RUNNING HEAD: FAILURE TO ENGAGE FAILS A FIXED-POINT TEST.

A Critical Test of the Failure-to-Engage Theory of Task-Switching

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Abstract

When people switch between two tasks, their performance on each is worse than when they perform that task in isolation. This "switch cost" has been extensively studied, and many theories have been proposed to explain it. One influential theory is the "failure to engage" (FTE) theory, which posits that observed responses are a mixture of prepared and unprepared response strategies. The probability that participants use prepared processes can be manipulated experimentally, by changing preparation time, for example. The FTE theory is a binary mixture model, and therefore makes a strong prediction about the existence of fixed points in response time distributions. We found evidence contradicting this prediction, using data from 54 participants in a standard task-switching paradigm.

The study of executive control mechanisms has benefited in recent years from experiments in the task-switching paradigm. These experiments require participants to perform two different tasks (A and B) repetitively, sometimes switching between the tasks and sometimes repeating a task. Rogers and Monsell (1995) developed a task-switching paradigm using alternating runs: participants were required to perform tasks in a sequence such as AABBAABB. This design ensured that both task switching (from A to B and from B to A) as well as task repetition (AA and BB) occurred within the same block of trials. Rogers and Monsell found a *task switching cost*: response time (RT) was slower on switch trials than on repeated trials. Rogers and Monsell also found that this switch cost decreased when the interval between one stimulus and the next (the response-to-stimulus interval, or RSI) was increased, but that there was an irreducible switch cost that was not removed, no matter how long RSI became. Other researchers have since replicated and extended these findings, using the repeated runs design (e.g., De Jong, 2000; Gilbert & Shallice, 2002; Karayanidis, Coltheart, Michie & Murphy, 2003; Lien, Schweickert & Proctor, 2003; Los, 1999; Nieuwenhuis & Monsell, 2002; Sohn & Anderson, 2003; Yeung & Monsell, 2003).

The Failure to Engage Hypothesis

Many theories have been proposed to explain the costs associated with switching between tasks. Many task-switching theories are “task set inertia” (TSI) models, which have substantial empirical support (e.g., Allport, Styles & Hseih 1994; Gilbert & Shallice, 2002; Los, 1999; Yeung & Monsell, 2003). TSI theories propose that each of the two tasks to be performed has an associated “task set”, loosely defined as a mental state that must be prepared in order to accomplish that task. Switch costs are explained as processing overhead due to changing task sets. Residual switch costs (i.e., switch costs that remain even at very long RSI values) are explained by “inertia” in task sets – changing one task set for another is effortful, and sometimes fails to occur during the response-to-stimulus interval. A prototypical TSI model is the “failure to engage” (FTE) theory of De Jong (2000), illustrated in Figure 1. The FTE theory proposes that responses arise from one of two processes: a “prepared” process, in which the participant is ready to perform the task, or an “unprepared” process in which the participant must first load the associated task set before the task can be performed. Prepared and unprepared processes lead to faster and slower RTs, respectively. According to the FTE theory, the observed RT on any given trial is either a sample from the distribution associated with the prepared process (with probability given by, say, α) or from the unprepared distribution (with probability $1-\alpha$). Thus, according to FTE theory, the observed RT distribution is a mixture of two unobserved distributions.

