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**Estimating Reliability of Self-Prioritization Effect as measured by the Self-Associative Learning Task: Evidence from Multiple Dataset**

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# **Abstract**

The self-prioritization effect (SPE) refers to the effect that performance is better when stimuli are related to the self than when they are not in cognitive tasks. The social-associative learning task (SALT) emerged as a mainstream paradigm to study SPE in the last decade for its simplicity and elimination of familiarity effects. As a simple button-pressing task, SALT yields two direct outcomes: reaction time and accuracy. Indirect indices can be derived from reaction times and accuracy, including sensitivity *d* prime under signal-detection theory, the efficiency index through a direct division between reaction times and accuracy, and drift rate (v) and starting point (z) estimated using drift-diffusion models. All these direct and indirect indices have been used to quantify SPE in the literature. However, the reliability of these SPE indices has never been tested. To fill this gap, we will re-analyze existing data from multiple datasets using intraclass correlation coefficient (ICC) and split-half reliability. Our results will provide a benchmark for future studies.

# **Introduction**

The Self-Prioritization Effect (SPE) refers to the phenomenon that is better when stimuli are related to the self than when they are not performance in cognitive tasks. This effect has been established as a robust finding since the 1950s. In the early days of cognitive psychology, researchers found that subjects could recognize their own names that mixed with noisy auditory background, even when the self-name is not the target of the task in dichotic listening tasks (Cherry, 1953; Moray, 1959). SPE effect was then reported in memory research by Craik and Tulving (1975), who reported that more words weree recaaled when participants related them to the self than when participant process these words in other levels (e.g., semantic). This SPE effect in memory was then replicated in by many other (Conway & Dewhurst, 1995; Rogers et al., 1977; Symons & Johnson, 1997). In the following decades, the SPE has also been found when different stimuli was used, such own face (Keenan et al., 2000; Kircher et al., 2000; Turk et al., 2002), own voice (Hughes & Harrison, 2013; Payne et al., 2021), own name (Constable, Rajsic, et al., 2019), and newly owned object (Strachan et al., 2020). SPE was found across a variety of cognitive tasks, such as perceptual decision-making task (), attentional task (), and social judgment (Cunningham & Turk, 2017; Desebrock et al., 2018; Sui & Humphreys, 2013).

Although SPE is often argued to be a self-specific effect, it can be challenging to disassociate it from the familiarity effect since most studies use stimuli owned by participants or by others. In 2012, Sui et al proposed a paradigm where participants first associate geometrical shapes (e.g., triangle, square, and circle) with labels of persons (e.g., "You," "friend," and "stranger") and then perform a perceptual matching task in which they decide if the shape-label pairs presented on the screen match the learned association or not (Sui et al., 2012). Because the task requires participants to learn the social meaning of different geomatric shapes, it is called social associative learning task (SALT). In this task, Sui et al (2012) found that shapes associated with the self are performed better, with faster response times, better accuracy, and/or higher sensitivity scores as compared to shapes associated with friends and strangers. Because the self-relatedness is immediately acquired right before they start the perceptual matching task, this paradigm eliminated the effect of familiarity of the simuli.

Since then, the SALT has become the mainstream method for investigating the mechanisms underlying the SPE. For instance, researchers have explored the importance of personality traits in identity labels (Golubickis et al., 2020), the self-relevant labels that include the past, present, and future self (Golubickis et al., 2017), as well as "good self" and "bad self" labels (Hu et al., 2020), and the group advantage effect of in-group labels (Constable, Elekes, et al., 2019; Constable & Knoblich, 2020; Enock et al., 2018; Enock et al., 2020). Moreover, the SALT has been applied to various fields. In neuroscience and physiology, researchers investigate which brain regions are activated during self-prioritization effect (Feng et al., 2018; Humphreys & Sui, 2015), and gender differences in self-prioritization effect due to oxytocin (Feng et al., 2020). In clinical research, SALT has been used to understand atypical self-processing in populations such as those with autism or depression (Gillespie‐Smith et al., 2018; Nijhof & Bird, 2019; Sui & Humphreys, 2017). Cross-cultural studies have shown that individuals from individualistic cultures demonstrate a stronger self-prioritization effect (Jiang et al., 2019), and that the language of the experimental stimuli can affect the strength of the effect (Ivaz et al., 2016). Finally, SALT has also been applied to child development, with studies examining developmental changes in self-positivity effects (Maire et al., 2020; Zhou et al., 2019).

