

## Inhibition-driven Button Click Response Times in the Attention Concentration Test

Ad van der Ven<sup>1\*</sup>, Risto Hotulainen<sup>2</sup> and Helena Thuneberg<sup>2</sup>

<sup>1</sup>Institute for Learning and Development, Department of Pedagogy, Radboud University Nijmegen, Nijmegen, The Netherlands

<sup>2</sup>Centre for Educational Assessment, University of Helsinki, Helsinki, Finland

**Corresponding Author:** Ad van der Ven, Institute for Learning and Development, Department of Pedagogy, Radboud University Nijmegen, Montessorilaan 3, 6500 HE Nijmegen, The Netherlands.

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### Abstract

In previous articles [1,2], research reports were made using the response times obtained from the Attention Concentration Test (ACT). The ACT consists of color bars or dice bars and the subject has to click on certain of these colors or dice (the so-called targets). The response times used were bar response times. However, the current research uses the response times of the button clicks, that is, the times  $T$  that elapse between clicking two consecutive target buttons. The general null hypothesis was examined that this time has an exponential distribution. This was investigated by looking at the regression of the standard deviation of  $T$  to the mean of  $T$  corrected for shift. The number of non-target buttons located between two consecutive target buttons still plays a role in this regression. Therefore, a linear regression analysis of  $T$  on  $K$  was also performed for the response times obtained with each individual test administration, and then, over test administrations, the ratio of the square root of the mean square residual and the absolute value of the smallest residual score was examined. The null hypothesis of an exponential distribution had to be rejected in favor of a probability distribution in which the transition rate increases with time. This result is favorable for the inhibition theory. The probability distribution with a square root hazard rate appeared to describe the data well. The discussion discussed how this result could be precisely understood in the context of the inhibition theory.

**Keywords:** Attention Concentration Test (ACT); Inhibition Theory

### Introduction

In the theory of inhibition it is assumed that whenever one has to use one's mind there are constantly alternating short periods of attention (really busy thinking) and distraction (getting away from it). During an attention period something like inhibition (inhibition to continue) rises and the rise is linear with slope  $a_1$  and during distraction periods inhibition falls and also the fall is linear with slope  $a_0$ . This inhibition is unintentional and not self-regulating. As the inhibition rises during a period of attention, the tendency (transition rate) to fall into a distraction increases, and as the inhibition decreases during a distraction period, the tendency (transition rate) to return to a period of attention increases. Instead of the amount of inhibition as the guiding force, one could instead have taken the amount of energy or better of mental energy as the guiding force. Mental energy is the opposite of inhibition. The idea of a diminishing mental energy during periods of attention and a restorative, increasing mental energy during periods of distraction has also been suggested by Spearman: **Usually hard work, we may suppose, produces an increased consumption of this energy, and thereupon a corresponding increase in**

its recuperation ([3], chapter XIX, page 327).

The process of raising and falling of the inhibition can be described as a random oscillator as a result of which the distraction times are sometimes a bit longer and sometimes a bit shorter, and that also applies to the attention times. The inhibition theory [4-6]. was originally designed to explain the fluctuation of response times as measured in simple self-repeating tasks such as the Bourdon-Wiersma Test [7]. The task as a whole is split into a number of equivalent subtasks (the lines in the Bourdon Wiersma test) and the response time for each subtask is measured. Each individual response time is considered to consist of a series of alternating real working times  $A_i$ , so-called attention times and non-working times  $D_i$ , so-called distraction times:

$$T = A_1 + D_1 + A_2 + D_2 + \dots + D_N + A_M = A_1 + A_2 + \dots + A_M + D_1 + D_2 + \dots + D_N$$

where  $M = N + 1$ . It is generally assumed that the sum of the real working times is constant, not random, because the work required for each sub-task is the same. This makes

$$T = A_1 + A_2 + \dots + A_M + D_1 + D_2 + \dots + D_N = A + D$$

where  $A$  is non-random constant and  $D$  is defined as

$$D = D_1 + D_2 + \dots + D_N$$

Notice that  $D$  is a random variable which is dependent on a random number of distractions  $N$ . Therefore, the random part of  $T$  is only the total distraction time  $D$ . In the case of the Poisson inhibition model [6] and also in the case of a simpler model, namely the model underlying the Poisson Erlang distribution [8],  $N$  has a Poisson distribution. If the time it takes to complete a subtask is very small, it can be reasonably assumed that the number of distractions will be close to one and then, for reasons of parsimony, it can further be assumed that the number is exactly equal to one i.e.  $N = 1$  with  $P(N = 1) = 1$ . The empirical study, reported in this article, used subtasks that yielded very short response times.

