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The Role Of Feedback In Temporal Learning

Zhuoran Zhang
Indiana State University

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Zhuoran Zhang

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COMMITTEE MEMBERS

Committee Chair: Jacqueline C. Shin, Ph.D.

Associate Professor of Psychology

Indiana State University

Committee Member: Virgil Sheets, Ph.D.

Professor of Psychology

Indiana State University

Committee Member: Veanne Anderson, Ph.D.

Professor of Psychology

Indiana State University

ABSTRACT

This study examined how feedback facilitated the learning of temporal positions. For this study, the implementation of feedback and temporal structures were manipulated. Subjects were either given or not given feedback and subjects were assigned to learn temporal positions either of *Deterministic* temporal structure or of *Probabilistic* temporal structure. The target stimulus appeared only at two temporal positions in the deterministic temporal structure. The target stimulus appeared 25% of the time equally in two temporal positions and 50% of the time in the rest of the temporal positions with the exception of first and last temporal positions in the probabilistic temporal structure. Two hypotheses were proposed for this study. The first hypothesis proposed that feedback facilitated learning of the temporal positions through explicit learning. The second hypothesis proposed that feedback facilitated learning of the temporal positions without explicit learning and by directly influencing implicit learning. The results of this study revealed a significant correlation between explicit learning and transfer score when feedback was implemented and the target stimulus was deterministic. In addition, a significant correlation between explicit learning and target identification accuracy of first block of transfer was revealed when feedback was not implemented and the target stimulus was probabilistic. These results suggest that feedback influences temporal learning by facilitating explicit learning.

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The Role of Feedback in Temporal Learning

It is common knowledge that when we do something such as riding a bike or tying our shoes repeatedly, we start to perform those actions without thinking. From a research perspective, this leads to the question—how much of these actions comes from explicit learning and how much comes from implicit learning? Explicit learning is the form of learning in which individuals are aware of what they learned and can verbally describe what they learned. Implicit learning is the form of learning in which individuals are not conscious of the learning that has taken place even though it is evident in their change of behavior. Therefore, the learners cannot easily verbalize what they have learned. Various experiments over the years have come up with conflicting results about the relationship between explicit and implicit learning. For example, serial reaction time tasks have shown that implicit learning can occur in place with or without explicit learning (Shin & Ivry, 2002; Stadler, 1992; Willingham, Nissen, & Bullemer, 1989), but probabilistic categorization tasks have shown that implicit learning can take place without explicit learning even when feedback is implemented (Knowlton, Squire, & Gluck, 1994; Shohamy, Myers, Kalanithi, & Gluck, 2008; Shohamy, Myers, Onlaor, & Gluck, 2004). Most studies have utilized the weather prediction task to study probabilistic learning. In the Shohamy et al. (2004) study, participants were given a set of four cards and using those four cards, participants classified the cards into one of two outcomes: rainy or sunny. Each of the four cards possess a unique geometric pattern that serves as cues. The cues indicate the percentage of the time that the card is associated with each of the two possible outcomes. After participants gave a response, the participants were given feedback in the form of a smile or frown. The results of this study showed individuals gradually learn the cue-outcome associations without conscious knowledge of the probabilistic frequencies determining the associations. Therefore, the relationship between explicit and implicit learning changes based on different types of learning tasks.

Less explored in the area of implicit learning is temporal learning. Temporal learning is a form of visual selective attention; the individual learns to focus on a target stimulus at a specific point in time. Previous works on temporal learning including Junker, Park, Shin, and Cho (2017) show that it’s difficult to find evidence of implicit learning in temporal learning. However, one area of temporal learning remains unexamined- can feedback influence temporal learning? Preliminary data from Zhang and Shin (2018) suggested feedback can facilitate temporal learning. Specifically, the implementation of feedback led to an increase in explicit knowledge and significant improvement in learning of the temporal positions of the target stimulus. The purpose of this study includes replicating the Zhang and Shin (2018) study and examining how feedback facilitates temporal learning. Does feedback help temporal learning by facilitating explicit learning, which leads to implicit learning? Or, can feedback facilitate the implicit learning of timing directly without explicit knowledge?

What is Visual Selective Attention and Why is Visual Attention Limited?

Due to the limited capacity of our attention, we select certain parts from our environment for our brain to process. For example, when focusing on a white duck, the color and the animal are processed separately at first and are later combined into a whole. According to Treisman and Gelade (1980), this is because features are first registered early, automatically, and on separate dimensions. In order to combine the separate features into one distinct object, focused attention is needed. Thus, focused attention acts as the glue that integrates the initially separable features into one object (Treisman & Gelade, 1980). The *rapid serial visual presentation* (RSVP) task has been utilized in many temporal learning experiments to track the position of attention at a point in time. RSVP is defined as a series of items presented at a rate of 8–12 items/second. Focused attention is often required to identify the target stimulus in the RSVP stream. However, focused attention can be disrupted during events like the *attentional blink.* Attentional blink refers to the failure to detect the second target in a pair of targets (T1 and T2) when targets are presented at a *stimulus onset asynchrony* (SOA) of 200 milliseconds to 500 milliseconds. Chun (1997) found that the attentional blink caused individuals to misreport the item appearing after the target as the target stimulus, that is, post-target intrusion errors were reported. Intrusion errors are errors made when a non-target item in the RSVP stream is misreported as the target. This misreporting of the target stimulus is theorized to result from focused attention being directed only on the first target while the second target is being presented during this 200–500 ms interval. When the second target is presented between 200-500 milliseconds after the presentation of first target, one's focused attention is still directed on the first target and this can cause the second target to be missed.

Visual Attention Can Be Controlled in Time

Studies on visual attention have shown that endogenous cues can facilitate the focus of attention to a point in time. Endogenous cues are often represented by arrows or other symbols that indicate where or when the target stimulus appears (Posner, 1980). Coull and Nobre (1998) discovered that through a *positron emission tomography* (PET)) and functional magnetic resonance imaging (fMRI) study, endogenous cues are found to facilitate the focus of attention to a point in time. In the study, participants viewed a visual display that was made up of a central cuing stimulus and two peripheral boxes. The central cuing stimulus was made up of a diamond and an outer and inner circle. The brightening of the outer circle, the temporal cue, indicated that the target would appear within a longer time interval while the brightening of the inner circle, another temporal cue, indicated that the target would appear within a shorter time interval. The left and right side of the diamond, the spatial cue, would inform the participant which box the target would appear in. For a neutral cue, both the diamond and circle brightened. The results of the study suggested that cues facilitated their respective tasks. For example, the temporal cues produced faster reaction times for tasks that informed the subjects to identify the target stimuli at a point in time compared to tasks that informed the subjects to identify the target stimuli at a point in space (Coull & Nobre, 1998).

The results of this study also suggested that a number of areas were activated in common by spatial and temporal orienting tasks. Frontal cortex, parietal cortex, visual cortex, and subcortical cortex were the common areas in the brain that were activated during the presentation of spatial and temporal cues. When participants were given a temporal cue, both PET and fMRI scans revealed that the left intraparietal sulcus was activated more compared to other areas of the brain.

Learning of Timing and Attention

Can attention be controlled in time in an RSVP task? Preparatory control is the act of maintaining attentional focus or preparing to perform a shift in attention. Sali, Anderson, and Yantis (2015) studied preparatory control by utilizing two rapid serial visual presentation streams, in which the central stimulus in both streams cued the subject to either hold attention or shift attention to the opposite stream. In addition, the experimenters manipulated the cues to which there was an equal probability of receiving a shift or hold cue at the 3000 milliseconds interval for all participants. For one third of the participants, 80% of the cues appearing at the 1000 milliseconds delay signaled a shift in attention while 80% of the cues appearing at the 5000 milliseconds delay signaled a hold in attention. The results of the study suggested that once participants determined the statistical regularity of the SOA to which the cues are presented, participants learned to adjust their preparatory control (Sali et al., 2015).