Despite the popularity of using SALT, little attention has been paid to the exact indices of SPE and their reliability, which need to be examined carefully (Parsons et al., 2019). This issue is especially important because SALT is increasingly being used to measure individual differences in psychiatry (Liu et al., 2022) , and social psychology (Enock et al., 2018). To address this gap, we plan to examine the reliability of SPE indices in SALT by reanalyzing data from multiple sources (see Table 1 for the details of the data sources).

To comprehensively assess the SPE indices from SALT, we have included six indices of SPE. All of these SPE indices are defined as the difference between self and other, while using different outcomes of the matching trials of SALT. Specifically, these indices include two direct indices based on SALT, reaction times and accuracy, as well as derived indices such as efficiency (Humphreys & Sui, 2015; Stoeber & Eysenck, 2008), *d* prime of SDT (Sui et a., 2012: Hu et al., 2020), and drift rate (*v*) and starting point (*z*) from DDM (Golubickis et al., 2017).

Given that there are multiple methods for calculating reliability of cognitive tasks, we will calculate Split-Half Reliability (SHR) and Intraclass Correlation Coefficient (ICC) for each of the SPE indices mentioned above.

Our main hypothesis are as follows:

1. The Self-Prioritization Effect (SPE) measured by the experimental indices in the Self-Associative Learning Task (SALT) paradigm is temporally stable
2. Among the multiple indices that measure Self-Prioritization Effect (SPE) in the Self-Associative Learning Task (SALT), there exists a most stable indicator

The results of this study will provide valuable insights into the reliability and consistency of the Self-Associative Learning Task (SALT), which could pave the way for its future use in research, clinical settings, and personal performance monitoring.

# **Methods**

## Ethics information

Our research involves a secondary analysis of pre-existing data obtained from publicly available datasets from studies that have used SALT in recent years. Therefore, informed consent and confidentiality are not applicable. Our data were obtained from publicly available datasets from studies that have used SALT in recent years or archived data from our group.

## Secondary Data Description

The data from our group were collected We also extracted the raw data from empirical studies that employed SALT. The articles are screen from an on-going meta-analysis (see protocol: ). All these articles shared their raw data publicly (Golubickis & Macrae, 2021; Qian et al., 2020; Schäfer & Frings, 2019; Svensson et al., 2022) and did not deviate from the original experimental paradigm.

Table 1. The computability of SPE index and the reliability test to be carried out

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Paper | Study | Self-Prioritization Effect Indices | | | | | | Reliability | |
| RT | ACC | *d* prime | Efficiency | *v* | *z* | ICC | SHR |
| Hu  (2016) | 1 | √ | √ | √ | √ | √ | √ | √ | √ |
| Qian et al. (2020) | 1 | √ | √ | √ | √ | √ | √ | √ | √ |
| Schäfer and Frings (2019) | 1 | √ | √ | √ | √ | √ | √ |  | √ |
| Golubickis and Macrae (2021) | 1 | √ | √ | √ | √ | √ | √ |  | √ |
| 2 | √ | √ | √ | √ | √ | √ |  | √ |
| Svensson et al. (2022) | 1 | √ | √ | √ | √ | √ | √ |  | √ |
| 2 | √ | √ | √ | √ | √ | √ |  | √ |
| 3 | √ | √ | √ | √ | √ | √ |  | √ |

## Experimental design

The origin experiment is a two-factor design (Sui et al., 2012), with 2 levels of match vs. non-match and 3 levels of identity (self, friend and stranger). As our study aims to explore the reliability of Self-Prioritization Effect (SPE) in Self-Associative Learning Task (SALT) and identify the most stable SPE index, the experimental design of all included dataset did not signficantly deviate from the original task.

