Investigating the Impact of Isoluminant Stimuli on Attentional Capture in Motor Sequence Learning

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Abstract

This study aimed to explore the role of isoluminant stimuli in reducing attentional capture in motor sequence learning using a Discrete Sequence Production (DSP) task. We predicted that using isoluminant stimuli could ignore later stimuli, improving performance in the DSP task. Participants were divided into three experimental groups: the Mix Incompatible group (MixInc), the Single Stimulus group (SinStim), and the Different Compatible group (DifCom)—each group practised by repeating two 4-key sequences, followed by three different test conditions. The Mix Incompatible group practised sequences with an isoluminant stimuli and incompatible Stimulus-Response (S-R) mappings, predicting that the isoluminant stimuli combined with incompatible S-R mappings would force participants to ignore the later stimuli and identify the sequence using only the first stimulus. The Single Stimulus group was provided with the complete sequence in terms of letters before the experiment and was required to complete the sequence based solely on the first stimulus. The Different Compatible group participated in a standard DSP task. Results showed that during the Single Stimulus test condition, where participants recreated the practised sequence based on the first stimulus, the Mix Incompatible group had significantly longer response times (RT) and higher error rates than the other groups. The Mix Incompatible group exhibited significant RT differences in the Random and Random Distractor conditions, which involved responding to a random order of stimuli, including isoluminant distractor stimuli. This indicates an inability to ignore isoluminant stimuli. The findings suggest that isoluminant stimuli with incompatible S-R mappings do not reduce attentional capture, indicating continued reliance on stimuli hindering motor sequence learning.

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List of Abbreviations

Com	Compatible S-R mapping
C-SMB	Cognitive Framework of Sequential Motor Behaviour
Dif	Difference luminance
DSP	Discrete Sequence Production
Inc	Incompatible S-R mapping
Mix	Mixed luminance condition (S1 luminant; S234 Isoluminant)
RT	Reaction Time
SEM	Standard Error of the Mean
SinStim	Single Stimulus condition
S-R	Stimulus-Response
Rand	Random condition
RanDis	Random Distractor condition

Introduction

Even though we may not consciously acknowledge it, the capacity to perform a sequence of movements with minimal attention is essential in our daily routines. Understanding how people learn to perform movements automatically is necessary to understand human motor performance complexities. Doyon and others (2003) argued that the development of motor automaticity involves learning arbitrary visuomotor mappings and executing movement sequences. This suggests that the development of motor automaticity is highly dependent on visual attention.

Verwey (1999) used a method known as the Discrete Sequence Production (DSP) task to investigate motor learning. In this task, sequences are generated as participants respond to successive stimuli that are mapped to response keys (Verwey, 2023). Through practice, mental representations form and are assumed to remove the necessity of key-specific stimuli (Abrahamse et al., 2013). However, the research showed that when key-specific stimuli were removed, many participants could not produce the practised sequence (Verwey, 2023). This meant that participants did not develop full sequential knowledge and were still dependent on the later key-specific stimuli.

Verwey (2021) conducted a study to explore how isoluminant stimuli in a Discrete Sequence Production (DSP) task affect attentional capture. Surprisingly, participants appeared to intentionally ignore these stimuli when they had acquired full explicit sequence knowledge. The present study aims to investigate further how isoluminant stimuli help participants develop motor automaticity, mainly focusing on how isoluminant stimuli can force participants to ignore attentional capture. The research employs the DSP task to investigate whether participants exhibit enhanced learning of motor sequences when presented with initially luminant stimuli, followed by isoluminant stimulus, within a DSP task featuring compatible and incompatible stimulus-response (S-R) mappings.

The Discrete Sequence Production (DSP) Task

The DSP task aims to examine the proficient execution of short key pressing sequences, which here involve repeating two fixed sets of 4 key presses in a randomised order (Verwey, 1999). Initially, participants react to stimuli indicating each keypress (Verwey, 1999). During practice, participants may use three different execution modes before reproducing a sequence (Verwey & Abrahamse, 2012). Initially, the reaction mode occurs within an unfamiliar sequence. It is characterised by persistent cognitive control, wherein the stimulus is the primary focus of attention to elicit the proper response (Verwey, 2023). Subsequently, after considerable practice, participants develop symbolic spatial/verbal sequence representation at a perceptual and motor level. Lastly, with more practice and experience, individuals transition to the associative mode. In this mode, participants develop the ability to execute the sequences rapidly and automatically (Verwey, 2023). They do this by associating successive items at various processing levels (Verwey, 2023). DSP studies usually end with a test phase in which variations of practised sequences are compared with control sequences. While pressing the key differs from real-world motor tasks, the DSP task offers insights into the underlying processing mechanisms responsible for serial motor skills development (Verwey, 2023).

Various studies utilising the DSP task explored different approaches to enhance motor sequence learning. For instance, researchers investigated the effectiveness of techniques such as mental practice (Sobierajewicz et al., 2016) and the potential learning benefits associated with non-invasive brain stimulation, specifically targeting areas like the prefrontal cortex through methods such as transcranial brain stimulation (Cohen et al., 2009). In this study, the DSP task utilised fillings with the same luminance as the background to reduce attentional capture (Riesenbeck, 2021; Verwey, 2021).

The second version of the Cognitive Framework of Sequential Motor Behaviour (C-SMB 2.0) emphasises the importance of cognitive psychology and neuroscience in understanding motor learning (Verwey, 2023). According to C-SMB 2.0, learning in a DSP task occurs through the repeated preparation of responses in short-term memory and the repeated co-activation of representations at each processing

level during actual sequence execution (Verwey, 2023). Within tens of trials, participants had already developed spatial and verbal central-symbolic sequence representations (Verwey, 2023). With practice, certain participants became adept at performing the two sequences upon encountering only the initial key-specific stimulus. Once participants identified the first stimulus, as suggested by the C-SMB 2.0, additional stimuli became unnecessary. However, it is essential to note that not all participants demonstrated this ability (Verwey, 2023).

C-SMB 2.0 proposes that motor sequences involve a race between cognitive systems to initiate each subsequent movement in the sequence (Hughes et al., 2016). This suggests that even a slower system increases its execution rate if its processing time distribution overlaps with that of a faster system (Abrahamse et al., 2013). In Riesenbeck's (2021) study, a DSP task was utilised with compatible and incompatible S-R mappings. The findings indicated that participants exhibited longer response times (RT) when confronted with incompatible S-R mappings (Riesenbeck, 2021). This aligns with the compatibility effect, suggesting that a compatible relationship between the stimulus and response resulted in shorter RTs (Kornblum et al., 1990).

Notably, in instances where key-specific stimuli were absent, Verwey (2023) observed that approximately one-third of the participants could not replicate the practised sequence. This observation suggests a persistent reliance on key-specific stimuli. This dependence might be attributed to the phenomenon Yantis and Hillstrom (1994) discovered, wherein luminance changes automatically capture visual attention. Thus, it is plausible that the inability of participants to rely on later key-specific stimuli stems from the attentional attraction caused by the luminance changes associated with a trigger to activate the sequence.

Why Visual Attention Is Drawn to Luminance Change

Visual attention is often drawn to luminance changes due to a phenomenon known as attentional capture, where attentional selection is driven by the intrinsic significance of stimuli regardless of individual goals (Theeuwes et al., 1992; Theeuwes et al., 1999). However, studies demonstrated that top-

down processes could quickly disengage from salient stimuli that do not match the target (Belopolsky, 2010; Folk et al., 1992). Subsequently, Theeuwes and Van der Burg (2008) showed that instruction cues with 100% validity effectively RTs but only partially diminish the distracting effect of irrelevant colour stimuli.

Treisman and Gelade (1980) discovered that stimuli with visual features differing from the background, such as colour or luminance intensity, are automatically detected (Jonides & Yantis, 1998). Research indicates that attentional capture might be specific to stimuli characterised by sudden visual onsets, suggesting that unexpected visual stimuli can automatically capture attention (Jonides & Yantis, 1984; Belopolsky, 2010).

Luck and others (2020) found two ways stimulus could be suppressed. The first is reactive suppression. In this instance, participants observed the feature of the distractor and quickly disengaged from the distractor. Theeuwes and others (2003) found subsequent disengagement can take place without resulting in a saccadic eye movement to the location, although the results were not always conclusive. The other way is through proactive suppression. This indicates that a spatial filtering map can be developed through statistical learning. Specifically, when distractors consistently appear in a specific location, the spatial filtering map will proactively suppress that location (Luck et al., 2020).

Why Attentional Capture Impairs Motor Learning

Studies have demonstrated the crucial role of attention in sensorimotor learning. Attention provides resources for learning and plays a pivotal role in selecting sensory stimulation and integrating it with motor memory (Song, 2019). This was evident because motor performance gradually became more efficient and automatic (Im et al., 2015). Research indicated that maintaining consistent focus during the learning and recall phases enhanced the retrieval of visuomotor memory (Song, 2019). This could explain why, in the DSP task, many participants were unable to reproduce the practised sequence when the key-specific stimuli were absent. This dependency on key-specific stimuli occurred due to attentional capture during the practised phase.

Previous research by Tubau and López-Molliner (2004) found that fully aware participants in a serial response time task involving an 8-element binary sequence ignored luminant key-specific stimuli after approximately 90 repetitions. However, participants are required to identify the first stimulus in the DSP task. Hence, the DSP task may not have been able to replicate the conclusions of Tubau and López-Molliner (Verwey, 2019).

Isoluminant Stimuli

Verwey (2019) used isoluminant stimuli in a DSP task to address the attentional capture triggered by a luminance change. In the study by Verwey (2019), the researchers tested whether participants stopped processing key-specific stimuli when they were displayed only occasionally. The study's results revealed that participants could intentionally ignore isoluminant key-specific stimuli when they possessed full explicit sequence knowledge (Verwey, 2019). When key-specific stimuli were isoluminant, participants demonstrated the ability to prepare whether their attention would be drawn to the colour change or not (Müller et al., 2003)

The current study closely followed the methodology of Riesenbeck (2021), who investigated the effects of different stimuli and S-R mapping on reaction time in the DSP task. Despite their efforts, the results revealed a consistent reliance on later stimuli (Riesenbeck, 2021). Previous research has proposed that participants did not disregard the later key-specific stimuli because they were still required to respond to the initial stimuli (Riesenbeck, 2021; Verwey, 2015). Specifically, Verwey (2023) proposed that the presence of the first isoluminant stimulus might have influenced participants to process subsequent isoluminant stimuli. Conversely, when the initial stimulus was of different luminance from the background, followed by isoluminant stimuli with the background, participants tended to ignore later isoluminant stimuli (Verwey, 2023).

Current Study

The studies conducted by Verwey (2019) and Tubau (2004) underscored the significance of full sequence knowledge in disregarding attentional capture. By engaging participants in practice sessions within the DSP task, they can acquire complete sequential knowledge. Full sequence awareness convinced participants to rely on implicit sequence knowledge rather than explicit visual cues (Verwey, 2021). This enables us to compare and study human motor learning.

The present study aims to investigate the effects of isoluminant stimuli in reducing attentional capture in motor sequence learning. Previous papers (Riesenbeck, 2021; Verwey, 2023) suggested that participants gradually ignore the later key-specific isoluminant stimuli in a DSP task when the first stimuli are of a different luminance from the background. In the current study, we will adopt Riesenbeck's (2021) methods of using isoluminant stimuli in a DSP task. The experiment will consist of five practice blocks containing 300 practice trials per sequence. The findings of Verwey and Eikelboom (2003) indicate that the motor buffer can only hold 3-5 movements at a time. Hence, we will simplify the task by employing two 4-key sequences.

Participants in the study were assigned to one of three groups: the Mix Incompatible (MixInc) practice group, the Single Stimulus (SinStim) practice group, and the Different Compatible (DifCom) group. In the MixInc group, participants will practice sequences with the first stimulus (S1) being a different luminance as the background, followed by isoluminant stimuli. Furthermore, the MixInc group had incompatible stimulus-response (S-R) mappings. The combination of incompatible S-R mappings and isoluminant stimuli makes it useful for the participants to try and ignore the key-specific stimuli. Conversely, the SinStim group will be instructed in advance to learn the four-sequence series using letters. They will complete the sequence based solely on the first key-specific stimulus. The SinStim group acts as a reference group for participants with explicit sequence knowledge who have practised replicating the sequence from the initial stimulus. Lastly, the DifCom group will engage in the standard DSP task with compatible S-R mappings, using stimuli that differ in luminance from the background.

Participants from this group will not try to ignore the key-specific stimuli, as there is no apparent benefit. Following the practice phase, all groups will proceed to the test phase, which comprises three tests. The first test is the Single Stimulus (SinStim) condition, where participants are assessed on their sequence knowledge based solely on the first stimulus. In this test, participants are only provided with the first stimulus and are instructed to complete the sequence from memory. The second test is the Random (Rand) condition, involving a random order of four stimuli differing from the practised sequences, featuring different luminance S1 and isoluminant S234. Finally, the third test is the Random Distractor (RanDis) condition, where participants are presented with a random order of four stimuli, similar to the Random condition, with different luminance stimuli (S1234), along with an isoluminant distractor. In this condition, participants must ignore the isoluminant distractor while responding to the sequence stimuli.

Our hypothesis posits that the compatibility effect in the MixInc group will diminish during practice sessions. This is because practising with isoluminant stimuli that match the background and incompatible S-R mapping encourages participants to ignore attentional capture. Furthermore, we expect the MixInc group's ability to ignore later stimuli will be demonstrated by their improved performance during the test phases. The Single Stimulus condition results will demonstrate whether the MixInc group had learned to replicate the sequence without S234 during practice. Specifically, we expect the MixInc and SinStim groups to demonstrate similar RTs in the Single Stimulus condition. The comparable RTs of the MixInc and SinStim groups should show the participants' ability to replicate the practised sequences based on the first stimulus. The results obtained from the Random and Random Distractor conditions will further elucidate whether participants of the three practice groups have learned to anticipate changes in luminance during sequence execution and whether they can more effectively ignore isoluminant stimuli. The participants in the MixInc group were expected to develop the ability to ignore isoluminant stimuli, which may also help them perform better in the Random and Random Distractor conditions. Hence, we expect the MixInc group to show no significant differences in RTs on the Random and Random Distractor conditions. This investigation aims to shed light on the comparative effectiveness of luminant

versus isoluminant stimuli relative to the background in ignoring attentional capture to facilitate motor skill development within the framework of a DSP task.

