**Reliability Assessment of Self-Prioritization Effect as Measured by the Perceptual Matching Task**

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***Abstract:***

The self-prioritization effect (SPE) refers to the phenomenon where individuals demonstrate faster and more accurate responses to self-relevant stimuli in cognitive tasks. The self-perceptual matching task (SPMT) has emerged as a mainstream paradigm for studying the cognitive mechanisms underlying the SPE. Additionally, the SPE measured by the SPMT has been utilized as an indicator of individual differences in research, including clinical studies. As a simple button-pressing task, SPMT eliminates familiarity effects and yields two outcome variables for quantifying SPE: reaction time (RT) and accuracy (ACC). Existing literature has also reported four additional outcome variables derived from reaction times and accuracy, including sensitivity *d’* under signal-detection theory, the efficiency (*η*), drift rate (*v*) and starting point (*z*) estimated using the drift-diffusion models. Moreover, the calculation of SPE can employ different baseline conditions, including “Close other”, “Stranger”, “Celebrity”, and “Non-person”. However, the reliability of SPE measures computed using different outcome variables under various baseline conditions has not been systematically examined, leaving the stability of using the SPMT for measuring individual differences unknown. To fill the gap, we conducted a pre-registered study wherein we re-analyzed eighteen datasets from nine papers and two projects (N = 857) using split-half reliability and intraclass correlation coefficient (ICC). The results revealed that the split-half reliabilities, weighted across multiple datasets, of RT (*r* Close = 0.58; *r*Stranger = 0.60) and Efficiency (rClose = 0.52; rStranger = 0.58), using close others and strangers as the baseline conditions, are relatively high but still lower than that required in psychometrics. The estimated split-half reliability for all other indices is approximately 0.5 or even lower. Similar results were obtained in ICCs, where the ICC2 for individual differences in the reaction time (ICC2Close = 0.53; ICC2Stranger = 0.58) and efficiency (ICC2Close = 0.52; ICC2Stranger = 0.34) are relatively high when using close other or stranger as baseline conditions, but still considerably lower than the desired level in psychometrics. For the ICC2k, which measures the stability of SPE on group level, the reaction time measures (ICC2kClose = 0.87; ICC2kStranger = 0.89) and efficiency measures (ICC2kClose = 0.86; ICC2kStranger = 0.76) are relatively high when using close other or stranger as baseline conditions, while the remaining ten other ICC2k indices are about 0.5 or even lower. These findings suggest that SPE measures based the reaction time and efficiency are reliable only at the group level, while further exploration is needed for measuring individual differences. These results provide insights into the reliability of the SPMT and its future applications.

***Keywords*:** Self-Prioritization Effect (SPE), Self-Perceptual Matching Task (SPMT), Reliability, Multiverse

**1 Introduction**

The Self-Prioritization Effect (SPE) refers to the phenomenon whereby performance in cognitive tasks is better when stimuli are related to the self than when they are not. This effect has been widely documented and confirmed since the 1950s. In the early days of cognitive psychology, researchers found that subjects were able to recognize their own names, even when they were mixed with a noisy auditory background and not the target of the task in dichotic listening tasks (Cherry, 1953; Moray, 1959). SPE was then reported in memory research by Craik and Tulving (1975), who found that participants were able to recall more words when they were related to the self compared to when they were processed at other levels (e.g., semantic). This SPE effect in memory was also replicated by many others (Conway & Dewhurst, 1995; Rogers et al., 1977; Symons & Johnson, 1997). In the following decades, the SPE has also been found to occur with different stimuli, such as 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 also found across a variety of cognitive tasks, such as perceptual task (Cunningham & Turk, 2017; Desebrock et al., 2018), decision-making task (Sui & Humphreys, 2013), attentional task (Shapiro et al., 1997), and ownership task (Cunningham et al., 2008).

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. Sui et al. (2012) iintroduced the Self-Perceptual Matching Task (SPMT), a cognitive paradigm designed to investigate the acquisition of social meaning attributed to different geometric shapes. In this task, participants are initially required to establish associations between specific geometrical shapes (e.g., triangle, square, and circle) and corresponding labels of persons (e.g., "You," "friend," and "stranger"). Subsequently, participants engage in a perceptual matching task, wherein they evaluate whether the shape-label pairs presented on the screen align with the previously learned associations. In this task, Sui et al. (2012) found that shapes associated with the self-showed superior performance, with faster reaction times, better accuracy and higher sensitivity scores (*d’*), compared to shapes associated with friends and strangers.

The most significant contribution of the SPMT lies in its successful elimination of the familiarity effect by strategically inducing self-relatedness just prior to the commencement of the perceptual matching task. As a result of this innovation, the SPMT has become the mainstream method for investigating the mechanism 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), self-related labels with moral values (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 SPMT has been applied to various fields. In neuroscience and physiology, researchers investigate which brain regions are activated during the SPE (Feng et al., 2018; Humphreys & Sui, 2015), and gender differences in SPE due to oxytocin (Feng et al., 2020). The SPMT has also been applied to child development, with studies examining developmental changes in SPE (Maire et al., 2020; Zhou et al., 2019). Cross-cultural studies have demonstrated variations in the magnitude of the SPE across different cultural contexts, particularly between individualistic and collectivist cultures (Jiang et al., 2019). Finally, in clinical research, SPMT has also been integrated 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).

Evaluating the reliability of a behavioral paradigm is essential for researchers planning to use the paradigm to investigate different research questions, such as individual differences and underlying mechanisms (Green et al., 2016; Hedge et al., 2018; Parsons et al., 2019). While SPMT has gained widespread adoption as a prominent method for investigating the underlying mechanism of SPE, there has been microscopic examination and report of the psychometric properties of the outcomes, leaving the reliability of using the SPMT for measuring individual differences and group level consistency unknown (Zorowitz & Niv, 2023). Furthermore, in tasks as simple as the SPMT, there are multiple approaches to quantify the SPE. The SPMT yields two direct outcome variables for quantifying SPE: mean reaction time (RT) and accuracy (ACC). In addition to these, the existing literature has identified four additional outcome variables derived from RT and ACC. These include efficiency (*η*) (Humphreys & Sui, 2015; Stoeber & Eysenck, 2008), sensitivity score (*d’*) under signal detection theory (Hu et al., 2020; Sui et al., 2012), and drift rate (*v*) and starting point (*z*) estimated using the drift-diffusion models (DDM) (Golubickis et al., 2017). Moreover, the calculation of SPE can employ different baseline conditions, such as “Close other” (Navon & Makovski, 2021; Svensson et al., 2022), “Stranger” (Constable et al., 2021; Orellana-Corrales et al.), “Celebrity” (Qian et al., 2020), and “Non-person” (Schäfer & Frings, 2019). Given the increasing use of SPMT to assess individual differences in fields such as psychiatry (Liu et al., 2022) and social psychology (Enock et al., 2018), it is crucial to ensure a high degree of measurement consistency to accurately assess human perceptual capacities. As a result, two pivotal questions remain unresolved: (1) Can the six outcome variables (RT, ACC, *d’*, *η*, *v*, *z*) reliably measure the SPE under various baseline conditions? Additionally, which of these outcome variables demonstrate the highest level of reliability? (2) Is the SPMT suitable for assessing individual differences and group-level variations in the manifestation of the SPE? Addressing these questions is crucial for establishing the reliability of SPMT measurements, allowing for accurate assessment of the SPE and its implications in various domains.

To address the existing research gap, the present study investigated the reliability of SPE measures computed using different outcome variables under various baseline conditions in the SPMT. This was achieved by re-analyzed data of 18 independent studies from 9 papers and 2 unpublished projects (N = 857) that employees SPMT. In order to comprehensively assess the SPE measures derived from SPMT, we examined six outcome variables ((RT, ACC, *d’*, *η*, *v*, *z*) under four baseline conditions (“Close other”, “Stranger”, “Celebrity”, and “Non-person”), as mentioned earlier, that is supposed to capture the disparity between self-related and other-related stimuli of the matching trials. Given the methods available for evaluating the reliability of cognitive tasks, we employed both the Split-Half Reliability (*r*) and Intraclass Correlation Coefficient (ICC) to determine the reliability of each SPE measures. The findings of our study aim to provide valuable insights into the reliability and consistency of SPMT and its outcome variables, having the potential to facilitate the future utilization of SPMT in research, clinical settings, and personal performance monitoring.

