Diffusion model of flanker task:

Does the severity of lockdown measures affect cognitive ability?

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Case Studies in the Analyses of Experimental Data

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Abstract

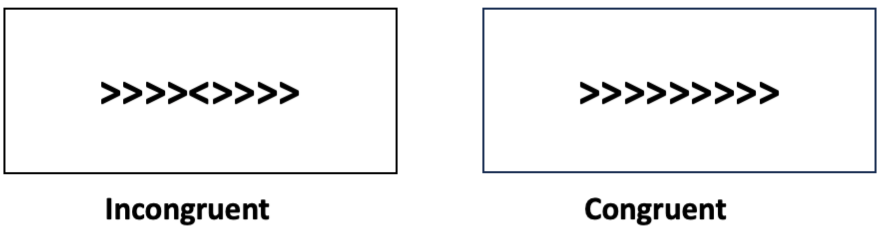
Conflict monitoring is a crucial process in our daily cognitive functions, enabling individuals to adapt their behavior to changing environmental demands. However, unforeseen circumstances such as COVID-19 can have an impact on conflict monitoring processes. Thus, this study specifically examines how COVID-19 guidelines, such as social isolation measures, may affect conflict monitoring. A group of participants from Japan, where guidelines were less strict, and a group of participants from Scotland, where guidelines were more stringent, were asked to perform a Flanker task. To gain a deeper understanding of the underlying mechanisms, a drift diffusion model (DDM) was employed, comparing various parameters between the Flanker task results of the Japanese and Scottish groups. The confirmatory results did not yield a significant effect of drift rate and non-decision time, although the average scores trended as expected (i.e., higher drift rate for Japan and higher non-decision time for Scotland). Exploratory results revealed that the noise was significantly higher for Scotland compared to Japan, and the decision boundary was significantly lower for Scotland compared to Japan. Interpretation of the findings should be approached cautiously, considering alternative explanations such as cultural differences and the direct effects of COVID-19, which are discussed. Further research on the specific restrictions imposed by COVID-19 is no longer viable since the WHO declares that COVID-19 was no longer a Public Health Emergency of International Concern, making future restrictions highly unlikely (WHO, n.d.). However, studying similar restrictions, such as social isolation measures, can provide valuable insights.

Introduction

Conflict monitoring is a cognitive process in which competing responses or stimuli are detected and resolved (Botvinick et al., 2001). This process is critical for the success of goal-directed behavior because it allows individuals to adapt their behavior in response to changing environmental demands (Botvinick et al., 2001). The flanker task (Figure 1), which involves the presentation of competing stimuli, is commonly used to study conflict monitoring (see Keye et al., 2009; Eben et al., 2019; D'Ippolito et al., 2023). More specifically researchers look at the reaction time and accuracy of the response to assess performance (see Stins et al., 2007; Davranche et al., 2009; Luks et al., 2010, Pe et al., 2013; Bulger et al., 2021). This is due to the fact that the participant must override the automatic response to the surrounding stimuli and select the correct response for the target stimulus. The incongruent stimuli can then cause interference which is observed as an increase in the reaction time (Stins et al., 2007). As a result, the amount of interference induced by incongruent stimuli is an indicator of the participant's capacity to monitor and resolve conflicting information (Stins et al., 2007; Bulger et al., 2021).

Figure 1

Congruent vs. incongruent trials



Note. This figure shows what congruent and incongruent trials of a Flanker task look like. In congruent trials, all the arrows point in the same direction. In the incongruent trials, the target arrow points in the opposite direction as the distractors.