Methods

Participants

Thirty-six bachelor students, aged between 18 and 29 (mean age: 22 years; 22 males and 14 females), participated in the study. Recruitment was conducted using a combination of convenience and snowball sampling methods. Twenty-nine participants volunteered, while seven received credits for their participation. Consistent with experiments in DSP studies, each group comprised twelve participants, randomly assigned to one of three groups.

Participants were permitted to experiment only when they were not heavy smokers and had not consumed alcohol 24 hours before the experiment. Eligibility criteria included demonstrating unimpeded control of all fingers. The study received ethical approval from the Faculty of Behavioural Sciences at the University of Twente (application number: 240130). All participants provided written and verbal informed consent before participating.

Apparatus

In this study, the experimental setup utilised the E-prime© 2.0 software package on a standard Windows 10 PC to present stimuli and record data. To ensure precise measurement of RTs, unnecessary Windows services were disabled. Stimuli were displayed on a 24-inch Eizo Flexscan EV2436W LCD monitor, operating at a resolution of 1920 by 1200 pixels with an 8-bit depth and a refresh rate of 59 Hz.

Participants utilised the C, V, B, and N keys on a Razer Huntsman V2 Tenkeyless Gaming Keyboard for accurate response input. Additionally, for the awareness task, participants used a Dell Optical Wired Mouse MS116. Luminance intensity was assessed using a UNI-T UT383 Mini Light Meter.

The experiment occurred in a dimly lit room with natural daylight supplemented by a video camera for monitoring purposes. Strict control over the monitor's viewing distance was not implemented.

The Task

The DSP task commenced with participants positioning their left index and middle fingers on the C and V keys and their right index and middle fingers on the B and N keys, respectively. Four 2.7 x 2.7 cm squares were horizontally displayed on the screen against a grey background (32 Lux, RGB values 80,80,80). These squares have black outlines and the same grey filling as the background. Each square represented a response key to be pressed.

During key-specific stimuli, the respective squares were filled with a distinct colour (Figure 1). Participants were presented with two 4-key sequences, chosen from a set of four counterbalanced sequences: CBNV, BCVN, NVBC, and VNCB. The counterbalancing involved rotating the four keys (C→B→N→V).

In the practice phase, squares representing S234 in the MixInc group were filled with a green-blue colour (RGB values 0,91,91) matching the background luminance (32 Lux). For S1 in the MixInc and SinStim groups and all stimuli in the DifCom group, squares were filled with a yellow colour (RGB values 248,248,0) differing in luminance from the background (116 Lux).

Upon pressing the correct key, the square reverted to the grey background, and the subsequent key-specific stimulus was immediately presented. The response-stimulus interval (RSI) during the transition was 0 ms. Deviations in luminance intensity across both experiment rooms were minimal, approximately ≤ 3 lux.

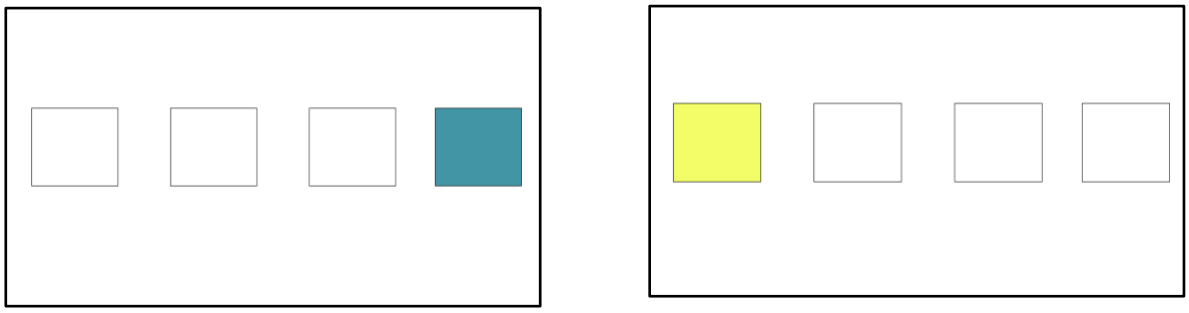


Figure 1: Colour Change of Isoluminant and Luminant Stimuli (left and right, respectively)

The S-R mappings were compatible with the DifCom, SinStim, and all test phases. On the other hand, they were incompatible for the MixInc group (see Figure 2).

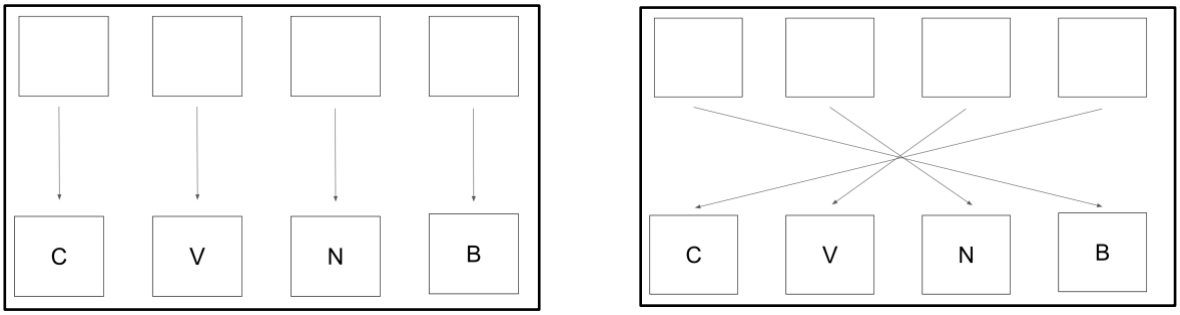


Figure 2: Compatible S-R mapping in DifCom and Incompatible S-R mapping in MixInc (left and right, respectively)

Following the final key-specific stimuli of a sequence, a brief pause of 2000 ms with an empty display was shown. This was followed by the reappearance of the empty squares for 500 ms. Subsequently, the first key stimulus of the following sequence was presented.

If a participant had pressed the wrong key, a message reading "error, try again" appeared in red above the squares for 1500ms. After this, the sequence was discontinued, and a new one started. Similarly, if a participant had not responded within 5000ms, a message reading "no response, try again" was displayed over the square for 1500ms, and the sequence was discontinued.

This procedure ensured that participants maintained engagement with the task and prevented prolonged delays in the experiment's progression.

The Practice Phase

The DSP task comprised five practice blocks consisting of 60 trial subblocks. The participants were given a 20-second break between subblocks and a 3-minute break following each block. During the practice phase, participants completed 300 trials per sequence.

Participants repeated the same two four-key sequences within each subblock, randomised based on their assigned practice groups (MixInc, DifCom, SinStim). Due to the randomisation, there were no group differences. In conclusion, The practice phase aimed to develop motor automaticity in participants' responses to the sequences, which was indicated by shorter RTs.

The Test Phase

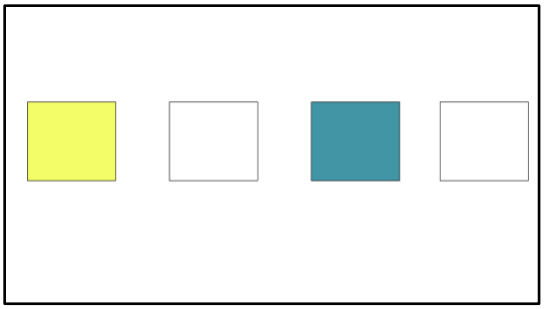
The subsequent test phase consisted of three distinct test blocks, each comprising 60 sequences with 30 trials per sequence. Key-specific stimuli were presented with compatible S-R mapping for all participants. The order of the three test blocks varied for each condition group and was counterbalanced across all participants. A display indicated the upcoming test block before its commencement.

The first test block, known as the Single Stimulus condition, involved displaying only the first stimulus (S1) of the two practised sequences. Participants had to recall and complete the sequence from memory. The two practised sequences were presented in a randomised order. Stimuli in the Single Stimulus condition was presented in yellow, as were those used during the practice phase.

In the second test condition, the Random condition, participants encountered randomly generated 4-key sequences that differed on each trial. Participants were instructed to respond quickly to these random sequences. In this condition, S1 was displayed in yellow, while the subsequent stimuli (S234) appeared in isoluminant green-blue, just like in the MixInc practice group.

The final test block, the Random Distractor condition, also featured random 4-key sequences, but this time alongside a distractor stimulus. Both key-specific and distractor stimuli were presented simultaneously. While the key-specific stimuli remained yellow, the distractor stimulus was displayed in isoluminant green-blue (refer to Figure 3). Participants were explicitly instructed to respond only to the key-specific stimuli in yellow. Responding to the distractor would result in an error.

Figure 3: Random Distractor test condition



Awareness Task

The participants' awareness was evaluated using a computerised awareness task adapted from Verwey and Dronkers (2019). This task comprised two distinct awareness tests.

In the Spatial test, participants were presented with four empty 2.5 × 2.5 cm squares arranged horizontally, mirroring the layout of the keys in the previous keying task (Figure 4). While the keyboard remained covered, participants used a mouse to click on the square in the same sequence as the keys they had pressed in each of the two practised keying sequences. Feedback was provided for each click with a brief green flash on the selected placeholder.

In the Verbal test, four letters were arranged in a rhombus configuration; each letter corresponded to the response keys pressed by the participants. The letter "N" was placed at the top, "B" at the bottom, and "V" and "C" at the left and right respectively (Figure 5). The letters were positioned at 10 cm vertically and 14 cm horizontally, with angles between the connecting lines set at 90°. Participants were instructed to click on the placeholders in the order of the response letters for each of the two practised sequences.

Both tests evaluated explicit sequence knowledge based on the letters and spatial location associated with the response keys. After completing these tasks, participants were asked to indicate how they determined the sequences they had just performed and their confidence level regarding the sequences they just identified.

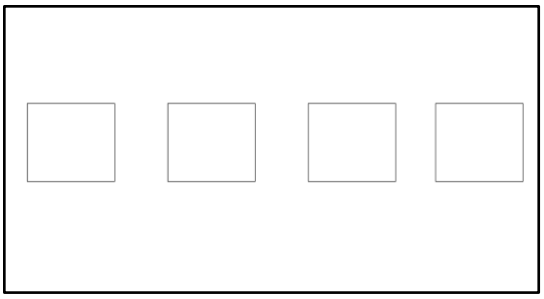


Figure 4: Sequence test in awareness task

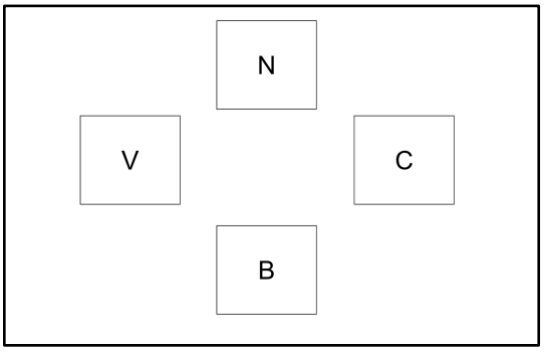


Figure 5: Letter test in awareness task

Procedure

Before participating in the experiment, participants completed an informed consent form and received written and oral instructions detailing the task. Additionally, the SinStim participants were given the letters of the two 4-key sequences to remember. Further instructions were displayed on the computer monitor throughout the experiment. As part of the preparation process, all participants underwent testing for colour blindness using a simplified version of the Ishihara test (e.g., Clark, 1924).

Participants were informed beforehand that the session would last approximately 1 hour and 30 minutes. They were instructed to respond as quickly as possible while maintaining accuracy during task performance, ensuring that error rates did not exceed 8%, as displayed at the end of each subblock. The experiment began with the practice phase, consisting of five practice blocks. Upon concluding the fifth practice block, participants transitioned to the test phase, which comprised three subblocks. Finally, after

completing the final test subblock, participants undertook the awareness task. Participants were granted 2 SONA credits for their complete participation.

Data Analysis

R Studio was used to analyse the data and answer our hypothesis. During the pre-processing phase, we structured the data to align with our analyses. In the analyses, we used the packages: afex (Singmann et al., 2024), psych (Ravelle, 2022), and rstatix (Kassambara, 2022). Mixed analyses of variances (ANOVA) were used to analyse and compare RTs. We assessed the assumption of sphericity and applied a Greenhouse-Geisser correction to adjust the degrees of freedom. Following significant results, pairwise comparisons were conducted.

Results

Practice Phase

The RTs from blocks 1-5 were analysed with a mixed 3 (Group: MixInc, SinStim, DifCom) x 5 (Block: 1-5) x 4 (Key: 1-4) ANOVA with Practice Group as the between-subject variable. The results indicated RTs differed in the different Practice Groups, $F(2, 33) = 15.65$, $p < .001$, $\eta_\rho^2 = 0.487$. A posthoc pairwise comparison revealed the MixInc group (M = 326 ms, SE = 19.6) had significantly longer RTs compared to both the DifCom group (M = 184 ms, SE = 19.6; $p < .001$) and the SinStim group (M = 202 ms, SE = 19.6; $p < .001$). On the other hand, the mean RTs between the DifCom and SinStim groups were not significantly different ($p = .787$).

Blocks showed the expected main effect, $F(2.40, 79.06) = 137.84$, $p < .001$, $\eta_\rho^2 = 0.807$, indicating all Practice Groups had shorter RTs in later blocks (Figure 6). Additionally, RTs decreased over consecutive Keys, $F(1.82, 59.94) = 265.00$, $p < .001$, $\eta_\rho^2 = 0.889$. The interaction between Practice Group and Key Positions, $F(3.63, 59.94) = 7.58$, $p < .001$, $\eta_\rho^2 = 0.315$, indicates that RTs of different practice groups vary concerning different Key positions. Furthermore, the interaction between Practice Group and Blocks, $F(4.79, 79.06) = 12.63$, $p < .001$, $\eta_\rho^2 = 0.434$, indicates the differences in RTs between practice groups are not uniform across different blocks (refer to Figure 6). The interaction between Key positions and Blocks, $F(3.99, 131.68) = 3.93$, $p = .005$, $\eta_\rho^2 = 0.106$, indicates that even though the RTs decreased over consecutive keys, it is not the same in each block. Lastly, the interaction between the Practice Groups, Blocks, and Key positions, $F(7.98, 131.68) = 7.36$, $p < .001$, $\eta_\rho^2 = 0.308$, implies that performance patterns highly depend on the interplay between the three factors.

