Master's Thesis
석사 학위논문

Individual differences in statistical learning

Jungtak Park (박 정 탁 朴 正 倬)

Department of
Brain and Cognitive Sciences

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Advisor: Professor Hyeon-Ae Jeon
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A thesis submitted to the faculty of DGIST in partial fulfillment of the requirements for the degree of Master of Science in the Department of Brain and Cognitive Sciences. The study was conducted in accordance with Code of Research Ethics[1]

11. 20. 2019

Approved by

Professor Hyeon-Ae Jeon (Advisor) ______________ (signature)

Professor Wookyung Yu (Co-Advisor) ______________ (signature)

[1] Declaration of Ethical Conduct in Research: I, as a graduate student of DGIST, hereby declare that I have not committed any acts that may damage the credibility of my research. These include, but are not limited to: falsification, thesis written by someone else, distortion of research findings or plagiarism. I affirm that my thesis contains honest conclusions based on my own careful research under the guidance of my thesis advisor.

Individual differences in statistical learning

Jungtak Park

Accepted in partial fulfillment of the requirements for the degree of Master of Science.

11. 20. 2019

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ABSTRACT

Statistical learning (SL) is an essential learning mechanism which enables humans to extract probabilistic regularities from the world. Even though previous studies have examined quality of SL, they overlooked quality of learning and efficiency of learning in SL. Moreover, the ultimate quality of learning with training, that is, the potential of learning has been known to be dissociated with the efficiency of learning. Therefore, in the present study, we elucidated the potential as well as the efficiency of SL separately and investigated which processes of executive functions mainly exerted on them. Specifically, we quantified the efficiency and the potential of SL through mathematical modeling, using participants' performances in alternating serial reaction time (ASRT) task and correlating them with individuals' executive functions such as set shifting, updating, and inhibition. In results, low efficiency of SL was closely related to good inhibitory function whereas potential of SL was not associated with any of the executive functions. Our results, via a novel approach of mathematical modeling, shed lights on the overarching role of inhibition in the efficiency of SL.

Keywords: statistical learning, mathematical modeling, executive functions

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I. Introduction

Statistical learning (SL) is an implicit mechanism which requires learners to extract probabilistic regularities from the environment[1-6]. SL is a critical process in daily lives based on the fact that, through SL, learners grasp probabilistic regularities which help us to predict upcoming events and to prepare appropriate actions effectively. SL has been examined across various types of tasks and stimuli, including visual stimuli[7], tactile stimuli[8], non-linguistic sounds[9], auditory syllables[10], and action segmentation[11]. The effect of SL has been examined by Alternating Serial Reaction Time (ASRT) task in which odd-numbered trials generate a fixed sequence and even-numbered trials are randomly made such that participants learn the sequence implicitly[12-14].

The effect of SL has been studied mostly through the quality of SL which denotes the performance difference between probable targets (i.e., high probable condition) and improbable targets (i.e., low probable condition)[14-16]. Interestingly, the quality of SL is known to be related to the frontal lobe of the brain which has been intertwined with higher-order cognitive functions, particularly executive functions[13,14,17-19]. For example, the quality of SL was negatively correlated with a composite score which is an average value of normalized scores of several neuropsychological tests for the assessment of executive functions[17]. An electroencephalography (EEG) study also found a dynamic human brain network, showing that a functional connectivity of frontal areas was negatively correlated with individuals' SL performance[14]. These studies posit a close relationship between the quality of SL and the executive functions. In fact, executive functions include cognitive processes such as response inhibition, working memory, and set shifting[20-23]. Among executive functions, which one is most pertinent to SL still remains unclear. Considering that executive functions are integral to high-level cognitive processes in humans, it is worth addressing potential effects of those processes on SL.

Speed of learning has been a critical component in learning mechanism in that it assists obtaining information more efficiently, so called, efficiency of learning[24-26]. The efficiency of learning is measured by the improvement in accuracy and speed per amount of learning time[27]. For example, when people performed a paired-associate learning task, slow learners needed more trials to achieve a criterion compared to fast learners, having low level of learning efficiency with relatively more time compared to fast learners[26]. Although many studies have investigated the efficiency of learning, no attempt has been made to understand SL specifically with respect to the efficiency of learning. Therefore, for the better understanding of SL mechanism in humans, we should scrutinize the efficiency of learning as well as the quality of learning during SL.

Since the quality of learning is closely related to the efficiency of learning [24], it is challenging to separate the quality of learning and the efficiency of learning in the participants' performance. Therefore, we should find another component which is separable from the efficiency of learning. Interestingly, it has been suggested that there is a dissociation between the efficiency of learning and the potential of learning which is the ability to accomplish an ultimate quality of learning with training[24]. For example, although old adults required more time in motor skill acquisition compared to younger participants, after the learning, the final performance in old adults was comparable to that of younger participants[28,29]. It indicates that although old and young adults had different efficiency of learning (i.e. different learning time between groups), the potential of learning (i.e., the final performance) was similar between each group. Since the potential and the efficiency of learning seem to play a different role in learning system, it is important to scrutinize the efficiency of learning and potential of learning separately. Therefore, in the present study, we distinguished the efficiency of learning from the potential of learning in SL.

In the present study, we investigate the progress of SL, aiming at elaborating on both potential and efficiency of SL with the help of mathematical modelling. So far, an exponential function and a power function have been mainly used for the explanation of learning progress[30-33]. In line with this, we tested both functions in the present study to delineate the performance change of SL over the course of learning. If participants' performance changes according to the exponential function, their performance would converge towards a saturation point where learning would be almost completed and thus participants would not make much progress anymore. In case of the power function, the performance of SL would diverge while learning progress would decrease.