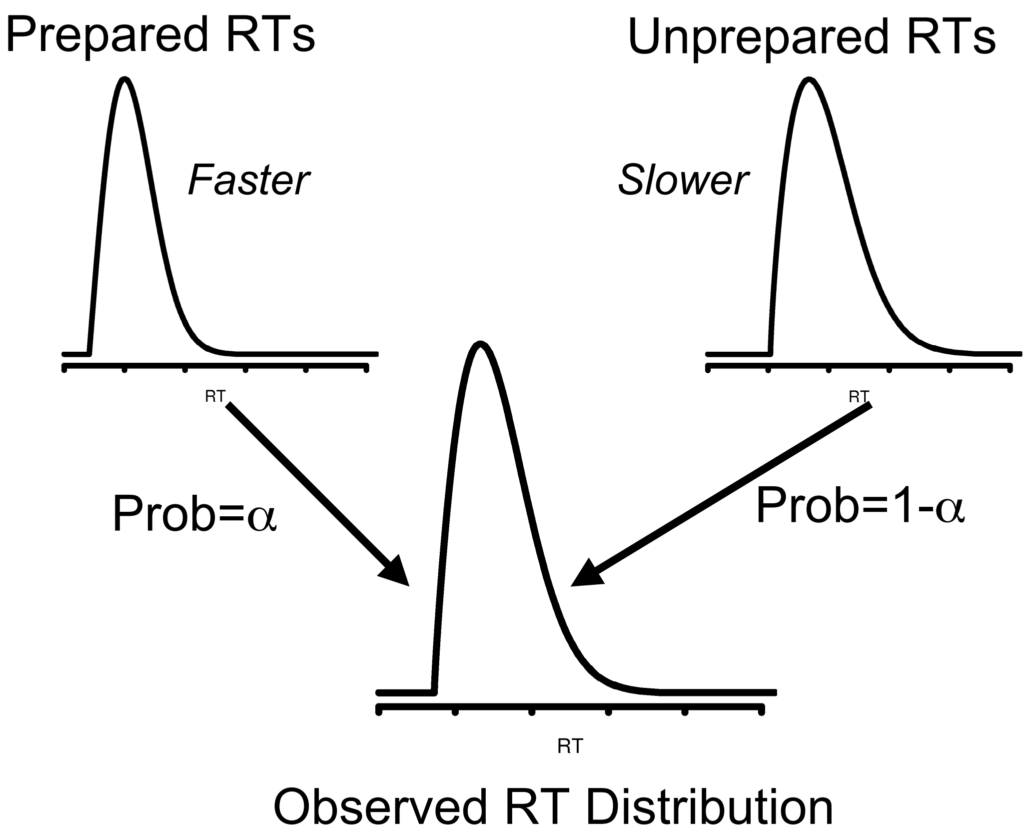

Figure 1: Schematic illustration of the Failure to Engage (FTE) theory of task switching. Observed RT distribution is a mixture of two unobserved distributions: those from "prepared" and "unprepared" mental states.

The FTE theory does not specify the form of the unobserved distributions, or the processes that give rise to them, but it does provide constraints on the value of α, the mixing parameter. In situations where the participant is relatively unprepared (e.g., short RSI conditions) α will be small: most observed responses will be drawn from the unprepared distribution, and so the observed distribution will be similar to the unprepared distribution. When the probability of preparation (i.e., α) increases the observed distribution is more similar to the prepared RT distribution.

According to the FTE theory, the probability of preparation (α) can be changed by experimental manipulations. For example, longer RSI values, or greater rewards for fast responses should both increase α. Nieuwenhuis and Monsell (2002) found that larger RSI values increased the value of α in model fits of the FTE theory, but there was a limit: across participants, the mean estimate of α was only 64%. This implies that residual switch costs are due to participants' failure to engage on over one third of trials, even when highly motivated and given ample preparation time. Nieuwenhuis and Monsell found that the FTE model fit the observed data well, lending support to that theory. Other researchers have also observed data that are generally consistent with the FTE theory, or at least are not in direct contradiction to it. Lien et al. (2003) found evidence supporting the assumption that executive control proposes can only accommodate processing of one task at a time, consistent with the mixture assumption of FTE. Yeung and Monsell's (2003) results were compatible with TSI theories in general, and hence with the FTE theory in particular. Los (1999) found evidence in favor of models that include two separate response strategies, like the FTE theory (as opposed to criterion shifting models). Monsell, Sumner and Waters (2003) observed that RT distributions were generally consistent with predictions from the FTE model, although that model was not uniquely supported by their data.