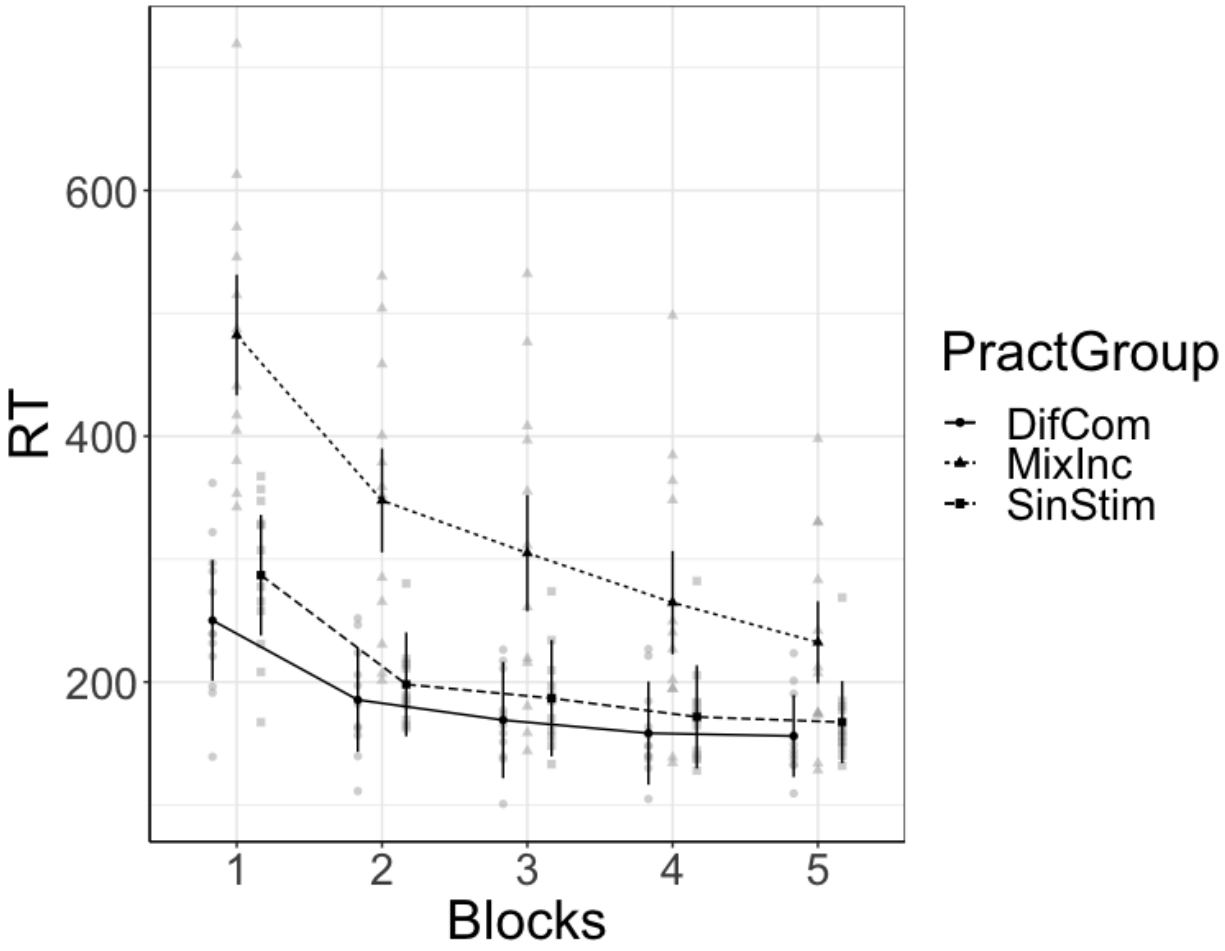


Figure 6: Comparison of mean reaction time between practice groups in 5 successive blocks. Error bars indicate the Standard Error of the Mean (SEM).

Error proportions were arcsine transformed before being analysed with an ANOVA (Winer, 1991). The ANOVA had a mixed 3 (Group: MixInc, SinStim, DifCom) x 5 (Block: 1-5) x 4 (Key: 1-4) design. Practice Group did not show a significant main effect, $F(2, 33) = 1.36$, $p = .271$, $\eta_p^2 = 0.076$. However, the error proportion varied for different Key positions, $F(2.18, 71.94) = 9.98$, $p < .001$, $\eta_p^2 = 0.232$, and Blocks, $F(2.56, 84.58) = 4.86$, $p = .006$, $\eta_p^2 = 0.128$ (Figure 7). The interaction between Practice Groups and Blocks resulted in varied error proportions, $F(5.13, 84.58) = 2.69$, $p = .026$, $\eta_p^2 =$

0.140. The interaction between Practice Groups and Key positions also resulted in different error proportions, $F(4.36, 71.94) = 2.06$, $p = .089$, $\eta_p^2 = 0.111$.

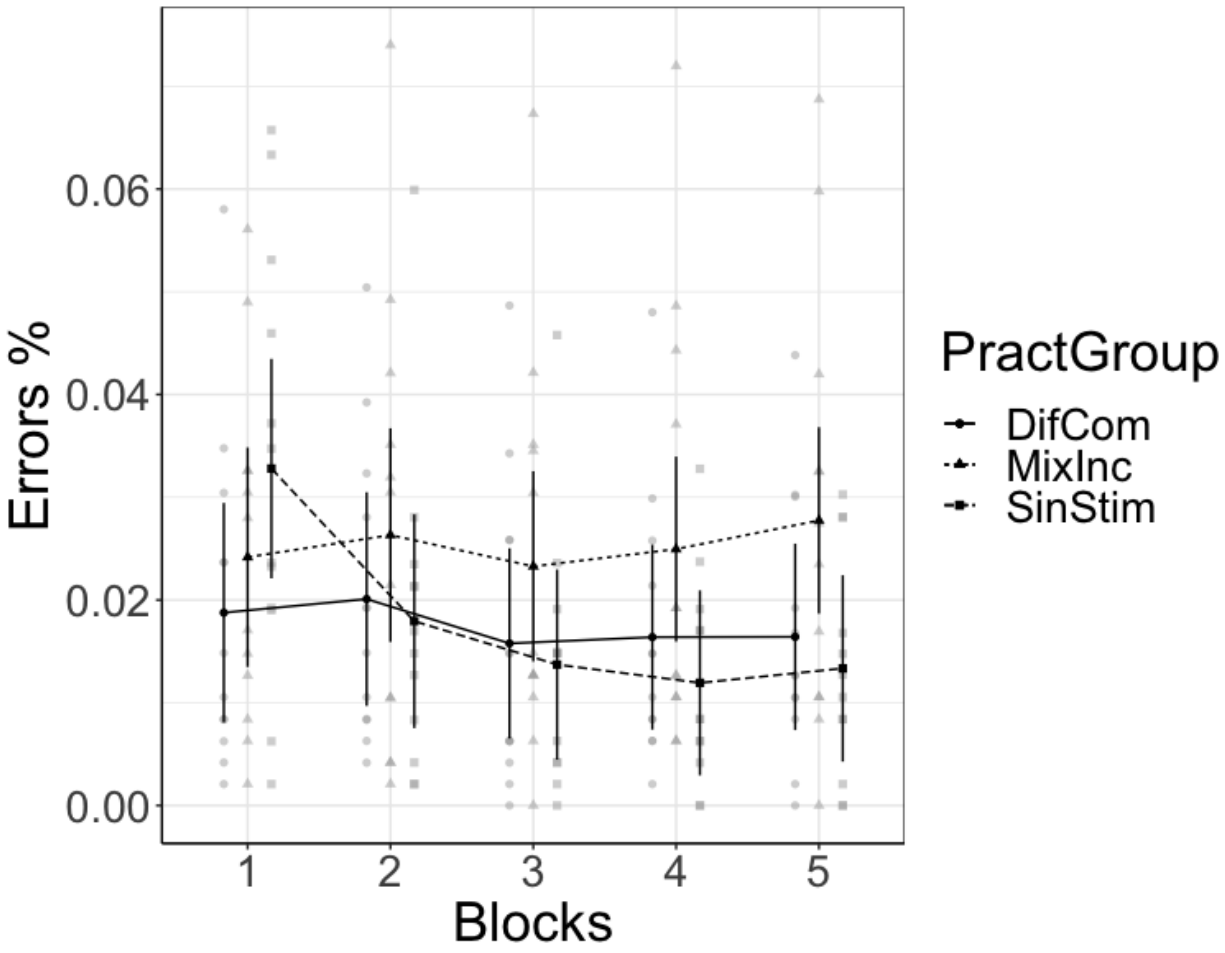


Figure 7: The variation in error percentages (%) across different keys between each practice group and across blocks. Error bars indicate the Standard Error of the Mean (SEM).

In short, RT decreased over later blocks and successive keys. These results indicate the development of motor automaticity in participants. The MixInc group had longer RTs compared to the DifCom and SinStim groups. Moreover, Key position significantly influenced RTs and error proportions, with the last key having faster RTs and lower error proportions.

Test Phase

The test phase had three conditions: Single Stimulus, Random, and Random Distractor. RTs in the Single Stimulus condition underwent analysis separately from Random and Random Distractor conditions. The RTs in the Single Stimulus condition were analysed using a 3 (Group: MixInc, SinStim, DifCom) x 4 (Key: 1-4) mixed ANOVA with the Practice Group as the between-subject variable. The main effect indicated RTs differed significantly in Practice Groups (MixInc = 296ms, DifCom = 157ms, SinStim = 157ms), $F(2, 33) = 11.82$, $p < .001$, $\eta_p^2 = 0.417$. Pairwise comparisons revealed differences between MixInc and DifCom, and MixInc and SinStim were significant ($p = .003$; $p < .001$). However, RT differences between DifCom and SinStim were not significant ($p = .521$). The ANOVA also revealed that RTs decreased significantly for later Keys, $F(2.05, 67.72) = 143.91$, $p < .001$, $\eta_p^2 = 0.813$ (Figure 8). Furthermore, the interaction between Practice Groups and Key positions affected the response time, $F(4.10, 67.72) = 6.29$, $p < .001$, $\eta_p^2 = 0.276$. This interaction implied that different practice groups had different levels of decrease in RTs in later Key positions.

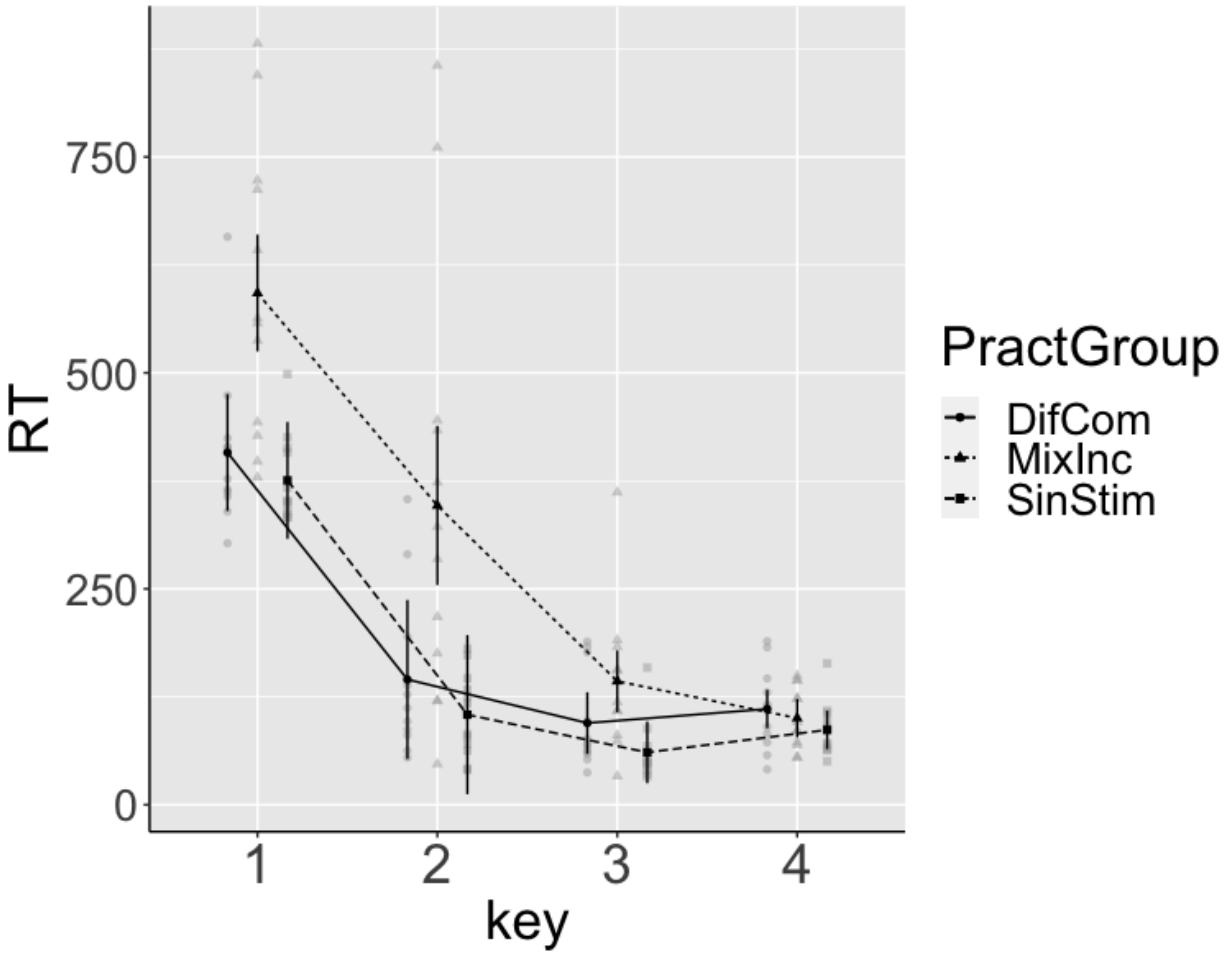


Figure 8: Comparison of response times among practice groups in the single stimulus test phase. Error bars indicate the Standard Error of the Mean (SEM).