Endogenous cues have also been found to attenuate the attentional blink. Martens and Johnson (2005) found that attentional blink can be reduced by providing information about *target onset asynchrony* (TOA) of the two RSVP targets. In the experiment, Martens and Johnson (2005) devised dashes to signify the TOA between the first and second target. A cue containing a single dash indicated a short TOA, and a cue containing a row of three dashes indicated a longer TOA. In an uncued condition, participants were not shown the dashes before the onset of the first trial. The results of the study showed a significant difference between the number of second targets reported correctly during the attentional blink period in the cued condition and the number of second targets reported correctly during the attentional blink period in the uncued condition. A greater number of second target stimuli were reported correctly for the cued condition as compared to the uncued condition. Therefore, the results of the study suggested that temporal cues can influence the temporal positions to which attention was shifted by providing information to the participants that enabled temporal control of attention in an attentional blink task.

Similarly, Shin, Chang, and Cho (2015) reported improvement in the attentional blink task after implementing consistent SOAs for three consecutive days without a temporal cue. There was a significant increase in the number of target stimuli correctly identified during the attentional blink period when the second target stimulus was presented 200–500 milliseconds after the presentation of the first target stimulus relative to when SOAs were presented randomly across trials.

Implicit and Explicit Learning in Various Tasks

After viewing the RSVP sequence numerous times, it is commonly assumed that the task becomes automatic. Our attention will implicitly learn to shift to the target stimulus of a specific color. However, there have been conflicting findings over the years explaining if and how implicit learning is formed. Willingham et al. (1989) utilized serial reaction time tasks to study implicit learning. The target stimulus, an asterisk, was programmed to appear in one of four positions. In the experiment, participants were tasked with pressing four keys in order to indicate where the target stimulus appeared on the computer monitor. The position of the stimulus followed a particular 10–trial sequence. There was a decrease in median reaction time, which provided evidence for implicit learning. However, it was also found that participants who displayed explicit knowledge of the sequence experienced a larger decrease in reaction time compared to participants who did not display explicit knowledge of the sequence. Explicit knowledge was assessed by the “generate” task in this experiment. In the “generate” task, participants were required to predict the next position of the target stimulus. These findings suggest that explicit learning plays an important role in sequence learning.

In contrast, some research suggests that implicit learning might be possible without explicit learning. In another serial reaction time experiment, Stadler (1992) examined how statistical structure influenced reaction times. Before the start of the experiment, participants were only told that the purpose of the study was to examine the effects of practice on performance of serial reaction time task and not that a repeating sequence of stimuli was to be presented. In the experiment, participants were shown a low structure sequence, a medium structure sequence, or a high structure sequence. In a low structure sequence, no two letters of a sequence were repeated. In a medium structure sequence, two letters of a sequence were repeated three times. In a high structure sequence, two letters of a sequence were repeated three times, three letters of a sequence were repeated two times, and four letters of a sequence were repeated once. In the random control condition the letters in the sequence were randomized. The results showed that reaction time decreased for all conditions. Specifically, the reaction time decreased slightly for the random control condition and successively more for low, medium, and high structure conditions. Therefore, the results suggested that as statistical structure increased, learning increased despite the lack of knowledge about the sequence. However, the article did not report or measure the participant's explicit knowledge of the sequence.

Shin and Ivry (2002) expanded on the serial reaction time task by implementing response-to-stimulus intervals (*RSI*s) and SOAs in order to examine whether participants could learn to predict the target position based on timing. Two experiments were conducted to investigate whether a spatial sequence and a temporal sequence could be learned together. Participants were presented with repeating temporal and spatial sequences which were same in length and presented in the same phase relative to each other in one condition. In another condition, participants were presented with temporal and spatial sequences that were not phase matched. In other words, the temporal and spatial sequences were unequal in length. The spatial sequence was learned regardless of whether the two sequences were phase matched or not. However, timing sequence was learned only in the phase matched condition. This was true regardless of whether the temporal sequence was manipulated by varying RSIs or SOAs. This study suggested that it is not possible to implicitly learn the timing of the sequences independently of the location sequence.

Temporal Attention and Implicit Learning

Junker et al. (2017) found no evidence of implicit learning in RSVP tasks based on three experiments. In the first experiment, four subjects took part in identifying four successive targets in the correct order over nine sessions conducted on separate days. Evidence of learning was found for only one of the four subjects. Performance increased with practice only for the subject who started at a high level of performance.

In the second experiment, which was originally conducted by Junker, Park, Shin, and Cho (in preparation), the number of target stimuli in a stream was reduced to one. The target stimulus appeared in two possible temporal positions for the first group, another two possible temporal positions for the second group, and in random temporal positions for the third group. The three groups were further divided among three conditions depending on how many days participants were trained in the RSVP task. The participants were trained for either 1-day, 2-days, or 3-days. Efficacy of selection, latency, and variability of an attentional pulse were estimated, and explicit learning was assessed for each participant. An attentional pulse can be described as a change in attention observed over a period of time. Specifically, following Vul, Nieuwenstein, and Kanwisher (2008), efficacy of selection was computed as the probability of reporting an item from a seven-item window around the actual target. Latency was defined as the center of mass in the seven-item window around a given target. A positive center of the mass would indicate that the subjects were more likely to report items that followed the target. A negative center of the mass would indicate that the subjects were more likely to report items preceding the target. Finally, the degree of explicit learning was assessed by computing explicit learning scores (Junker et al., in preparation). Evidence of learning was found for groups who participated in 1-day and 2-days training sessions and were assigned to learn specific temporal positions. The learning then leveled off on the third day for the groups who participated in the 3-days training session. This learning curve conformed to the expectations of power law learning characteristic of a wide range of perceptual-motor and cognitive skills (Newell & Rosenbloom, 1981). Importantly, after one day and two days of training, the efficacy of selection increased, the precision of selection decreased, and the latency of selection shifted towards the actual target. Interestingly, declarative knowledge changed gradually over days of practice and explicit learning scores were positively correlated with measures of RSVP performance in the three-day training condition. Furthermore, all of the groups assigned to the three-day condition, except for the group assigned to learn random temporal positions, demonstrated significant improvement in correctly identifying the practiced target positions during the transfer phase. These results suggest that explicit learning might affect temporal learning. Another interpretation of those results might be that better performance led to more explicit knowledge.

Finally, in a third experiment of Junker et al. (2017), the target stimulus appeared in only one possible position, presumably enhancing explicit learning of the target position. Over the course of five days, subjects quickly learned to adjust their attention to the target stimulus at its correct position. In this experiment, performance was shown to improve with practice.

In conclusion, the first experiment showed that when subjects were tasked with identifying successive targets in their correct order, performance increased with practice only for the subject who started at a high level of performance. The second experiment showed that explicit temporal learning was associated with higher level of performance after 2 days of practice. The last experiment showed that performance improved with practice for up to 5 days when explicit learning was likely. Specifically, the attentional pulse becomes more efficacious, becomes more centered on the target position, and becoming more precise. Two questions arise from those experiments: What is the role of explicit learning in the learning of temporal positions? Can explicit learning facilitate the learning of temporal positions?