A Critical Test of the FTE Theory

Other results have been less clear in their support of FTE theory. Gilbert and Shallice's (2002) data supported the general idea of TSI, but they also observed that the binary assumption of FTE – that task-set preparation is "all or nothing" – was not required to explain the data. Lien et al. (2003) observed interactions between RSI and task response style that were inconsistent with the basic version of FTE theory. Sohn and Anderson (2003) found effects of task foreknowledge and stimulus-related priming that were not predicted by FTE theory, and may be inconsistent with it. None of these studies represent a direct test of the FTE model – they were each designed to meet some other goal, and only observed support (or not) for the FTE theory indirectly. Nieuwenhuis and Monsell's (2002) study was designed as a direct test of the FTE theory, but the test was an evaluation of goodness of fit: data were collected and the ability of the FTE theory to fit those data was tested. The FTE theory successfully fit the data, but the value of this kind of test is unclear (e.g., Roberts & Pashler, 2000). The ability of a model to adequately fit data does not necessarily provide strong evidence for that model, unless the ability of the model to fit unobserved data is also tested.

A better way to test the FTE hypothesis is to derive a strong prediction and test it in data. The more surprising and unlikely the prediction, the stronger the test of the theory. Falmagne (1968) outlined a surprising prediction of all binary mixture models – that their distributions must have a fixed point across changes in mixture probabilities. Falmagne (1968) used this property to disprove another binary mixture model of RT (Falmagne's, 1965, "fast guess" theory). Falmagne's (1968) fixed-point property applies to any binary mixture model, including the FTE theory. Falmagne's observation was that, if the probability distribution functions (PDFs) of the two mixture components cross at some point, then all mixtures of those two distributions must also cross at that same point[1]. For FTE theory, this means that if the PDFs for prepared and unprepared RTs cross at some point, then all observed RT distributions formed as mixtures from those two must also cross that the same point, as illustrated in Figure 2.