Similar to the practice phase, the error proportion was arcsine transformed and analysed with a 3 (Group: MixInc, SinStim, DifCom) x 4 (Key: 1-4) mixed ANOVA, with Practice Group as the between-subject variable. The results indicated that the error proportion varied with regards to Practice Groups, $F(2, 33) = 10.98$, $p < .001$, $\eta_p^2 = 0.399$, and Key position, $F(1.49, 49.27) = 54.66$, $p < .001$, $\eta_p^2 = 0.624$. The interaction between Practice Groups and Key positions indicated a relationship resulting in different error proportions, $F(2.99, 49.27) = 7.78$, $p < .001$, $\eta_p^2 = 0.320$. Pairwise comparisons showed that the MixInc group (M = 0.736, SE = 0.052) had significantly higher error proportions compared to the SinStim group (M = 0.398, SE = 0.052; $p < .001$). Subsequently, the SinStim group had a significantly

lower error proportion than the DifCom group (M = 0.628, SE = 0.052; p = .010). However, there was no significant difference in error proportions between the DifCom and MixInc groups (p = .319). The results can be seen in Figure 9.

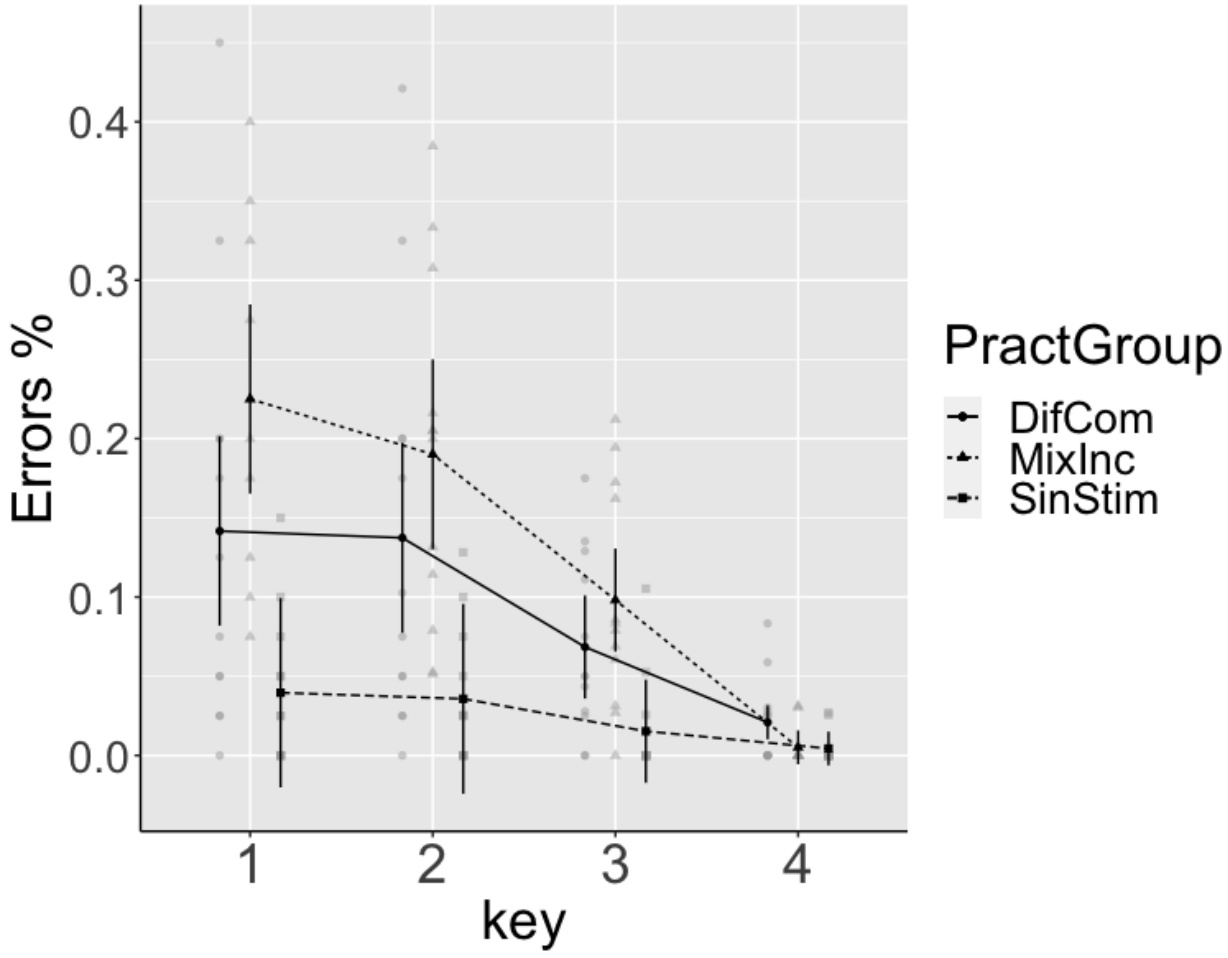


Figure 9: Comparison of error percentages (%) between practice groups in the single stimulus condition. Error bars indicate the Standard Error of the Mean (SEM).

We then analyse the performance of different practice groups on the Random and Random Distractor conditions. A 3 (Group: MixInc, SinStim, DifCom) x 4 (Key: 1-4) x 2 (Condition: Rand vs RanDis) mixed ANOVA was conducted. Based on the results, RTs dropped significantly for later Keys,

$F(1.73, 56.95) = 14.95$, $p < .001$, $\eta_p^2 = 0.312$. Furthermore, the RTs difference between conditions varied across different groups $F(2.14, 70.67) = 4.06$, $p = .019$, $\eta_p^2 = 0.109$ (see Figure 10).

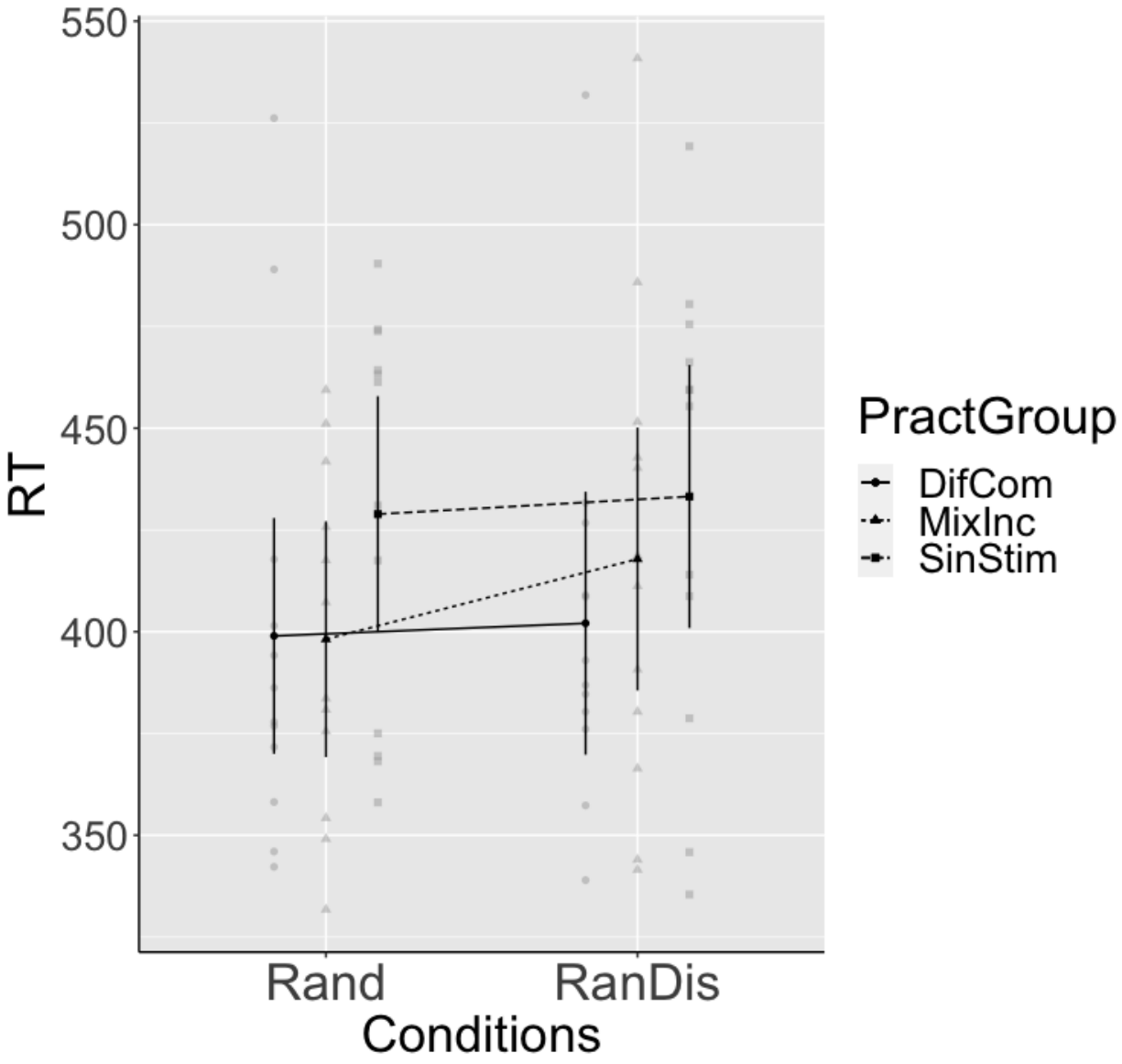


Figure 10: Comparison of mean response time between practice groups in the random and random distractor conditions. Error bars indicate the Standard Error of the Mean (SEM).

Lastly, we analysed the same ANOVA using arcsine transformed error proportions. Results indicated no significant difference in error proportions between Practice Groups, $F(2, 33) = 1.42$, $p = 0.256$, $\eta_p^2 = 0.079$. On the other hand, error proportions differed significantly with regard to Key

positions, $F(1.59, 52.34) = 71.16$, $p < .001$, $\eta_p^2 = 0.683$ (Figure 11). Furthermore, most participants had higher error proportions at the Random condition than the Random Distractor condition (Random = 0.66; RanDis = 0.58), $F(1, 33) = 8.13$, $p = 0.007$, $\eta_p^2 = 0.198$. However, an interaction revealed that the MixInc Group had a higher error proportion in the Random Distractor condition, while the other groups showed higher error proportions in the Random condition., $F(2.00, 33.00) = 3.69$, $p = 0.037$, $\eta_p^2 = 0.183$. Results are illustrated in Figure 12.

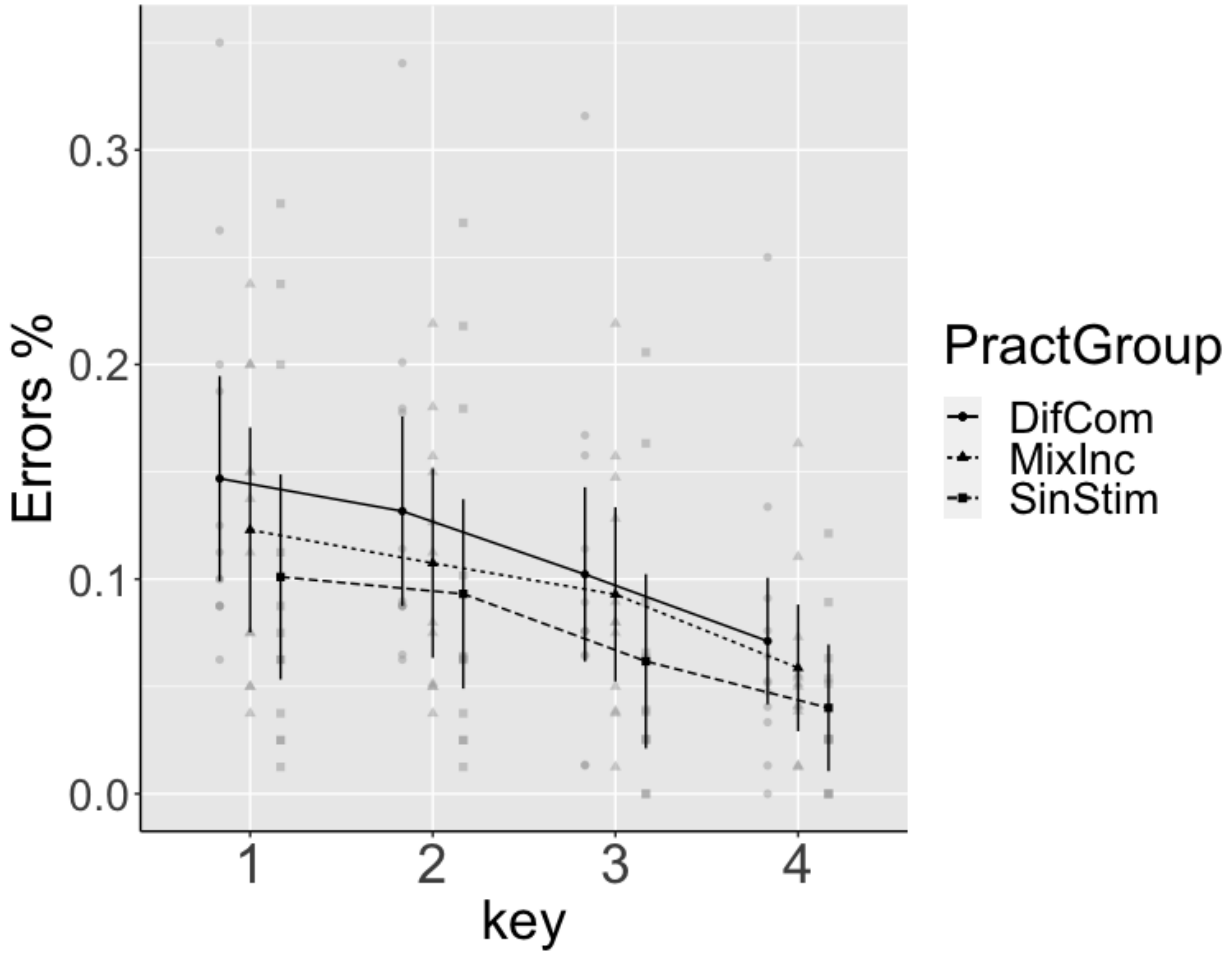


Figure 11: Comparison of error percentages (%) between practice groups (with keys) in Random vs Random Distractor conditions. Error bars indicate the Standard Error of the Mean (SEM).