## Stimuli materials and Procedure

The experiment was conducted individually in a dimly lit room, using E-Prime 2.0 software on a PC with a 1024 x 768 resolution monitor, refreshing at 100 Hz. Participants recorded their keypresses, reaction time, and accuracy during each trial.

The experiment was divided into two phases following the method of Sui et al. (2012). In the first phase (learning phase), participants completed a learning task where they associated three geometric shapes (circle, triangle and square) with three labels (self, friend, and stranger) for approximately 60 seconds. The shape-label associations were balanced across participants. In the second phase (formal experimental phase), participants completed a matching task. Each trial started with a fixation cross displayed in the center of the screen for 500 ms, followed by a shape-label pairing and fixation cross for 100 ms. the screen then went blank for 1500 ms, or until a response was made. Participants were required to judge whether the presented shape and label matched the learned associations from the learning phase and respond as quickly and accurately as possible by pressing one of two buttons within the allotted timeframe.

Prior to the formal experimental phase, participants completed a training session consisting of 24 practice trials. After the training, participants completed six blocks of 60 trials in the matching task, with two match types (match/mismatch) and three shape associations, for a total of 60 trials per association. Short breaks lasting up to 60 seconds were provided after each block.



**Figure 1.** Experimental procedure of the SALT in dataset 1 (Hu et al., 2023)

## Pilot data simulated data

To avoid any potential biases in hypothesis formation, we didn't conduct any statistical analysis on the real data during stage 1 registration. Instead, we generated a faked dataset with the same format as the primary data. We used an open dataset from a previous study examining the self-prioritization effect as a reference to create our pilot data.

We utilized Bootstrap methods, drawing samples from Hu et al. (2020) open dataset (accessible at <https://osf.io/mhdsn/>) with replacement (allowing the same sample to be repeated in the pilot data). The pilot data includes 6 sessions of data from 34 participants, with each participant having 24 practice trials and 360 experimental trials (6 different types of shape-label associations: two matches (matched/mismatched) x three identity associations (self, friend, stranger), 60 trials per association) per session. Figure 1 shows the first 6 rows of the pilot data.

Table

Description automatically generated

**Figure 2.** The first six rows of the pilot data

In the publicly available data from the 5 studies we collected, not all studies had repeated measures like our simulated data. If a publicly available data did not have repeated SALT measurements within a certain time interval, we would not calculate its ICC, but only calculate split-half reliability.