Overall, conflict monitoring is advantageous as it allows individuals to adapt their behavior in response to changing environments (Botvinick et al., 2001). However, it's crucial to acknowledge that various factors can influence one's conflict monitoring abilities. For instance, situations like social isolation and limitations on personal freedom (Ingram et al., 2021) may have a negative impact on conflict monitoring skills. An illustrative example of this can be seen in the stringent restrictions imposed during the COVID-19 pandemic. The strict measures during the COVID-19 pandemic had a number of detrimental effects on cognition, more specifically on working memory, attention (Ingram et al., 2021), but also in particular cognitive flexibility (Prime et al., 2020) and conflict monitoring (O'Connor et al., 2022). Many people saw their cognitive flexibility reduced as a result of the pandemic and its accompanying guidelines (Prime et al;, 2020). This is because the stringent rules and restrictions decrease people's ability to adapt to new situations and develop creative solutions (Prime et al., 2020), which are crucial to cognitive flexibility. For example, individuals who were used to working in a specific environment struggled to adjust to new work-from-home arrangements due to this (Ipsen etal., 2021). In the case of conflict monitoring, many people also experienced a decrease in their abilities as a result of the strict pandemic guidelines (O'Connor et al., 2022). This was because the stringent norms resulted in fewer social encounters and conflict situations. Individuals became less competent at spotting and handling disputes as a result (O'Connor et al., 2022). Overall, the COVID-19 epidemic and its accompanying rules had a profound impact on how people think and behave (Prime et al., 2020; Ingram et al., 2021; O'Connor et al. 2022). While the lockdowns helped combat the pandemic and slow down contagion, some studies found it also led to a decrease in cognitive flexibility and conflict monitoring.

To gain a deeper understanding of the underlying mechanisms contributing to conflict monitoring in a flanker task, it is interesting to investigate the specific parameters associated with the drift diffusion model (White et al., 2011; Ong, Sewell et al., 2017). In cognitive psychology and decision-making research, the drift diffusion model is a popular computational framework (Ratcliff, 1978). It simulates the accumulation of data over time until a decision threshold is achieved, providing a mathematical description of the decision-making process (Pedersen et al., 2017). Decisions in this model are based on the integration of noisy evidence that is continuously acquired over time and directed towards one of the various response alternatives (Voss et al., 2013).

Voss (2004) describes the drift diffusion model and its parameters (i.e. drift rate, boundary separation, non-decision time, starting point and noise) as the following. The drift rate is the rate at which evidence accumulates in favor of one response option over another. It represents the quality of information processing and is impacted by factors such as stimulus salience and task difficulty. Some studies even suggest a low drift rate is indicative of cognitive dysfunction (Feldman & Huang-Pollock, 2021; Lazurdo et al., 2013). The boundary separation parameter represents the distance between the decision boundaries and defines the level of caution in decision-making. A larger boundary gap denotes a more conservative decision-making method, whereas a smaller separation indicates a more liberal or risk-taking attitude. The non-decision time parameter accounts for the time spent on non-decision processes such as stimulus encoding and response execution that are unrelated to the evidence accumulation process. This happens before making the decision. Studies have shown that this parameter increases as a result of isolation and resulting cognitive dysfunction (Ong, Sewell et al., 2017). The starting point refers to the location between the boundaries where evidence accumulation begins and can be used to express a bias in the response. Finally, the noise parameter describes the unpredictable fluctuations or uncertainty that might affect evidence accumulation over time.

Current study

The current interest lies in examining whether the severity of COVID-19 lockdown measures has an impact on cognitive ability, and more specifically conflict monitoring. To investigate this, we worked with an already existing data set (https://osf.io/qsbuk/) where two different groups were investigated. The first group was a Scottish sample which underwent stringent COVID-19 rules and regulations, while the second group, a Japanese sample, experienced a lockdown with rather flexible guidelines. The difference in cognitive ability between these two groups was measured using a series of tasks including a flanker task (Figure 1), which as already mentioned assesses conflict monitoring. It is expected that more strict COVID-19 rules will have a greater negative impact on cognitive ability, resulting in worse performance on the flanker task (Ingram et al. 2021).

Hypotheses

Research indicates that higher levels of conflict monitoring are associated with a higher drift rate and a shorter non-decision time (Feldman & Huang-Pollock, 2021; Ong, Sewell et al., 2017; Lazurdo et al., 2013). Moreover, previous studies have demonstrated that COVID-19 guidelines can have a detrimental effect on cognition (Ingram et al. 2021) and potentially impact conflict monitoring as well. Since Scotland has stricter COVID-19 guidelines compared to Japan (Ingram et al. 2021), we expect a slower drift rate and a longer non-decision time for the Scottish sample in comparison to the Japanese sample.

H1 The drift rate will be slower for Scottish participants compared to Japanese participants.

H2: The non-decision time will be longer for Scottish participants compared to Japanese participants.