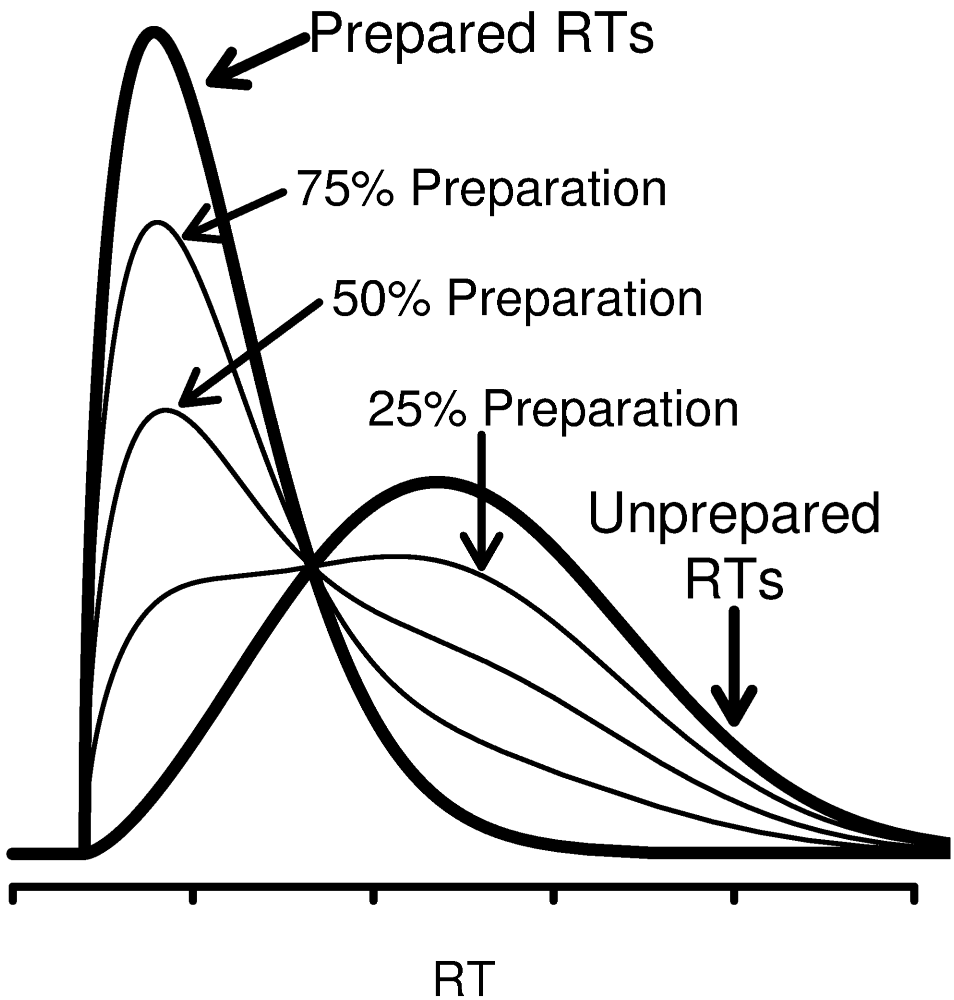

Figure 2. Falmagne's (1968) fixed point property as it applies to the FTE theory. PDFs produced from different levels of preparedness must share a common crossing point.

For the FTE theory this implies that if an experimental manipulation varies the probability of preparation (α) the PDFs produced under different levels of that manipulation must share a common crossing point. This property suggests a critical test for the FTE theory: experimentally manipulate the probability of preparedness and observe the crossing points of the resulting PDFs. If a binary mixture process underlies RT, the PDFs should share common crossing points. We carry out this test below, using RSI to manipulate the probability of preparation (α).

Method

Participants

Fifty-four undergraduate students from UC Irvine participated in this study, receiving partial course credit in return.

Stimuli and Design

Our tasks and experimental design were based on Rogers and Monsell's (1995) Experiment 3. One task was to classify a letter as a vowel (A, E, O or U) or a consonant (all consonants except Y and V), the other task was to classify a digit as odd (3, 5, 7 or 9) or even (2, 4, 6 or 8). Note that the letters I, Y, and V and the numbers 0 and 1 were omitted, as they were perceptually confusing. Two rectangles were drawn side-by-side on a computer screen, and the stimuli were presented side-by-side within either the left or the right rectangle (e.g. "G7"). The use of the left or right rectangle reliably indicated the participants' task, digit or letter, with task assignments counterbalanced across participants. Tasks alternated on a two-run schedule: that is DDLLDDLL… and so on. There were 18 blocks of 24 trials each, and the task on the first trial in each block was chosen randomly. Two buttons on a standard keyboard ("/" and "Z") were used for all responses, one for even and vowel responses, the other for odd and consonant responses, counterbalanced across participants. A reminder of which side of the screen corresponded to the digit task and which to the letter task, as well as which response key corresponded to even/vowel and to odd/consonant, was continuously displayed at the bottom of the screen.

Procedure

Each trial began with presentation of the stimulus, synchronized with the video monitor's vertical retrace. The stimulus remained on screen until a response was made, then a mask consisting of hash symbols (#) covered the stimulus. If the response was incorrect, a 128Hz tone was sounded for 200msec. Otherwise, a delay (RSI) of either 150msec or 500msec was enforced between the previous response and the presentation of the next stimulus. RSI values were always equal within a block, and were randomly assigned to blocks with replacement. At the start of each block, participants were informed what RSI value was coming in the next block ("long" or "short"), and were specifically instructed to use the RSI time to prepare for the upcoming stimulus. At the end of each block, participants were told their percent accuracy and average RT for that block. If their accuracy level fell below 80% for a single block, participants were given a flashing red warning screen and advised to take a rest.

Results

To observe the fixed-point property, we needed to estimate RT distributions. This required stationary data, to meet the iid assumption of standard estimation procedures. We carefully censored our data to help meet this assumption, at the possible cost of reduced power. Mean RT showed large practice effects in the first few blocks (left panel of Figure 3) and so the data from blocks 1-5 were not included in further analyses. Similarly, data from the first five trials of each block were much slower than the others (right panel of Figure 3) and were also excluded. As a check on our censoring procedures, we re-calculated all analyses without censoring any blocks, and only the first trial of each block, and found no substantive differences. RTs associated with incorrect responses, or immediately preceded by an incorrect response, were also censored. Finally, RTs greater than 2500msec were censored for the standard analyses of the mean, as these data were unlikely to originate from the process under examination. Long RTs were not censored for distribution estimation.