We explore the effect of response bias on the performance of ASRT task in the present study. Response bias is a systematic preference to a particular answer or a response over others[34,35]. This may cause a performance difference between high probable condition and low probable condition in SL tasks. Previous study showed that the error occurred more frequently in the low probable condition than high probable condition in a motor sequence learning task[36]. Moreover, the error rate of low probable condition considerably increased with time although that of high probable condition did not. Another study using ASRT task also reported that participants had a tendency to anticipate high probable targets more than low probable targets[12]. These studies indicate that participants were presented with high probable targets more frequently than low probable targets, whereby participants tended to press the high probable button by mistake even in the low probable condition, having response bias. However, the relation between response bias and the error rate in the low probable condition has not been thoroughly investigated yet. Therefore, in the present study, we quantified participants' response bias and investigated its influence on the performance of SL.

We aimed to elucidate, among several executive functions, which one was most influential on the potential and the efficiency of SL. To this end, through mathematical modeling[37] we firstly quantified participants' potential and efficiency of learning in SL using ASRT task. Secondly, we calculated correlation coefficients between scores of neuropsychological tests for executive functions and the potential and the efficiency of SL, providing a novel and precise explanation for the potential and the efficiency of SL mediated by various executive functions. To foreshadow the core findings, exponential function was selected as a best model to represent our data. Thereby, we measured both efficiency of SL and potential of SL in the exponential model, and inhibitory control, among several executive functions, was significantly pertinent to the efficiency of SL while the potential of SL did not show a significant relation with any of those executive functions. Our study makes great strides towards unraveling the overarching features of SL by means of mathematical modeling of the performance in SL which is closely interwoven with executive functions.

II. Methods

2.1 Participants

Forty-four Koreans (mean age = 20.32, SD = 1.35; 22 females) participated in the experiment. All of them were right-handed with normal or corrected-to-normal vision. Every participant signed an informed consent form prior to the experiment. Four participants' data were excluded from the analysis due to mild depression and a color vision deficiency. Therefore, the data of 40 participants (mean age = 20.30, SD = 1.38; 20 females) were used for the analysis. This study was approved by the Daegu Gyeongbuk Institute of Science and Technology (DGIST) ethics committee.

2.2 Procedure

Participants were tested with two sessions on two separate days. In Session 1, they were administered with seven neuropsychological tests (Word fluency test, Counting span test, Corsi-block test, Wisconsin card sorting test, Stroop test, Attention network test, and Go/Nogo test) which are known to assess the executive functions. Through this, we could examine statistical learning (SL) performance in relation to individuals' executive functions. In Session 2, participants performed ASRT task[12-14].

2.3 Neuropsychological test

2.3.1 Word fluency test (category and letter)

We administered two kinds of word fluency test to measure an ability of individuals' verbal fluency[38-40]. In the category fluency test, participants produced words which belong to the category of animals and supermarket items. In the letter fluency test, they generated words starting with Korean consonants of 'ㄱ', 'ㅇ', and 'ㅅ'[41]. In both tests, participants should generate words as many as possible in 60 s. Responses such as repetition, proper nouns, superordinate items, and derivatives were not counted as correct responses[42]. Average number of correct responses was used for scoring.

2.3.2 Counting span test (forward and backward)

Individuals' ability of verbal working memory was measured by counting span test[43]. A different quantity of blue circles, blue squares, and yellow circles were randomly displayed on a computer screen. Participants verbally counted only blue circles (targets) one by one in every trial. When they finished counting the targets, experimenter changed the screen and participants started counting newly presented targets. When a recall cue appeared, participants should report the numbers of blue circles (targets) presented in the previous trials in order (forward span) or in reverse order (backward span). The level, that is, the length of presented trials varied from 2 to 8 in a set, and there were three sets in both forward and backward tests. The final level which was the maximum number of trials correctly produced forwards or backwards in each set were averaged and used as the score of the counting span test.

2.3.3 Corsi-block test (forward and backward)

Corsi-block test assessed an individual's visuo-spatial working memory capacity[44]. Nine purple colored squares were presented on a monitor in a random position, and some of them flickered with a yellow color in a consecutive order. Participants were required to memorize both the locations and the order of the flickering squares and repeated them by clicking the positions in a forward or backward way using a mouse-click. The test began with a small number of flickering squares which gradually increased in length up to nine squares. The longest length of correctly retrieved squares was measured as span scores.

2.3.4 Wisconsin card sorting test (WCST)

The ability of set-shifting was measured by WCST[23,45-47]. Four cards were shown on the top position of the monitor, and another card was presented at bottom of the screen. Participants were asked to classify the card at the bottom according to three criteria such as color, shape, or number of symbols and to match it to one of the four cards in the upper card deck with a mouse-click. They were given with a feedback in every card selection such that they could adjust the classification rule. The rule changed every 10 cards but participants were not aware of it so that they should concentrate on feedbacks to recognize the rule change[48]. When participants stuck to the previous rule and failed in adjusting a new rule, this was considered to be a perseverative error. The number of perseverative errors was counted as a WCST score.

2.3.5 Stroop test

We used computerized Korean version of Stroop test to look into the ability of inhibitory control, using four color words (red, green, blue, and yellow) displayed in a different font color[47,49,50]. Participants indicated the font color by pressing keys (r, g, b, and y for the colors of red, green, blue, and yellow, respectively) on a keyboard[51]. There were two kinds of conditions; one is a congruent condition where the color words correspond to the font colors and the other is an incongruent condition where the color words and the font colors do not match. The difference in reaction times (RTs) between incongruent and congruent conditions were measured as a Stroop score.

2.3.6 Attention network test

This test is known to assess inhibition and selective attention[47]. There were four different types of star cues such as a spatial cue, a double cue, a center cue, and no cue. In the spatial cue, a star was presented on the upper or lower part of a cross fixation positioned at the center. In the double cue, two stars appeared on both upper and lower parts simultaneously. In the center cue, a star was shown at the center. The no cue showed nothing on the screen. After the presence of the cue, flanker arrows were presented on the upper or lower part of the cross fixation. There were three kinds of flanker type. Firstly, a neutral type contained only one arrow indicating a right or left direction. Secondly, a congruent type had five arrows in a row pointing the same direction (either right or left). Lastly, an incongruent type showed four arrows pointing the same direction (e.g., right) and the middle arrow pointing the opposite direction (e.g., left). Participants should press a right or left shift key on the keyboard which corresponded to the direction of the middle arrow[52]. The score of attention network test was calculated as follows (1)[53].

$$Score\ of\ attention\ network\ test = \frac{RT_{Incongruent} - RT_{Congruent}}{RT_{Congruent}} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots \quad (1)$$

2.3.7 Go/Nogo test

Go/Nogo test assessed an individual's ability of inhibitory control[54]. The test started with a 2×2 array containing star shaped four blue objects. In P-go condition, participants pressed the right shift key on a keyboard when the letter P was presented on one of the four positions in the array. On the other hand, in R-nogo condition, participants should not respond when the letter R was presented. This rule changed in another session with R-go and P-nogo conditions. The accuracy of no-go conditions represented the Go/Nogo score[54,55].