Feedback and Implicit Learning

In a number of studies pertaining to feedback, feedback was found to facilitate tasks that deter explicit reasoning. Ashby, Alfonso-Reese, Turken, and Waldron (1998) coined the terms *rule-based category learning* and *information-integration category learning* to describe two strategies used to distinguish two categories of lines. *Rule-based category learning* uses strategies that involve explicit learning and in most common cases, only one stimulus dimension is relevant and the observer is tasked with discovering the relevant dimension. *Information-integration category learning* uses strategies that involve almost no explicit reasoning and integrate information from two or more stimulus components. Ashby, Maddox, and Bohil (2002) subsequently implemented feedback to test whether feedback facilitated *rule-based category learning* and *information-integration category learning.* The results of this study found that feedback did not help with *rule-based category learning* but feedback did help with *information-integration category learning.* In the experiment, participants were divided into either a *unidimensional* category structure learning condition or a *diagonal* category structure learning condition, both of which required participants to categorize two lines into either “A” or “B”. Participants in both conditions were further divided into groups that were either given feedback or not. Under the *unidimensional* category structure learning condition, the contrasting categories were separated using a simple explicit rule. Under the *diagonal* category structure learning condition, the contrasting categories are separated based on integrating length and orientation information. Because the *diagonal* category learning structure falls under *information-integration category learning,* it is not easy to verbalize the rules of categorization. Instead, participants learn to categorize through implicit learning and feedback. The results of the study found that feedback facilitated only the learning of *diagonal* category structure. Thus, this study suggested that feedback was particularly helpful to category learning when the category structure was learned implicitly, but not when it was learned explicitly.

The implementation of feedback has also been found to facilitate probabilistic learning. Probabilistic learning is implicit. Probabilistic learning was first studied in Knowlton, Squire, and Gluck's (1994) weather prediction task. In the weather prediction task, four cards were shown to the subjects and the subjects were tasked with identifying one of the two possible outcomes associated with the cards. Feedback was provided after every trial. The results from the study showed that feedback facilitated the performance of amnesiac patients during first 50 trials, improving from 50% correct during the first 10 trials to about 65% correct for the later trials. The control participants were employees or volunteers recruited from communities in San Diego. During the first 50 trials, control participants displayed similar performance to that of amnesiac patients but when the training was extended beyond 50 trials, the control participants performed significantly better than the amnesiac patients (Knowlton et al., 1994). However, the study did not compare the group of individuals who were given feedback to the group of individuals who were not given feedback.

Brain imaging studies found that when feedback is given consistently after every trial, subjects switched from relying on medial temporal lobe to basal ganglia for learning (Poldrack et al., 2001). Packard and Knowlton (2002) noted that the stimulus-response component of a sequential learning task can be disrupted by a lesion to the medial dorsal striatum. Therefore, those findings suggested that this type of implicit learning is controlled by basal ganglia. Another line of evidence pointing to the role of the basal ganglia in operant conditioning, a form of implicit learning, is the work of Wickens (1993). Wickens (1993) showed that dopamine in the basal ganglia is released into the tail of the caudate nucleus—one of the structures making up the dorsal striatum—from the substantia nigra shortly after the individual received an unexpected reward. The presence of the dopamine is widely thought to strengthen the active synapses (Ashby et al., 2002). Thus, this study also supports the idea that feedback strengthens implicit learning supported by the basal ganglia.

Temporal Learning and Implementation of Feedback

The effect of feedback on temporal learning has not been examined. In a previous study (Zhang & Shin, 2018), participants performed an RSVP task during a training phase and a transfer phase. The study had a 2 (Feedback Implementation: Feedback vs. No Feedback) x 2 (Position Consistency: Change of Positions During Transfer Phase vs. No Change of Positions During Transfer Phase) factorial design. Specifically, in the training phase, implementation of feedback was manipulated. Feedback was presented in the form of the words "correct" or "incorrect" after the subject input the response. In addition, the consistency of the target positions was manipulated. Target positions either stayed constant between training and transfer phases or changed from training to transfer.

Two measures were used to assess learning: The main measure was the transfer score, defined as the difference between the percentage of correct identification of the target positions from the last block of the training phase and the percentage of correct identification of the target positions from the first block of the transfer phase. The transfer score was used to measure positive transfer. The second measure was the accuracy of target identification across training blocks.

The main results were that the transfer scores were greater when feedback was provided than when it was absent. The conditions in which positions did not stay constant showed that there was no difference in transfer scores between feedback and no feedback conditions when target positions were changed. In terms of accuracy across training blocks, performance was found to improve across blocks but feedback was not found to improve performance. In addition, the degree of explicit learning for the target positions during the transfer phase was positively correlated with the transfer score only when feedback was provided but not when feedback was not provided.

It is possible that the lack of effect found for feedback in terms of accuracy across training blocks was due to the performance level of target identification accuracy pertaining to the four conditions found at different places for practice block. Therefore, the progression of learning due to feedback was difficult to interpret. With respect to the finding that the positioning of target stimulus changed from later in the sequence to earlier in the sequence, it is possible that a decrease in target identification accuracy resulted from positioning of the target stimulus. Ariga and Yokosawa (2008) discovered that targets that appeared early in sequence were reported less accurately compared to the targets that appeared late in the sequence. This result was named as *Attentional Awakening*. Therefore, change in performance at transfer would depend on the relationship between training and transfer positions.

This study raised the question of whether feedback facilitated temporal learning by helping explicit learning, which leads to implicit learning or whether feedback can facilitate the implicit learning of timing directly without explicit knowledge.

Current Study

The current study addressed the issues raised in the Zhang and Shin (2018) study. Zhang and Shin's (2018) study involved identifying the target stimulus in only two possible temporal positions. Therefore, it is possible that explicit reasoning strategy was utilized to identify the two temporal positions in the RSVP stream. Utilizing this strategy may have led to the significant correlation between the explicit learning score and the transfer score in the conditions where subjects were given feedback. For this experiment, the temporal structure of the target stimulus position in an RSVP stream was manipulated by varying whether the target position occurred at two fixed positions 100 % of the time or only 50 % of the time. A lower probability of the target stimulus appearing at a fixed position would be expected to decrease the chances of developing explicit knowledge. This manipulation will further allow us to test whether feedback facilitates only implicit learning when the probabilistic property of a stimulus is manipulated.

For this experiment, two competing hypotheses were proposed. The first hypothesis was that feedback led to the learning of temporal positions through explicit learning. The second hypothesis was that feedback led to the learning of temporal positions without explicit learning and by directly influencing implicit temporal learning.

In order to test these hypotheses, four changes in study design were made in response to the Zhang and Shin (2018) study design. First, in order to better observe how feedback facilitated temporal learning, two types of temporal structures were created: *Deterministic* and *Probabilistic*. In a deterministic temporal structure, the target stimulus appeared in two fixed positions appearing 50% of the time for each position. In a probabilistic temporal structure, the target stimulus appeared in various positions but also appeared in two fixed positions 25% of the time for each position. Second, the temporal positions of the target stimulus during the training and transfer phase were switched for deterministic conditions in order to observe whether this would still result in a decrease in target identification accuracy. Third, a power analysis was conducted to increase the likelihood of observing an effect of feedback. Lastly, the data was transformed for each participant in order to observe trends in learning more clearly independent of group differences that were inherent prior to training.

Both of the hypotheses had three predictions. Based on the hypothesis that feedback led to learning of temporal positions through explicit learning, we first predicted an interaction between the Feedback Implementation and Temporal Structure for transfer score. In this study, Temporal Structure can be defined as the frequency in which the target stimulus appeared at certain positions. Similar to the Zhang and Shin (2018) study, feedback was manipulated to appear or not appear after inputting a response. Specifically, the presence of feedback would result in a greater transfer score relative to when feedback was not provided in the deterministic conditions but not in the probabilistic conditions. Second, the same interaction was predicted for explicit learning. The presence of feedback would cause a significant increase in explicit learning for the deterministic condition but not the probabilistic condition. Finally, a positive strong significant correlation was expected between explicit learning and the transfer score only when the target positions are deterministic.