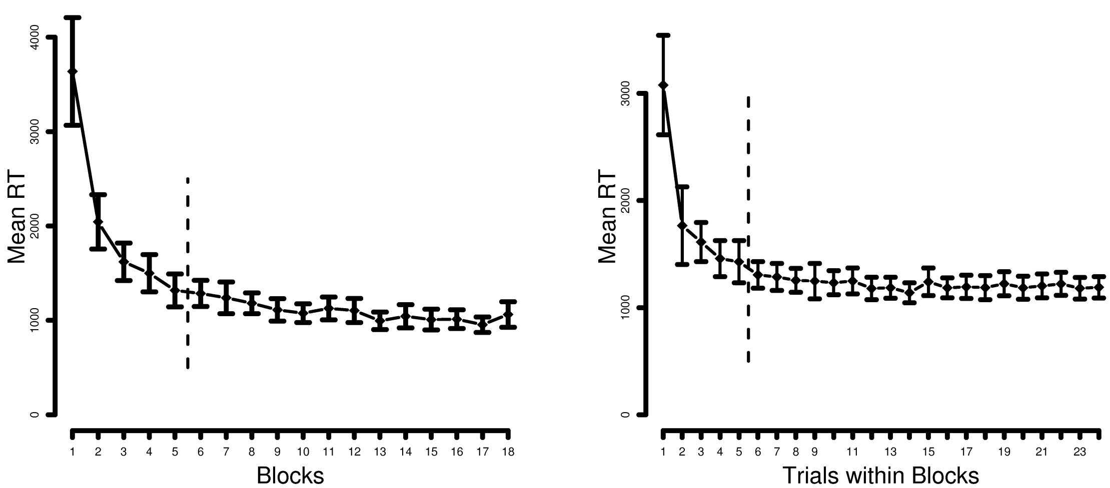

Figure 3: Mean RT, +/- twice the standard error of the group means, for blocks (left panel) and trials (right panels). Data from the first five blocks were censored, and from the first five trials of each block thereafter. Axis limits are different on each graph.

Task-switching Effects

As expected, longer RSI was associated with smaller RT and with lower switch costs. For the digit task, mean RT on repeating trials (i.e., those trials preceded by another digit task trial) was 755msec. Switching trials (i.e., preceded by a letter task) were slower: for short RSIs, mean RT was 1075msec (switch cost of 320msec); for long RSIs, mean RT was 1033msec (switch cost of 278msec). A similar pattern was observed for the letter task. Mean RT on repeated trials was 744msec, mean RT on short RSI switch trials was 1084msec (switch cost of 340msec) and mean RT on long RSI switch trials was 1046msec (switch cost of 302msec). A three-way repeated measures ANOVA (RSI x switch/repeat x digit/letter) confirmed that these effects were reliable (main effect of RSI: $F(1,53)=8.8$, $p<.01$, $MS_E=22262$; main effect of switch/repeat: $F(1,53)=175$, $p<.0001$, $MS_E=55720$; interaction of RSI with switch/repeat: $F(1,53)=5.0$, $p<.05$, $MS_E=5150$; all four other tests non-significant). Separate 2x2 ANOVAs for digit and for letter data showed that the RSI manipulation was more effective for the digit task ($F(1,53)=13.4$, $p<.001$, $MS_E=11096$) than the letter task ($F(1,53)=3.6$, $p=.06$, $MS_E=16119$), due mainly to less variability in the data from the digit task.

Distribution Crossing Points

For each participant, data were separated by digit vs. letter tasks. Data were further classified into three distributions: repeated trials (from the long RSI condition); switching trials from the short RSI condition (RSI=150msec); and switching trials from the long RSI condition (RSI=500msec). For each of these six data conditions, separately for each participant, an empirical estimate of the PDF was calculated using a standard kernel density estimator (see, e.g., Fan & Gijbels, 1996; Silverman, 1986). We used a Gaussian kernel and chose the bandwidth to be 1.25 times the value given by Silverman's (1986, p48) "rule of thumb" automatic bandwidth selector. We chose this method to avoid subjective bias in manual bandwidth selection, and chose a factor of 1.25 to provide a little "over smoothing", helping to minimize problems associated with multiple PDF crossing points. The empirical estimate of the density function was evaluated at each millisecond in the interval from 180msec to 5000msec. Our use of long-RSI repeated data and not short-RSI repeated data assumes that these data provide the best estimate of the "prepared" RT distribution (see also de Jong, 2000). This assumption is not crucial for our test – even if the probability of preparation in the long-RSI repeated trials is less than unity, the fixed-point property still holds (for any α-mixture). We also checked the assumption by re-calculating all analyses pooling both long and short RSI repeated trial data, with no major changes in the statistical conclusions.