2.4 Alternating Serial Reaction Time (ASRT) task

We used modified version of ASRT task (Fig. 1)[14,56]. Different from the original ASRT task, no feedback was given here. The task was composed of 36 blocks where each block was alternated with a cross fixation shown for six to eight s as a rest block. Each test block took 52.9 s and the entire ASRT task took about 38-40 min. The block started with five warm-up trials followed by 10 sequences. Each sequence was composed of 8 target trials. Therefore, one block contained 85 trials [5 warm-up trials + (8 target trials x 10 sequences)]. The block began with four empty circles shown in the middle of the gray screen for 200 ms. In the target trial, a target stimulus (a face of a dog) was presented for 500 ms in one of the four empty circles. Participants were asked to press a button which corresponded to the position where the target was presented as accurate and fast as possible using a Chronos four button box (Psychology Software Tools Inc, Sharpsburg, PA). Between target trials, four empty circles were presented for 120 ms as an inter-trial-interval.

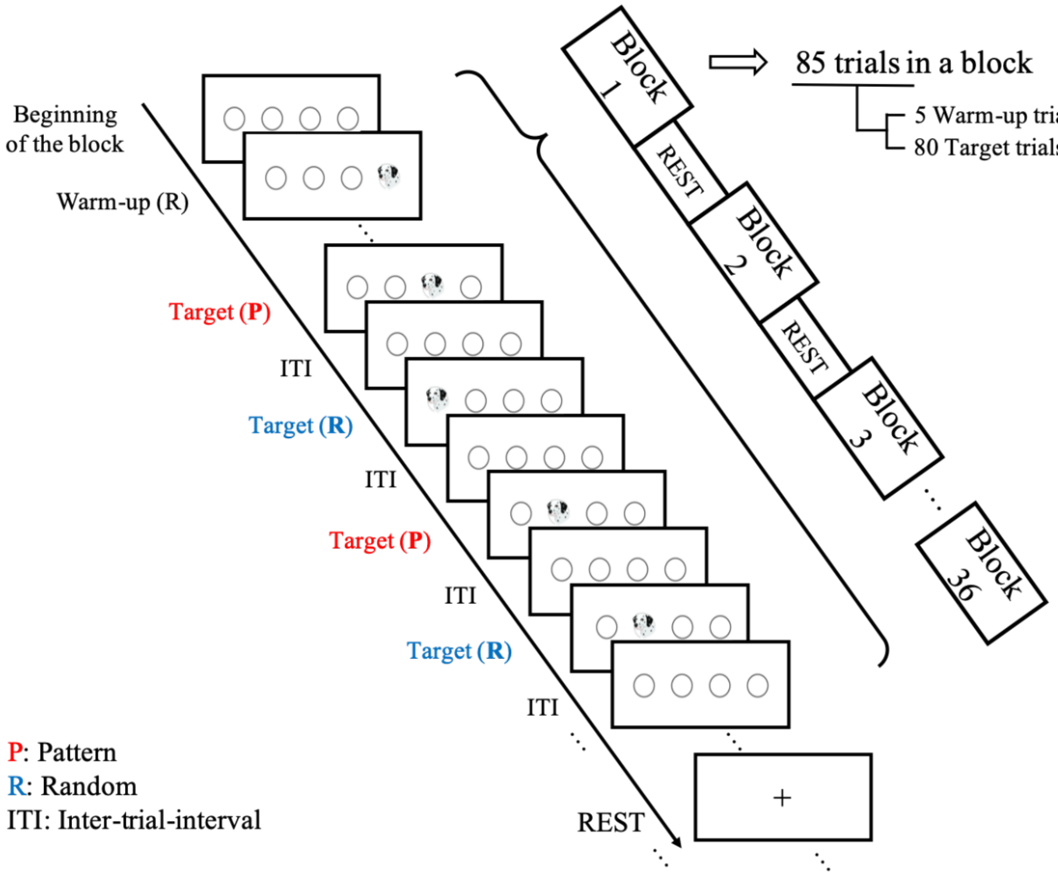
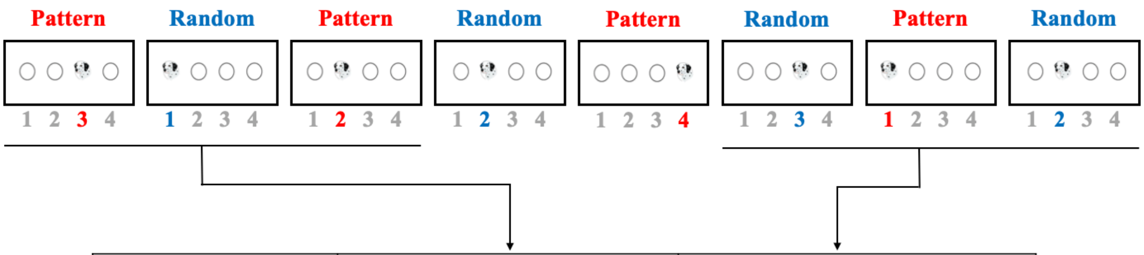


Figure 1. *Design of ASRT task.* Four empty circles were shown on the screen for 200 ms, then the 5 warm-up trials were presented in the middle of a monitor for 500 ms. After that, 80 target trials were appeared in the one of four positions with alternating serial sequence. The inter-trial-interval was inserted between stimuli for 120 ms. These 85 trials were consisted of a block which took 52.9 s. The total 36 test blocks were conducted, and 6, 7 or 8 seconds of rest block was inserted between test blocks.