# **2 Methods**

## 2.1 Ethics information

As this study entails a secondary analysis of pre-existing data sourced from publicly available datasets or archived data previously collected by the author's group, informed consent and confidentiality are not applicable.

## 2.2 Experimental Design

We first provided a brief overview of the original experimental design of SPMT, as described in the Experiment 1 by Sui et al. (2012). The original SPMT used a 2 by 3 within-subject design. The first independent variable, labeled “Matching,” consisted of two levels: “Matching” and “Nonmatching,” indicating whether the shape and label were congruent. The second independent variable, labeled “Identity”, comprised three levels: “Self”, “Friend”, and “Stranger”, representing the corresponding identity associated with the shape.

The original SPMT consisted of two stages (see Fig. 1). In the first stage (learning stage), participants completed a learning task in which 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 counter-balanced across participants. In the second phase (formal experimental phase), participants completed a perceptual 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 matching types (matching/nonmatching) and three shape associations, for a total of 60 trials per association. Short breaks lasting up to 60 seconds were provided after each block.



**Fig. 1.** Procedure of the original SPMT in the Experiment 1 (Sui et al., 2012).

## 2.3Datasets Acquisition

Initially, two datasets that employed the SPMT were available to us: one from an unpublished project conducted in our laboratory (Hu et al., 2023), and the other provided by our collaborators (Liu et al., 2023). Concurrently, we are conducting a meta-analysis on SPE using the SPMT (pre-registration available at <https://osf.io/euqmf>). During this process, we identified an additional thirteen papers with datasets potentially suitable for our present study. The selection of these papers was based on specific criteria:

1. The paper must primarily utilize the SPMT as their method.
2. The experimental design should align with the original SPMT by Sui et al. (2012).
3. The trial-level data is either openly available or declared to be obtainable upon request, enabling us to estimate at least one reliability index.

Among the thirteen papers included, seven papers made their raw data publicly available (Constable et al., 2021; Constable & Knoblich, 2020; Golubickis & Macrae, 2021; Navon & Makovski, 2021; Qian et al., 2020; Schäfer & Frings, 2019; Svensson et al., 2022). For the remaining six papers, we reached out to the authors and requested access to their trial-level data. Out of those six requests, three papers provided us with usable trial level data (Kolvoort et al., 2020; Woźniak et al., 2018; Xu et al., 2021); two papers provided us only with descriptive results, which unfortunately could not be used for calculating reliability (Cheng & Tseng, 2019; Martínez-Pérez et al., 2020); one paper referred to data being shared on the Open Science Framework (OSF) platform (<https://osf.io/pcv3u/>) (Bukowski et al., 2021), but we found that the repository was empty, making it ineligible for the current analysis.

In total, our analysis comprised raw data from nine papers and two unpublished projects from our laboratory and collaborators. It is important to highlight that the research culture discourages direct replications (Makel et al., 2012). As a result, all the datasets included in our analysis underwent some degree of modification to the original design, including the incorporation of additional independent variables or the use of different experimental materials (refer to Table 1 for specification). For our analysis, we exclusively utilized the data that resemble the original design. In the end, we were able to incorporate 18 independent datasets from the above-mentioned papers and projects. Nonetheless, not all studies incorporated retest sessions. If a publicly available datasets did not include retest session with SPMT, we excluded it from calculating the Intraclass Correlation Coefficient and only considered the split-half reliability. The details of the included studies and conditions in the datasets are described in Table 1.

Table 1. Dataset Information

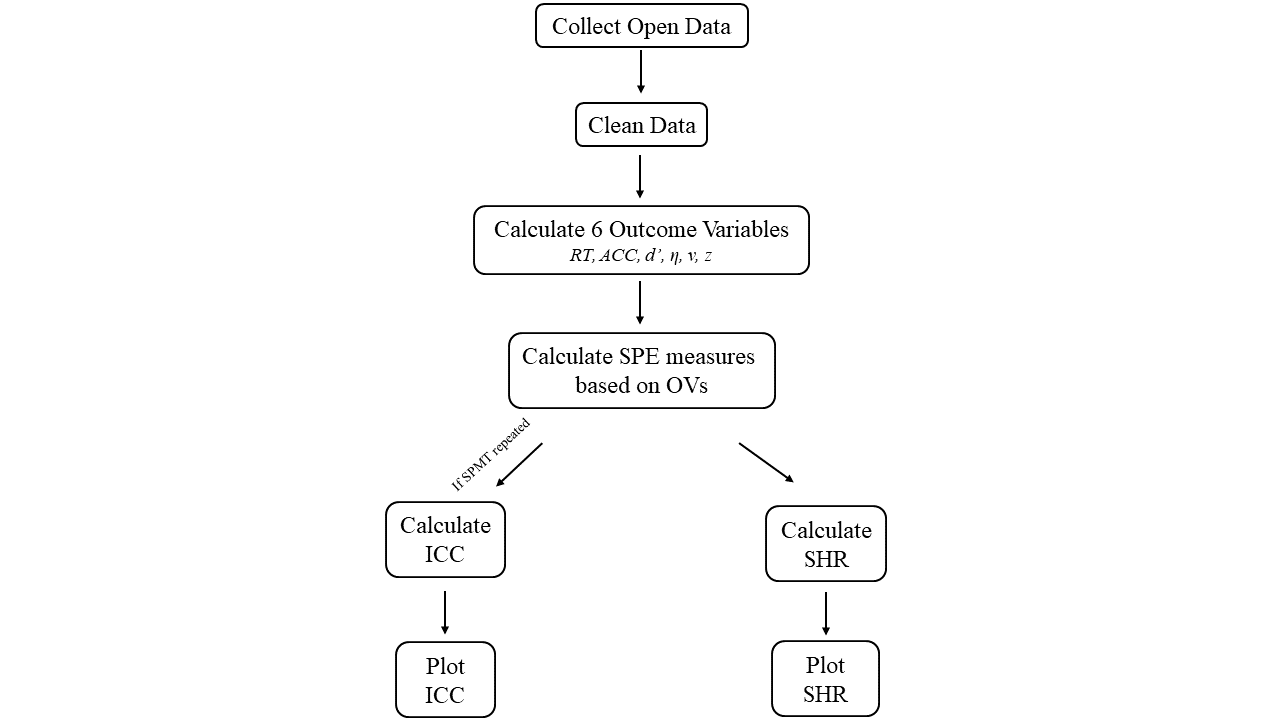
| Paper | Exp. | Independent Variable | | | | Sample  Size | # of Trials per Condition | Self-Prioritization Effect Indices | | | | | | Reliability | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| IV 1 | IV 2 | IV 3 | IV 4 |  |  | RT | ACC | d | Eff | v | z | ICC | SHR |
| Hu et al. (2023) | 1 | Matching | Identity | Emotion  **Control**, Neutral,  Happy, Sad | Session  **1-6** | 33 | 60 | √ | √ | √ | √ | √ | √ | √ | √ |
| Constable and Knoblich (2020) | 1 | Matching | Identity | Switch Identity  Partner, Stranger | Phase  **1**; 2 | 46 | 20 | √ | √ | √ | √ | √ | √ |  | √ |
| Constable et al. (2021) | 2 | Matching | Identity  Self; Stranger |  |  | 56 | 48 | √ | √ | √ | √ | √ | √ |  | √ |
| Qian et al. (2020) | 1 | Matching | Identity Self; Celebrity; Stranger | Mood (Session) |  | 24 | 24 | √ | √ | √ | √ | √ | √ |  | √ |
| 2 | Matching | Identity Self; Celebrity | Cue  With, **Without** |  | 25 | 25 | √ | √ | √ | √ | √ | √ |  | √ |
| Schäfer and Frings (2019) | 1 | Matching | Identity Self; Mother; Acquaintance/none |  |  | 32 | 18 | √ | √ | √ | √ | √ | √ |  | √ |
| 3 | Matching | Identity Self; Mother; Acquaintance |  |  | 35 | 24 | √ | √ | √ | √ | √ | √ |  | √ |
| Golubickis and Macrae (2021) | 1 | Matching | Identity | Presentation **Mixed;** Blocked |  | 30 | 30 | √ | √ | √ | √ | √ | √ |  | √ |
| Navon and Makovski (2021) | 1 | Matching | Identity |  |  | 13 | 60 | √ | √ | √ | √ | √ | √ |  | √ |
| 3 | Matching | Identity  Self; Father; Stranger |  |  | 28 | 60 | √ | √ | √ | √ | √ | √ |  | √ |
| 4 | Matching | Identity |  |  | 27 | 60 | √ | √ | √ | √ | √ | √ |  | √ |
| Svensson et al. (2022) | 1 | Matching | Identity Self; Friend |  |  | 20 | 50 | √ | √ | √ | √ | √ | √ |  | √ |
| 2 | Matching | Identity Self; Friend | Frequency  self > friend |  | 24 | 100 | √ | √ | √ | √ | √ | √ |  | √ |
| 3 | Matching | Identity Self; Friend | Frequency  self < friend |  | 25 | 100 | √ | √ | √ | √ | √ | √ |  | √ |
| Xu et al. (2021) | 1 | Matching | Identity | Tasks  Modified; **Unmodified** |  | 105 | 60 | √ | √ | √ | √ | √ | √ |  | √ |
| Woźniak et al. (2018) | 1 | Matching | Identity | Facial Gender  Mele; Female |  | 18 | 56 | √ | √ | √ | √ | √ | √ |  | √ |
| 2 | Matching | Identity | Facial Gender  Mele; Female |  | 18 | 60 | √ | √ | √ | √ | √ | √ |  | √ |
| Liu et al. (2023) | 1 | Matching | Identity  Self; Stranger |  |  | 298 | 16 | √ | √ | √ | √ | √ | √ |  | √ |