Based on the hypothesis that feedback leads to the learning of temporal positions without explicit learning and by directly influencing implicit temporal learning, an interaction was not predicted between Feedback Implementation and Temporal Structure for transfer score. However, a main effect was expected for Feedback Implementation and a main effect was also expected for Temporal Structure. Specifically, the presence of feedback would result in greater transfer scores in both the deterministic and probabilistic conditions. Second, the same interaction was predicted for explicit knowledge as predicted for the first hypothesis. The presence of feedback would cause a significant increase in explicit learning for the deterministic condition but not the probabilistic condition. Finally, the correlation between ELS and the transfer score was predicted to be weak when target positions are deterministic and probabilistic.

METHOD

Participants

Based on Zhang and Shin (2018) study, a small effect size of η_p^2 = 0.3 was expected in order to find an effect of feedback. The necessary sample size of one hundred and eleven participants was needed to detect an effect size of η_p^2 = 0.3 with a power of 0.95. All of the subjects were 18 years or older and had normal or corrected vision. None of the subjects have a history of seizures or migraines. See Appendix A for Recruitment Statement. 191 students signed up for this study. Out of the 191 students that signed up, 151 students participated in this study. The other 40 students who signed up for the study did not show up. Out of the 151 students who participated in the study, 44 (29.1%) students identified themselves as males and 107 (70.9%) students identified themselves as females. In terms of education, 96 (63.6%) students identified themselves as freshmen, 22 (14.6%) students identified themselves as sophomores, 21 (13.9%) students identified themselves as juniors, and 12 (7.9%) students identified themselves as seniors. Of the 151 students reporting their ethnicities, 85 (56.3%) identified as White or European Americans, 48 (31.8%) as Black or African Americans, 8 (5.3%) as Hispanic or Latino, 5 (3.3%) as multiracial, 4 (2.6%) as Asian or Asian Americans, and 1 (0.7%) as American Indians. Participants' ages ranged from 18 to 28 (*M*= 19.31, *SD*= 1.53). During the data collection phase, 2 students did not complete the experiment. One student did not finish the experiment due to program malfunctioning and the other student did not finish the experiment because the flashing letters made his eyes uncomfortable. After the data collection was finished, 10 subjects' data whose accuracy were above or below the mean by 2 standard deviations were removed. Upon taking out the outliers and incomplete data, the number of participants who participated in each of the four experimental conditions were as follows: 36 students were assigned to *deterministic-feedback* condition, 36 students were assigned to the *deterministic-no feedback* condition, 31 students were assigned to the *probabilistic-feedback* condition, and 36 students were assigned to the *probabilistic-no feedback* condition. These four experimental conditions are described below in the Procedure.

Materials

Informed Consent Form. Each participant received an informed consent form outlining the study, questions that would be asked, possible risks involved, and confidentiality agreement. To review the informed consent, see Appendix B.

Demographics Questionnaire. Each participant was administered a 5-item questionnaire. Items included two options for gender identity, nine options for race/ethnicity, five options for year in college, and two options for handedness. Participants also provided information on their age. To review the demographic questionnaire, see Appendix C.

Instructions. Each participant saw instructions that took up four pages on the computer screen. The instructions first informed the participant to turn off any electronic device in order to avoid distractions. The instruction then gave the participant an overview of the visuals presented on the screen and what the participant was tasked to do upon the end of visual presentation. To review the instructions, see Appendix D.

Post-experiment Questionnaire. Participants were administered a two-page long questionnaire after completing the task. The questionnaire was comprised of three questions. The first question asked participants whether they noticed any pattern in the RSVP stream; the second question asked participants if they used any strategies in order to identify the target letter in the RSVP stream. Finally, the last question was divided into two sections. Both sections consisted of 16 rows represented as position numbers. The last question was designed to measure the participant's explicit learning score. The participant indicated what percentage of time the target stimulus appeared in any of the 16 possible temporal positions. To review the questionnaire, see Appendix E.

Debriefing Form. Participants were given a form that explained the purpose of this study and the contact information of the experimenters if they had any questions about the study. To review the debriefing form, see Appendix F.

Procedure

Stimuli were presented on a 24-inch LCD monitor using E-Prime 3.0 program. The monitor was set up in a dimly-lighted room with the lamp angled horizontally toward the wall directly centered behind the monitor.

Stimuli would be presented as uppercase letters of the English alphabet excluding letters I, O, U, and V. Sixteen of the remaining 22 letters were randomly selected in each trial and were represented sequentially at a rapid pace in the center of the screen. All stimuli were presented in a 13 point Arial font. Distractor stimuli were presented in white while the target stimuli were presented in blue; all of them were presented on a gray background. The SOA was set at 80 milliseconds with the stimulus duration set at 32 milliseconds and inter-stimulus interval duration at 48 milliseconds. Inter-stimulus interval is the interval between the end of the presentation of an old stimulus and the beginning of the presentation of a new stimulus.

Prior to the beginning of the experiment, the subject signed an IRB-approved informed consent form. After signing the consent form, the subject was asked to answer a series of demographic questions on the computer including age and gender. After the subject finished answering the demographic questions, the subject was directed to the instructions shown on the computer screen. The last page of the instructions informed the subject that he or she would start the practice trials. The subject then pressed the SPACEBAR to begin the experiment.

Participants completed 10 practice trials followed by three blocks of training and three blocks of transfer. Each block consisted of 54 trials. Out of the 54 trials, there were six catch trials and 48 trials with the target stimuli. Catch trials were trials that did not contain the target stimuli. On each trial of the practice and actual experimental trials, a gray screen appeared for 500 milliseconds followed by a fixation cross that also lasted for 500 milliseconds. Immediately, a sequence of 16 letters flashed on the screen individually followed by an ampersand marking the end of a trial. Each sequence was made up of one blue letter and the rest as white letters. After the sequence ended, the participant was directed to the screen that asked the participant to input the letter that they thought was highlighted in blue from the sequence. Depending on the conditions they were assigned to, participants were given feedback. The feedback was presented in the form of the words "correct" or "incorrect" after the subject input the response. The feedback screen was displayed for 500 milliseconds followed by a gray screen that was displayed for 500 milliseconds. In the condition where no feedback would be given, the participant was directed to a gray screen that would be displayed for 500 milliseconds.

Participants completed a training phase and a transfer phase. Participants were assigned to four conditions. In the *deterministic-feedback* condition, the target stimulus appeared in the 4^{th} or 10^{th} position, and feedback about whether the response was accurate or not was given immediately after the input of the response. In the *deterministic-no feedback* condition, the target stimulus appeared in the 4th or 10th position, but feedback was not given after the input of the response. In the *probabilistic-feedback* condition, the target stimulus appeared in 25% of the trials in the 4th position, 25% of the trials in the 10th position, and appeared in the remaining 12 positions an equal percentage of the time, excluding positions at the beginning and the end (that is, the 1st and 16th positions). In this condition, feedback was given immediately after the input of response, as in the deterministic-feedback condition. In the *probabilistic-no feedback* condition, the target stimulus appeared in 25% of the trials in the 4th position, 25% of the trials in the 10th position, and equally likely for the remaining target positions, excluding positions at the beginning and the end (that is, also at the 1st and 16th positions). However, feedback was not given after the input of response. Thus, the design with respect to the training phase was a 2 (Feedback Implementation: Feedback vs No Feedback) x 2 (Temporal Structure: Deterministic vs. Probabilistic) factorial design.

During the transfer phase for all four conditions, the target appeared equally in the 7th and 13th positions, and feedback was not given. To see the design of this experiment, see Figure 1. When the experiment ended, all participants were given a questionnaire to answer. See Appendix E for the post-experiment questionnaire.

RESULTS

Because the experimental design of Zhang and Shin (2018) study revealed conflicting results for transfer score and accuracy across training blocks, this study's experimental design examined how other measures can be used to assess learning.