There were two kinds of target trials being alternated with each other: a pattern trial and a random trial (Fig. 2A). In the pattern trial, a target (a dog) was presented in a fixed position whereas, in a random trial, a target was shown randomly in one of four positions. For example, a sequence composed of 3r2r4r1r (number: a fixed position in the pattern trial, r: a random position in the random trial) indicates an alternating serial sequence between pattern trials (3_2_4_1_) and random trials (_r_r_r_r). A specific pattern in the sequence was determined by an order of permutation (e.g., 1r2r3r4r, 1r2r4r3r, …, 4r3r2r1r) for each participant so that the number of occurrences of every alternating serial sequence was counterbalanced across participants. After the ASRT task, participants were asked if they noticed a regular pattern during the experiment. Nobody reported regularities, which indicated that participants did not recognize the structure of alternating serial sequence explicitly.

(A) **Alternating Serial Sequence**



(B)

	Pattern-type triplets [P – R – P]	**Random**-type triplets [R – P – R]
High-probability triplets	<Pattern-High> 3 – 1 – 2 (50%)	<Random-High> 3 – 1 – 2 (12.5%)
Low-probability triplets	Not Available	<Random-Low> 3 – 1 – 1 (12.5%) 3 – 1 – 3 (12.5%) 3 – 1 – 4 (12.5%)

Figure 2. *Alternating serial sequence in ASRT task.* (A) Pattern trials and random trials were shown in an alternating order. An alternating serial sequence consisted of eight target trials (e.g. 3r2r4r1r). (B) When we analyzed this sequence, we combined three trials into a triplet so that alternating serial sequence generated three conditions such as Pattern-High, Random-High, and Random-Low. Interestingly, Pattern-High and Random-High shared the same triplets. In this example, '3-1-2' is a Pattern-High, but this triplet could also appear in the Random-High (e.g. 3-1-2).

Three different conditions were constructed by combining the type (Pattern v. Random) and the probability (High vs. Low) of triplet occurrence: Pattern-High, Random-High, and Random-Low (Fig. 2B). As for the type, three trials making a triplet were classified as either a Pattern-type triplet or a Random-type triplet[57]. For example, 3r2, 2r4, 4r1, or 1r3 were the Pattern-type triplets because they had two pattern trials shown regularly in a sequence and only one random trial in between. However, r3r, r2r, r4r, or r1r triplets were Random-type because these triplets included two random trials and only one pattern trial in between. With respect to the probability, some triplets (e.g., 3-1-2 and 3-1-2 in Fig. 2B) were shown more often than others because they were found in both Pattern-type and Random-type whereas others (e.g., 3-1-1, 3-1-3, and 3-1-4) were presented only in the Random-type. Based on this probability difference in the occurrence of the triplet, we categorized High-probability and Low-probability triplets. Taken together, we manipulated three conditions by integrating the type with the probability: Pattern-High (Pattern-type x High-probability), Random-High (Random-type x High-probability), and Random-Low (Random-type x Low-probability). In particular, it is important to note that Random-High and Random-Low were separated solely by the probability of triplet occurrence, that is, a different probability of occurrence with the same type of triplet. Comparing these two conditions (i.e., Random-High vs. Random-Low) made it possible to investigate the genuine effect of SL. Pattern-Low condition was not available in the ASRT task.

The exact probability of occurrence in triplets was calculated as follows. The Pattern-type and the Random-type were shown in the same proportion of 1:1. In the Random-type, Random-High and Random-Low were shown in the proportion of 1:3. Thus, the probabilities of occurrence in Pattern-High, Random-High, and Random-Low were 50%, 12.5%, and 37.5%, respectively. In consequence, high probability triplets and low probability triplets were shown in the proportion of 5:3 [62.5% (50%+12.5%): 37.5%]. We should also consider the total number of triplets in each condition. Since the number of Low-probability triplets were three times more than the number of High-probability triplets (48 triplets in Low-probability triplets; 16 triplets in High-probability triplets), this indicates that the High-probability triplet was shown 5 times more than the Low-probability triplet probabilistically. This probability is calculated as the following calculation (2).

$$\frac{5\ (\text{probability of occurence of High}-\text{probability triplets})}{16\ (\text{number of High}-\text{probability triplets})} : \frac{3\ (\text{probability of occurence of Low}-\text{probability triplets})}{48\ (\text{number of Low}-\text{probability triplets})} = 5:1 \quad \cdots (2)$$

2.5 Data analysis

2.5.1 Investigation of participants' performance in SL

Three steps of analyses were performed to examine whether participants successfully learned the probabilistic sequence in the ASRT task or not. In Step 1, we explored the effect of type by comparing two conditions in the High-probability triplets (Pattern-High vs. Random-High). In addition, the effect of the probability of occurrence was investigated in the comparison of two different probability triplets in the Random-type triplets (Random-High vs. Random-Low). T-test with individuals' mean RTs and accuracy of each condition were used in Step 1. In Step 2, simple linear regression was performed to investigate the change in accuracy over the course of block number in each condition, using individual's accuracy in every block. The block number was used as a predictor in the simple linear regression. Through these steps, we could investigate the effect of SL on raw performance data such as accuracy and RT. After that, in Step 3, we examined the effect of dynamic changes of SL using SL scores. The SL score was defined as an absolute value of difference in performance between Random-High and Random-Low, indicating that participants have learned the statistical probabilities of stimuli[1-3,14]. We calculated the SL score in every block to investigate the dynamic changes of SL over the course of learning time (blocks). For all the analyses, we used RTs of correct responses only.