Smit and van der Ven [6] have proposed two model variants, namely the gamma or Poisson inhibition model and the beta inhibition model. Both models are controlled by four parameters, including parameters  $a_1$  and  $a_0$ . The response times for the consecutive subtasks are used to investigate whether the model is actually correct. The number of these is generally quite limited, which is why researchers usually only look at the mean and the variance. The problem, however, is that with a model with two or more parameters it is always possible to find parameter values that are consistent with the observed mean and variance. It would therefore be much more convenient if a single parameter model were available. The simplest one-parameter model one can think of is the model underlying the exponential distribution. However, that model has a constant hazard rate and therefore conflicts with the idea that response times are driven by an underlying inhibition process. The assumption of a constant hazard rate underlying the exponential distribution can therefore at most act as a kind of null hypothesis. But this raises the question of whether there exists a probability distribution, where the hazard rate increases with time. Such a distribution is the Weibull distribution. The Weibull distribution (see Wikipedia) has two parameters: a scale parameter  $\lambda$  and a shape parameter  $k$ . For  $1 < k$ , the hazard rate  $h(t)$  always increases, which is consistent with an underlying inhibition process. For a given value of  $k$ , the Weibull distribution has only one parameter, namely the parameter  $\lambda$ . If the exponential distribution should be rejected, then it can be seen which value of  $k$  can be used as an alternative to the exponential distribution.

This article is a report of a study that has taken place to see if the exponential distribution holds for the response times obtained with subtasks that require very little time to complete. It concerns the button click response times, which are obtained with the ACT. Such an investigation has previously taken place for the so-called bar response times [2]. A bar actually represents a series of buttons to be clicked

upon.

**The test**

The test used, i.e. the ACT, has been extensively discussed in van der Ven., *et al* [2]. It would therefore be completely redundant to repeat all of this in this article. It is sufficient to state that the default version of the test consists of a series of 25 bars with the colors blue, green, yellow, orange, red and purple. Each of these colors occurs exactly three times. An example of such a bar can be found in figure 1. The order of the colors is random. Each color occurs once with the first six colors, once with the second six colors and once with the third six



*Figure 1: Sample bar of the colours task of the Attention Concentration Test*

colors. There are no adjacent colors that are the same. The intention is that the red colors, the so-called targets, are clicked on as quickly as possible, whereby no mistakes may be made.

**Theoretical consideration**

In the article by van der Ven., *et al.* [2] the statistical analyzes were done based on the bar response times. In this article the statistical analyzes will be based on the individual button click response times. In the default version of the test there are three types of response times and for that matter also three types of numbers of non-target buttons between consecutive target buttons:

1.  $T_1$  the time that elapses between clicking the start button and clicking the first target button.  $K_1$  the number of non-targets plus one before the first target button.
2.  $T_2$  the time that elapses between clicking on the first target button and clicking on the second target button.  $K_2$  the number of non-targets plus one between the first target button and the second target button.
3.  $T_3$  the time that elapses between clicking on the second target button and clicking on the third target button.  $K_3$  the number of non-targets plus one between the second target button and the third target button.
4.  $T_4$  the time that elapses between clicking on the third (last) target button and clicking on the start button for the next bar.  $K_4$  the number of non-targets plus one after the third (last) target.