*Note*. SPE: IV: independent variable. For IV3 and IV4, we only included the baseline conditions that are similar to the original design in Sui et al. (2012), which were highlighted in BOLD font. Similarly, if there are other variables besides the baseline condition, indicated by underscores, we will only use these variables as stratification variables during split-half and not conduct further analysis.

# **3 Analysis**

Analysis plans for this study were preregistered on OSF (https://osf.io/6dghm/). The drift rate (*v*) and starting point (*z*) of the drift-diffusion model (DDM) was obtained in Python, using the “RWiener” package (Wabersich & Vandekerckhove, 2014). All the other analyses in this paper were performed using the statistical software R (R Core Team, 2023).

The research flow of the current study is visually represented in Fig. 2. After collecting the data from each independent study, we performed data cleaning and calculated the six outcome variables as well as the twenty-four SPE measures computed using different outcome variables and baseline conditions. Finally, we calculated the split-half reliabilities of these SPE measures. If there were test-retest data, we also calculated the test-retest reliability using the intraclass correlation coefficient (ICC2, ICC2k).



**Fig. 2** Roadmap of the current study. *Note:* OV denoted outcome variables.

## 3.1 Deviation from Preregistration

In our pre-registration plan, we intended to estimate the drift rate (v) and starting point (z) of the drift-diffusion model using the “fit\_ezddm” function from the “hausekeep” package (Lin et al., 2020). This function served as a wrapper for the EZ-DDM function (Wagenmakers et al., 2007). However, during parameter recovery analysis, we observed that this algorithm yielded distinct results when compared to the widely adopted HDDM package (details provided in the Supplementary materials). Upon further evaluation, we found that the "RWiener" package (Wabersich & Vandekerckhove, 2014) achieved a favorable balance between accuracy, confidence interval width, and computational efficiency, making it the most suitable choice for our analysis. Nevertheless, for transparency, we have included the detailed results from ezDDM in the supplementary materials (see Supplementary, Figure 2-4).

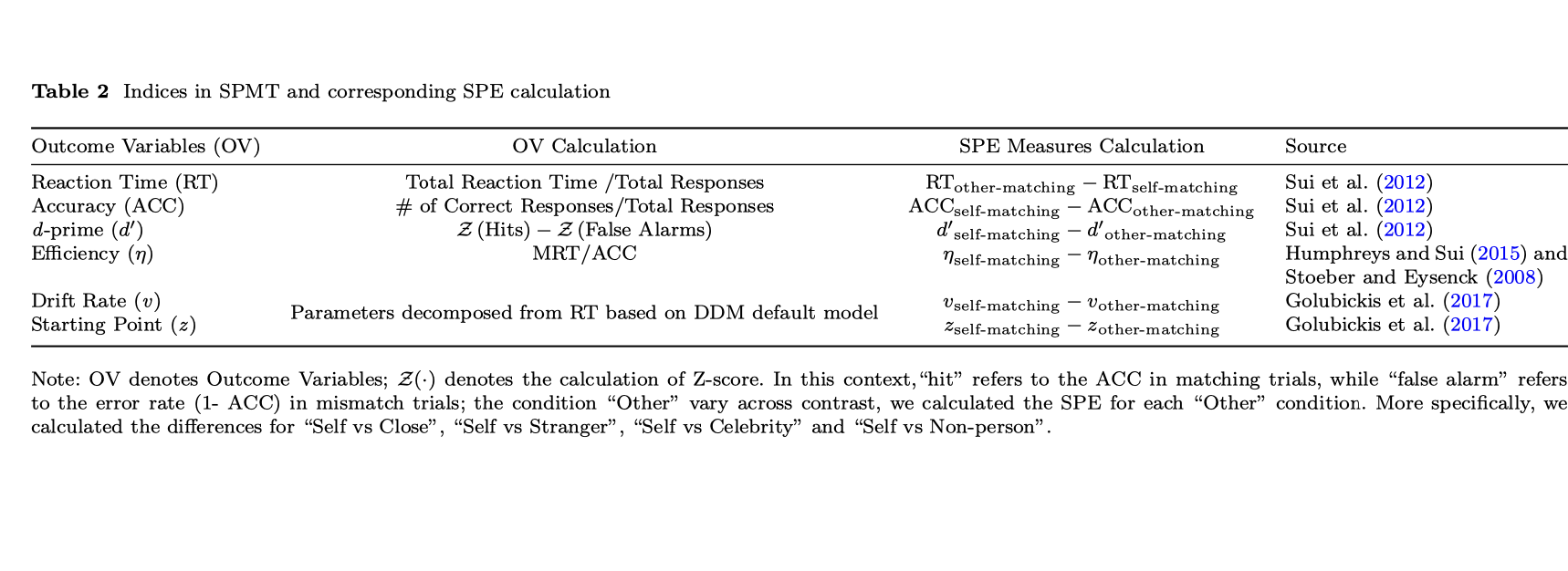
## 3.2 Data Pre-processing

For all the eighteen datasets (see Table 1), we applied the following exclusion criteria for excluding data:

1. Participant exclusion criteria
2. Participants who had wrong trial numbers due to procedure errors is excluded from the analysis,
3. Participants with an overall accuracy < 0.5 is excluded from the analysis,
4. Participants with any of the conditions with zero accuracy is excluded from the analysis.
5. Trial level data exclusion criteria
6. Incorrect trials and non-responsive trials are excluded from the analysis,
7. The practice trials are excluded from the formal analysis,
8. The data under conditions other than the “control condition” would not be used in the current study.

## 3.3 Calculating the Outcome Variables and SPE Measures

For each study, we calculated six outcome variables for each experimental condition: Mean Reaction Time (RT), Accuracy (ACC), Sensitivity Score (*d′*), Efficiency (*η*), Drift Rate (*v*), and Starting Point (*z*). Reaction Time and Accuracy are obtained directly from the datasets, while Sensitivity Score and Efficiency are calculated based on Reaction Time and Accuracy (see Table 2).



## 3.4 Estimating the Reliability

**Split-half Reliability.** To ensure methodological rigor, we assessed the weighted average split-half reliability of the SPE measures using four distinct data splitting approaches: first-second, odd-even, permutated, and Monte Carlo (Kahveci et al., 2022; Pronk et al., 2022). The first-second split-half reliability involved dividing the trials into two halves: the first half and the second half. The odd-even split-half reliability separated the trials into sequences based on their odd or even numbers. On the other hand, the permutation split-half reliability shuffled the trial order and randomly assigned each half to a group. The Monte Carlo split-half approach was similar to the permutated split-half method, but it repeated the process thousands of times to calculate the average and 95% confidence interval of the split-half reliability.