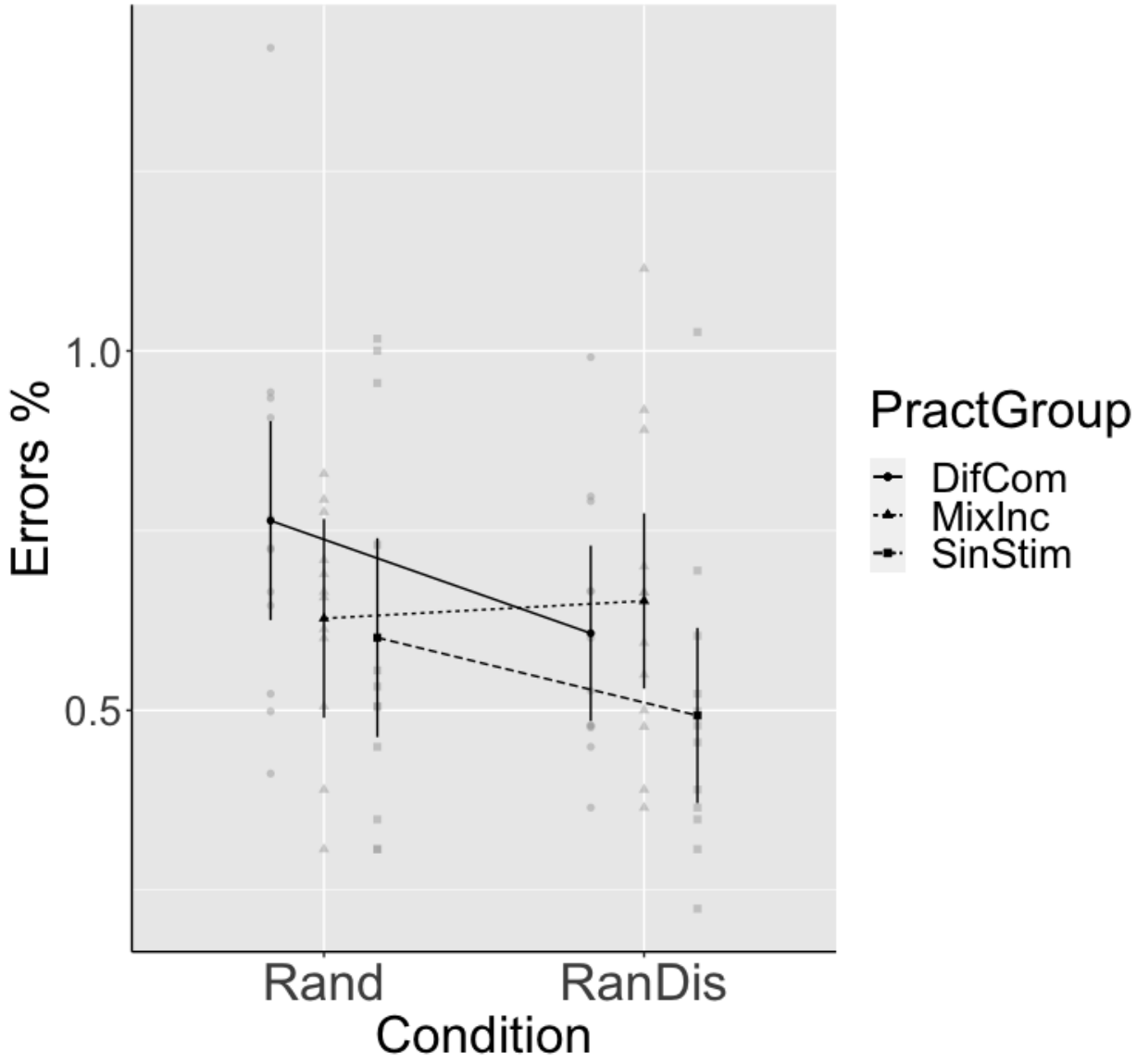


Figure 12: Comparison of error percentages (%) between practice groups in Random vs Random Distractor conditions. Error bars indicate the Standard Error of the Mean (SEM).

Hence, contrary to our initial expectations, the MixInc group exhibited longer RTs and had the highest error proportions compared to the other group in the Single Stimulus phase. Moreover, the MixInc group was the only group with higher error proportions in the Random Distractor conditions. RTs did decrease over successive keys, which indicates the development of motor automaticity in participants.

Discussion

The current study aimed to investigate the effects of isoluminant stimuli in reducing attentional capture in motor sequence learning using a DSP task. Our hypothesis posited that practice with isoluminant stimuli, which blend with the background, would reduce attentional capture and lead participants to develop motor automaticity quicker, thereby improving performance in the subsequent test phase. To test our hypothesis, we compared three different groups in the practice and test conditions. The main question was whether participants in the MixInc group learned to ignore later key-specific stimuli. We expected that using isoluminant stimuli, which blend with the background, would help participants learn sequences better by not forcing their attention on the stimuli. Additionally, the incompatible S-R mappings were designed to increase cognitive load, encouraging participants to ignore subsequent key-specific stimuli as visual cues. These factors should lead participants to associate the sequences primarily with the initial key-specific stimulus, ignoring the later stimuli.

Hence, we predicted that the MixInc group would show similar reaction times (RTs) to the SinStim and DifCom groups in the latter half of the practice phase. We expected the MixInc group to learn the sequence representation similarly to the SinStim group, which explicitly learned the sequence beforehand, and the DifCom group, which had compatible S-R mappings.

Secondly, in the Single Stimulus test condition, we predicted that participants in the MixInc group would demonstrate similar RTs to the SinStim group because they should have learned to associate the sequence based on the first stimulus (S1). Thus, they were expected to be as fast as the SinStim group, which had explicitly learned the sequence and practised responding solely to the first stimulus.

Lastly, we expected participants in the MixInc group to learn how to switch from luminant to isoluminant stimuli better. They should have developed the ability to ignore isoluminant stimuli from the practice phase. We aimed to confirm this by analysing the results from the Random and Random Distractor conditions. We anticipated that participants in the MixInc group would show less difference between Random and Random Distractor conditions than the SinStim and DifCom groups.

The results of the practice phase do not support our hypothesis. Results revealed that in the last block of the practice phase, MixInc group participants had longer RTs than the DifCom and SinStim groups. This suggests that the isoluminant stimuli and incompatible S-R mappings failed to remove attentional capture in the later keys. Hence, contrary to our initial prediction, participants in the MixInc group still relied on later key-specific stimuli (S234). We also expected the DifCom group not to learn the sequence representation because the compatible S-R mappings were natural for them. However, it became apparent that they had still learned the sequence, as evidenced by their faster RTs.

Further analysis of the practise phase revealed that all groups demonstrated shorter RTs in later blocks and keys. Furthermore, despite initial difficulties, participants in the Mixinc group improved more than the two groups with compatible S-R mapping. This would mean that participants had learned to deal with the incompatible S-R mappings. This decrease in RTs over blocks and consecutive keys indicates the development of motor automaticity (Verwey, 1999). Participants in all groups transition from reaction mode to chunking mode, where they begin to execute sequences more rapidly and automatically (Verwey, 2023).

In the Single Stimulus test condition, the MixInc group had significantly longer RTs and higher error proportions than the DifCom and SinStim groups. Contrary to our hypothesis, this further suggests that participants still relied on later key-specific stimuli, even though they were isoluminant. However, a possible explanation might be that participants from the MixInc group had to switch from an incompatible S-R mapping in the practice phase to a compatible S-R mapping in the test phase. This could cause them to have longer RTs and higher error proportions due to the visuo-spatial mapping of the practised sequence they knew had changed. It is also important to note that the MixInc group had reaction times and error proportions similar to those of the other groups on the last key. This similarity suggests that the MixInc group did develop implicit sequence knowledge, even though the first stimulus was shown in a different location. On the other hand, the similar RTs and error proportions between DifCom and SinStim in the Single Stimulus condition suggest that both groups developed implicit sequence knowledge, allowing them to perform the sequences based on the initial stimulus alone. This finding is consistent with

Verwey (2023), who stated that participants with full sequence knowledge could effectively rely on the first stimulus.

In the Random and Random Distractor conditions, we initially predicted that the MixInc group would show less difference than the SinStim and DifCom groups. This assumption was based on the fact that MixInc should have learned to switch between luminance and isoluminance. This prediction was not confirmed. The MixInc had RTs similar to those of the DifCom group in the Random condition. However, the MixInc group had longer RTs in the Random Distractor condition than the DifCom group.

Furthermore, the MixInc group was the only group with higher error proportions in the Random Distractors conditions, indicating the inability to ignore isoluminant stimuli. The error proportions of the Random and Random Distractors conditions revealed that the assumption of accuracy-speed proportion applies to this study. This is shown by the SinStim group having the longest RTs but the lowest error proportions.

The findings of this study contribute to understanding motor sequence learning and the suggested effects of isoluminant stimuli on attentional capture in a DSP task. Although previous research has suggested that participants could learn to ignore the isoluminant stimuli (Verwey, 2019; Riesenbeck, 2021), our results indicate that this ability is not generalised to conditions with incompatible S-R mappings. Following our study's findings, future research is needed to understand why participants failed to ignore the subsequent isoluminant key-specific stimuli. One possible explanation for their poor performance in the test phase could be the switch from incompatible S-R mappings during the practice phase to compatible S-R mappings in the test phase. Although we proposed that combining isoluminant stimuli and incompatible S-R mapping would help participants ignore later key-specific stimuli, in hindsight, the incompatible S-R mapping hindered participants in the test phases, as all three test phases were conducted with compatible S-R mappings. To clarify this, a Different Incompatible (DifInc) group could be added to the current study. The DifInc group would allow for comparing the effects of isoluminant stimuli in test phases with incompatible S-R mappings relative to the existing MixInc and SinStim groups. Another potential improvement to this study could be adding a Mix Compatible

(MixCom) condition. The MixCom condition could be compared to the existing DifCom condition, enabling us to compare the effects of isoluminant and luminant stimuli in a DSP task with compatible S-R mappings. Additionally, future studies could employ eye-tracking technology to determine whether isoluminant stimuli force participants to ignore key-specific stimuli.

Conclusion

The current study demonstrates that isoluminant stimuli in a DSP task with incompatible S-R mapping do not reduce attentional capture. The results revealed that the MixInc group exhibited longer RTs and higher error proportions than the DifCom and SinStim groups. This indicates that the practice with isoluminant stimuli and incompatible S-R mappings did not help participants ignore later key-specific stimuli and, therefore, did not improve their motor sequence learning. Results from the Single Stimulus condition showed that the MixInc group had the worst performance, which further suggested that participants in the MixInc condition did not learn the sequence as well as the other two groups. Moreover, the Random and Random Distractor conditions showed that the MixInc group did not develop the ability to ignore the isoluminant stimuli, as evidenced by the significant difference in RTs between the two test conditions. This is further supported by the MixInc group being the only group to show higher error proportions in the Random Distractor condition. However, a possible explanation could be that participants in the MixInc group had difficulty transitioning the practised sequences to a compatible S-R mapping. The significantly shorter reaction times of the MixInc group in the Single Stimulus test condition for the last key-specific stimulus suggest that they did develop motor automaticity. However, the different visual cues hindered their progress early on due to the switch to compatible S-R mappings. Hence, future research should investigate alternative approaches to studying the effects of isoluminant stimuli on attentional capture in the development of motor automaticity.

References

Abrahamse, E. L., Ruitenberg, M. F. L., De Kleine, E., & Verwey, W. B. (2013). Control of automated behaviour: Insights from the Discrete Sequence Production task. *Frontiers in Human Neuroscience*, *7*(82), 1-16.

Allingham, E., & Wöllner, C. (2021). Effects of attentional focus on motor performance and physiology in a slow-motion violin bow-control task: Evidence for the constrained action hypothesis in bowed string technique. *Journal of Research in Music Education, 70*(2), 168-189.

Belopolsky, A. V., Schreij, D., & Theeuwes, J. (2010). What is top-down about contingent capture? *Attention, Perception, & Psychophysics, 72*(2), 326-341.

Clark, J. H. (1924). The Ishihara Test for Color Blindness. *American Journal of Physiological Optics, 5*, 269–276.

Cohen, N. R., Cross, E. S., Wymbs, N. F., & Grafton, S. T. (2009). Transient disruption of M1 during response planning impairs subsequent offline consolidation. *Experimental Brain Research, 196*(2), 303–309.

Doyon, J., Penhune, V. B., & Ungerleider, L. G. (2003). Distinct contribution of the cortico-striatal and cortico-cerebellar systems to motor skill learning. *Neuropsychologia, 41*(3), 252–262.

Folk, C. L., Remington, R. W., & Johnston, J. C. (1992). Involuntary covert orienting is contingent on attentional control settings. Journal of Experimental Psychology: *Human Perception & Performance, 18,* 1030-1044.

Hughes, M. E., Fulham, W. R., Michie, P. T. (2016). Electrophysiological signatures of the race model in human primary motor cortex. *Psychophysiology, 53*(2), 229-236

Im, H. Y., Bédard, P., & Song, J. H. (2015). Encoding attentional states during visuomotor adaptation. *Journal of vision, 15*(8), 20.

Jonides, J., & Yantis, S. (1988). Uniqueness of abrupt visual onset in capturing attention. *Perception & Psychophysics, 43*(4), 346–354.

Kassambara, A. (2022). *rstatix: Pipe-Friendly Framework for Basic Statistical Tests*. R package version 0.7.1.