The research study, the results of which are discussed below, worked only with response times  $T_2$  and  $T_3$ . As suggested in the introduction, it is assumed that since the time required to complete each subtask is relatively short, each response time consists of only one distraction. So the response time  $T$  for completing a subtask can then be written as

$$T = A + a K + D,$$

where  $A$  and  $a$  are each constant and  $D$  is a random variable, which is assumed to have a distribution characterized by only one parameter. If  $K$  and  $D$  are assumed to be independent of each other, then with a linear regression of  $T$  on  $K$  the intercept is an estimate for  $A + E(D)$  and the slope is an estimate for  $a$ . In addition, the mean square residual (MSR) is an estimate for the variance of  $D$  and the absolute value of the smallest value of the residual scores an estimate for the expectation of  $D$ . These last two properties in particular will be used to investigate the different hypotheses about the distribution of  $D$ .

## Method

### Sample

The sample consisted of 540 cases. Notice, that there can be more than one case for a single subject (person). The age varied from 7 to 71 years. The frequency table

Age in years	7	8	9	10	11	12	13	15	16	17	18	19	20	21-71
Frequency	27	25	98	126	33	49	16	19	16	10	19	2	2	42

**Table 1:** Frequency distribution of age for the ages 7 - 71 (missing 56).

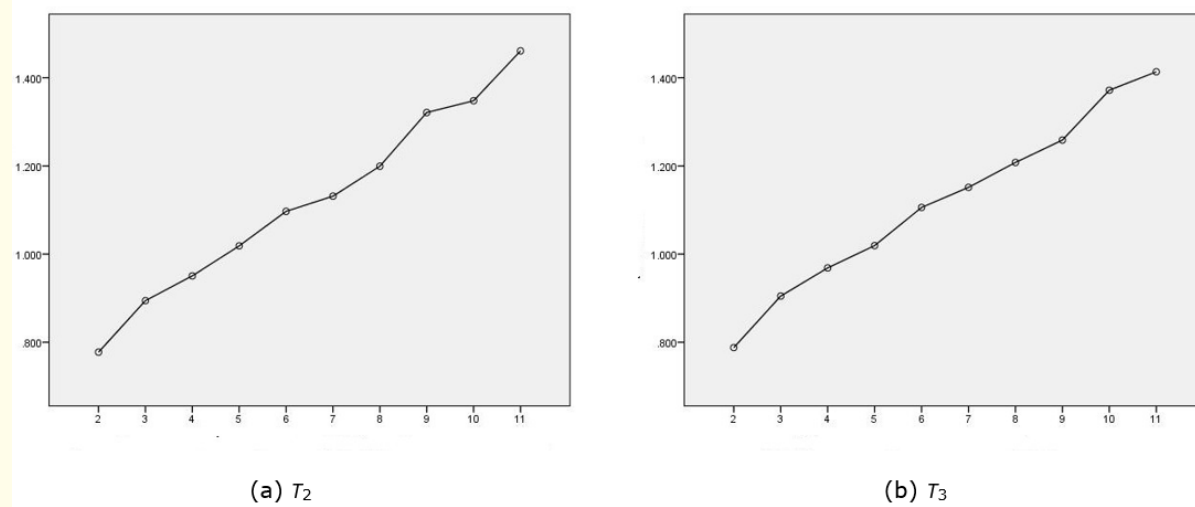
of age is given in table 1. Notice that the majority of the cases has the age of 9 - 10 years. Most cases came from testees from Finland. This number was equal to 389. In all these cases, the age ranged from 7 to 20 years. In 55 cases, the country of origin was unknown.

## Results

The time  $T_1$  that elapses between clicking the start button and the first target button can still be determined by a kind of start effect. Likewise, the time  $T_4$  that elapses between clicking the last target button and the start button for the next bar can also be determined by a possible end effect. Therefore, these times were not used in the analyzes that follow and only the response times  $T_2$  and  $T_3$  were considered. A separate analysis was made for the time  $T_2$  that elapsed between clicking the first target button and the second target button and the time  $T_3$  that elapsed between clicking the second target button and the third target button.