First, the data were stratified per condition and then split into two halves (Pronk et al., 2022). For example, when using Monte Carlo Split-Half, we randomly split the stratified data into two halves for 5000 times, which resulted in 5000 pairs of two halves of the data. Next, we calculated 5000 Pearson correlation coefficients based on these 5000 pairs of data and calculated the mean and 95% confidence interval of the 5000 correlations coefficients. The first-second split, odd-even split, and permutated split are similar to Monte Carlo method, but each only resulted in single reliability coefficient.

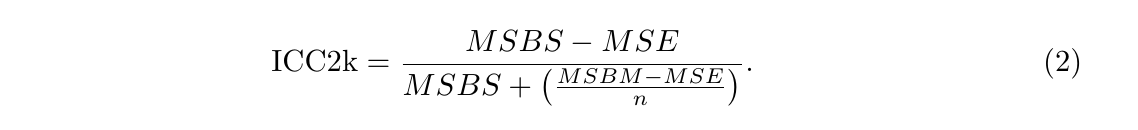
Finally, after computing split-half reliability coefficients for each dataset, substantial variations were observed across the datasets. To derive a representative overall value for each SPE measures, we adopted an approach akin to meta-analysis, allowing for a more accurate estimation of the average split-half reliability. As noted by Kucina et al. (2023), the number of trials significantly influences the reliability of cognitive experiments, with higher trial numbers resulting in increased reliability (similar pattern was also found in SPMT, see Supplementary Fig. 6). Hence, to account for the impact of trials, we assigned weights to the split-half reliability based on the trial numbers present in each dataset using the “metafor” Package (Viechtbauer, 2010). Employing a method similar to weighted averaging, we obtained the final split-half reliability as well as its 95% confidence interval, ensuring a comprehensive and robust evaluation of the SPE measures across the datasets.

**Test-Retest Reliability (ICC).** We assessed the test-retest reliability of the six outcome variables for our dataset that involved test-retest sessions by calculating the Intraclass Correlation Coefficient (ICC) using “psych” package (Revelle, 2017). ICC is a well-established measure used in test-retest, intra-rater, and inter-rater studies to assess reliability (Fisher, 1992). Unlike the Pearson correlation coefficient, ICC considers both the correlation and agreement between multiple measurements, making it a more comprehensive measure of test-retest reliability.

Our primary aim is to evaluate the appropriateness of the SPMT in assessing individual differences and group-level variations. To achieve this objective, we focused on using two specific types of Intraclass Correlation Coefficients (ICC) within the ICC family, namely ICC2 and ICC2k. ICC2 focuses on the individual-level reliability of the indices, while ICC2k evaluates the reliability of mean ratings furnished by a group of judges (Koo & Li, 2016). For the calculation of ICC2 estimates, the formula is:A math equations on a white background

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where MSBS is the mean square between subjects, MSE is the mean square error, MSBM is the mean square between measurements, k is the number of measurements, n is number of participants. For the calculation of ICC2k estimates, the formula is:



Although there is no strict criterion for defining the level of reliability, a widely accepted guideline for Cronbach’s alpha is that a value of 0.60 is “acceptable”, and a value greater than 0.8 means excellent reliability (Cicchetti & Sparrow, 1981; Kupper & Hafner, 1989).

# **4** **Results**

In eighteen independent datasets, fourteen of them contain data for the Self vs Close other contrast, 12 of them contain data for Self vs Stranger, 2 of them have the data for Self vs Celebrities, 1 of them has the data for Self vs none condition. We reported the results for all these baseline conditions.

## 4.1 Split-Half Reliability

As described in method part, we applied four different methods to calculate split-half reliability, namely the first-second, odd-even, permuted, and Monte Carlo methods. We presented the results from Monte Carlo split-half method in the main text due to its robustness (Pronk et al. (2022). The results of the other three split-half methods can be found in the supplementary materials (see Supplementary Fig. 2 -4), which also have quite similar result pattern with the Monte Carlo methods.

The split-half reliabilities using of Monte-Carlo method for different SPE measures is presented in figure 3. Among the measured outcome variables, the four highest ranking split-half reliabilities are as follows: Reaction Time (RT) with the "Stranger" contrast (*r* = .65, SE = .02, p <.001, 95% CI [.60, .70]); Efficiency (*η*) with the "Stranger" contrast (*r* = .63, SE = .02, p <.001, 95% CI [.58, .68]); RT with the "Close other" contrast (*r* = .58, SE = .02, p <.001, 95% CI [.54, .63]); *η* with the "Self vs Close" contrast (*r* = .57, SE = .02, p <.001, 95% CI [.52, . 61]). These SPE measures achieved a split-half reliability around 0.6 or higher, which is considered an acceptable level of reliability.

For the remaining 4 outcome variables, the reliability is around 0.5 or lower, indicating poor test-retest reliability. These include Accuracy (ACC), Sensitivity Score (*d’*), Drift Rate (*v*), and Starting Point (*z*). It is notice that almost all the split-half reliability of *z* using different contrasts are around 0, which suggests a complete lack of reliability.

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**Fig. 3.** The weighted average of split-half reliabilities (Monte-Carlo) for different SPE measures.

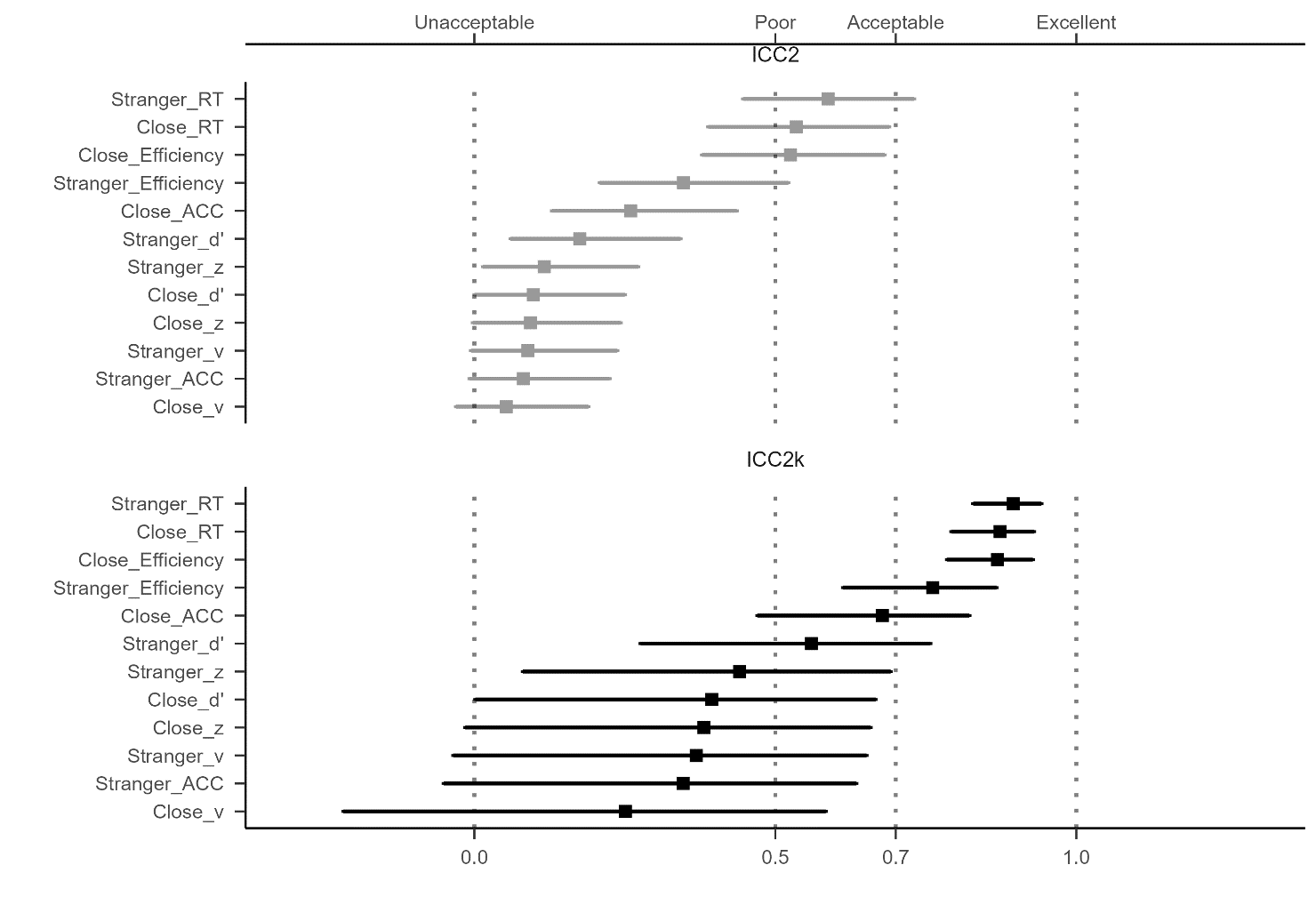
***NOTE:*** The vertical axis represents 24 different SPE measures, combining six outcomes variables (RT, ACC, *d’*, *η*, *v*, *z*) and four baseline conditions (close other, stranger, celebrity, and non-person). The weighted average split-half reliability and 95% confidence intervals are shown by points and lines.