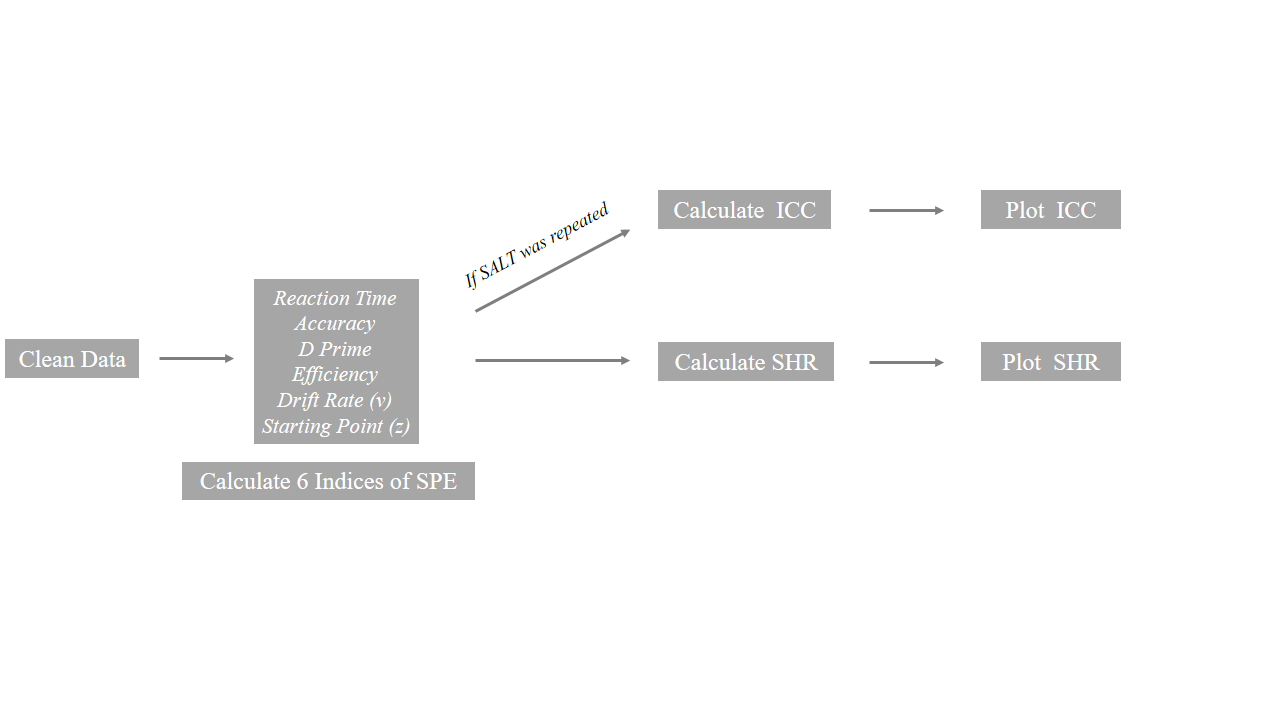
We ran the pilot data through our proposed statistical analysis to see whether our proposed analysis is appropriate for the secondary data structure (see analysis plan).

## Analysis Plan

All analyzes will be performed in R 4.2.2 (R Core Team, 2022).

First, we will clean the 11 publicly available datasets that we collected to obtain data in a form similar to the pilot data mentioned earlier. Then, we will calculate six indices that represent SALT for each dataset, namely reaction time, accuracy, *d* prime, efficiency, drift rate (*v*), and starting point (*z*). Reaction time and accuracy can be obtained directly from the datasets, while *d* prime and efficiency will be calculated based on reaction time and accuracy using a simple formula (see Table 2). The calculation of drift rate (*v*) and starting point (*z*) will be based on the drift-diffusion model, with drift rate (*v*) indicating faster evidence accumulation and the starting point (*z*) reflecting a bias in the beginning of information accumulation (Golubickis et al., 2017; Macrae et al., 2017; Yankouskaya et al., 2020). Specifically, we will use the "fit\_ezddm" function in the "hausekeep" package in R to obtain these two indices. However, these 11 publicly available datasets do not all adhere strictly to the original experimental design of SALT. For example, some experiments did not use the Friend label or the Stranger label. Therefore, we will make some adjustments when calculating the SPE.

We will only calculate the Split-Half Reliability (SHR) for this dataset. Specifically, we will use four methods for calculating split-half reliability, namely first-second, odd-even, permutation and Monte Carlo split-half. And we will present the results of Monte Carlo split-half in the main text, while the results of other split-half reliability methods will be presented in the supplementary materials. As there is no R package that can directly calculate split-half reliability as we require, we will write our codes for this purpose. In addition, if the data was obtained by conducting multiple SALT experiments at a certain time interval, we will calculate the Intraclass Correlation Coefficient (ICC) for these SPE values to evaluate the test-retest reliability of these six indices. Specifically, we will use the "psych" package to calculate ICC for these indices (William Revelle, 2022).