After estimating these densities, six cross points were located for each participant. These were the crossing point of the repeated (long-RSI) trials with the short-RSI switch trials, the cross point of the repeated (long-RSI) trials with the long-RSI switch trials, and the cross point of the short-RSI and long-RSI switch trials, both for digit and for letter data. It was possible that each distribution pair had many crossing points (e.g., all RT distributions must converge at PDF(t=0)=0). We always selected the crossing point closest to the mid-point between the modes of the estimated distributions. Other choices were possible, but the mid-point between modes is associated with high data density and so presumably with higher cross-point location accuracy. Figure 4 shows the mean crossing points for digit (left side) and letter (right side) tasks, with error bars corresponding to standard error of the mean across participants.

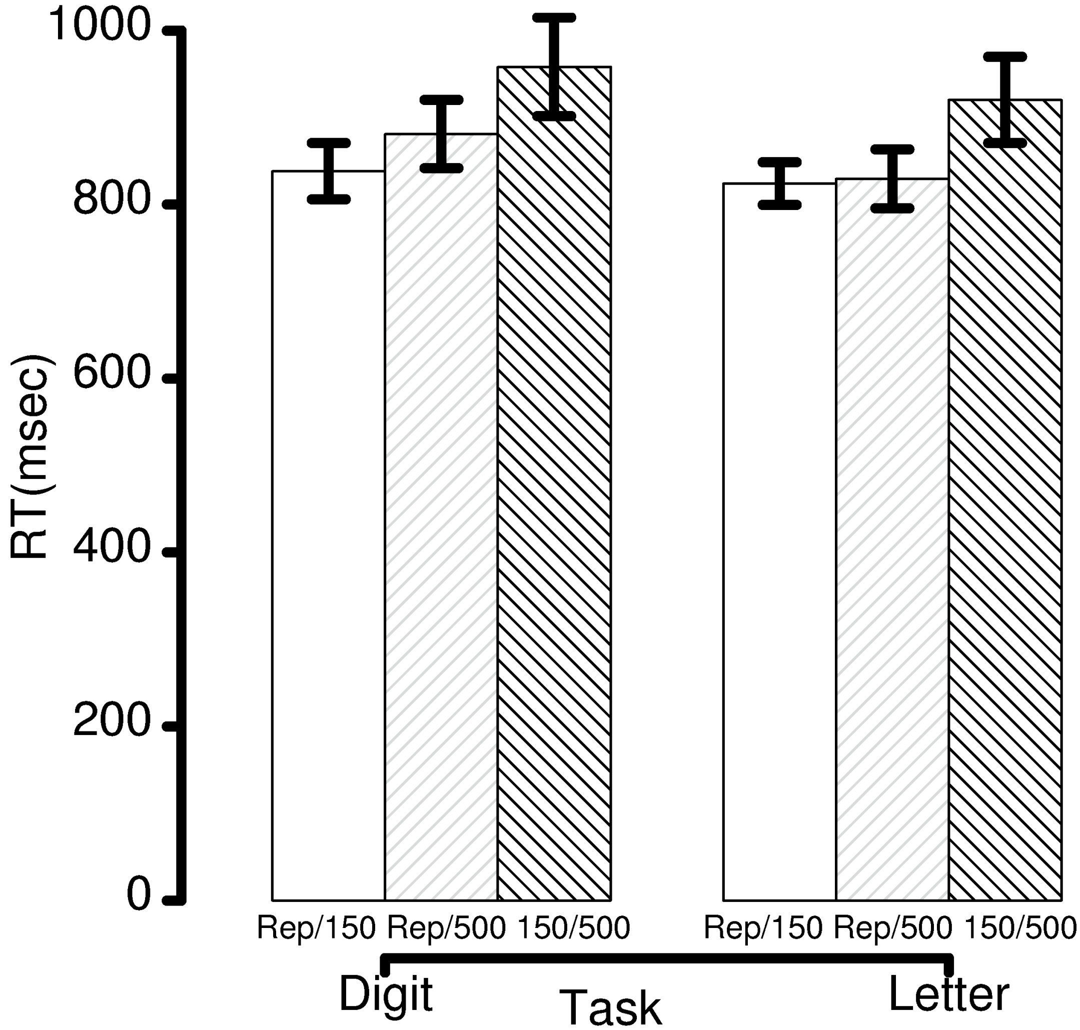

Figure 4: Mean crossing point RT (msec) for three distribution pairs: repeated data with short RSI switch data (unfilled bars); repeated data with long RSI switch data (gray diagonal lines); and long vs. short RSI switch data (black diagonal lines). Left side shows data from the digit task, right side shows data from the letter task. Error bars show +/- S.E.M. across participants.

In Figure 4, the crossing point for the long- and short-RSI switching distributions appears to be significantly greater than the crossing point for the other two distribution pairs; both for digit and letter tasks. We tested the reliability of this trend by calculating a two-way repeated measures ANOVA on the estimated crossing points, using digit/letter and distribution pair (repeated/short-RSI-switch *vs*. repeated/long-RSI-switch *vs*. long-RSI-switch/short-RSI-switch) as factors. The only significant test was the main effect of distribution pair: $F(2,106)=8.05$, $p<.001$, $MS_E=43078$, both other Fs<1. This test implies that the mean cross points (across digit and letter tasks) for the three distributions in question were different. Separate one-way ANOVAs for digit and for letter tasks showed that the crossing point differences were reliable for both: digits $F(2,106)=4.00$, $p<.05$, $MS_E=49733$; letters $F(2,106)=3.55$, $p<.05$, $MS_E=44353$.

Discussion