## 4.2 Intraclass correlation coefficient (ICC)

It is important to note that we could only calculate ICC for the study in our labprtory (Hu et al., 2023) since all other datasets did not include re-test sessions. For our own dataset, we only have 2 contrasts, the “Close other” and “Stranger”. To test the robustness of the results reported here, we also explored two datasets that included re-test session but devivated quite strongly from the original SPMT (see Supplementary Fig. 5).

The ICC2, which measure the reliability for individual differences, confirmed the results from split-half reliability: only RT and Efficiency display reliability ranging from poor to acceptable. Specifically, under the "Self vs Close" contrast, the ICC2 for RT is 0.53 (95% CI = [.39, .69]), and for Efficiency, it is 0.52 (95% CI = [.38, .68]). Meanwhile, for the "Self vs Stranger" contrast, the ICC2 for RT is 0.58 (95% CI = [.45, .73]), and for Efficiency, it is 0.34 (95% CI = [.21, .52]). All the other outcome variables exhibit unacceptable to poor ICC2.

However, it is worth noting that the ICC2k values, which measure the reliability of effect on group level, for Reaction Time (RT) and Efficiency demonstrate notably high levels of reliability, while the other outcome variables exhibit unacceptable to poor ICC2k. When considering the "Close" contrast, the ICC2k for RT is 0.87 (95% CI = [.79, .93]), and for Efficiency, it is 0.86 (95% CI = [.78, .93]). Similarly, for the "Stranger" contrast, the ICC2k for RT is 0.89 (95% CI = [.82, .94]), and for Efficiency, it is 0.76 (95% CI = [.61, .87]).



**Fig. 4** Intraclass correlation coefficient.

***NOTE:***The vertical axis represents 12 different SPE measures, combining 6 outcomes variables (RT, ACC, d’, η, v, z) and 2 contrasts (close other, stranger).The upper facet of the figure presents the results for ICC2k, while the lower facet displays the results for ICC. The ICC values and their corresponding 95% confidence intervals are illustrated using points and lines.

# **5 Discussion**

Despite the significance of assessing the reliability of a behavioral paradigm before its implementation, this practice is not yet extensively embraced by researchers (Green et al., 2016; Hedge et al., 2018; Parsons et al., 2019). In this pre-registered study, our objective is to investigate the reliability of the outcome variables related to the SPE measures in the SPMT. To achieve this, we re-analyzed eighteen datasets from nine papers and two unpublished projects (N = 857), utilizing split-half reliability (*r*) and intraclass correlation coefficient (ICC2, ICC2k). Our findings reveal that the Reaction Time and Efficiency demonstrated better results, with weight average split-half reliability around 0.6 or higher, ICC2 around 0.5 or higher, ICC2k higher than 0.7. All the other outcome variables performed poorly, with weight average split-half reliability lower than 0.5, ICC2 lower than 0.5, ICC2k lower than 0.7. The comprehensive analysis of these datasets collectively suggests that Reaction Time and Efficiency are the most reliable measure of SPE, among all measures available in the SPMT. Moreover, the pattern observed in the ICC values suggests that reaction time and efficiency in the SPMT are better suited for group-level analysis rather than assessing individual-level variation.

Although Reaction Time and Efficiency yielded relatively better results compared to other indices, they still fell short of achieving commonly considered excellent reliability levels (typically a value greater than 0.8 means excellent reliability) (Cicchetti & Sparrow, 1981; Kupper & Hafner, 1989). The low split-half reliability and low ICC2 may suggest that the SPMT, like other traditional cognitive tasks such as Flanker, Simon, or Stroop tasks (Clark et al., 2022; Mollon et al., 2017), is not suitable for assessing individual-level variation. Several plausible reasons as well as potential solutions can be identified. Firstly, the insufficient number of trials per condition may contribute to the low split-half reliability. A recent study by Kucina et al. (2023) emphasized the importance of trial numbers for cognitive tasks in determining reliability. The findings revealed that increasing the number of trials and considering greater conflict effects or individual differences can enhance reliability compared to the original paradigm. Specifically, the study identified that satisfactory reliability required 48 or more trials, while achieving a higher level of reliability necessitated 72 trials. As shown in Supplementary (Fig. 5), we calculated the correlation coefficient between the trial numbers and the Monte Carlo split-half reliabilities and found a strong positive correlation between several metrics, such as RT and Efficiency. Therefore, incorporating a higher number of trials in future implementations of the SPMT paradigm may enhance the split-half reliability by improving measurement consistency.

Secondly, the presence of a practice effect or fatigue effect could be another significant factor influencing reliability. If these effects are substantial enough to cause a noticeable change in participants' performance between measurement occasions, it can introduce additional variability in the measurements and lower the ICC2 values (Oswald et al., 2015; Siegelman et al., 2017). This highlights the need for a more nuanced task setting that can consistently capture performance nuances and reveal individual differences more sensitively (Hedge et al., 2018). Recent study on gamification of cognitive tasks have shown that incorporating gamification elements can effectively improve data quality and assessment efficacy (Friehs et al., 2020). Therefore, modifying the SPMT with a more dynamic paradigm, such as incorporating gamification elements, may enhance split-half reliability by improving measurement consistency.

Finally, it is worth mentioning the influence of serial dependence effects on task reliability. A recent set of studies has examined serial dependence effects in a variety of cognitive tasks (Braun et al., 2018; Zhang & Alais, 2020). Serial dependence refers to the phenomenon in which the outcome of one trial is influenced by preceding trials, resulting in a systematic relationship between consecutive trials (Pascucci et al., 2023). Notably, studies in the field of perceptual decision making have demonstrated strong serial dependence effects in perception, even when the visual stimuli were reliable and varied randomly over time (Fischer & Whitney, 2014; John-Saaltink et al., 2016). In particular, if the split-half design unintentionally separates temporally adjacent trials in the SPMT, the presence of serial dependence may introduce performance differences between the halves, leading to a reduction in the reliability estimate. Thus, to accurately control for the impact of serial dependence in experiments, further research should employ appropriate statistical methods that account for the temporal dependencies between trials. Time series analysis techniques (Huitema, 1986) or modeling approaches that capture the serial correlation (Mei et al., 2023) can be utilized to obtain more accurate results.

Apart from the results of Reaction Time and Efficiency, we were surprised by the low reliability of parameters (*v* and *z*) obtained from the drift diffusion model. In our analysis, we used common and easy-to-use methods to estimate parameter values for each condition of each participant and then calculated the reliability. As for drift rate (*v*), we found that *r*Close = .52, 95% CI [.47, .58] and *r*Stranger = .20 95% CI [.11, .28]. As for starting point (*z*), we found that *r*Close = .13, 95% CI [.05, .20] and *r*Stranger = .08 95% CI [-.02, .17]. Several factors may account for these discouraging outcomes. Firstly, it appears that the standard DDM might not adequately capture the underlying cognitive processes in the SPMT. Previous studies often applied the DDM in a somewhat arbitrary manner, without adhering to a comprehensive cognitive modeling workflow, as recommended by Wilson and Collins (2019). As a consequence, the standard DDM exhibited suboptimal performance when applied to task structures similar to the SPMT (Groulx et al., 2020). Consequently, these results raise questions regarding the validity of employing the standard DDM to analyze data from the SPMT. To address this issue, future research should explore hierarchical models (which may require more time for parameter estimation) or develop new variations of the DDM that better capture the latent cognitive processes involved in completing the SPMT. Theoretically, this could enhance the reliability of these parameters. These efforts will contribute to the development of formal models for understanding SPE, leading to more reliable and valid interpretations of cognitive processes in the SPMT and similar paradigms.