Method

The sample of the data set contained 139 participants from Japan and 138 participants from Scotland. During data-cleaning of the files, we had one participant whose average RT was higher than the boundary we had determined (i.e. 3 seconds). This was due to a very high

RT in 11 of the trials, which we decided to exclude to be able to keep this participant's data. We calculated the power to ensure the sample was large enough to detect a small effect (Cohen's d = 0.20), and confirmed that our power was high enough ($\boldsymbol{\beta}$ = 0.90).

As mentioned before, in order to test our hypotheses we used the Drift Diffusion Model (DDM). This involves several parameters that can be estimated from experimental data, including the starting point, drift rate, boundary separation, and non-decision time. Before we built our model we needed to pre-process the data in order to be able to run it through our code. The initial data set contained two CSV files, one with the reaction times (RT) and another one with the accuracy (ACC) of all the trials for all the participants. However, we quickly ran into a problem with the data; it only included the participant number, the RT and the ACC. All other additional information regarding the trial was missing. This was especially problematic for two reasons. First, the length of the two files was different; the accuracy file was longer and without the trial numbers we could not correctly identify which trials were excluded from the RT file. Second, without the trial type information (i.e. congruent or incongruent) we could not calculate the parameters separately for each condition. We attempted to gain access to this additional information, however in the end this was impossible.

Given the situation, we decided to execute the analysis with the data as it was. In order to be able to use the data in our model we needed one file per participant which had the reaction time and accuracy for each trial. Therefore we merged the RT and ACC files together for each participant, if we had more values for ACC then the last extra values would be excluded. We could not guarantee that in the final file the RTs and the ACCs corresponded to the same trial, but this was the best solution available at the time if we wanted to move forward with the project. The files that resulted from this process are available on Github (https://github.com/SofiaDiazVil/CaseStudies/tree/main), as well as the scripts used for the analysis.

Once we had a dataset we could process, we could continue to develop the model. To create our DDM, we wrote our code using Python on Spyder. More specifically we used the PyDDM package (Shinn et al., 2020) which was specially developed to build a DDM. In order to build the code we worked in a series of steps which is why there are several versions of the code available on Github, a specific explanation of what each code is meant for can be found there as well. During the initial stage of the development of the model we built what we named the "Basic DDM", which is a model which calculates all of the standard parameters (i.e. drift rate, non-decision time, boundary separation and the noise) for all the data taken together. This means across both congruent and incongruent trials. Additionally, we did not estimate the starting point from the model and assumed it layed in the middle between the boundaries for all participants. This was due to the fact that we found no evidence in the literature for a possible bias in the flanker task, meaning that the starting point will be equally far from the upper and lower boundary. Across all versions of the model we used “Robust Likelihood” for the loss function which is a method available in the PYDDM package that can deal with trials that have a likelihood of zero. In other words this method is better at dealing with noisy trials and outliers. Additionally, we chose “Differential Evolution” as our optimization method. It is not only the suggested method by the package but also has been proven to be quite robust when dealing with a large number of parameters. Finally, for all the versions we set the same limits for the parameters. PYDDM requires a minimum and maximum value to be given for each fitted parameter; these values were decided based on the literature (Myers et al., 2022). After finishing the code we ran the data of each participant through the model to estimate their parameters and saved them in a CSV file that included all the parameters per participant as well as their participant number and the group they belonged to (i.e. country).

For the second stage we decided to develop a model that would calculate two drift rates and non-decision times per participant, one for each trial type (i.e. congruent and incongruent). However this code could not be tested since there was no available trial type information. This model was written in the case that additional data was acquired via the authors of the data set as well as an exercise to learn how to build a more complex DDM using the PYDDM package.

In the third stage we built a DDM which was very similar to the Basic DDM but with two additional parameters; the variance of the drift rate and the variance of the non-decision time. Even though none of our hypotheses directly involved these two parameters, when looking at the literature we realized most studies do calculate them.

In the end we only ran the “Basic DDM” since we did not have the information necessary for the “Congruency DDM” and the “Variance DDM” had a much higher computation time but did not provide data relevant to our hypotheses. We used a multivariate ANOVA to test our initial hypotheses, with drift rate and non-decision time as the dependent variables and group (i.e. what country the participant was in) as the independent variable. Additionally we decided to execute some exploratory analyses for the remaining parameters also using a multivariate ANOVA with the 4 parameters (i.e. drift rate, non-decision time, boundary and noise) as the dependent variables and group as the independent variable.