**Figure 3.** Analysis Flow Chart

### Data pre-processing

First, we will pre-process the secondary data using the following criteria (we do not pre-process the secondary data at stage 1 registration):

1. Participant exclusion criteria
2. Participant who has the wrong trial numbers because of procedure errors should be excluded from the analysis.
3. Participants with an overall accuracy < 0.5 should be excluded from the analysis.
4. Participants with any of the conditions with zero accuracy should be excluded from the analysis.
5. Behavioural data exclusion criteria
6. Trials with no response or wrong key press should be excluded from the analysis.
7. Trials with responses less than 200 ms or faster than 1500 ms should be excluded from the analysis.
8. The practice trials will be excluded from the formal analysis.
9. The data under conditions other than the “control condition” will not be used in the current study.
10. Organize data structures
11. Standardize the labels in the variable 'Match' to 'Match' and 'Mismatch’
12. Standardize the labels in the variable 'Identity' to 'Self', ‘Friend’ and 'Stranger’
13. Convert the unit of reaction time from milliseconds to seconds or from seconds to milliseconds, and name them as RT\_ms and RT\_sec respectively, while keeping both variables.
14. Arrange the variables in the order of Subject, Session (if applicable), Match, Identity, RT\_ms, RT\_sec, and ACC.
15. TBC(maybe)

### Calculation of indices & quantifying SPE in the SALT

Second, we will calculate six indices based on the cleaned SALT data, which will represent the SPE in the SALT. Table 2 provides details on the calculation of these metrics and how they contribute to the determination of the SPE.

Table 2. Indices in SALT and corresponding calculation of indices and SPE

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Indices** | **Indices Calculation** | **SPE Calculation Based on Indices** | | **Source** |
| Mean  Reaction Times  (RT) |  | Type 1 calculation |  | Sui et al. (2012) |
| Type 2 calculation |  |
| Accuracy (ACC) |  |  | | Sui et al. (2012) |
| *D* prime |  |  | | Sui et al. (2012) |
| Efficiency |  |  | | Humphreys and Sui (2015); Stoeber and Eysenck (2008) |
| Drift rate  (*v*) | DDM：parameters will be identified through model selection |  | | Golubickis et al. (2017) |
| Starting Point  (*z*) |  | | Golubickis et al. (2017) |

*Note.* DDM =Drift Diffusion Model.

We'll present the average and standard deviation for each index for each session, along with other important descriptive statistics.

### Split-half reliability of SPE in SALT

Third, we will calculate the split-half reliability of the six indices. In psychological research, Cronbach's alpha is often used to determine the reliability of experiments. However, using this method in cognitive experiments can lead to biased results. As a result, more and more studies are using split-half reliability instead of Cronbach's alpha to assess the reliability of cognitive experiments. This is because Cronbach's alpha is calculated based on different experimental conditions, while split-half reliability is calculated based on trial sequences. (Kahveci et al., 2022)

There are four types of split-half reliability: odd-even, front-back, permutation, and Monte Carlo. The odd-even split separates trials into odd and even numbered sequences, while the front-back split separates the first and second halves of trials. The permutation split shuffles the trial order and randomly assigns each half to a group. Monte Carlo split-half is similar to the permutation split-half, repeating the process thousands of times to calculate the average and 95% confidence interval of the split-half reliability. This study will primarily use Monte Carlo split-half to determine the split-half reliability of SALT.

First, the data will be stratified according to Session (if it has), Match, and Identity. If not stratified, directly splitting the data in half will result in uneven distribution of trials for each experimental condition in the two halves, thereby overestimating or underestimating the reliability of the split. Therefore, after the data is stratified, we split the data. For example, when using Monte Carlo Split-Half, we randomly split the data into two half. Then we repeat this operation 1000 times. This will result in 1000 pairs of two halves of the data. Next, we use these 1000 pairs of data to calculate 1000 Pearson correlation coefficients, and then obtain the average and 95% confidence interval of the Monte Carlo split reliability. As for first-second split, odd-even split, and permutated split, they are similar to Monte Carlo division, but they only perform one split, so only one split-half reliability is obtained without interval estimate of the split-half reliability.