Kornblum, S., Hasbroucq, T., & Osman, A. (1990). Dimensional overlap: Cognitive basis for stimulus-response compatibility - A model and a taxonomy. *Psychological Review, 97*(2), 253–270.

Lambert, A., Wells, I. & Kean, M (2003). Do isoluminant color changes capture attention?. *Perception & Psychophysics, 65*(4), 495–507.

Livingstone, M., & Hubel, D. (1988). Segregation of form, color, movement, and depth: Anatomy, physiology, and perception. *Science, 240*, 740-749.

Luck, S. J., Gaspelin, N., Folk, C. L., Remington, R. W., & Theeuwes, J. (2020). Progress toward resolving the attentional capture debate. *Visual Cognition, 29*(1), 1-21.

McNevin N. H., Shea C. H., Wulf G. (2003). Increasing the distance of an external focus of attention enhances learning. *Psychological Research*, *67*(1), 22–29.

Müller, H. J., Reimann, B., & Krummenacher, J. (2003). Visual search for singleton feature targets across dimensions: Stimulus-and expectancy-driven effects in dimensional weighting. *Journal of Experimental Psychology: Human perception and performance*, *29*(5), 1021.

Poolton J. M., Zachry T. L. (2007). So you want to learn implicitly? Coaching and learning through implicit motor learning techniques. *International Journal of Sports Science & Coaching, 2*(1), 67–78.

Posner M. I, Snyder C. R. R . (2004) Attention and Cognitive Control. In D. A. Balota & E. J. Marsh (Eds.), *Cognitive psychology: Key readings* (pp. 205–223).

Revelle, W. (2022). *psych: Procedures for Personality and Psychological Research, Northwestern University, Evanston, Illinois, USA*. R package version 2.2.5.

Riesenbeck, L. (2021). *The role of visual attention when executing a motor sequence production task* [Unpublished Master Thesis, University of Twente]. Enschede. https://essay.utwente.nl/86114/ (downloaded Feb. 7th, 2022).

Singmann, H., Bolker, B., Westfall, J., Aust, F., & Ben-Shachar, M., S., (2024). *afex: Analysis of Factorial Experiments*. R package version 1.3-1

Sobierajewicz, J., Szarkiewicz, S., Przekoracka-Krawczyk, A., Jaśkowski, W., & van der Lubbe, R. H. J. (2016). To what extent can motor imagery replace motor execution while learning a fine motor skill? *Advances in Cognitive Psychology*, *12*(4), 179.

Song J. H. (2019). The role of attention in motor control and learning. *Current opinion in psychology*, 29, 261–265.

Theeuwes, J. (1991). Cross-dimensional perceptual selectivity. *Perception & Psychophysics*, *50*(2), 184-193.

Theeuwes, J. (1992). Perceptual selectivity for colour and form. *Perception & Psychophysics*, *51*(6), 599-606.

Theeuwes J., de Vries G-J., & Godijn, R. (2003). Attentional and oculomotor capture with static singletons. *Perception & Psychophysics, 65(5)*, 735–746.

Theeuwes, J., Kramer, A. F., Hahn, S., Irwin, D. E., & Zelinsky, G. J. (1999). Influence of attentional capture on oculomotor control. *Journal of Experimental Psychology: Human Perception & Performance, 25(6)*, 1595-1608.

Theeuwes, J., & Van der Burg, E. (2008). The role of cueing in attentional capture. *Visual Cognition, 16*(2-3), 232-247.

Treisman, A.M., Gelade, G. (1980) A feature-integration theory of attention. *Cognitive Psychology*, *12* (1).

Tubau, E., & López-Moliner, J. (2004). Spatial interference and response control in sequence learning: The role of explicit knowledge. *Psychological Research*, *68*(1), 55–63.

Van der Lubbe, R. H. J., & Abrahamse, E. L. (2011). The premotor theory of attention and the Simon effect. *Acta Psychologica*, *136*(2), 259-264.

Verwey, W. B. (1999). Evidence for a multistage model of practice in a sequential movement task. Journal of Experimental Psychology: *Human Perception and Performance*, *25*(6), 1693–1708.

Verwey, W. B. (2021). Isoluminant stimuli in a familiar discrete keying sequence task can be ignored. *Psychological Researc*h, *85*(2), 793–807.

Verwey, W. B (2023). C-SMB 2.0: Integrating over 25 years of motor sequencing research with the Discrete Sequence Production task. *Psychonomic Bulletin & Review*.

Verwey, W. B., & Abrahamse, E. L. (2012). Distinct modes of executing movement sequences: reacting, associating, and chunking. *Acta Psychologica, 140*(3), 274–282.

Verwey, W. B., & Dronkers, W. J. (2019). Skill in discrete keying sequences is execution rate specific. *Psychological Research: An International Journal of Perception, Attention, Memory, and Action, 83*(2), 235–246.

Verwey, W. B., & Eikelboom, T. (2003). Evidence for lasting sequence segmentation in the discrete sequence-production task. *Journal of Motor Behavio*r, *35(2)*, 171–182.

Verwey, W. B., Shea, C. H., & Wright, D. L. (2015). A cognitive framework for explaining serial processing and sequence execution strategies. *Psychonomic Bulletin & Review*, *22*(1), 54–77.

Winer, B. J., Brown, D. R., & Michels, K. M. (1991). *Statistical principles in experimental design* (3rd ed.). New York: McGraw-Hill.

Wulf, G. (2013). Attentional focus and motor learning: A review of 15 years. *International Review of Sport and Exercise Psychology*, *6*(1), 77–104.

Yantis, S., & Hillstrom,A. P. (1994). Stimulus-driven attentional capture: Evidence from equiluminant visual objects. *Journal of Experimental Psychology: Human Perception & Performance*, *20*(1), 95-107.

Yantis, S., & Jonides, J. (1984). Abrupt visual onsets and selective attention: Evidence from visual search. *Journal of Experimental Psychology: Human Perception & Performance*, *10*, 601-621.