Finally, we tested the parameter retrieval since participants had a low number of trials, between 60 and 80 for most participants. We tested the retrieval for the “Basic DDM” with 60, 70, 80 and 200 trials to test whether it improved with a larger number of trials. To check retrieval we simply compared the original and retrieved parameters for 5 random files and calculated how much they differed on average per participant.

Results

Parameter Retrieval

We first wanted to evaluate how well our model performed. When there were 60 trials, the retrieved parameters varied between 0.05 and 0.5 from the original or "real" parameters. For 70 trials as well as for 80 trials, the retrieved parameters varied between 0.05 and 0.2 from the original parameters. Whereas for 200 trials, the retrieved parameters varied between 0.1 and 0.2 from the original parameters. The higher the amount of trials, the better the fit. However, the difference in retrieval was marginal between 60 and 80 trials (most participants had between 60 and 80 trials). Retrieval did not improve from 80 to 200 trials.

Confirmatory analysis

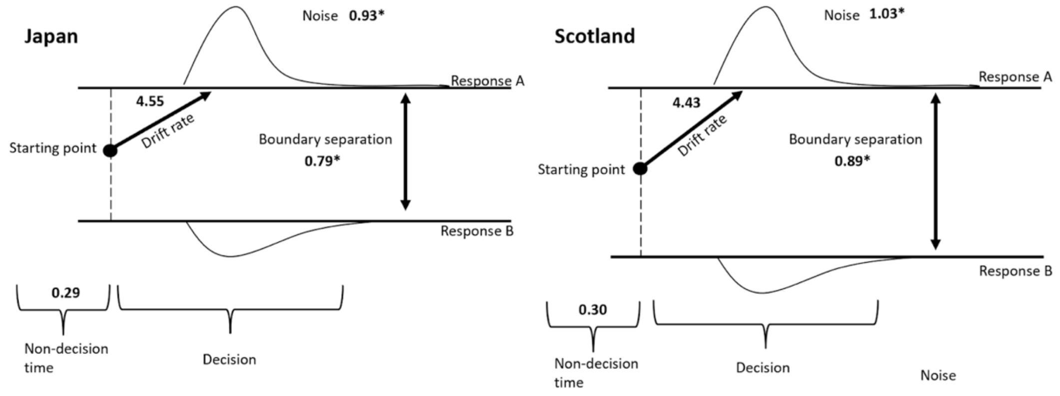
The average drift rate was higher for Japan ($M = 4.549$, $SD = 0.565$) compared to Scotland ($M = 4.431$, $SD = 0.535$), while the average non-decision time was higher/longer for Scotland ($M = 0.306$, $SD = 0.070$) than for Japan ($M = 0.294$, $SD = 0.058$) (see Appendix). However, the multivariate ANOVA showed that the model was not significant ($F =2.6$, $p = 0.077$), implying that neither of the parameters had a significant difference between the two samples (see Appendix for the specific p-values).

Exploratory analysis

Performing a multivariate ANOVA to test all the parameters of our DDM together revealed the model to be significant ($F = 4.5$, $p = 0.002$) implying other parameters were significant (see Figure 2). Looking more closely, there was a significant effect for the noise ($F = 5.727$, $p < 0.05$) as well as for the boundary parameter ($F = 4.981$, $p < 0.05$). The noise for the Scottish sample showed higher values ($M = 1.036$, $SD = 0.415$) in comparison to the Japanese sample ($M = 0.930$, $SD = 0.370$). Similarly, the Scottish sample had a larger decision boundary ($M = 0.886$, $SD = 0.390$) compared to the Japanese sample ($M = 0.785$, $SD = 0.345$). The drift rate and ($F = 3.564$, $p = 0.060$) and the non-decision time parameters ($F = 2.744$, $p = 0.099$) were non-significant.