### Test-Retest Reliability (ICC) of SPE in SALT

Finally, if the data was obtained by conducting multiple SALT experiments at a certain time interval, we'll assess the test-retest reliability of the six SPE indices using the Intraclass Correlation Coefficient (ICC). ICC is a well-established measure of reliability in test-retest, intra-rater, and inter-rater studies(Fisher, 1992). Compared to Pearson correlation coefficient, ICC considers both the degree of correlation and agreement between multiple measurements, making it a more comprehensive measure of test-retest reliability(Koo & Li, 2016).

ICC2 measures the proportion of the total variance that is due to between-subject variance. For the calculation of ICC2 estimates and their 95% confidence intervals, the formula is:

*Note.* MSR = mean square for rows; MSE = mean square for error; MSC = mean square for columns; n = number of subjects;

ICC2k measures the proportion of the total variance that is due to within-subject variance. For the calculation of ICC2k estimates and their 95% confidence intervals, the formula is:

*Note.* MSR = mean square for rows; MSE = mean square for error; MSC = mean square for columns; n = number of subjects; k = number of raters/measurements.

A value less than 0.6 means poor reliability, a value between 0.6 and 0.8 indicates substantial reliability, and a value greater than 0.8 means excellent reliability (Cicchetti & Sparrow, 1981; Kupper & Hafner, 1989). We hope that the ICC2 is as large as possible and the ICC2k is as small as possible, indicating that SALT is stable across time and the differences in our experimental measures are mainly due to individual differences between subjects rather than the passage of time.

# **Data availability**

We will adhere to the following open science practices: open materials, open data. We will share the raw data, excluding sensitive participants’ information on acceptance of our Stage 2 manuscript. The simulated data is accessible on the Open Science Framework () and GitHub ().

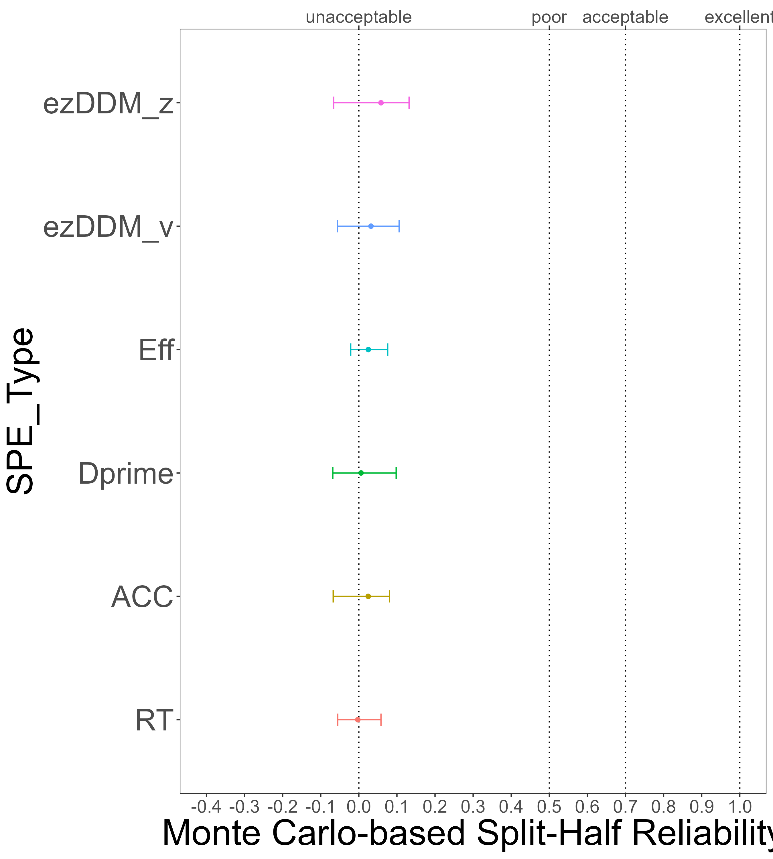
# **Code availability**

Code used to simulate and analyze the pilot data is made accessible in the same location: Open Science Framework () and GitHub ().