It is important to note that ICC values should not be interpreted solely as a measure of the test's overall quality, but rather as an indication of the specific types of questions it can effectively address (Koo & Li, 2016). The results obtained from the intraclass correlation coefficients indicate that the SPMT, particularly the Reaction time and efficiency, is more appropriate for group-level analysis rather than assessing individual-level variation. Specifically, we found that the RT and efficiency measures exhibited excellent test-retest reliability at the group level (ICC2k), regardless of whether the target is, indicating strong group-level consistency over time. On the other hand, the ICC2 values for RT and Efficiency were relatively lower, below 0.7. This discrepancy suggests that these outcome variables are more influenced by variations between participants rather than within participants. The findings also align with the concept of the reliability paradox proposed previously (Hedge et al., 2018; Logie et al., 1996). Behavioral paradigms, including the SPMT, are susceptible to factors such as external conditions and contextual differences, which contribute to greater within-participant variability and lower ICC2 values (Clark et al., 2022; Mollon et al., 2017). However, when averaging performance across different individuals, the task still demonstrates good consistency, leading to higher ICC2k values (Liljequist et al., 2019). In practical terms, our results suggest that the SPMT is better suited for discerning performance differences between individuals or groups rather than capturing consistent performance within the same individuals over time. Therefore, researchers should consider these factors when investigating individual differences using the SPMT.

Our study has several limitations that should be acknowledged. Firstly, although we made efforts to enhance sample diversity by including open data whenever possible, it is important to note that the majority of our samples still consisted of individuals from what is commonly referred to as "WEIRD" populations (Rad et al., 2018; Yue et al., 2023). As a result, our findings may not be fully representative of the broader population, and it is necessary to include a more diverse sample to ensure greater generalizability of the paradigm. Additionally, when assessing the intraclass correlation coefficients (ICCs), only our own dataset had longitudinal data available, which could potentially limit the representativeness of the results. This issue is mitigated by the fact that additional analysis of two datasets that with different design showed similar results as we reported in the main text. Furthermore, the majority of the studies included in our analysis focused on adults from healthy populations. Therefore, further investigation is needed to include more datasets with a more diverse population in order to determine the reliability of the SPMT in different settings. Finally, it is important to clarify the aim of our study, which primarily focused on exploratory purposes and providing information regarding the current state of reliability for the assessed outcome variables. Consequently, future research could concentrate on modifying the paradigm and conducting tests to assess potential improvements (see Zorowitz and Niv (2023)).

In conclusion, this study provides significant insights into the reliability of the self-perceptual matching task (SPMT) and highlights important considerations for interpreting its reliabilities. We have demonstrated that the Reaction Time and Efficiency measures exhibit greater reliability compared to other outcome variables in the SPMT. Furthermore, our findings indicate that the SPMT is more suitable for group-level analysis rather than assessing individual-level variation. These findings have important implications for future task design and data collection protocols aimed at improving reliability. Ultimately, our study paves the way for the prospective utilization of these tasks, in various domains including research, clinical applications, and personal performance monitoring. The information obtained from our study contributes valuable knowledge to the field and sets the stage for further investigations and advancements in utilizing SPMT effectively.

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# **Author contributions**

HCP contributed to the conception and supervision of the study. JS contributed to fund raising, HCP contributed to data collection. ZL, ZYR write the simulation code for pre-registration. HMZ collected the datasets and performed the data pre-processing, analysis and visualize the results. In addition, ZL, HMZ and HCP contribute to discussing the results and the drafting of the final manuscript. All authors critically revise the manuscript.

# **Data and Material Availability**

The pre-registration plan is available at <https://osf.io/zv628>. The de-identified raw data from our lab is available at <https://doi.org/10.57760/sciencedb.08117>. The simulated data is accessible on GitHub (<https://github.com/Chuan-Peng-Lab/ReliabilitySPE>).

# **Code Availability**

Code used to simulate and analyze the data is made accessible at <https://github.com/Chuan-Peng-Lab/ReliabilitySPE>.

# **Competing interests**

The authors declare no competing interests.

# **Supplementary Information**

## Parameter Recovery Result for Package Comparison

We chose not to utilize the HDDM package (Wiecki et al., 2013) for several reasons. Firstly, the computation process of the HDDM package is notably time-consuming, which would considerably prolong the overall analysis time. Secondly, the parameters estimated by the hierarchical model in HDDM are not independent across different individuals due to the sharing of a common hyperparameter. This lack of independence might complicate the interpretation of individual differences and impede result clarity.

In order to identify the most appropriate package for our analysis, we performed a package comparison by generating 100 datasets using the HDDM package in Python. These datasets were specifically configured with parameters *a* = 2, *t* = 0.3, *v* = 1, and *z* = 0.7. Subsequently, we utilized three different DDM packages in R (RWiener, hausekeep, and FastDMinR) to compute parameter estimates for these generated datasets. The evaluation process involves comparing the computed values obtained from the R packages with the set parameters. If the computed values from the R packages are found to be closer to the set values, it signifies that the respective R package provides more accurate parameter estimation for the drift-diffusion model.

Figure 1 presents the results of the package comparison. The estimated drift rate (v) obtained from RWiener is 1.01, with a 95% confidence interval of [.98, 1.03], which closely aligns with our pre-defined values. Similarly, the estimated starting point (z) is 0.77, with a 95% confidence interval of [.76, .78], also very close to our pre-defined value. On the contrary, the parameters calculated using other packages either showed high inaccuracies, excessively wide confidence intervals, or required extended computation times. As a result, we have opted to utilize RWiener for our calculations. It strikes a favorable balance between accuracy, confidence interval width, and computational efficiency, making it the most suitable choice for our analysis.



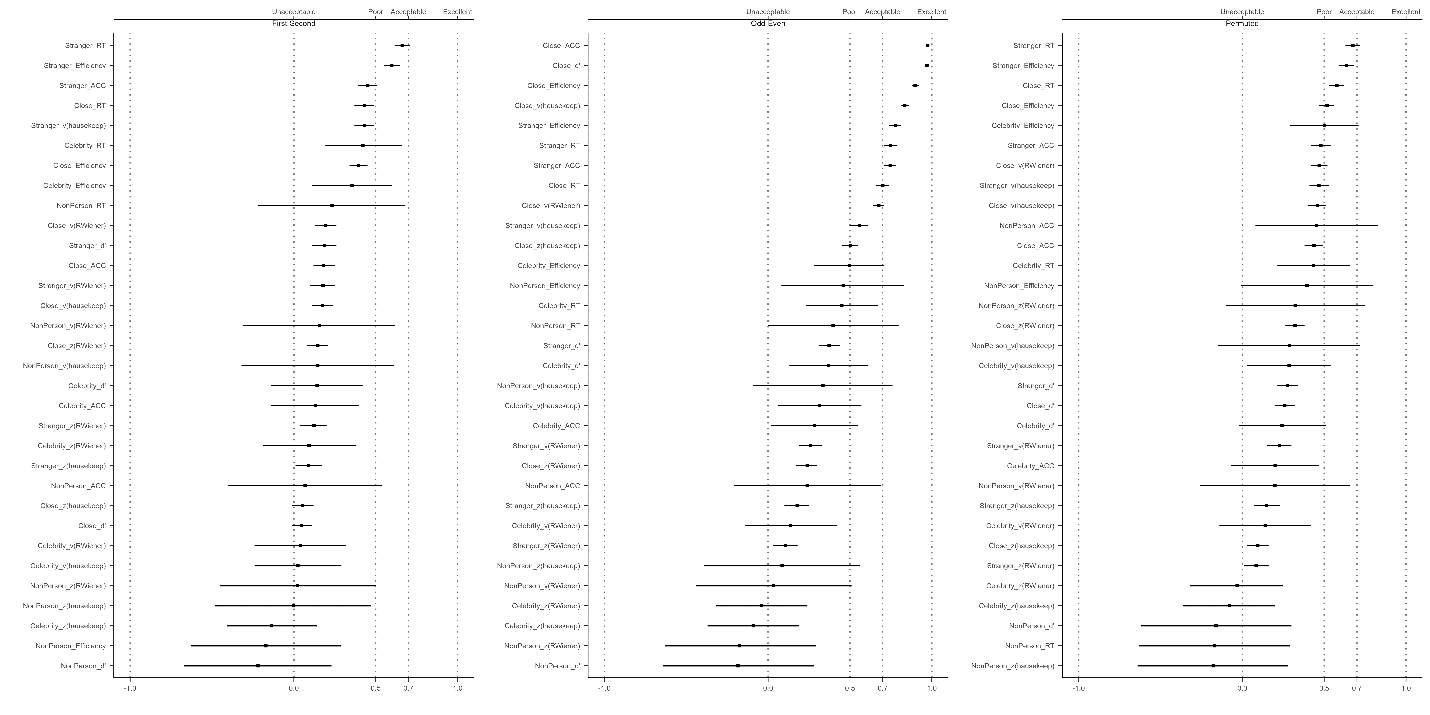
**Supplementary Fig. 1 DDM Packages Comparison.**