Figure 2

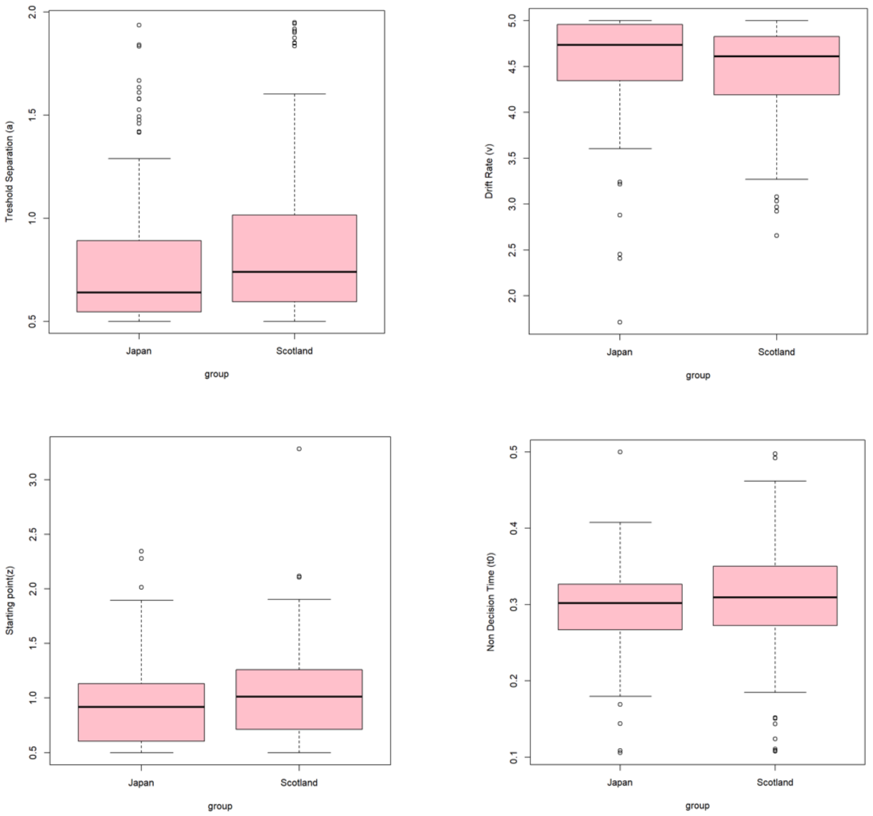
DDM (Drift Diffusion Model) of Japan compared to Scotland



Note. The figure shows a visual representation of the parameters for each group and how they affect the model.

Figure 3

Boxplots of the threshold separation, drift rate, starting point and non-decision time.



Note. The figure shows the distribution of each of the estimated parameters for each sample separately.

Discussion

The main goal of this study was to research if certain differences or similarities can be found between Scottish and Japanese participants when performing the Flanker task during the period of COVID-19; using a DDM for the analysis. Our first hypothesis regarding the drift rate revealed that for Japan this parameter had a higher value in comparison to Scotland, in line with our hypothesis. However, this difference was not significant. To continue, for the second hypothesis, which looked at the non-decision time, the descriptives showed lower values for Scotland compared to Japan, however the difference was not significant. For these results, it could be that the stricter COVID-19 guidelines in Scotland did not significantly impair the non-decision time of the participants which is also in agreement with the results found for the drift rate parameter. Participants got tested on the 21st of January, while in Scotland the second lockdown started the 5th of January (Ingram et al., 2021). When executing the Flanker task during the previous study by Ingram et al. (2021) only testing the Scottish sample across multiple time points, revealed an impairment from week 3 to week 5 and from week 5 to week 9. The fact that the lockdown had just recently resumed, may be the reason why the cognitive impairment is not visible yet. However, for both the drift rate and the non-decision time parameter we have to be careful drawing these conclusions, as these are both the parameters of the drift diffusion model which differentiate based on trial condition (i.e. congruence) (Ong, Abutalebi, et al., 2017; Ong, Sewell, et al., 2017). Unfortunately, the congruence of the trials was not available in the dataset used in this study.