2.5.2 Modeling of the SL score

We tested the first-order exponential function ($y = -w_1 e^{-x/w_2} + w_3$), the power function ($y = w_1 x^{w_2} + w_3$), and additionally a linear function ($y = w_1(x - w_2) + w_3$). Here, w indicates estimated parameters of the models. Maximum likelihood estimation (MLE) was used to fit the data into learning curves[58,59]. Two criteria of goodness-of-fit were used to find a winning model which explains the SL score best between the learning models. One is the corrected Akaike information criterion (AICc)[60]. Since we did not have many numbers of data point

(36 blocks) and participants (40 participants), we used a corrected term (AICc) instead of original AIC[60,61]. The other alternative criterion is Bayesian information criterion (BIC)[62]. The equation of AICc and BIC are described below in (3) and (4). Here, k is the number of estimated parameters; n is the sample size; and L is the saturated value of the likelihood function for the model.

$$\mathrm{AICc} = 2\mathrm{k} \times \frac{n}{n-k-1} - 2 \times \log L \cdots\cdots \quad (3)$$

$$\mathrm{BIC} = \mathrm{k} \times \log n - 2 \times \log L \cdots\cdots \quad (4)$$

We compared the models following the scale of Table 1[60,63,64]. Specifically, when we compared the BIC values, we used Bayes factor[65]. Bayes factor for model M_1 against model M_0 was calculated by the following equation (5).

$$\text{Bayes factor} = e^{-0.5(\mathrm{BIC}_{M_1} - \mathrm{BIC}_{M_0})} \cdots\cdots (5)$$

In result, the exponential function fit best to the SL score compared to other models. This function is described as follows: $y = -Ae^{-x/\tau} + y_0$ (y: estimated SL score in RT/accuracy data, y_0: saturation level of estimated SL score, A: curve amplitude, x: block number, τ: exponential time constant). This equation is similar to a step response function of a first-order system[66]. In the step response, the curve amplitude— "A"—indicates the amount of increase in the performance of SL scores (the difference in performance between Random-High and Random-Low, as mentioned earlier) and the saturation level of the estimated SL score—"y_0"—reflects the predicted ultimate SL score with practice[30]. If the first-order increasing system responds to a step input, the time constant (τ) is defined as a time point to reach $1-\frac{1}{e}$ ($\approx 63.2\%$) of A (curve amplitude)[66]. In principle, arbitrary large τ represents the late block number in the task and thus τ is a reliable factor to determine an efficiency of SL[66-71].

Table 1. Scale for interpreting the ΔAICc and Bayes factor for model M_1 against model M_0

ΔAICc	Bayes factor	Interpretation
< 2	< 1	Substantial support for the M_0
2-4	1-3	Not worth more than bare mention
4-7	3-20	Positively support for the M_1
7-10	20-150	Strongly support for the M_1
> 10	> 150	Very strongly support for the M_1

Abbreviations: AICc, corrected Akaike information criterion.

2.5.3 Response bias

We scrutinized a bias score which is the probability of participants' tendency towards pressing the button of High-probability target in spite of the presence of Low-probability target. We defined a bias error as the case of pressing the button of High-probability targets in the presence of the Low-probability targets. The bias score was calculated as in the equation (6) in a way that number of responses of High-probability targets in the Low-probability targets, that is number of bias errors, were divided into the total number of incorrect responses in the Low-probability targets[36].

$$\text{Bias score} = P(H|I) = \frac{P(H \cap I)}{P(I)} = \frac{n(H \cap I)}{n(I)} \cdots\cdots (6)$$

- $P(H)$: Probability associated with pressing buttons of High-probability targets
- $P(I)$: Probability associated with pressing incorrect buttons in the Low-probability targets
- $P(H \cap I)$: Probability associated with occurrence of bias errors
- $n(H \cap I)$: Number of bias errors.
- $n(I)$: Number of total incorrect responses in the Low-probability targets

Then, a change of the bias score was investigated over the course of SL by a simple linear regression. Moreover, we estimated the accuracy in each condition using a multiple linear regression with predictors of the block numbers and the bias score so that we could investigate if participants' performance in accuracy was influenced by response bias.

2.5.4 Correlation analysis

We calculated Kendall's tau coefficient between the scores of participants' neuropsychological tests and the two parameters—y_0 (potential of SL) and τ (efficiency of SL)—to explore the relationship between SL and an individual's executive functions[72,73]. We transformed all scores into standard z-scores to better fit the normal distribution.

III. Results

3.1 Success in SL: Higher accuracy and faster RT in Random-High than Random-Low

The effect of the probability of occurrence was investigated using mean accuracy and mean reaction times (RTs) of Random-High and Random-Low (Step 1 of Data Analysis in Methods section). Accuracy was significantly higher in Random-High (92.9 %, SD = 0.033) than in Random-Low (90.2 %, SD = 0.041, $t_{(78)}$ = 3.034, $P < 0.01$). In the RT data, Random-High (279.9 ms, SD = 23.13) was marginally faster than Random-Low (290.0 ms, SD = 21.90, $t_{(78)}$ = -1.981, P = 0.051). These results indicated that participants succeeded in learning probabilistic sequences in the ASRT task. However, when we examined the effect of type by comparing Pattern-High (Accuracy = 92.7 %, SD = 0.032; mean RTs = 284.0 ms, SD = 22.79) with Random-High (Accuracy = 92.9 %, SD = 0.033; mean RTs = 279.9 ms, SD = 23.13), no significant differences were found in accuracy ($t_{(78)}$ = -0.244, P = 0.808) or mean RTs ($t_{(78)}$ = 0.786, P = 0.434).

3.2 Decrease of accuracy in Random-Low triggered by response bias

A simple linear regression was used to look into the change of accuracy as the learning time (i.e., block number) progressed (Step 2 of Data Analysis in Methods section). Contrary to our expectation, β coefficients for block number which represent the slope of accuracy with the learning time (block number) were negative across all the conditions, which indicated the decrease of accuracies along with the increase of the block number (Table 2A). The β coefficient for block number in Random-Low was smallest compared to Pattern-High or Random-High (Pattern-High = -0.0008, Random-High = -0.0011, and Random-Low = -0.0015). The lowest β coefficient for the block number in Random-Low indicated that among the three conditions, Random-Low showed the most abrupt decrease in accuracy over the course of learning, which may be derived from response bias.