The analysis of distribution crossing points provides evidence against the binary mixture mechanism, used by the FTE model of task switching. If task-switching behavior actually was generated from a binary mixture process, the observed repeated and switch distributions would all have crossed at a common RT value, and the ANOVAs would have shown no significant effects of distribution pair. This was not the case. There were significant overall effects of distribution pair on crossing point, and these effects were reliable even when analyzing crossing points from the digit or letter tasks alone. Our data should not be construed as general evidence against TSI or two-process models of task-switching. The test we employ applies only to binary mixture models, and so does not constitute evidence against two-state models in forms other than binary mixtures.

The FTE model cannot accommodate the current results without some modification. There seem to be several obvious ways the model could be changed to allow the distribution crossing points to vary with RSI, although none seem entirely satisfactory. Falmagne's (1968) fixed-point property only applies to *binary* mixture models. If the mixture mechanism in the FTE model was broadened to include more than just the two states of "prepared" and "unprepared", our test would not apply. Our method also assumes that nothing in the model changes between the different conditions except for the mixture probability, α. While this is consistent with the extant form of the FTE model, the model could reasonably be extended to allow other changes with RSI, perhaps in the form of the mixing distributions. Although both of these modifications allow the FTE theory to accommodate our data, they are intellectually dissatisfying. One of the main benefits of the FTE theory is its simplicity – just two distributions and a mixture parameter. Elaboration weakens this advantage.

Even in light of our data, the elegant simplicity of the FTE theory of task switching, with its binary mixture mechanism, justifies continued exploration of the FTE theory. Its simplicity makes the FTE theory useful as a descriptive measurement tool, if not as a process model of task switching. The FTE theory can be fit to data more easily than any other quantitative theory of task switching, providing useful parameter estimates and distribution measurements. This quality makes the FTE theory useful as a descriptive tool, similarly to the way signal detection theory is used in memory research.

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[1] The proof is elementary: suppose the PDFs of two mixing distributions are $f(x)$ and $g(x)$, and $f(y)=g(y)$ for some y. The PDF of an α-mixture of f and g is given by $w(x)=\alpha f(x)+(1-\alpha)g(x)$, and so $w(y)= \alpha f(y)+(1-\alpha)g(y)=f(y)$, by assumption.