An overall analysis of the model suggested the drift diffusion model for the Scottish sample to be significantly different in comparison to the model of the Japanese sample. When looking at each parameter separately, we found that the noise was significantly larger for Scotland in comparison to Japan. This would suggest that the Scottish sample had more fluctuations of uncertainty (Voss et al., 2004). Similarly, the boundary parameter was also significantly higher for Scotland. Regarding the literature, this would suggest the Scottish sample is more cautious and in need of more information that can be accumulated to make their final decision (Voss et al., 2004). Combining both of these parameters and what they measure, it seems as if the Scottish sample in general seems to have more doubts when making their decision. However, no pre-restriction data is available so it remains unclear if this is a result of the COVID-19 limitations or a more universal trait.

An alternative explanation of our results may be due to cultural differences, such as individualism and collectivism, which also play a role in shaping conflict monitoring. In collectivist countries, such as Japan, there is typically a greater emphasis on maintaining social harmony (Ting-Toomey et al., 1991; Trubisky et al., 1991), which may result in individuals being more attuned to their environment and displaying stronger skills in conflict monitoring. This could possibly explain why the drift diffusion models for both countries were significantly different. On the other hand, individualistic countries like Scotland tend to prioritize independence and self-expression (Ting-Toomey et al., 1991; Trubisky et al., 1991). Consequently, individuals in these cultures may be less proficient in conflict monitoring, as it may be given less importance according to their cultural norms. Therefore, the effects observed might also be influenced by cultural norms. If so, we cannot fully attribute our findings as a result of COVID-19 restrictions. Further research is needed that can make these contributions more clear.

The current study presents a few important limitations. To begin, the amount of trials for each participant could be considered rather low, as a sufficient number of trials is necessary to make better estimations (Voss et al., 2013). Additionally, we need to be cautious when interpreting the parameters given that the retrieval test revealed a large variance between the 'real' and the estimated parameters. During the Flanker task, congruent and incongruent trials are presented. However, in this dataset the condition of the trials (i.e. congruence) was not included which made a comparison impossible. Previous research has shown drift rate and non-decision time behave differently for congruent and incongruent trials (Ong, Abutalebi, et al., 2017; Ong, Sewell, et al., 2017; White et al., 2011). This means that the missing conditions could also have impaired the fit of the parameters which would also explain the problems with parameter retrieval. Finally, there was no possibility to control for COVID-19 infections, as during the study of Ingram et al. (2021) these questions were omitted for the Japanese sample due to cultural sensitivities.

After conducting this study, some interesting ideas rose for possible future research. Due to the limitations, having a larger dataset with more trials per participant and also including the congruency will possibly result in a more reliable model fit. It might be interesting to execute a similar study now that the stricter COVID-19 guidelines could be considered as removed in order to compare both periods of time. As COVID-19 restrictions are mostly in the past (WHO, n.d.), it could be conceivable to locate individuals in socially isolating situations and conduct similar comparisons in a larger cross-cultural study using the drift diffusion model.

Conclusion

In conclusion, we did not find a significant difference between the Scottish and Japanese sample when looking at their drift rate and non-decision time. However, exploratory analyses revealed that the Scottish sample had a larger noise and boundary separation. These results point towards the Scottish sample having more doubts when coming to a final decision in comparison to the Japanese sample. However, it is not possible to claim with absolute certainty that this is a result of COVID-19 restrictions given the lack of pre-restriction data and control for COVID-19 infections. Future research is encouraged to further understand the current findings.