Figure 2 showed target identification accuracy plotted as a function of Feedback Implementation and Temporal Structure. The performance level of target identification accuracy pertaining to *deterministic-feedback, deterministic-no feedback*, *probabilistic-feedback,* and *probabilistic-feedback* conditions were found at different places for the practice block. A 2 (Feedback Implementation: Feedback vs. No Feedback) x 2 (Temporal Structure: Deterministic vs. Probabilistic) analysis of variance (ANOVA) was performed for accuracy in the practice block. A main effect was found for Temporal Structure. Specifically, target identification accuracy was greater in the probabilistic conditions (M = .74, SE = .02) than in the deterministic conditions (M = .64, SE = .02), $F(1,135) = 4.13$, $p < .05$. Therefore, the data were transformed for each participant such that the target identification accuracy for the practice block was subtracted from that of each training and transfer block. Specifically, the data was transformed for each participant in order to observe trends in learning more clearly independently of group differences that were inherent prior to training. See Figure 3 for the transformed graph.

The transfer score was computed by subtracting the target identification accuracy pertaining to the last block of training by the target identification accuracy pertaining to the first block of transfer. A 2 (Feedback Implementation) x 2 (Temporal Structure) ANOVA conducted on the transfer score showed a main effect for Temporal Structure, $F(1,135) = 8.46$, $p < .01$. Participants in the deterministic conditions showed higher transfer scores (M = -0.07, SE = .01) compared to the individuals assigned to the probabilistic conditions (M = -0.02, SE = .01). However, there was no significant difference in transfer score due to Feedback Implementation, $F(1,135) = 0.68$, $p = .41$, and Feedback Implementation x Temporal Structure interaction, $F(1,135) = 0.06$, $p = .81$. See Table 1 for the means and standard deviations for transfer score separated by Temporal Structure and Feedback Implementation.

Learning of the temporal positions not only can be measured by transfer performance but also by examining the extent to which performance improved over practice. Therefore, a 2

(Feedback Implementation) x 2 (Temporal Structure) x 3 (Blocks 1-3) ANOVA was conducted for the training phase. However, the main effect was not significant for blocks, Temporal Structure, or Feedback implementation. Interaction for Feedback Implementation x Temporal Structure was also not significant. See Table 2 for *F*-Values, degrees of freedom, and *p*-values for all the main effects and interactions during training phase and Table 3 for means and standard deviations of each training block.

Even though individuals did not learn the temporal positions across training blocks, it is possible that learning occurred later during transfer blocks. Therefore, a 2 (Feedback Implementation) x 2 (Temporal Structure) x 3 (Blocks 4-6) ANOVA was conducted for the transfer phase. The analysis revealed a main effect only for Block, $F(2,135) = 4.23$, $p < .01$. Target identification accuracy decreased across blocks. Interaction for Feedback Implementation x Temporal Structure was found to be not significant. See Table 4 for *F*-Values, degrees of freedom, and *p*-values for all the main effects and interactions during transfer blocks and Table 5 for means and standard deviations of each transfer block.

For each participant, an *explicit learning score* (ELS) (Junker et al., in preparation) was computed as follows:

$$\text{ELS}=\left(\sum_{i=-1}^{i=1} x_i\right)/t,$$

where x_i represents the frequency of reported occurrence of the target at position *i*, and *t* represents the sum of all of the reported frequencies for the target at all 16 positions. An ELS was computed relating to both the training and transfer phases.

In order to test the prediction regarding ELS, a 2 (Feedback Implementation) x 2 (Temporal Structure) ANOVA was conducted for ELS calculated from transfer phase. The main effect was not significant for Feedback Implementation, $F(1,135) = 2.53$, $p = .11$ nor for

Temporal Structure, $F(1,135) = 0.26$, $p = .61$. Interaction for Feedback Implementation x Temporal Structure was also not significant, $F(1,135) = 0.01$, $p = .94$.

In order to test whether ELS could impact transfer score by the presence of feedback, a correlation was performed on ELS and transfer scores. When ELS and transfer scores were correlated and separated by Feedback Implementation and Temporal Structure, a significant correlation in the deterministic-feedback condition, $r(34) = 0.41$, $p < .01$ was found. Feedback was associated with higher explicit learning scores and higher explicit learning scores were associated with higher transfer scores. See Table 6 for correlation between ELS and transfer scores separated by Feedback Implementation and Temporal Structure. Surprisingly, when ELS and target identification accuracy from the first block of transfer were correlated and separated by Feedback Implementation and Temporal Structure, a significant correlation was found in the probabilistic-no feedback condition, $r(34) = 0.35$, $p <.05$. Based on this finding, explicit knowledge could also develop when the target stimulus is probabilistic and feedback is not implemented. See Table 6 for correlation between ELS and target identification accuracy from the first block of transfer separated by Feedback Implementation and Temporal Structure.

DISCUSSION

This study examined how feedback facilitated temporal learning. Did feedback facilitate temporal learning through explicit knowledge or did feedback facilitate temporal learning through implicit knowledge?

The goal of this study was to test two hypotheses. In the Explicit Learning Hypothesis, it was assumed that feedback facilitated temporal learning through explicit learning. In the Direct Facilitation Hypothesis, it was assumed that feedback facilitated temporal learning without explicit learning and by directly influencing implicit temporal learning.

A strong effect of feedback was predicted for this study. In contrast, neither a main effect for Feedback Implementation nor an interaction for Feedback Implementation and Temporal Structure was found in terms of transfer score or when assessing the change in target identification accuracy over training blocks. Those findings do not support either the Direct Facilitation Hypothesis or the Explicit Learning Hypothesis. Closer examination of learning curves over training blocks suggest that effect of feedback may grow with practice. Although no effects of feedback during training were significant, if people had more extended practice with feedback, observing the effect of feedback might become more prominent.

For both the Direct Facilitation Hypothesis and the Explicit Learning Hypothesis, it was predicted that individuals given feedback would produce more explicit knowledge than individuals not given feedback only when the target stimulus appeared in two positions in a RSVP sequence. However, individuals given feedback would not produce more explicit knowledge than individuals not given feedback when target stimulus appeared in various positions in a RSVP sequence. In general, individuals given feedback when tasked with identifying the target stimulus that was deterministic would produce significantly more explicit knowledge than individuals given feedback when tasked with identifying the target stimulus that was probabilistic. In contrast, the results of this study showed that individuals who were given feedback tasked with identifying the target stimulus that was deterministic did not develop significantly more explicit knowledge than individuals who were given feedback tasked with identifying the target stimulus that was probabilistic. The trend towards greater explicit knowledge being displayed when the target stimulus was deterministic than when it was probabilistic might become more robust with extended practice. Therefore, like the target identification accuracy, if people had more extended practice with feedback, observing a significant difference in explicit knowledge might become possible.

Feedback led to a moderate significant correlation between explicit knowledge of temporal positions and learning measured by transfer score only when target stimulus appeared equally in two positions. This result is in line with the Explicit Learning Hypothesis. Similarly, Zhang and Shin (2018) found a moderate significant correlation between explicit knowledge of temporal positions and learning measured by transfer score when target stimulus appeared equally in two positions and changed from training phase to transfer phase.

Temporal learning and explicit learning were not predicted to be correlated when target stimulus appeared in various positions. Surprisingly, a significant correlation between ELS computed from the transfer phase and target identification accuracy from the first block of transfer was found when feedback was not implemented and the target stimulus appeared in various positions. One possible reason for this finding was that this reflects a broader distribution of performance measured by ELS and by the target identification accuracy of the first block of transfer. This finding shows that explicit knowledge may also occur when target stimulus appeared in various positions. This finding is also in line with the Explicit Learning Hypothesis since it reinforced the assumption that temporal learning occurs when explicit knowledge is displayed and is consistent with Junker et al. (in preparation) which showed evidence that after practicing 432 trials over the span of 2 days, participants developed explicit knowledge of the positions they did not practice without feedback.