The chance level of bias score was at 33% because each trial had one correct response and three possible incorrect responses. Interestingly, our data showed that the mean bias score was 39.94% which was significantly higher than the chance level ($t_{(70)}$ = -3.591, P < 0.001) (Fig. 3). In addition, a simple linear regression was computed to observe how the bias score changed over the course of learning (i.e., the increase of block number). A marginally significant linear regression equation was found [$F_{(1,34)}$ = 4.068, P = 0.052, R^2 = 0.107] with the slope of the line (0.0017) and the intercept of the line (0.3313). This result indicates that the predictor variable (i.e., the block number) is likely to predict the outcome variable (i.e., bias score). Therefore, we suggest that, as SL progressed, participants were more likely to press High-probability target buttons even when they were supposed to press Low-probability target buttons, being influenced by response bias. And this effect was more noticeable in Random-Low compared to Pattern-High and Random-High.

Table 2. Regression models for the decrease of accuracy

A. Simple linear regression model

		Coefficients				Model Summary				
		β	*SE*	*t*	*P*	$F_{(1,34)}$	*P*	R^2	AICc	BIC
Pattern-High	(Constant)	.9411	.002	441.5	$P < .001$	58.70	6.61×10^{-9}	.633	-260.8	-258.0
	Block number	-.0008	.000	-7.7	$P < .001$					
Random-High	(Constant)	.9476	.004	227.7	$P < .001$	29.74	4.42×10^{-6}	.467	-212.6	-209.8
	Block number	-.0011	.000	-5.5	$P < .001$					
Random-Low	(Constant)	.9304	.003	302.3	$P < .001$	112.6	2.51×10^{-12}	.768	-234.3	-231.5
	Block number	-.0015	.000	-10.6	$P < .001$					

B. Multiple linear regression model

		Coefficients				Model Summary				
		β	*SE*	*t*	*P*	$F_{(2,33)}$	*P*	R^2	AICc	BIC
Pattern-High	(Constant)	.9465	.007	128.8	$P < .001$	29.29	4.85×10^{-8}	.640	-261.4	-255.0
	Block number	-.0007	.000	-6.9	$P < .001$					
	Bias score	-.0161	.021	-0.8	$P = .448$					
Random-High	(Constant)	.9511	.014	66.3	$P < .001$	14.49	3.04×10^{-5}	.468	-212.7	-206.3
	Block number	-.0011	.000	-5.0	$P < .001$					
	Bias score	-.0106	.041	-0.3	$P = .799$					
Random-Low	(Constant)	.9532	.010	97.5	$P < .001$	67.42	2.21×10^{-12}	.803	-240.3	-233.9
	Block number	-.0014	.000	-9.9	$P < .001$					
	Bias score	-.0688	.028	-2.4	$P < .05$					

Abbreviations: *SE*, standard error; AICc, corrected Akaike information criterion; BIC, Bayesian information criterion.

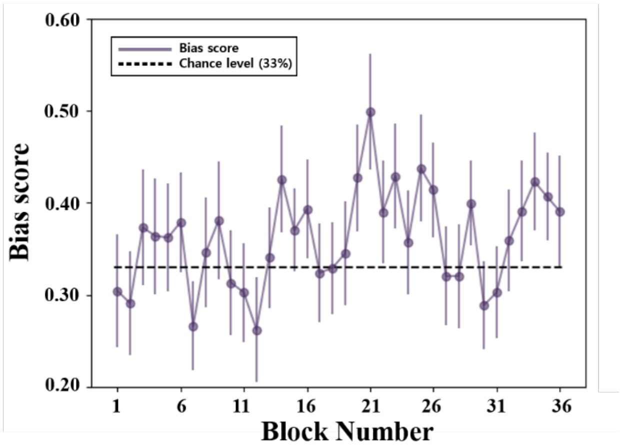


Figure 3. *Increase of bias score over the course of learning.* The change of bias score along the block number was shown with purple color, and dashed black line means the chance level (33%). Error bars exhibit the standard error of the mean. In results, bias scores significantly higher than chance level, marginally increasing over time.

To verify the influence of response bias on the decrease of accuracy specifically in Random-Low, we computed multiple linear regression in all the conditions by using the block number and bias score as predictor variables. In Table 2B, the result showed that the block number predicted the decrease of accuracy in all conditions. However, the bias score predicted the decrease of accuracy only in Random-Low ($P < 0.05$). Moreover, the model comparison between simple and multiple linear regressions with AIC and BIC values supported the multiple linear regression model in Random-Low ($\Delta AICc = 6$ and Bayes factor = 3.3), but not in Pattern-High and Random-High (Table 3). It indicates that appending the bias score in the regression model enhanced model fit only in Random-Low. In other words, response bias seemed to contribute to the decrease of accuracy particularly in Random-Low, but not in Pattern-High and Random-High.

Table 3. Comparison between simple and multiple linear regression models

	Pattern-High	Random-High	Random-Low
ΔAICc	0.6	0.1	6.0
$Bayes\ factor$	0.22	0.17	3.3

Abbreviations: AICc, corrected Akaike information criterion.

3.3 Modeling SL score for the investigation of individuals' potential and efficiency of SL

We examined the effect of SL in the conditional performances so far. Here now on, we pore over the effect of SL score which is defined as an absolute value of difference in the Random-High and Random-Low (Step 3 of Data Analysis in Methods section). The SL score in RTs increased significantly as the block number increased ($F_{(1,34)}$ = 25.84, P = 1.34 × 10^{-5}, R^2 = 0.432). Contrary to the RT data, no significant increase of SL score was observed in the accuracy ($F_{(1,34)}$ = 3.795, P = 0.06, R^2 = 0.1). The SL score of accuracy marginally increased over time with a large variance of performance, whereas the SL score of RT remarkably increased over the course of learning. Thus, we used only the SL score of RT for further analyses.