# **Results**

## Split-Half Reliability (SHR)

First, we stratified the data based on three variables: Session (if it has), Match, and Identity, and then split the stratified data into two halves using four methods. Next, we calculated the SPE for each of the six indices for each half of the data. Finally, we calculated the split-half reliability for each of the six SPEs. As shown in Figure 5, when using the Monte Carlo split-half, the split-half reliability of the six indices obtained is very high, with the highest value of XXX, which means that it is the most stable of the six SPE indexing calculations for half-confidence. The results from the other three split-half methods were similar to the Monte Carlo method, which will be presented in the supplementary material.

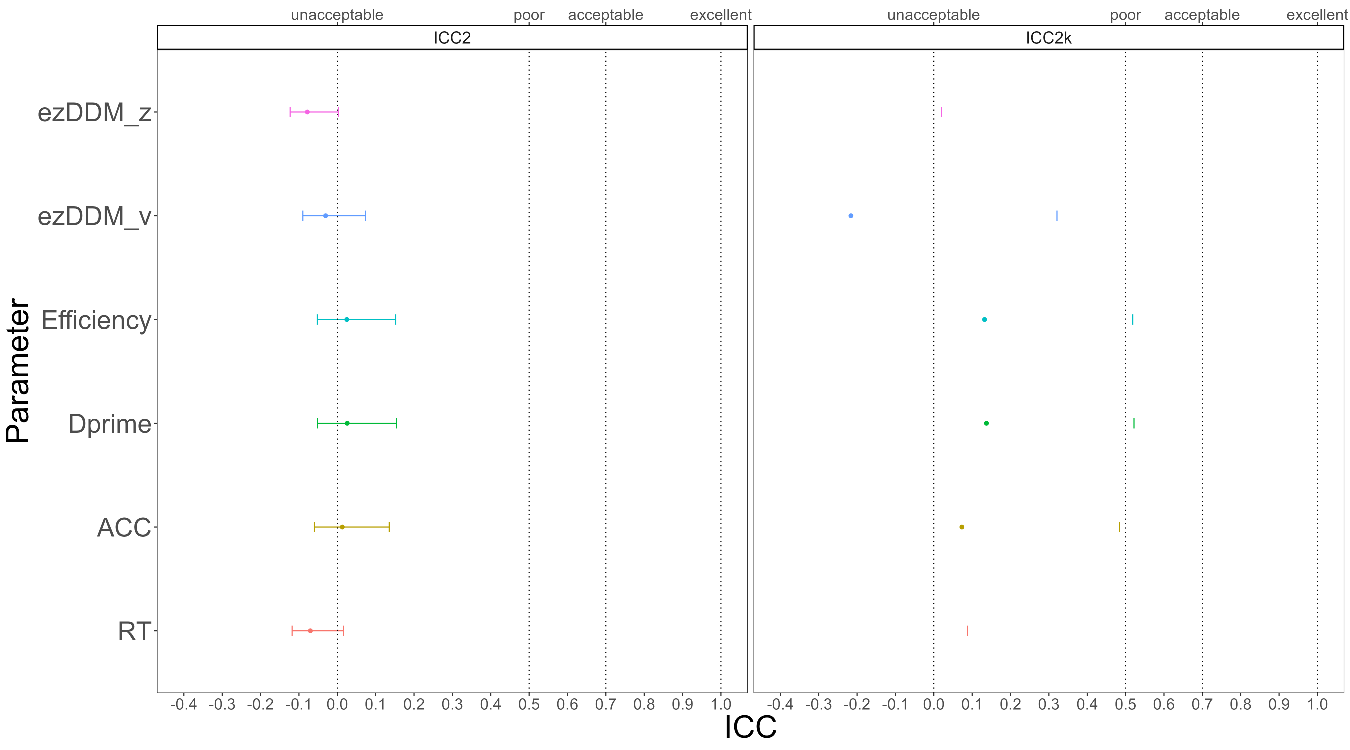


**Figure 5.** Monte Carlo-based Split-Half Reliability

## Intraclass correlation coefficient (ICC)

Intraclass correlation coefficient (ICC) is a measure of the consistency or reliability of measurements made by different raters (observers) or repeated measurements made by the same rater (observer). We will calculate ICC only if the study involves repeated measurements of SALT. In essence, it tells us how much of the variation in the data can be attributed to differences between raters or repeated measurements, and how much of it can be attributed to differences within the subjects being measured. In simple terms, it gives an idea of the proportion of total variation in the data that is due to the true differences between subjects, versus due to measurement error or random fluctuations.

The present study aimed to investigate the stability of six indices, including reaction time (RT), accuracy (ACC), *d* prime, Efficiency, drift rate (*v*) and starting point (*z*) in the diffusion decision model (DDM), across six time sessions. We use the Intraclass Correlation Coefficients (ICC) to evaluate how much of the variation in SALT can be attributed to within-subject repeatability over time, and how much can be attributed to between-subject differences. Among them, we are most interested in ICC2 and ICC2k, where ICC2 represents the ratio of between-subject variance to total variance, and ICC2k represents the ratio of within-subject variance to total variance. Therefore, we want ICC2 to be as large as possible and ICC2k to be as small as possible, indicating that the differences in our experimental measures are mainly due to between-subject individual differences, and each subject's performance is relatively stable across the six sessions. As shown in Figure 4, the ICC2 values of the six indices are relatively large and ICC2k values are relatively small, supporting our hypothesis.