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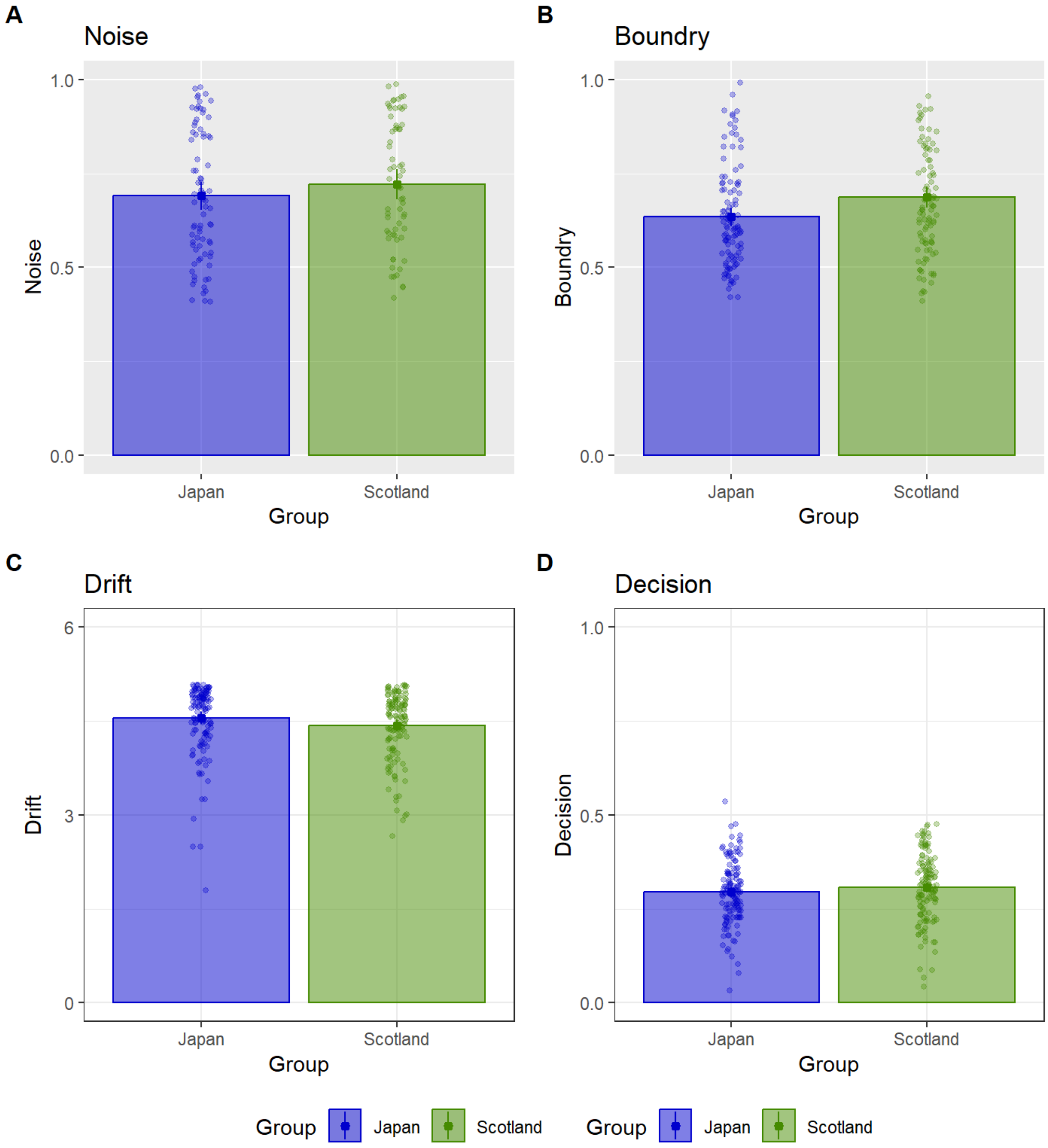
Appendix

Figure 1
Distribution of the parameters



Note. This is an illustration of the distribution of the parameters estimates divided between Japan and Scotland..

Table 1

Descriptives of the model parameters

	Japan		Scotland	
Parameters	Mean	SD	Mean	SD
Drift rate	4.549	0.565	4.431	0.535
Noise	0.930	0.370	1.036	0.415
Non-decision time	0.294	0.058	0.306	0.070
Boundary	0.785	0.345	0.886	0.390

Note. The means and standard deviations for all four parameters separated for each group.

Table 2

Results of confirmatory analyses

	Sum Sq	Df	F-value	Pr (>F)
Drift rate	0.938	1	3.092	0.079
Non-decision time	0.008	1	2.132	0.145

Note. This table showed the results of the confirmatory MANOVA for the drift rate and non-decision time separately. For both parameters the summed squares, degrees of freedom, F-values and p-values are given.

Table 3

Results of exploratory analysis

	Sum Sq	Df	F-value	Pr (>F)
Drift rate	1.082	1	3.563	0.060
Non-decision time	0.011	1	2.743	0.098
Noise	0.877	1	5.726	0.017 *
Boundary	0.677	1	4.981	0.026 *

Note. This table showed the results of the exploratory MANOVA. For all parameters the summed squares, degrees of freedom, F-values and p-values are given. * < 0.05