Based on the design of this study, a decrease in target identification was predicted when temporal positions of the target stimulus changed from the last block of training to first block of transfer similar to Zhang and Shin (2018) study. However, this study revealed an increase in target identification accuracy from the last block of training to the first block of transfer for all conditions. The increase in accuracy could be caused by the change of temporal positions from early in the temporal sequence to later in the temporal sequence. This result is congruent to the results of Ariga and Yokosawa (2008), who discovered that targets which appeared early in sequence were reported less accurately compared to the targets that appeared late in the sequence. This finding could suggest that the transfer score is not a reliable way of studying factors that influence learning. Other methods, such as finding the rate of increase during training blocks could be more useful in studying factors that influence learning.

Taken together, the results of our study were not congruent with the results of Ashby et al. (2002), who concluded that feedback facilitated implicit learning in categorization learning when two dimension were integrated for categorization judgments. In contrast, our study did not find evidence supporting that feedback facilitated implicit learning in temporal learning. One possible reason for this finding could be that temporal learning in the RSVP task is different from categorization learning. Ashby et al. (2002) conducted categorization learning by instructing individuals to categorize two lines into two categories. In contrast, Shin, Chang, and Cho (2015) and Junker et al. (in preparation) conducted temporal learning using RSVP stream. In a RSVP stream, individuals are instructed to identify the target letter in a stream of distractor letters. The target letter can be any letter out of the English alphabet. Therefore, unlike categorization learning, participants are tasked with identifying the target stimulus based on various features.

The main strength of this study is that this study expanded on the research of implicit learning in temporal learning. Feedback had been found to facilitate implicit learning in categorization tasks but the mechanism of feedback had not been examined in the context of temporal learning. Zhang and Shin (2018) found feedback to facilitate with temporal learning but it was not clear as to how feedback facilitated temporal learning. This study was conducted in order to examine whether feedback facilitated temporal learning through implicit learning or explicit learning. This study found a significant positive correlation between explicit knowledge and transfer score when the target stimulus appeared in two distinct temporal positions and feedback was implemented. Therefore, feedback is found to facilitate temporal learning through explicit learning.

However, some limitations should be noted. First, the questionnaire used to assess explicit knowledge of certain temporal positions has no known information on its internal consistency. Future studies that utilize this questionnaire can examine the internal consistency of individuals' numerical responses for temporal positions. Second, participants were asked to self-report the percentage of the time that they saw the target stimulus appear out of each sixteen temporal positions. Participants may overestimate or underestimate the percentage of time that they saw target stimulus appearing out of each sixteen temporal positions. Lastly, in contrast to Zhang and Shin (2018), measuring learning of temporal positions using transfer score in this study did not show a significant effect for feedback. Future studies can examine other measures to assess learning of temporal positions.

In conclusion, this study further expands on the research of feedback on temporal learning. The results from this study support the hypothesis that feedback influences temporal learning by facilitating explicit learning. Future studies could examine how effect of feedback changes with more extended practice.

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Table 1

Means and Standard Deviations (in parentheses) for Transfer Scores by Temporal Structure and Feedback Implementation

	Deterministic	Probabilistic
Feedback	-0.08 (0.09)	-0.03 (0.09)
No Feedback	-0.06 (0.09)	-0.02 (0.09)
Total	-0.07 (0.09)	-0.02 (0.09)

Table 1

Inferential Statistics for the 2 (Feedback Implementation) x 2 (Temporal Structure) x 3 (Block) ANOVA conducted on Target Identification Accuracy in Training Blocks

	F-Value	df	*p*-value
Feedback Implementation	0.14	(1, 135)	0.714
Temporal Structure	1.38	(1, 135)	0.241
Block	1.42	(2, 135)	0.245
Feedback Implementation x Temporal Structure	0.08	(1, 135)	0.781
Feedback Implementation x Block	0.38	(2, 135)	0.687
Temporal Structure x Block	0.27	(2, 135)	0.762
Feedback Implementation x Temporal Structure x Block	1.36	(2, 135)	0.258

Table 2

Means and Standard Deviations (in parentheses) for Target Identification Accuracy by Temporal Structure, Feedback Implementation, and Blocks (Training Phase)

	Deterministic		Probabilistic	
	Feedback	No Feedback	Feedback	No Feedback
Block 1	0.08 (0.16)	0.05 (0.14)	0.03 (0.15)	0.03 (0.20)
Block 2	0.09 (0.17)	0.07 (0.17)	0.03 (0.14)	0.05 (0.20)
Block 3	0.07 (0.18)	0.06 (0.18)	0.05 (0.18)	0.03 (0.25)

Table 3

Inferential Statistics for the 2 (Feedback Implementation) x 2 (Temporal Structure) x 3 (Block) ANOVA conducted on Target Identification Accuracy in Transfer Blocks

	F-value	df	*p*-value
Feedback Implementation	0.63	(1, 135)	0.429
Temporal Structure	2.37	(1, 135)	0.126
Block	4.23	(2, 135)	0.019
Feedback Implementation x Temporal Structure	0.03	(1, 135)	0.869
Feedback Implementation x Block	0.78	(2, 135)	0.447
Temporal Structure x Block	1.71	(2, 135)	0.186
Feedback Implementation x Temporal Structure x Block	1.45	(2, 135)	0.238

Table 4

Means and Standard Deviations (in parentheses) for Target Identification Accuracy by Temporal Structure, Feedback Implementation, and Blocks (Transfer Phase)

	Deterministic		Probabilistic	
	Feedback	No Feedback	Feedback	No Feedback
Block 4	0.14 (0.17)	0.12 (0.17)	0.08 (0.15)	0.04 (0.25)
Block 5	0.12 (0.19)	0.10 (0.17)	0.07 (0.15)	0.07 (0.23)
Block 6	0.10 (0.22)	0.08 (0.18)	0.08 (0.16)	0.02 (0.31)

Table 5

Correlation Between ELS and Transfer Score by Temporal Structure and Feedback Implementation

	Deterministic	Probabilistic
Feedback	0.41*	-0.27
No-Feedback	-0.27	0.06

*Note: * p < .05*

Table 6

Correlation Between ELS and Target Identification Accuracy by Temporal Structure and Feedback Implementation