Using maximum likelihood estimation (MLE), we fitted exponential model ($y = -w_1 e^{-x/w_2} + w_3$), power model ($y = w_1 x^{w_2} + w_3$), and linear model ($y = w_1(x - w_2) + w_3$) to every participants' SL score from each block. The values of AICc and BIC for each model were shown in the Table 4. The exponential function

($y = -Ae^{-x/\tau} + y_0$) had the smallest value of AICc and BIC compared to other two models, and thus we argued that the exponential function fit best to SL score. Based on this result, we considered only the exponential model for further analyses.

Table 4. Parameters and value of AICc and BIC of exponential model, power model, and linear model

	Models for the SL score of RT		
	Exponential	*Power*	*Linear*
Parameter w_1	13.01	13.73	0.27
Parameter w_2	9.67	-0.18	4.80
Parameter w_3	13.18	-12.29	-0.40
AICc	12565	12568	12573
BIC	12559	12562	12568

Abbreviations: *Exponential*, exponential model; *Power*, power model; *Linear*, linear model; AICc, corrected Akaike information criterion; BIC, Bayesian information criterion.

The estimated learning curve in the exponential model was illustrated in Figure 4. We used the individual saturation level of SL score (y_0) and time constant (τ) to investigate the individual potential of SL and the efficiency of SL, respectively. The estimated equation for SL score of RT is $y = -13.01e^{-x/9.67} + 13.18$, which indicated that the total participants' saturation level of SL score was 13.18ms, and the SL score reached at the 63.2% of A in the 9th block.

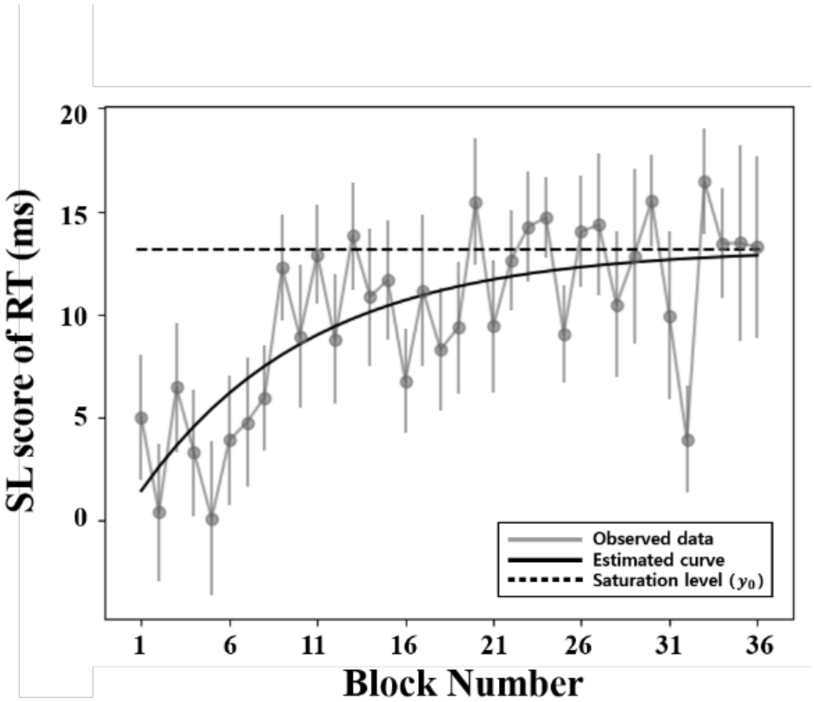


Figure 4. *The increase of SL score in RTs over time.* X-axis and y-axis indicate the block number and the SL score of RT, respectively. Gray dots represent averaged SL score of RT and the black solid line is an estimated curve from the exponential model. Dashed line exhibits the saturation level of SL score (y_0).

3.4 A significant correlation between the efficiency of SL and inhibition across all the participants

We calculated correlation coefficients between the scores of neuropsychological tests and saturation level of SL score (y_0) and time constant (τ) (Table 5). Across all the participants, τ indicating the efficiency of SL showed a significant correlation with the Stroop score (r = -0.269, P = .021) whereas y_0 denoting the potential of SL showed no significant correlation with any other tests. These results indicated that inhibition function was closely related to the efficiency of SL, suggesting that the participants with better inhibition might tend to be slow in SL.

Table 5. Correlations between score of neuropsychological tests and both saturation level of SL score (y_0) and time constant (τ).

			Neuropsychological tests									
			Category	Letter	CST (F)	CST (B)	CBT (F)	CBT (B)	WCST	Stroop	ANT	GNG
Parameters	y_0	*r*	-.132	-.042	.035	-.003	.127	-.024	.0	.064	.128	-.193
		p	.238	.709	.760	.981	.297	.845	1.0	.560	.244	.082
	τ	*r*	-.050	-.160	-.072	-.030	.101	.133	-.193	**-.269**	-.145	.206
		p	.670	.177	.556	.806	.435	.297	.132	**.021***	.215	.080

Abbreviations: Category, Category fluency test; Letter, Letter fluency test; CST, Counting span test: CBT, Corsi-block test; WCST, Wisconsin card sorting test; Stroop, Stroop test; ANT, Attention network test; GNG, Go/Nogo test; y_0, Saturation level of SL score; τ, Time constant; F, Forward; B, Backward (*: $P < .05$).

IV. Discussion

To the best of our knowledge, we are the first to use mathematical modeling to better understand the potential as well as the efficiency of SL. As there were few attempts to investigate SL from the perspectives of potential and efficiency, our study sheds new lights on the profound understanding of SL process. Using correlation analysis, we examined the relation between individuals' executive functions and the potential and the efficiency of SL, providing a possible explanation of individual differences in SL. Moreover, we quantitatively examined the effect of response bias on the decrease of accuracy in the Random-Low using a multiple linear regression, unraveling the mechanism of response bias in more details.

4.1 A negative correlation between the efficiency of SL with an inhibitory control

There is ample evidence emphasizing the importance of executive functions in learning[74-77]. More specifically, inhibitory control is known to be related with learning process[78,79]. For example, kindergarteners who have better inhibitory control achieved higher improvement in the performance of number-line estimation task than those with poorer inhibitory control[79], which provides a close relationship between inhibitory control and mathematics learning in young children. Another study also showed that participants who had high score in the second language learning task exhibited a good inhibitory control[78]. These studies support a significant contribution of inhibitory control in learning.