*Note:* The parameters of interest in the drift-diffusion model (DDM) are represented as follows: "*a*" denotes the threshold parameter, "*t*" represents the non-decision time, "*v*" indicates the drift rate, and "*z*" corresponds to the starting point. The y-axis of the graph displays the estimation of these DDM parameters using three different R packages: "RWiener," "hausekeep," and "FastDMinR." In total, there are five methods for estimating DDM parameters, with three methods originating from the "FastDMinR" package. On the x-axis, the values of the estimated parameters are plotted. The dashed line on the graph indicates the true value of the parameter being estimated.

## Other Three Split-half Methods

In this section, we present the split-half reliabilities result for SPE measures using other three split-half methods (first-second, odd-even, permutated).

In the following three split-half methods, the results of the odd-even approach differ significantly from the other two. This could be due to the odd-even split-half becoming an experimental condition, confounding with the task design (Pronk et al., 2022).

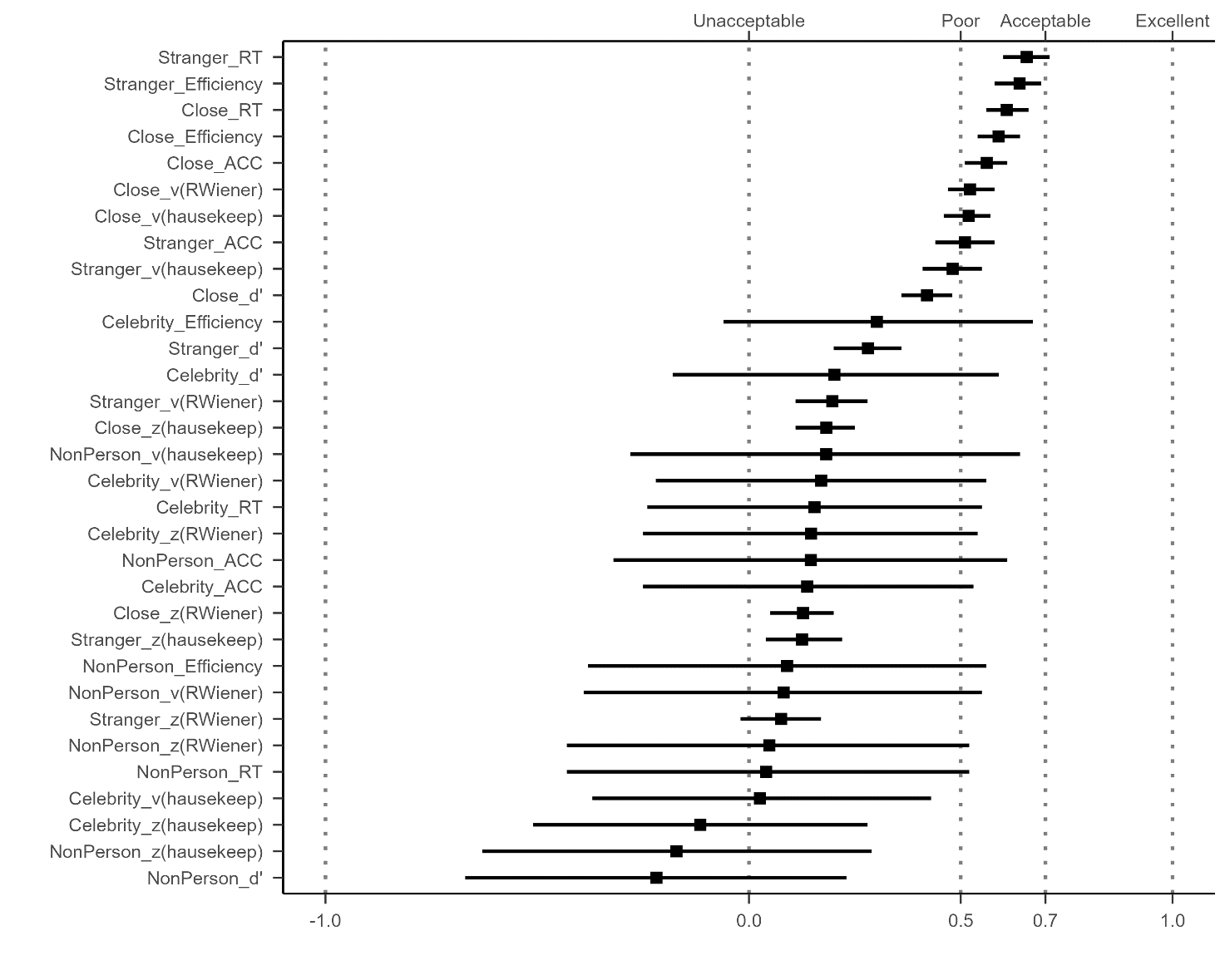


**Supplementary Fig. 2** Results of other three split-half methods for different SPE measures.

*Note:* The vertical axis represents 24 different SPE measures, combining six outcomes variables (RT, ACC, d’, η, v, z) and four baseline conditions (close other, stranger, celebrity, and non-person), which includes two additional indices from the DDM, implemented using the "hausekeep" package. The weighted average split-half reliability and 95% confidence intervals are shown by points and lines. The figure is divided into separate facets arranged from left to right, each representing weighted average split-half reliability calculated using three distinct methods: first-second, odd-even, and permuted.

## SHR for SPE Measures Using Four Split-half Methods

In this section, we present the results of Monte Carlo SHR (Fig. 3) for estimating the drift rate (v) and starting point (z) from the EZ-DDM ("hausekeep" package). It should be noted that the estimation of parameter "a" in hausekeep is highly deviant from HDDM due to the assumption of z = a / 2 (see suppl. Fig. 1). Consequently, we do not report the results obtained from this package in the main text.