**Figure 4.** ICC2 and ICC2k

# **Discussion**

Do **not** include a **Discussion** section.

# **Acknowledgements**

The present research is support by xxx.

# **Author contributions**

HCP contributed to the conception and supervision of the study and will provide the methodology expertise. JS contributed to fund raising, HCP contributed to data collection. ZL and ZYR will perform the data pre-processing, analysis and visualize the results. In addition, ZL, JS and HCP will contribute to discussing the results and the drafting of the final manuscript. All authors will critically revise the manuscript.

# **Competing interests**

The authors declare no competing interests.

# **Figures**

You are encouraged to include Figures in the text or at the end of the protocol. Keep in mind that a total of 8 display elements (i.e., combination of Tables and Figures) is permitted in the final, Stage 2, submission. However, to enable typesetting of papers, we advise making the number of display items commensurate with your overall word length (that is, for a shorter paper the number of display items should be lower, for a longer manuscript a higher number may be allowed). Figures/Tables that are not essential should be included in your Supplementary Information file.

# **Figure Legends**

**Figure 1. Guidelines for the preparation of figure captions.** Figure captions should be concise. Begin with a brief title and then describe what is presented in the figure and detail all relevant statistical information. If you show pilot data, list the N of each plot and report full statistics. Aim not to exceed 350 words per legend.

# **Supplementary information**

Please report pilot data in detail here and include any other material that provides background information.

Supplementary Table 1 Split-Half Reliability of Other Split Method

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Indices of SPE | Method of SH | SHR |  | Indices of SPE | Method of SH | SHR |
| RT | First-Second | .01 |  | Efficiency | First-Second | .07 |
| RT | Odd-Even | -.05 |  | Efficiency | Odd-Even | -.04 |
| RT | Permuted | .01 |  | Efficiency | Permuted | .05 |
| ACC | First-Second | .02 |  | DDM: v | First-Second | .04 |
| ACC | Odd-Even | -.05 |  | DDM: v | Odd-Even | -.05 |
| ACC | Permuted | .07 |  | DDM: v | Permuted | .10 |
| Dprime | First-Second | .01 |  | DDM: z | First-Second | .07 |
| Dprime | Odd-Even | -.08 |  | DDM: z | Odd-Even | .01 |
| Dprime | Permuted | -.02 |  | DDM: z | Permuted | .13 |

*Note.* SH = split-half, SHR = split-half reliability, SPE = self-prioritization effect

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