Appendix A

R Codes

```
#Set working directory

install.packages("afex")

install.packages("readxl")

install.packages("rstatix")

library(afex)

library(tidyverse)

library(ggplot2)

library(psych)

library(readxl)

library(rstatix)

library(emmeans)


#Citation

citation("afex")


citation("psych")


citation("rstatix")


setwd("~/Desktop/THESIS/Data Analysis")

getwd()


#Load Data (Block 1-5 RT)
```

```
PracticeBl_RT <- read_excel("Irvin Bl1-5 RT.xlsx", col_names = TRUE)


# Re-structure the data
PracticeBl_RT_Long <- PracticeBl_RT %>%
  pivot_longer(cols = c(B1K1, B1K2, B1K3, B1K4, B2K1, B2K2, B2K3, B2K4,
                        B3K1, B3K2, B3K3, B3K4, B4K1, B4K2, B4K3, B4K4,
                        B5K1, B5K2, B5K3, B5K4),
               names_to = "Variable",
               values_to = "RT") %>%
  separate(Variable, c("Blocks", "Keys"), sep = "K")%>%
  mutate(Blocks = gsub("B", "", Blocks))


#Removing nas
PracticeBl_RT_Long_clean <- drop_na(PracticeBl_RT_Long)


complete_cases <- complete.cases(PracticeBl_RT_Long)
complete_data <- PracticeBl_RT_Long[complete_cases, ]


# Convert to factors
PracticeBl_RT_Long_clean$Subject <- as.factor(PracticeBl_RT_Long_clean$Subject)
PracticeBl_RT_Long_clean$PractGroup <- factor(PracticeBl_RT_Long_clean$PractGroup)
PracticeBl_RT_Long_clean$Keys <- factor(PracticeBl_RT_Long_clean$Keys)
PracticeBl_RT_Long_clean$Blocks <- factor(PracticeBl_RT_Long_clean$Blocks)


# Check the levels of each factor
str(PracticeBl_RT_Long)
```

```
levels(PracticeBl_RT_Long_clean$PractGroup)

levels(PracticeBl_RT_Long_clean$Keys)

levels(PracticeBl_RT_Long_clean$Blocks)


# ANOVA (without GG correction)

model_rt <- PracticeBl_RT_Long_clean %>%

  lmer(RT ~ PractGroup + Keys + Blocks + (1|Subject), data = .)


anova(model_rt)


#ANOVA (With GG correction)

model_rt2 <- anova_test(data = PracticeBl_RT_Long_clean, dv = RT, wid = Subject, between =

PractGroup, within = c("Keys", "Blocks"), effect.size = "ges")


get_anova_table(model_rt2, correction = "GG")


##Break##

model_rt3 <- anova_test(data = PracticeBl_RT_Long_clean, dv = RT, wid = Subject, between =

PractGroup, within = c("Keys", "Blocks"), effect.size = "pes")


get_anova_table(model_rt3, correction = "GG")


##Results##

#              Effect  DFn    DFd       F        p p<.05   pes

#           PractGroup 2.00  33.00  15.648 1.66e-05     * 0.487
```

```
#                 Keys 1.82  59.94 265.006 1.58e-29     * 0.889
#               Blocks 2.40  79.06 137.841 1.29e-28     * 0.807
#       PractGroup:Keys 3.63  59.94   7.589 8.59e-05     * 0.315
#     PractGroup:Blocks 4.79  79.06  12.634 8.06e-09     * 0.434
#           Keys:Blocks 3.99 131.68   3.925 5.00e-03     * 0.106
# PractGroup:Keys:Blocks 7.98 131.68   7.359 4.73e-08     * 0.308

##Visualisation
library(ggplot2)

#The mean RT
mean_RT <- PracticeBl_RT_Long_clean %>%
  group_by(PractGroup, Blocks) %>%
  summarise(mean_RT = mean(RT))

#Plot
model_rt4 <- aov_ez("Subject", "RT", PracticeBl_RT_Long_clean, between = "PractGroup", within =
"Blocks")
anova(model4, na.rm = TRUE)

# Plot
afex_plot(model_rt4, "Blocks", "PractGroup") +
  theme_bw() +
  theme(text = element_text(size = 25),  # Adjust font size
        axis.text.x = element_text(size = 20),
        axis.line = element_line(color = "black")) +  # Adjust x-axis label font size
```

```
  scale_x_discrete(labels = c("1", "2", "3", "4", "5"))  # Customize x-axis labels

plot  # Display the plot



#T-test
# Independent t-test between MixInc and SinStim
t.test(RT ~ PractGroup, data = PracticeBl_RT_Long_clean, subset = PractGroup %in% c("MixInc",
"SinStim"))

# Independent t-test between MixInc and Diffcom
t.test(RT ~ PractGroup, data = PracticeBl_RT_Long_clean, subset = PractGroup %in% c("MixInc",
"Diffcom"))

# Independent t-test between SinStim and Diffcom
t.test(RT ~ PractGroup, data = PracticeBl_RT_Long_clean, subset = PractGroup %in% c("SinStim",
"Diffcom"))

#EMMs
# Compute estimated marginal means (EMMs) for each factor level or combination of levels
RT_emm <- emmeans(model_rt, ~ PractGroup)

# Display
summary(RT_emm)
```

```
pairs(RT_emm)


##Results##

#summary(RT_emm)

#PractGroup emmean   SE df lower.CL upper.CL

#DifCom       184 19.6 33      144      224

#MixInc       326 19.6 33      286      366

#SinStim      202 19.6 33      162      242


#Results are averaged over the levels of: Keys, Blocks

#Degrees-of-freedom method: kenward-roger

#Confidence level used: 0.95


#pairs(RT_emm)

#contrast        estimate   SE df t.ratio p.value

#DifCom - MixInc    -142.6 27.7 33  -5.141  <.0001

#DifCom - SinStim    -18.3 27.7 33  -0.661  0.7873

#MixInc - SinStim    124.2 27.7 33   4.480  0.0002


#Results are averaged over the levels of: Keys, Blocks

#Degrees-of-freedom method: kenward-roger

#P value adjustment: tukey method for comparing a family of 3 estimates


#Plot with SEM

# Calculate SEM for each block

sem_RT <- PracticeBl_RT_Long_clean %>%
```

```
  group_by(PractGroup, Blocks) %>%
  summarise(mean_RT = mean(RT),
            sem = sd(RT) / sqrt(n()))

# Plot with error bars representing SEM
ggplot(sem_RT, aes(x = Blocks, y = mean_RT, group = PractGroup, color = PractGroup)) +
  geom_line() +
  geom_point() +
  geom_errorbar(aes(ymin = mean_RT - sem, ymax = mean_RT + sem), width = 0.1) +  # Add error bars
  labs(x = "Blocks", y = "Mean Reaction Time", color = "Practice Group") +
  theme_minimal()

##Errors in Block 1-5
setwd("~/Desktop/THESIS/Data Analysis")
getwd()

#Load Data (Block 1-5 Errors)
PracticeBl_Error <- read_excel("Irvin Bl1-5 Error.xlsx")
PracticeBl_ErrorArc <- read_excel("Irvin Bl1-5 ErrorArc.xlsx")

# Re-structure the data
PracticeBl_ErrorArc_Long <- PracticeBl_ErrorArc %>%
  pivot_longer(cols = c(B1K1, B1K2, B1K3, B1K4, B2K1, B2K2, B2K3, B2K4,
                        B3K1, B3K2, B3K3, B3K4, B4K1, B4K2, B4K3, B4K4,
                        B5K1, B5K2, B5K3, B5K4),
               names_to = "Variable",
```

```
            values_to = "Errors") %>%
  separate(Variable, c("Blocks", "Keyss"), sep = "K")

#Removing nas
PracticeBl_ErrorArc_Long <- drop_na(PracticeBl_ErrorArc_Long)

# ConveErrors to factors
PracticeBl_ErrorArc_Long$Subject <- as.factor(PracticeBl_ErrorArc_Long$Subject)
PracticeBl_ErrorArc_Long$PractGroup <- factor(PracticeBl_ErrorArc_Long$PractGroup)
PracticeBl_ErrorArc_Long$Keyss <- factor(PracticeBl_ErrorArc_Long$Keyss)
PracticeBl_ErrorArc_Long$Blocks <- factor(PracticeBl_ErrorArc_Long$Blocks)

# Check the levels of each factor
str(PracticeBl_ErrorArc_Long)

levels(PracticeBl_ErrorArc_Long$PractGroup)
levels(PracticeBl_ErrorArc_Long$Keyss)
levels(PracticeBl_ErrorArc_Long$Blocks)

# ANOVA (without GG correction)
model_error <- PracticeBl_ErrorArc_Long %>%
  lmer(Errors ~ PractGroup + Keyss + Blocks + (1|Subject), data = .)

anova(model_error)

#ANOVA (With GG correction)
```

```
model_error2 <- anova_test(data = PracticeBl_ErrorArc_Long, dv = Errors, wid = Subject, between =
PractGroup, within = c("Keyss", "Blocks"), effect.size = "pes")

get_anova_table(model_error2, correction = "GG")

##Results##
#      Effect   DFn    DFd     F        p p<.05   pes
#             PractGroup  2.00  33.00 1.358 2.71e-01       0.076
#                  Keyss  2.18  71.94 9.978 9.54e-05     * 0.232
#                 Blocks  2.56  84.58 4.861 6.00e-03     * 0.128
#        PractGroup:Keyss  4.36  71.94 2.063 8.90e-02       0.111
#       PractGroup:Blocks  5.13  84.58 2.685 2.60e-02     * 0.140
#            Keyss:Blocks  6.91 228.07 1.094 3.67e-01       0.032
# PractGroup:Keyss:Blocks 13.82 228.07 1.132 3.31e-01       0.064

##Break##
# Calculate EMMs
emm_results <- emmeans(model_error, ~ PractGroup)

# Print the EMMs
emm_results

#Restructuring data
PracticeBl_Error <- PracticeBl_Error %>%
  pivot_longer(cols = c(B1K1, B1K2, B1K3, B1K4, B2K1, B2K2, B2K3, B2K4,
                        B3K1, B3K2, B3K3, B3K4, B4K1, B4K2, B4K3, B4K4,
```

```
                B5K1, B5K2, B5K3, B5K4),
            names_to = "Variable",
            values_to = "Errors") %>%
  separate(Variable, c("Blocks", "Keys"), sep = "K")

# Create a linear mixed effects model
model_error3 <- lmer(Errors ~ PractGroup + Keys + Blocks + (1|Subject), data = PracticeBl_Error)

# Display the summary of the model
summary(model_error)

# Calculate EMMs
emm_results <- emmeans(model_error3, pairwise~PractGroup)

key_comparisons <- emmeans(model_error3, pairwise ~ Keys)

# Print the EMMs
emm_results

key_comparisons

##Results##
#PractGroup emmean      SE df lower.CL upper.CL
#DifCom     0.0175 0.00417 33  0.00900   0.0260
#MixInc     0.0253 0.00417 33  0.01680   0.0338
#inStim    0.0179 0.00417 33  0.00946   0.0264
```

```
#Results are averaged over the levels of: Keys, Blocks
#Degrees-of-freedom method: kenward-roger
#Confidence level used: 0.95

#Keys1 - Keys2 -0.01317 0.00234 677  -5.623  <.0001
#Keys1 - Keys3 -0.01622 0.00234 677  -6.926  <.0001
#Keys1 - Keys4 -0.00454 0.00234 677  -1.940  0.2123
#Keys2 - Keys3 -0.00305 0.00234 677  -1.303  0.5614
#Keys2 - Keys4  0.00862 0.00234 677   3.683  0.0014
#Keys3 - Keys4  0.01168 0.00234 677   4.986  <.0001


#Visualisation
library(ggplot2)

#Plot
model_error4 <- aov_ez("Subject", "Errors", PracticeBl_Error, between = "PractGroup", within =
"Blocks")
anova(model_error4, na.rm = TRUE)

# Plot
afex_plot(model_error4, "Blocks", "PractGroup") +
  theme_bw() +
  theme(text = element_text(size = 25),  # Adjust font size
        axis.text.x = element_text(size = 20),
```

```
      axis.line = element_line(color = "black")) +  # Adjust x-axis label font size
  scale_x_discrete(labels = c("1", "2", "3", "4", "5")) +
  ylab("Errors %") # Customize x-axis labels

#SinStim RT
setwd("~/Desktop/THESIS/Data Analysis/Selin's Data/Excel")
TstBI6_RT_SinStim <- read_excel("TstBI6 RT SinStim.xlsx")



############################ TEST BLOCK 6 SINSTIM CONDITION RT
############################

#make data into long format
TstBI6_RT_SinStim_Long <- TstBI6_RT_SinStim %>%
  pivot_longer(cols = c(RT1, RT2, RT3, RT4), names_to = "key", values_to = "RT")

#change variables into factor variables
TstBI6_RT_SinStim_Long <- TstBI6_RT_SinStim_Long %>%
  mutate(PractGroup = as.factor(PractGroup))
TstBI6_RT_SinStim_Long <- TstBI6_RT_SinStim_Long %>%
  mutate(key = as.factor(key))
TstBI6_RT_SinStim_Long <- TstBI6_RT_SinStim_Long %>%
  mutate(Subject = as.factor(Subject))

############################ CHECKING NORMALITY ############################
```

```
ggdensity(TstBI6_RT_SinStim_Long$RT, fill = "lightgray", main = "Density Plot Response Times", xlab
= "Response Times")

ggqqplot(TstBI6_RT_SinStim_Long$RT, title = "Q + Q Plot for Response Times")

TstBI6_RT_SinStim_Long %>% shapiro_test(RT)
# variable statistic        p
# <chr>        <dbl>    <dbl>
#   1 RT           0.808 1.85e-12

TstBI6_RT_SinStim_Long %>% group_by(PractGroup) %>% shapiro_test(RT)
# PractGroup variable statistic           p
# <fct>      <chr>        <dbl>       <dbl>
#   1 DifCom     RT           0.842 0.0000131
# 2 MixInc     RT           0.845 0.0000162
# 3 SinStim    RT           0.787 0.000000668

TstBI6_RT_SinStim_Long %>% group_by(key) %>% shapiro_test(RT)
# key   variable statistic          p
# <fct> <chr>        <dbl>      <dbl>
#   1 RT1   RT           0.806 0.0000219
# 2 RT2   RT           0.738 0.00000118
# 3 RT3   RT           0.809 0.0000241
# 4 RT4   RT           0.947 0.0842
```

```
############################ ANOVA MODEL ############################
model <- TstBI6_RT_SinStim_Long %>%
  lmer(RT ~ PractGroup * key * (1|Subject), data = .)

anova(model)
summary(model)
# Type III Analysis of Variance Table with Satterthwaite's method
#                Sum Sq Mean Sq NumDF DenDF  F value    Pr(>F)
# PractGroup      170173   85086     2    33  11.8180 0.0001347 ***
# key            3108483 1036161     3    99 143.9166 < 2.2e-16 ***
# PractGroup:key  271679   45280     6    99   6.2891 1.255e-05 ***
# ---
# Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


# effect size  practice group
F_to_eta2(11.818, df=2, df_error = 33)

# η² (partial) |       95% CI
# ---------------------------
#   0.42         | [0.19, 1.00]

#effect size key
F_to_eta2(143.9166, df=3, df_error = 99)

# Eta2 (partial) |       95% CI
```

```
# ----------------------------
#   0.81          | [0.76, 1.00]


############################## ANOVA WITH CORRECTION ############################

model2 <- anova_test(data = TstBI6_RT_SinStim_Long, dv = RT, wid = Subject, between = PractGroup,
within = key, effect.size = "ges")
get_anova_table(model2, correction = "GG")
#effect sizes generalized ets squared
# ANOVA Table (type II tests)
#
# Effect  DFn   DFd       F        p p<.05   ges
# 1     PractGroup 2.00 33.00  11.818 1.35e-04     * 0.263
# 2            key 2.05 67.72 143.917 2.25e-25     * 0.687
# 3 PractGroup:key 4.10 67.72   6.289 2.04e-04     * 0.161

model3 <- anova_test(data = TstBI6_RT_SinStim_Long, dv = RT, wid = Subject, between = PractGroup,
within = key, effect.size = "pes")
get_anova_table(model3, correction = "GG")

# effect sizes partial ets squared
# ANOVA Table (type II tests)
#
# Effect  DFn   DFd       F        p p<.05   pes
# 1     PractGroup 2.00 33.00  11.818 1.35e-04     * 0.417
```

```
# 2           key 2.05 67.72 143.917 2.25e-25     * 0.813
# 3 PractGroup:key 4.10 67.72   6.289 2.04e-04     * 0.276

model4 <- aov_ez("Subject", "RT", TstBI6_RT_SinStim_Long, between = "PractGroup", within = "key")
anova(model4, na.rm = TRUE)
# Anova Table (Type 3 tests)
#
# Response: RT
# num Df den Df   MSE        F     ges    Pr(>F)
# PractGroup     2.0000 33.000 21354  11.8180 0.26258 0.0001347 ***
#   key          2.0521 67.718 10526 143.9166 0.68681 < 2.2e-16 ***
#   PractGroup:key 4.1041 67.718 10526   6.2891 0.16084 0.0002039 ***
#   ---
#   Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

afex_plot(model4, "key", "PractGroup") +
  theme(text = element_text(size = 25),  # Adjust font size
        axis.text.x = element_text(size = 25),
        axis.line = element_line(color = "black")) +  # Adjust x-axis label font size
  scale_x_discrete(labels = c("1", "2", "3", "4", "5"))  # Customize x-axis labels



em1 <- emmeans(model4, "PractGroup")
em1
# PractGroup emmean   SE df lower.CL upper.CL
# DifCom        190 21.1 33      147      233
```

```
# MixInc       296 21.1 33     253     338
# SinStim      157 21.1 33     114     200
#
# Results are averaged over the levels of: key
# Confidence level used: 0.95


pairs(em1)
# contrast         estimate   SE df t.ratio p.value
# DifCom - MixInc    -105.9 29.8 33  -3.551  0.0033
# DifCom - SinStim     32.8 29.8 33   1.100  0.5210
# MixInc - SinStim    138.7 29.8 33   4.651  0.0001
#
# Results are averaged over the levels of: key
# P value adjustment: tukey method for comparing a family of 3 estimates


#SinStim Error
setwd("~/Desktop/THESIS/Data Analysis/Selin's Data/Excel")


data_errorP <- read_excel("TstBl6 Error SinStim Error Proportions.xlsx")


############################ TEST BLOCK 6 SINSTIM CONDITION ERROR PROPOErrorIONS
############################


#make data into long format
data_long <- data_errorP %>%
  pivot_longer(cols = c(E1, E2, E3, E4), names_to = "key", values_to = "Error")
