition. Six participants withdrew from the experiment, resulting in nine and twelve participants working in the No Support and Three Candidate conditions, respectively.
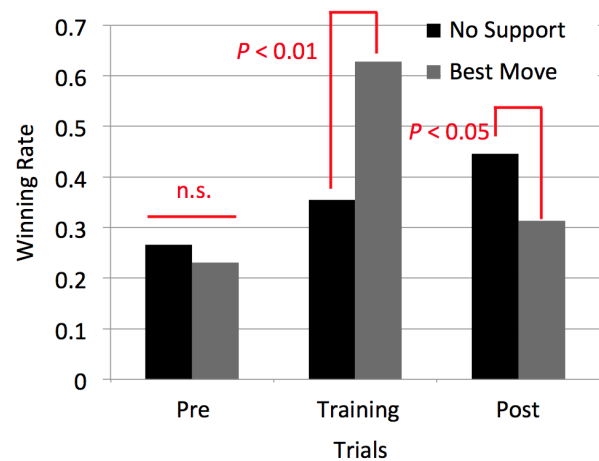

Figure 6. Winning rate as a function of experimental conditions.

C. Experimental procedure

In the initial stage, participants were instructed on how to operate the experimental system. In the Best Move condition, they were taught that a virtual agent would present the best move in each trial, but they were not required to follow its suggestions. After the instruction phase, a pre-test was given. Participants then played three games against the virtual opponent without the partner agents' supports.

After the pre-test, the participants were instructed to play three games a day over two weeks to train themselves. They were required to report their trials daily via e-mail to the experimenter. To ensure that the participants continuously engaged in games throughout two weeks, the experimenter sent e-mail reminders to participants if their daily e-mail reports were not received.

After two weeks, a post-test was performed. The experimental setting was identical to that of the pre-test phase. The participants played three games as a post-test.

VI. RESULTS

A. Winning Rate

As in Experiment 1, we first evaluated participants' performance in the training phase. Figure 6 shows the winning rates in the pre-test, two-week training period, and the post-test.

In the following analysis, the average scores over the three games were used as the pre- and post-test scores. To calculate the training scores, we first calculated the average values of each day's three games, then averaged the values over two weeks.

A two (Condition: No Support and Best Move) $\times$ three (Trials: Pre, Training, Post) ANOVA revealed a significant interaction ($F(2, 38) = 8.59$, $p < 0.01$). The simple main effect of the Condition factor did not reach a significant level at Pre ($F(1, 19) < 1$, n.s.), but revealed significance at Training and Post ($F(1, 19) = 9.52$, $p < 0.01$; $F(1, 19) = 4.81$, $p < 0.05$), indicating that the winning rates during training were higher, but the rates in the post-test were lower in the Best Move condition than those in the No Support condition.
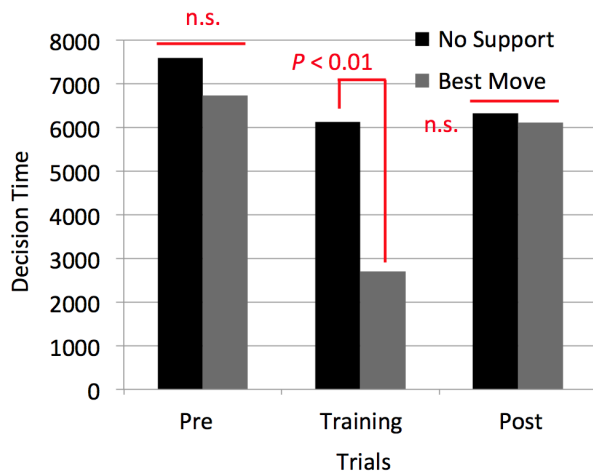
Figure 7. Decision time as a function of experimental conditions.

B. Decision Time

Second, we also evaluated the participants' behavior based on their average times for determining one move during their turn. Figure 7 shows the result.

A two (Condition: No Support and Best Move) × three (Trials: Pre, Training, and Post) ANOVA did not reveal a significant interaction ($F(2, 38) = 3.13$, n.s.). The main effect of the Condition factor did not reach a significant level ($F(1, 19) = 2.48$, n.s.). However, the figure obviously predicts a difference between the two experimental conditions in the training phase. Therefore, we performed individual statistical analyses at Pre, Training, and Post, respectively. The results show that the decision times at Training in the No Support condition were longer than that in the Best Move condition ($F(1, 19) = 15.82$, $p < 0.01$), even though there were no significant differences in decision times in the Pre and Post phases ($F(1, 19) < 1$, n.s.; $F(1, 19) < 1$, n.s.).