Even though all the participants were successful in learning probabilistic sequences in the ASRT task, their efficiency of SL (τ) showed a negative relationship with the Stroop scores across all the participants. Based on the fact that the Stroop test has been known to measure an individual's inhibitory function[47,49,50], this result lends support to the relatively good inhibitory control in association with decrease in the efficiency of SL. Good inhibition has been known to disrupt a process of habituation in motor responses[80-82]. Habituation is regarded as decreased responsiveness to repeated stimulus[81] and the inhibition process can prevent responsiveness from the repeated stimulus. For example, previous study showed that inhibiting prior distractors which participants learned during a learning phase hindered habituation in a test phase[82]. From this point of view, we argue that our participants having a good inhibition keep the responsiveness to all types of stimulus (Pattern-High, Random-High, and Random-Low). Therefore, these participants may be slow in grasping probabilistic associations of sequence structures in SL because their inhibitory function might disrupt the response bias toward motor response (i.e., button press) of High-probability targets.

It should be noted that learning performance does not linearly increase as learning makes progress and shows more complex form such as quadratic curve[30-33]. This nonlinear curve of learning performance complicates the investigation of the efficiency of learning[83] since we cannot directly measure the non-visible efficiency with undecided form of learning curve. Therefore, mathematical modeling may be helpful in representing learning performance with respect to the efficiency of learning, whereby we used exponential function to depict participants' SL performance, focusing on the efficiency and the potential of SL. As a result, the exponential model makes it possible to estimate the ultimate gain of SL (i.e., the potential of SL) because the exponential function converges to the idealized saturation level (y_0). Moreover, it predicts the efficiency of SL through the exponential time constant (τ) which is known to be related to the efficiency of first-order system[66,70,71]. Taken together, it is crucial to point out that the present study differs from others in unraveling the significance of not only the potential of SL but also the efficiency of SL in virtue of mathematical modeling.

4.2 A significance of response bias in SL

One interesting and unexpected finding revealed by the present study is the decrease of accuracies along with the increase of the block number as evidenced by negative β coefficients across all the conditions, even if the total mean accuracy was high (91.8%). This might be explained by fatigue effect[84-86]. Previous studies showed that when participants performed a prolonged task without intervention of external stimuli, it impaired goal-directed attention[86] and action monitoring[85], resulting in decrease of accuracy. In the present study, the task difficulty of the ASRT task was low, which was substantiated by the high score of total accuracy (91.8%) across conditions and there was no feedback during the task. Therefore, participants had to stay focused for 40 minutes tediously during the ARST task and resultingly, they would get bored and tired easily. In fact, several participants had reported that taking part in the ASRT task for 40 minutes was so boring.

What is more interesting is that, Random-Low showed a large decrease in accuracy compared with Pattern-High and Random-High. Here, we suggest that the response bias may be a good way of explaining this unique phenomenon. Participants' bias scores marginally increased over time, which might be derived from their propensity for pressing the buttons of High-probability targets even when Low-probability targets were presented. This result was underpinned by multiple linear regression (Table 2B), showing that bias scores affected the accuracy only in Random-Low. Previous studies have also reported a frequent occurrence of bias errors more in the low probable condition than high probable condition[12,36,57,87]. In the present study, we advanced our understanding of response bias by quantifying it with response scores and observing the transition of bias score over the course of SL**.**

4.3 Limitations

Despite the prevailing account of the exponential function to describe SL, other possible mathematical models should be further considered to explain SL. It has been noted that there are various types of learning pattern in SL such as gradual learning pattern, decreasing pattern, stepwise pattern and so on[88]. These several types of learning pattern may involve different cognitive functions or learning strategies[89]. Therefore, a future study should look into possible mathematical models intrinsic to these various learning patterns in SL.

4.4 Conclusions

In summary, our study reveals a significance of exponential function in SL to portray a learning performance enabling us to quantify both potential and efficiency of SL. Moreover, the mathematical modeling provides significant insight into the fundamental properties of SL, revealing the close relationship between efficiency of SL and executive functions, more specifically, inhibition. Since both potential and efficiency are one of the critical factors in learning[14-16,25], our approach using mathematical modeling renders a straightforward and objective investigation in SL possible.

V. References

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요 약 문

통계학습에서의 개인차

통계학습은 사람들이 확률적 규칙성을 파악을 하는데 필요한 학습 메커니즘이다. 기존에 통계학습의 질적 연구가 많이 되어 왔지만, 통계 학습에서의 질과 효율성을 모두 확인한 연구는 없었다. 그리고 학습에 의해 도달할 수 있는 질적 최대치인 학습의 잠재력이 학습의 효율성과 분리되어 있다는 것이 알려져왔다. 따라서 본 연구에서는 학습의 잠재력과 효율성을 구분하여 세밀히 살피고, 나아가 집행기능 중 어떤 기능이 주가 되어 학습의 잠재력과 효율성을 설명할 수 있는지 알아보았다. 특히, 수학적 모델링을 통해 alternating serial reaction time (ASRT) 과제에서의 수행 능력으로부터 통계학습의 잠재력과 효율성을 정량화 하였으며, 정량화된 값을 통해 개개인의 집행기능중 어떤 기능 (주의 전환, set shifting; 정보 갱신, updating; 반응 억제, inhibition)과 상관관계가 있는지 보았다. 그 결과, 억제기능 (inhibition)과 통계학습의 효율성 사이에서 유의한 부적 관련성을 확인할 수 있었다. 하지만, 통계학습의 잠재력은 어떠한 집행기능과도 관련성을 찾을 수 없었다. 결론적으로, 본 연구에서는 수학적 모델링 방법을 통해 새로운 접근을 시도하였고, 억제기능이 통계학습에서의 효율성에 중요한 역할을 한다는 사실을 확인할 수 있었다.

핵심어: 통계학습, 수학적 모델링, 집행기능