	Deterministic	Probabilistic
Feedback	0.05	-0.19
No-Feedback	-0.02	0.35*

Note: * *p* < .05

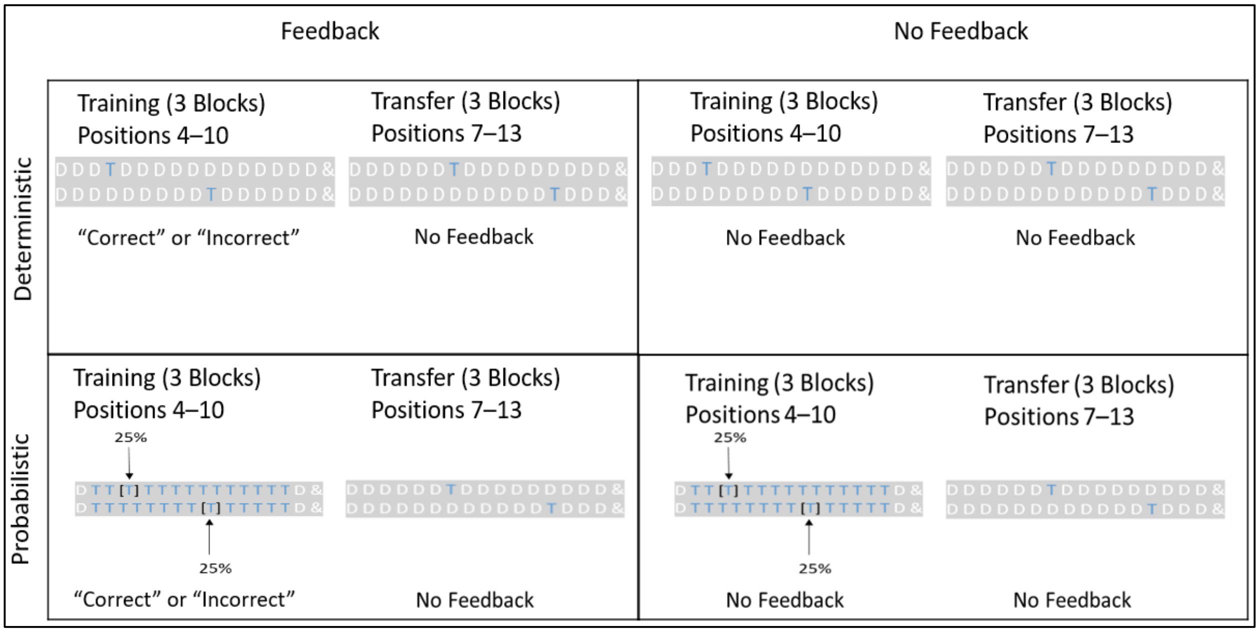

Figure 1. In the *Deterministic-Feedback* condition, the target stimulus would appear in two different positions equally likely during the training phase and transfer phase; feedback would be given during the training phase but not the transfer phase. In the *Deterministic-No Feedback* condition, the target stimulus would appear in two different positions equally likely during the training phase and transfer phase; feedback is not given in either the training phase or the transfer phase. In the *Probabilistic-Feedback* condition, the target stimulus would appear 25% of the time in position 4 and 25% of the time in position 10 and equally likely in the remaining positions excluding first and last positions during the training phase; the target stimulus would appear equally likely in positions 7 and 13 during the transfer phase. Feedback would be given during the training phase but not the transfer phase. In the *Probabilistic-No Feedback* condition, the target stimulus would appear 25% of the time in position 4 and 25% of the time in position 10 and equally likely in the remaining positions excluding first and last positions during the training phase; the target stimulus would appear equally likely in positions 7 and 13 during the transfer phase. Feedback would not be given in the training or transfer phase. (*D*: Distractor Letters; *T*: Target letter; distractor letters are highlighted in white and target letter is highlighted in blue)

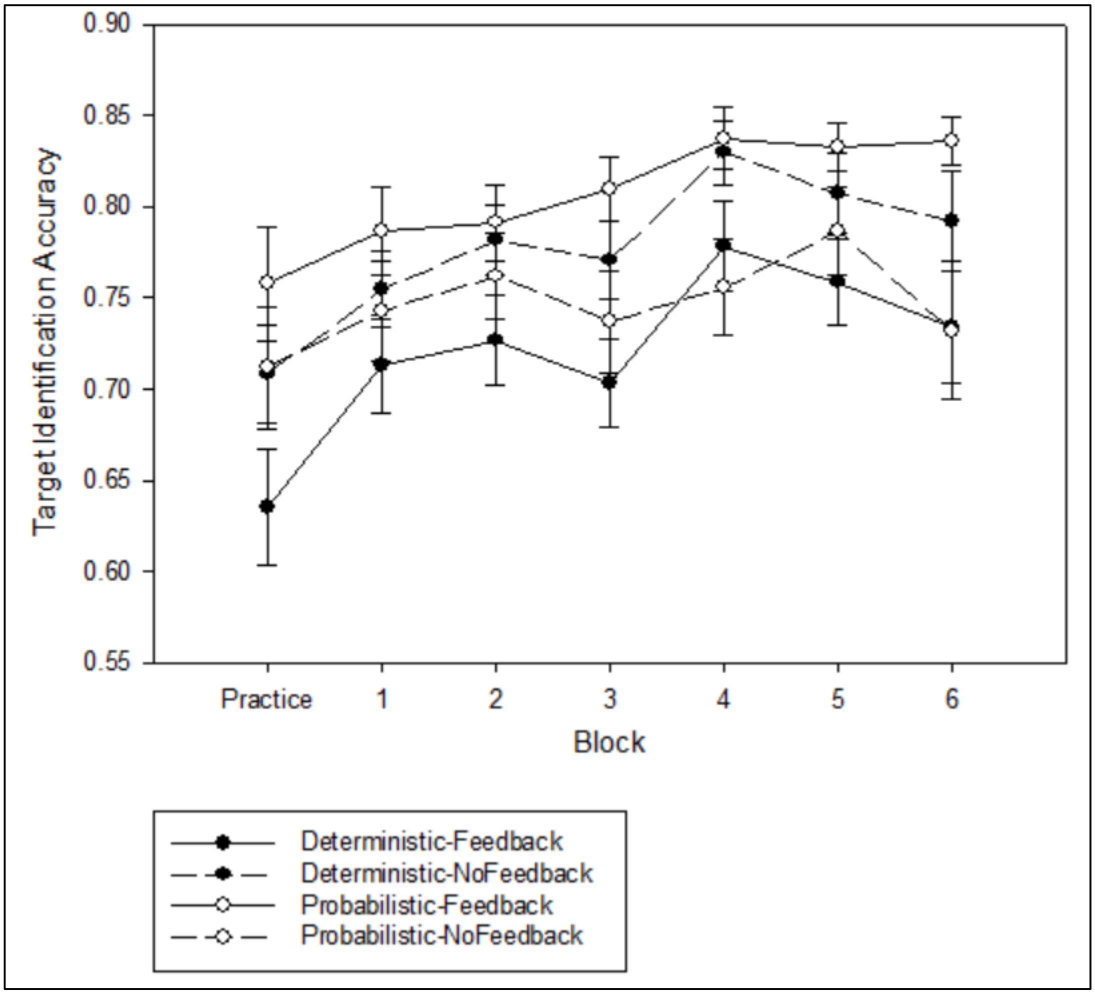

Figure 2. Target identification accuracy for *Deterministic-Feedback*, *Deterministic-No Feedback*, *Probabilistic-Feedback*, and *Probabilistic-No Feedback* conditions (created from original dataset) Training blocks: 1-3, Transfer blocks: 4-6