C. Discussion

In the training phase, the winning rates were higher and the decision times were shorter in the Best Move condition, confirming that the performance-oriented activities increase in a higher-support situation. More importantly, for the post-test, the winning rates in the Best Move condition were lower than that in the No Support condition, implying that the learning-oriented activities are inhibited in the Best Move condition. These results support the learning activities inhibition hypothesis.

VII. DISCUSSION AND CONCLUSIONS

A. Summary

In the training phase, Experiments 1 and 2 indicated that the participants' winning rates were the highest in the Best Move condition, and their decision times for determining each move were the shortest. Experiment 2 indicated that, the participants' post-test scores measured as learning gains were lower in the Best Move condition than that in the No Support condition. These results confirmed that a higher level of support promotes the performance-oriented activities,

but inhibits the learning-oriented activities of training, thus supporting the learning activities inhibition hypothesis.

B. Assistance Dilemma

Similar findings have been reported in studies on intelligent tutoring systems. Koedinger and Aleven (2007) posed a crucial question: How should learning environments balance assistance and the withholding of assistance to optimize the learning process? [7] This assistance dilemma is considered a central topic for establishing instructional principles in tutoring. While high assistance provides useful scaffolding that sometimes facilitates problem solving in the learning phase, it also elicits superficial responses given without serious consideration. On the other hand, low assistance encourages self-learning in students, but may introduce major errors and sometimes impede problem solving in learning.

The assistance dilemma implies that, in some cases, reducing support levels increases learning effects, even while incurring a partial loss of problem-solving performance. This speculation is consistent with the findings confirmed in this paper.

C. Cognitive Load Theory

Cognitive load theory gives us another informative perspective about the cognitive mechanisms underlying the tradeoff between the performance-oriented and learning-oriented activities confirmed in this study.

Cognitive load theory has provided design principles for learning environments constrained by cognitive architecture. The theory distinguishes three types of cognitive loads: intrinsic, extraneous, and germane [8][9]. The intrinsic load is the basic cognitive load required to perform a task. The intrinsic load increases with the increasing difficulty of a task and the decreasing expertise of the performer. The extraneous load is the wasted cognitive load unrelated to learning activities, and is reluctantly processed. One source of extraneous load is inappropriately designed learning material. The extraneous load can also be increased by a lack of related knowledge and problem solving skills. Finally, the germane load is the cognitive load for learning, such as constructing schemata.

From the perspective of cognitive load theory, the intrinsic load presumably contributes to the performance-oriented activities, and the germane load contributes to the learning-oriented activities.

Adequate assistance decreases the extraneous load by presenting related information for problem solving. Many design principles for reducing the extraneous load have been proposed [8]. However, note that decreasing the extraneous load by providing high-level assistance does not necessarily increase the germane load when superficial problem solving without deliberate thinking is performed.

Producing the germane load sufficient for maximizing learning gains is a challenging problem [10][11]. Only a limited number of design principles exist for raising the germane load while maintaining sufficient intrinsic load for performing a task. In this study, we have presented a case in which low levels of assistance may guide students toward deeper consideration, activating their learning-oriented activities for expertise.

D. Future Work

To maximize learning gains, the balance between the performance-oriented and learning-oriented activities is crucial. It is important to find ways to manipulate the balance between these two types of cognitive activities. One important factor for such manipulation comes from goals established by performers.

Goal achievement theory has provided theoretical perspectives on the relationships between students' goals and their learning activities, and also accumulated a vast amount of empirical findings [12]. In goal achievement theory, students' goals are divided into mastery and performance goals. The former motivates students to develop their own abilities, while the latter motivates them to seek higher social evaluation rather than their own development. This implies that mastery goals activate the learning-oriented activities and performance goals activate the performance-oriented activities. In the early stages of goal achievement theory, mastery goals were found to be more important than performance goals [13][14].

A recent study found the relationship between students' goals and their seeking of computer support [15]. According to this study, mastery-goal-oriented students tend to seek abstract (i.e., low-level) supports first, and then move to more specific (high-level) supports, whereas performance-goal-oriented students preferred quick and direct supports during the initial stage. This implies that mastery oriented-students tend to focus their cognitive load on learning-oriented activities.

In our future work, it will be important to conduct further experiments controlling for participants' goal factors in order to seek a way to promote the learning-oriented activities while cultivating sufficient performance-oriented activities.

Acknowledgment

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