```

```
#change variables into factor variables
data_long <- data_long %>%
  mutate(PractGroup = as.factor(PractGroup))
data_long <- data_long %>%
  mutate(key = as.factor(key))
data_long <- data_long %>%
  mutate(Subject = as.factor(Subject))

############################## CHECKING NORMALITY ##############################
ggdensity(data_long$Error, fill = "lightgray", main = "Density Plot Error Proportionss", xlab = "Error
Proportionss")

ggqqplot(data_long$Error, title = "Q + Q Plot for Error Proportionss")

data_long %>% shapiro_test(Error)
# A tibble: 1 × 3
# variable statistic        p
# <chr>        <dbl>    <dbl>
#   1 Error          0.782 2.34e-13

data_long %>% group_by(PractGroup) %>% shapiro_test(Error)
# A tibble: 3 × 4
# PractGroup variable statistic            p
# <fct>      <chr>        <dbl>        <dbl>
#   1 DifCom     Error          0.783 0.000000536
```

```
# 2 MixInc     Error          0.902 0.000757
# 3 SinStim    Error          0.680 0.00000000601

data_long %>% group_by(key) %>% shapiro_test(Error)
# A tibble: 4 × 4
# key   variable statistic            p
# <fct> <chr>        <dbl>        <dbl>
#   1 E1    Error          0.899 0.00319
# 2 E2    Error          0.870 0.000583
# 3 E3    Error          0.860 0.000322
# 4 E4    Error          0.593 0.00000000837

############################ ANOVA MODEL ############################
model <- data_long %>%
  lmer(Error ~ PractGroup + key + (1|Subject), data = .)

anova(model)
# Type III Analysis of Variance Table with SatteErrorhwaite's method
#             Sum Sq  Mean Sq NumDF DenDF F value    Pr(>F)
# PractGroup 0.07642 0.038209     2    33  9.3229 0.0006172 ***
# key        0.36001 0.120003     3   105 29.2808 7.744e-14 ***
# ---
# Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

summary(model)
```

```
# effect size  practice group
F_to_eta2(9.3229, df=2, df_error = 33)
# η² (paErrorial) |       95% CI
# ---------------------------
#   0.36        | [0.13, 1.00]

#effect size key
F_to_eta2(29.2808, df=3, df_error = 105)
# η² (paErrorial) |       95% CI
# ---------------------------
#   0.46        | [0.33, 1.00]


############################ ANOVA WITH CORRECTION ############################

model2 <- anova_test(data = data_long, dv = Error, wid = Subject, between = PractGroup, within = key,
effect.size = "ges")
get_anova_table(model2, correction = "GG")

#effect sizes generalized ets squared
# ANOVA Table (type II tests)
#
# Effect  DFn  DFd      F        p p<.05   ges
# 1     PractGroup 2.00 33.0  9.323 6.17e-04     * 0.258
# 2            key 1.32 43.4 38.610 1.54e-08     * 0.311
# 3 PractGroup:key 2.63 43.4  6.576 1.00e-03     * 0.133
```

```
model3 <- anova_test(data = data_long, dv = Error, wid = Subject, between = PractGroup, within = key,
effect.size = "pes")
get_anova_table(model3, correction = "GG")

#effect sizes paErrorial ets squared
# ANOVA Table (type II tests)
#
# Effect  DFn  DFd      F        p p<.05   pes
# 1     PractGroup 2.00 33.0  9.323 6.17e-04     * 0.361
# 2            key 1.32 43.4 38.610 1.54e-08     * 0.539
# 3 PractGroup:key 2.63 43.4  6.576 1.00e-03     * 0.285

model4 <- aov_ez("Subject", "Error", data_long, between = "PractGroup", within = "key")
anova(model4, na.rm = TRUE)



afex_plot(model4, "key", "PractGroup") +
  theme(text = element_text(size = 25),  # Adjust font size
        axis.text.x = element_text(size = 25),
        axis.line = element_line(color = "black")) +  # Adjust x-axis label font size
  scale_x_discrete(labels = c("1", "2", "3", "4", "5"))+
  ylab("Errors %")# Customize x-axis labels



em1 <- emmeans(model4, "PractGroup")
```

```
em1



pairs(em1)


#Ran RT
setwd("~/Desktop/THESIS/Data Analysis")
getwd()


#Load Data
TestBl_Rand_RT <- read_excel("Irvin TstBl6 RT-Random-RanDist.xlsx")


#Re-structure the data
TestBl_Rand_RT_Long <- TestBl_Rand_RT%>%
  pivot_longer(cols = c(Ran_RT1, Ran_RT2, Ran_RT3, Ran_RT4, RanDist_RT1, RanDist_RT2,
RanDist_RT3, RanDist_RT4),
               names_to = "Variable",
               values_to = "RT") %>%
  separate(Variable, c("Conditions", "Keys"), sep = "RT")


#Removing nas
TestBl_Rand_RT_Long <- drop_na(TestBl_Rand_RT_Long)


# Convert to factors
TestBl_Rand_RT_Long$Subject <- as.factor(TestBl_Rand_RT_Long$Subject)
TestBl_Rand_RT_Long$PractGroup <- factor(TestBl_Rand_RT_Long$PractGroup)
```

```
TestBl_Rand_RT_Long$Keys <- factor(TestBl_Rand_RT_Long$Keys)

TestBl_Rand_RT_Long$Conditions <- factor(TestBl_Rand_RT_Long$Conditions)


# Check the levels of each factor

str(TestBl_Rand_RT_Long)


levels(TestBl_Rand_RT_Long$PractGroup)

levels(TestBl_Rand_RT_Long$Keys)

levels(TestBl_Rand_RT_Long$Conditions)


# ANOVA (without GG correction)

model_test <- TestBl_Rand_RT_Long %>%

  lmer(RT ~ PractGroup + Keys + Conditions + (1|Subject), data = .)


anova(model_test)


#ANOVA (With GG correction)

model_test2 <- anova_test(data = TestBl_Rand_RT_Long, dv = RT, wid = Subject, between =

PractGroup, within = c("Keys", "Conditions"), effect.size = "pes")


get_anova_table(model_test2, correction = "GG")


##Results##

#Effect  DFn   DFd      F        p p<.05   pes

#               PractGroup 2.00 33.00  1.276 0.293000       0.072

#                     Keys 1.73 56.95 14.948 0.000016     * 0.312
```

```
#              Conditions 1.00 33.00  2.119 0.155000       0.060
#           PractGroup:Keys 3.45 56.95  1.490 0.223000       0.083
#     PractGroup:Conditions 2.00 33.00  0.737 0.486000       0.043
#           Keys:Conditions 2.14 70.67  4.055 0.019000     * 0.109
# PractGroup:Keys:Conditions 4.28 70.67  1.472 0.217000       0.082

# Compute estimated marginal means (EMMs) for each factor level or combination of levels
RT_emm <- emmeans(model_test, ~ PractGroup)

# Pairwise comparisons
pairwise <- pairs(RT_emm)

pairwise

##Results##
#contrast         estimate   SE df t.ratio p.value
#DifCom - MixInc     -7.48 19.9 33  -0.376  0.9254
#DifCom - SinStim   -30.53 19.9 33  -1.532  0.2891
#MixInc - SinStim   -23.05 19.9 33  -1.157  0.4868

#Results are averaged over the levels of: Keys, Conditions
#Degrees-of-freedom method: kenward-roger
#P value adjustment: tukey method for comparing a family of 3 estimates

#EMMS on Conditions
em2 <- emmeans(model_test, "Conditions")
```

```
em2

pairs(em2)
#contrast        estimate  SE  df t.ratio p.value
#Ran_ - RanDist_    -9.05 4.5 248  -2.012  0.0453

#Results are averaged over the levels of: PractGroup, Keys
#Degrees-of-freedom method: kenward-roger

em3 <- emmeans(model_test2, ~ PractGroup * Condition)
em3

#Visualisation
library(ggplot2)

#The mean RT
mean_RT <- TestBl_Rand_RT_Long %>%
  group_by(PractGroup, Conditions) %>%
  summarise(mean_RT = mean(RT))

#Afex
model_test4 <- aov_ez("Subject", "RT", TestBl_Rand_RT_Long, between = "PractGroup", within =
"Conditions")
anova(model4, na.rm = TRUE)

afex_plot(model_test4, "Conditions", "PractGroup") +
```

```
  theme(text = element_text(size = 25),  # Adjust font size
        axis.text.x = element_text(size = 20),
        axis.line = element_line(color = "black"))  # Adjust x-axis label font size


#Ran Error
setwd("~/Desktop/THESIS/Data Analysis/Selin's Data/Excel")
data <- read_excel("TstBI6 Error Random RandomDistractor Transformed.xlsx")



############################ TEST BLOCK 6 RANDOM AND RANDOM DISTRACTOR ERROR
TRANSFORMED ############################

#make data into long format
data_long <- data %>%
  pivot_longer(cols = c(Random1, Random2, Random3, Random4, RandomDistr1, RandomDistr2,
RandomDistr3, RandomDistr4), names_to = "Condition", values_to = "RT")

data_long <- data_long %>%
  mutate(key = case_when(
    Condition == "Random1" ~ 1,
    Condition == "Random2" ~ 2,
    Condition == "Random3" ~ 3,
    Condition == "Random4" ~ 4,
    Condition == "RandomDistr1" ~ 1,
    Condition == "RandomDistr2" ~ 2,
    Condition == "RandomDistr3" ~ 3,
```

```
    Condition == "RandomDistr4" ~ 4
  ))

data_long <- data_long %>%
  mutate(Condition = case_when(
    Condition == "Random1" ~ "Random",
    Condition == "Random2" ~ "Random",
    Condition == "Random3" ~ "Random",
    Condition == "Random4" ~ "Random",
    Condition == "RandomDistr1" ~ "RandomDistr",
    Condition == "RandomDistr2" ~ "RandomDistr",
    Condition == "RandomDistr3" ~ "RandomDistr",
    Condition == "RandomDistr4" ~ "RandomDistr"
  ))

#change variables into factor variables
data_long <- data_long %>%
  mutate(PractGroup = as.factor(PractGroup))
data_long <- data_long %>%
  mutate(key = as.factor(key))
data_long <- data_long %>%
  mutate(Condition = as.factor(Condition))
data_long <- data_long %>%
  mutate(Subject = as.factor(Subject))

############################## CHECKING NORMALITY ##############################
```

```
ggdensity(data_long$RT, fill = "lightgray", main = "Density Plot Response Times", xlab = "Response Times")

ggqqplot(data_long$RT, title = "Q + Q Plot for Response Times")

data_long %>% shapiro_test(RT)
# A tibble: 1 × 3
# variable statistic           p
# <chr>        <dbl>       <dbl>
#   1 RT           0.954 0.0000000695

data_long %>% group_by(PractGroup) %>% shapiro_test(RT)
# A tibble: 3 × 4
# PractGroup variable statistic           p
# <fct>      <chr>        <dbl>       <dbl>
#   1 DifCom     RT           0.940 0.000268
# 2 MixInc     RT           0.973 0.0454
# 3 SinStim    RT           0.891 0.000000846

data_long %>% group_by(key) %>% shapiro_test(RT)
# A tibble: 4 × 4
# key   variable statistic        p
# <fct> <chr>        <dbl>    <dbl>
#   1 1     RT           0.951 0.00676
# 2 2     RT           0.934 0.000928
# 3 3     RT           0.951 0.00717
```

```
# 4 4     RT          0.919 0.000186

data_long %>% group_by(Condition) %>% shapiro_test(RT)
# A tibble: 2 × 4
# Condition   variable statistic         p
# <fct>       <chr>        <dbl>     <dbl>
#   1 Random      RT           0.951 0.0000519
# 2 RandomDistr RT           0.951 0.0000537

############################ ANOVA MODEL ############################
model <- data_long %>%
  lmer(RT ~ PractGroup + key + Condition + (1|Subject), data = .)

anova(model)
# Type III Analysis of Variance Table with Satterthwaite's method
#             Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
# PractGroup 0.04395 0.02197     2    33  1.4197    0.2562
# key        2.24743 0.74914     3   248 48.4008 < 2.2e-16 ***
# Condition  0.46331 0.46331     1   248 29.9334 1.092e-07 ***
# ---
# Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

summary(model)

# effect size  practice group
F_to_eta2(1.4197, df=2, df_error = 33)
```

```
# η² (partial) |       95% CI
# ---------------------------
#   0.08         | [0.00, 1.00]

#effect size key
F_to_eta2(48.4008, df=3, df_error = 248)
# η² (partial) |       95% CI
# ---------------------------
#   0.37         | [0.29, 1.00]

#effect size condition
F_to_eta2(29.9334, df=1, df_error = 248)
# η² (partial) |       95% CI
# ---------------------------
#   0.11         | [0.05, 1.00]

############################ ANOVA WITH CORRECTION ############################

model2 <- anova_test(data = data_long, dv = RT, wid = Subject, between = PractGroup, within = c("key",
"Condition"), effect.size = "ges")
get_anova_table(model2, correction = "GG")

# ANOVA Table (type II tests)
#
# Effect  DFn   DFd      F        p p<.05      ges
# 1              PractGroup 2.00 33.00  1.420 2.56e-01       0.062000
```

```
# 2                   key 1.59 52.34 71.162 4.02e-14     * 0.134000
# 3             Condition 1.00 33.00  8.125 7.00e-03     * 0.031000
# 4         PractGroup:key 3.17 52.34  0.592 6.32e-01       0.003000
# 5    PractGroup:Condition 2.00 33.00  3.693 3.60e-02     * 0.028000
# 6          key:Condition 1.94 64.14  0.593 5.51e-01       0.000519
# 7 PractGroup:key:Condition 3.89 64.14  1.218 3.12e-01       0.002000
```

```
model3 <- anova_test(data = data_long, dv = RT, wid = Subject, between = PractGroup, within = c("key",
"Condition"), effect.size = "pes")
get_anova_table(model3, correction = "GG")
```

```
# ANOVA Table (type II tests)
#
# Effect  DFn   DFd      F        p p<.05   pes
# 1             PractGroup 2.00 33.00  1.420 2.56e-01       0.079
# 2                   key 1.59 52.34 71.162 4.02e-14     * 0.683
# 3             Condition 1.00 33.00  8.125 7.00e-03     * 0.198
# 4         PractGroup:key 3.17 52.34  0.592 6.32e-01       0.035
# 5    PractGroup:Condition 2.00 33.00  3.693 3.60e-02     * 0.183
# 6          key:Condition 1.94 64.14  0.593 5.51e-01       0.018
# 7 PractGroup:key:Condition 3.89 64.14  1.218 3.12e-01       0.069
```

```
model4 <- aov_ez("Subject", "RT", data_long, between = "PractGroup", within = c("key", "Condition"))
anova(model4, na.rm = TRUE)
```

```
# Anova Table (Type 3 tests)
```

```
#
# Response: RT
# num Df den Df     MSE       F      ges    Pr(>F)
# PractGroup              2.0000 33.000 0.33729  1.4197 0.062067  0.256172
# key                   1.5861 52.342 0.01991 71.1624 0.134420 4.022e-14 ***
#   PractGroup:key          3.1723 52.342 0.01991  0.5918 0.002576  0.632234
# Condition               1.0000 33.000 0.05702  8.1254 0.031021  0.007468 **
#   PractGroup:Condition    2.0000 33.000 0.05702  3.6931 0.028278  0.035698 *
#   key:Condition           1.9436 64.139 0.00651  0.5934 0.000519  0.550821
# PractGroup:key:Condition 3.8872 64.139 0.00651  1.2178 0.002126  0.312014
# ---
#   Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

afex_plot(model4, "PractGroup", "key") +
  theme_bw()

em1 <- emmeans(model4, "PractGroup")
em1

# PractGroup emmean     SE df lower.CL upper.CL
# DifCom      0.686 0.0593 33    0.565    0.806
# MixInc      0.640 0.0593 33    0.519    0.761
# SinStim     0.547 0.0593 33    0.426    0.668
#
# Results are averaged over the levels of: Condition, key
# Confidence level used: 0.95
```

```
pairs(em1)

# contrast         estimate     SE df t.ratio p.value
# DifCom - MixInc    0.0455 0.0838 33   0.543  0.8509
# DifCom - SinStim   0.1386 0.0838 33   1.653  0.2384
# MixInc - SinStim   0.0931 0.0838 33   1.110  0.5147
#
# Results are averaged over the levels of: Condition, key
# P value adjustment: tukey method for comparing a family of 3 estimates

em2 <- emmeans(model4, "Condition")
em2

# Condition   emmean     SE df lower.CL upper.CL
# Random       0.664 0.0393 33    0.584    0.744
# RandomDistr  0.584 0.0346 33    0.514    0.654
#
# Results are averaged over the levels of: PractGroup, key
# Confidence level used: 0.95

pairs(em2)

# contrast             estimate     SE df t.ratio p.value
# Random - RandomDistr   0.0802 0.0281 33   2.851  0.0075
#
```

```
# Results are averaged over the levels of: PractGroup, key

em3 <- emmeans(model4, ~ PractGroup * Condition)
em3

#PractGroup Condition   emmean     SE df lower.CL upper.CL
#DifCom     Random       0.764 0.0680 33    0.626    0.902
#MixInc     Random       0.628 0.0680 33    0.490    0.766
#SinStim    Random       0.601 0.0680 33    0.463    0.739
#DifCom     RandomDistr  0.607 0.0599 33    0.485    0.729
#MixInc     RandomDistr  0.652 0.0599 33    0.530    0.774
#SinStim    RandomDistr  0.493 0.0599 33    0.371    0.615

#Results are averaged over the levels of: key
#Confidence level used: 0.95
```