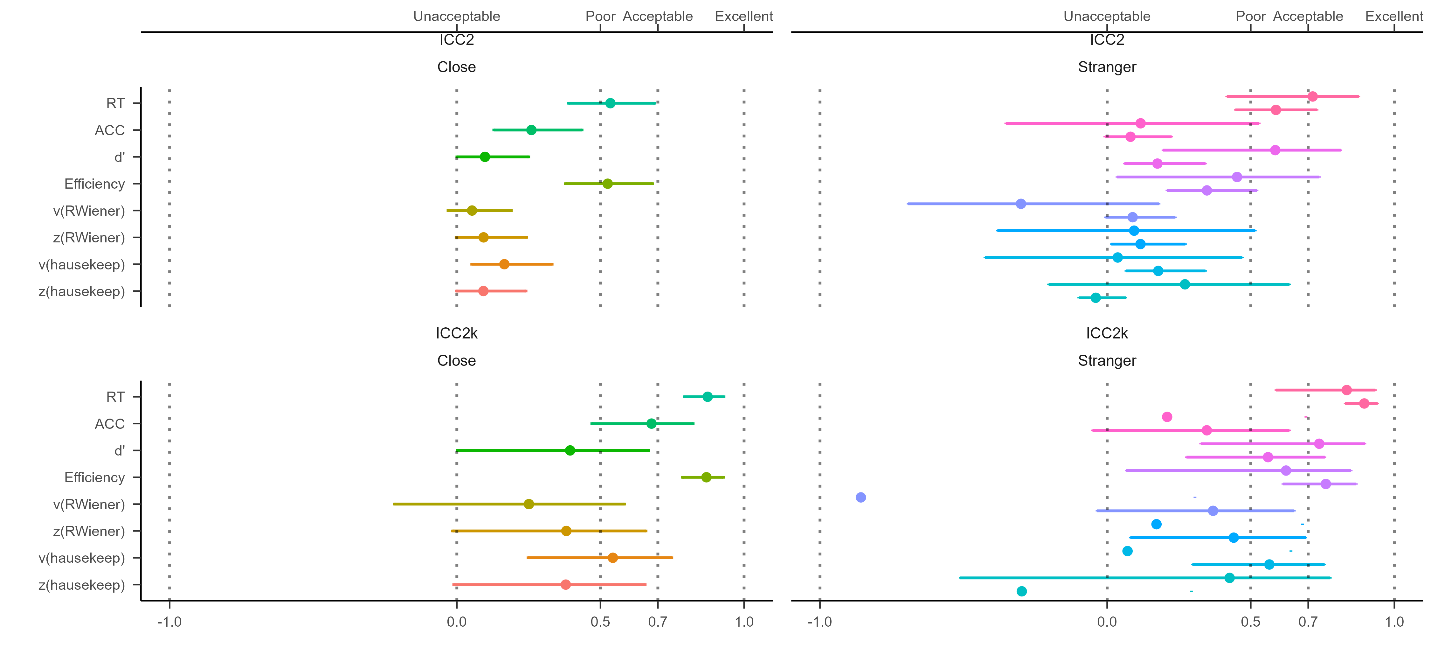


**Supplementary Fig. 3.** Monte Carlo SHR for SPE measures.

*Note:* The vertical axis of the graph illustrates eight distinct outcome variables, which includes two additional indices from the DDM, implemented using the "hausekeep" package. The line and dots on the graph represent the split-half reliability estimated using Monte Carlo split-half method, along with their corresponding 95% confidence intervals.

From the result, it is evident that EZ-DDM demonstrates higher stability in estimating the drift rate (v). This may be attributed to the estimation method used in "hausekeep," which relies on average reaction time and accuracy, as opposed to the method employed in "RWiener," which relies on individual trial-level reaction times and correctness. The chosen split-half procedure may have a greater impact on the estimation by "RWiener," leading to lower split-half reliabilities for both of its indices. These observations imply that the reliability of calculating DDM parameters through split-half reliabilities is influenced by two key factors. Firstly, the stability of the parameter itself plays a significant role, and secondly, the stability of the package used to compute that parameter is equally crucial.

## ICCs for different SPE indices.



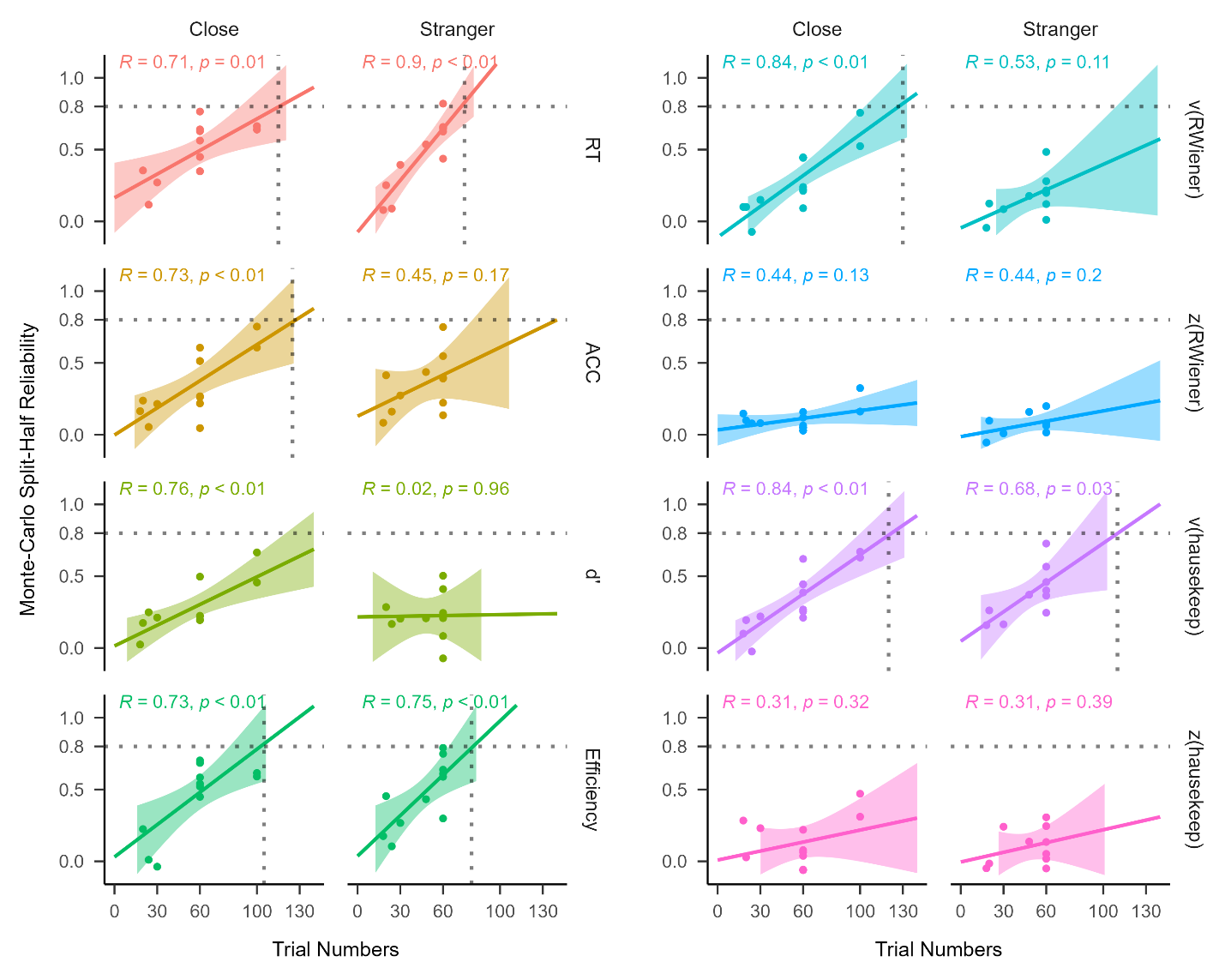
**Supplementary Fig. 4** ICCs for different SPE indices.

*Note:*The vertical axis of the graph illustrates eight distinct outcome variables, which includes two additional indices from the DDM, implemented using the "hausekeep" package. The line and dots on the graph represent the value of ICC, along with their corresponding 95% confidence intervals. If only the point is shown in the graph, it indicates that the confidence interval for that point estimate extends beyond the range of our coordinate axes (0, 1). The upper facet of the figure presents the results for ICC2k, while the lower facet displays the results for ICC.

## Correlation Between Monte Carlo SHR and Trial Numbers

In this section, we present the results of the correlation between Monte Carlo SHR and trial numbers (Fig. 5). Some outcome variables, such as RT, efficiency shown significant correlation between Monte Carlo SHR and trial numbers. However, for outcome variables like *d’* and *v*, there is minimal correlation between trial numbers and SHR. It is found that the SPMT paradigm requires approximately 80 trials to achieve a Monte Carlo SHR of 0.8 when the SPE measure is RT under 'Stranger', and about 120 trials under 'Close.' Additionally, achieving a Monte Carlo split-half reliability of 0.8 for *v* may require more than 130 trials. On the other hand, high Monte Carlo SHR is challenging to achieve for the remaining three outcome variables, particularly for the *z*, even with 150 or more trials.

It is important to emphasize that here we only conducted a simple regression analysis of trial numbers and Monte Carlo SHR based on the collected datasets. This analysis was not part of the pre-registered plan, and our primary aim was not to provide a well-validated improvement for the SPMT. However, considering the significant correlation between the number of trials and Monte Carlo split-half reliability, our findings suggest that, for the SPMT paradigm, achieving higher reliability for clinical evaluation would necessitate conducting more trials. As a reasonable approach, it might be beneficial to consider having more than 120 trials under each experimental condition.



**Supplementary Fig. 5** Regression analysis between Monte Carlo SHR and trial numbers using different SPE measures.

*Note:* The vertical axis represents Monte-Carlo split-half reliability, and the horizontal axis represents the number of trials. Each facet represents one SPE measures.

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