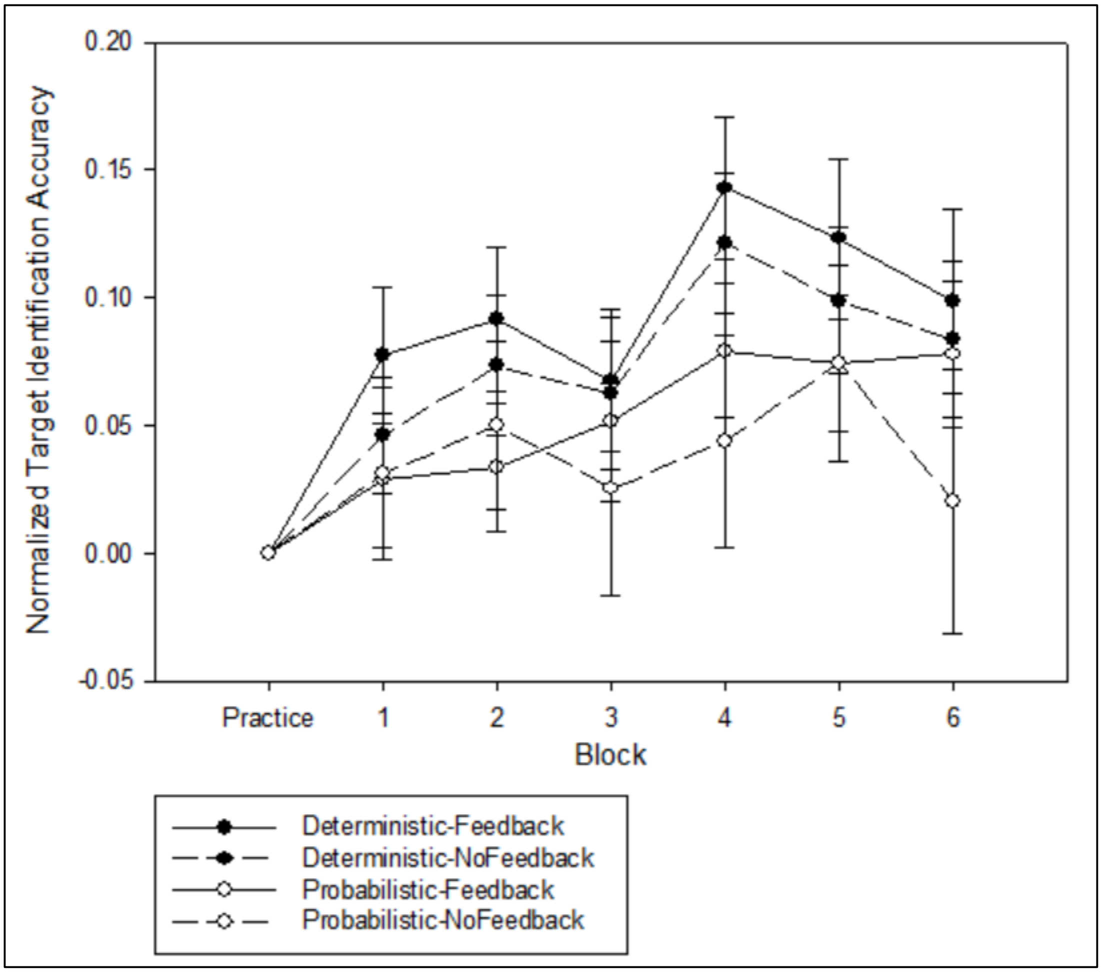

Figure 3. Target identification accuracy for *Deterministic-Feedback*, *Deterministic-No Feedback*, *Probabilistic-Feedback*, and *Probabilistic-No Feedback* conditions (created from transformed dataset) Training blocks: 1-3, Transfer blocks: 4-6

APPENDIX A: RECRUITMENT STATEMENT

SONA Systems Recruitment: Students will see the following title for the study: “The Role of Feedback in Temporal Learning.” They can click on this study and then they will be taken to the menu that contains all the available timeslots. Students will sign up for one of the available timeslots and will get a confirmation email informing them that they’ve successfully signed up for the study; the email will also inform them of the time and place of the study.

APPENDIX B: RAPID VISUAL PROCESSING INFORMED CONSENT FORM

You are being asked to participate in research conducted by Zhuoran Zhang, Master's student in the Department of Psychology at Indiana State University in the laboratory of Dr. Jacqueline Shin, Department of Psychology, Indiana State University. The study investigates how people process and identify information that is available only for a brief period of time. In this study, you will sit in front of a computer. A stream of numerals, letters, or other symbols will be shown to you one at a time very quickly. Your job will be to identify target letters or numerals within each stream and to press the appropriate keys on the computer keyboard to indicate those targets.

The only foreseeable risk or discomfort associated with this study beyond what is encountered in daily life is a minor headache. Tylenol or Aspirin is available to you if you experience a headache. If you have a history of migraines or epileptic seizures, you cannot participate in this study, since there is a small risk for these symptoms to occur during the study for those who are prone to these conditions. You should have normal or corrected to normal vision and be at least 18 years of age to participate in this study.

There is no direct benefit to you if you participate in this study other than the experience of contributing to research.

This experiment will last one session. The session will last for approximately 50 minutes. For your participation, you will receive 4 SONA credits.

No information about your identity will be collected in this research other than your date of birth in order to compute your age at the time of the study. Then, that information will be deleted from our records.

Your participation is entirely voluntary, and discontinuing participation at any time will not result in loss of extra credit. If you decide you would like to discontinue participation during the experiment, verbally notify the experimenter that checked you in. Alternatively, you may notify Zhuoran Zhang by E-Mail (listed below).

At the end of the experimental session, you will be debriefed in more detail with respect to the purpose, hypotheses, and predictions of the study, at which time you are invited to ask any questions about the study. If you have any remaining questions about this research, please feel free to contact:

Zhuoran Zhang, B-227 Root Hall, Department of Psychology, Indiana State University, Terre Haute, IN 47809, Phone: 305-281-4593, E-Mail: zzhang4@sycamores.indstate.edu

Professor Jacqueline C. Shin, Ph.D., B-232 Root Hall, Department of Psychology, Indiana State University, Terre Haute, IN 47809, Phone: 812-237-2461, E-Mail: jacqueline.shin@indstate.edu

If you have questions about your rights as a participant of this research, or if you feel you've been placed at risk, you can contact the Institutional Review Board at Indiana State University at (812) 237-8217 or irb@indstate.edu.

____ ________________

Signature of Participant

APPENDIX C: DEMOGRAPHIC QUESTIONNAIRE

1. Please enter the Subject's Age (0–150):

2. Please enter Subject's Sex:
    a. Male
    b. Female

3. What is your ethnicity?
    a. American Indian
    b. Asian or Asian American
    c. Black or African American
    d. Hispanic or Latino (of any race)
    e. Multiracial
    f. Pacific Islander
    g. White or European American
    h. Other
    i. I prefer not to say

4. What class are you at ISU?
    a. Freshman
    b. Sophomore
    c. Junior
    d. Senior
    e. Other

5. Enter Subject's Handedness:
    a. Left
    b. Right

APPENDIX D: INSTRUCTIONS

Instruction page 1
Welcome to the experiment. The Skill and Coordination Lab appreciates your participation. Please Silence all cellphones and other electronic devices now, leave them off until the experiment is completed.
(Press SPACEBAR to continue)

Instruction page 2
In this experiment you will be presented with a “stream” of letters on each trial.
By “stream” we mean that a series of letters will be shown in the same location, but one after another and very quickly.
All the letters in a “stream” will be WHITE except for one BLUE letter. It is your job to identify that BLUE letter. Please note that there will be times when there will NOT be a BLUE letter in the stream. If you didn’t see a blue letter, put the number “0” as your answer.
If you find that you are not sure of the blue letter, then please take your best guess.
(Press SPACEBAR to continue)

Instruction page 3
Some letters will not be included in this experiment because they closely resemble another letter.
Letters which will never occur are: I, O, U, V
These characters are programmed not to appear as stimuli and the computer will not accept them as response.
(Press SPACEBAR to continue)

Instruction page 4
To ensure that you are comfortable with the task, we ask that you complete a few practice trials before beginning the experimental trials.
(Press SPACEBAR to begin practice trials)

APPENDIX E: POST-EXPERIMENT QUESTIONNAIRE

(Subject #)

The questions here relate to what you might have noticed about the timing of the target (blue letter) in this experiment.

1. Did you notice any patterns in the way the letters were presented in the experiment? If so, please describe them.

2. Did you use any strategies to help you identify the blue letters? If so, please describe them.

3. In each letter stream, 16 letters were rapidly presented. Indicate in the table to the right how likely it was that a blue letter would appear in each of the possible 16 positions within the stream of letters. During the first half of the experiment, where did the blue letter appear? During the second half of the experiment, where did the blue letter appear? If a blue letter never appeared in a position, leave that part of the table blank. If you are unsure, use your best estimate. (Note: the first and second half of the experiment is separated by a forced 30-second break)

First Half

Position	Percentage (%)
1	
2	
3	
4	
5	
6	
7	
8	
9	
10	
11	
12	
13	
14	
15	
16	

Second Half

Position	Percentage (%)
1	
2	
3	
4	
5	
6	
7	
8	
9	
10	
11	
12	
13	
14	
15	