### Analysis of variance of $T_2$ and of $T_3$

Two separate univariate analyses of variance ( $N = 13500$ ) were performed: one with  $T_2$  as dependent variable and  $K_2$  as independent and one with  $T_3$  as dependent variable and  $K_3$  as independent. The effect of  $K$  was significant in both analyzes. In both analyzes, the first-degree polynomial effect was also significant, but the higher-order effects were not. A graph with  $K_2$  on the x-axis and the mean of  $T_2$  on the y-axis is shown in figure 2a. A graph with  $K_3$  on the x-axis and the mean of  $T_3$  on the y-axis is

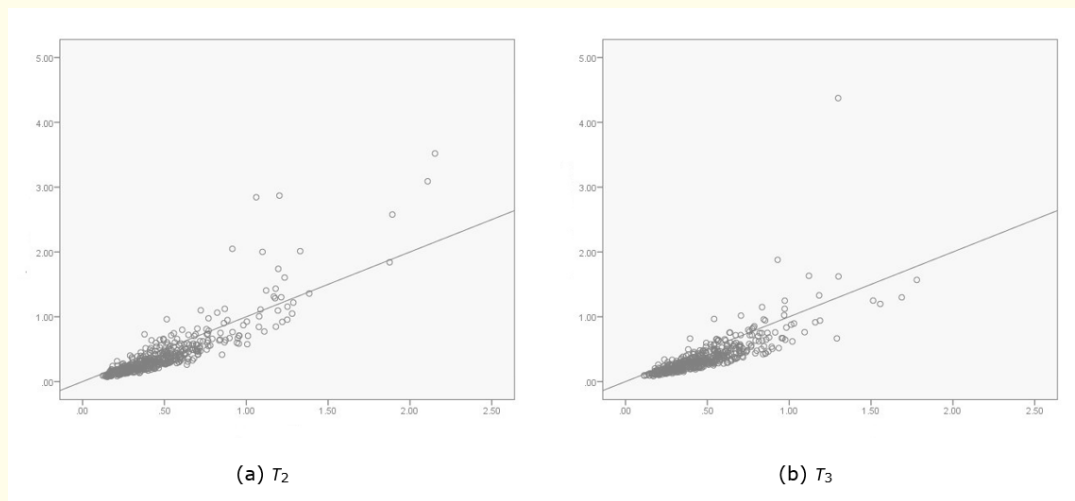


**Figure 2:** Average response times in seconds, depending on  $K$  (x-axis:  $K$ , y-axis: mean  $T$ ).

is shown in figure 2b. Both graphs show a nice linear relationship between the number of non-targets plus one between two consecutive targets and the time elapsed between clicking on the consecutive targets. This means that the number of non-targets located between two consecutive targets plays an important role in establishing the response time that elapses between clicking on the consecutive targets.

**Regression of  $s_2$  on  $m_2 - \min_2$  and of  $s_3$  on  $m_3 - \min_3$**

To investigate the null hypothesis that the random component of  $T_2$  and of  $T_3$  would follow an exponential distribution, the mean, minimum and standard deviation of  $T_2$  and of  $T_3$  were calculated on a case by case basis. A graph was then plotted separately for  $T_2$  and  $T_3$ , plotting the standard deviation against the difference between the mean and minimum response times. The latter was taken to correct for the above-mentioned shift parameter A. In the case of an underlying exponential distribution, one can expect that in the regression plot of  $s$  on  $m - \min$  the point cloud will be grouped around the line  $y = x$ , because in the case of an exponential distribution it holds that  $E(T) = SD(T)$ , where  $SD(T)$  is equal to the square root of  $Var(T)$ . The plots are shown in figure 3a and figure 3b, respectively. The two graphs clearly show that most points are below the line  $x = y$ , so the null hypothesis, that  $T$ , corrected for the shift parameter A, has an exponential distribution, must be rejected. The question then arises which distribution can be the underlying distribution instead of the exponential distribution. A possible candidate is the Weibull distribution (see Wikipedia) with  $\kappa = 3/2$ , where  $\kappa$  is a shape parameter, where the parameter  $k$  as used in the Weibull article in Wikipedia has been replaced by the Greek letter  $\kappa$ . This probability distribution has a transition rate  $h(t)$  that is proportional to the square root of  $t$  and is further determined by one parameter i.e.  $\lambda$ , where  $\lambda$  is a scale parameter. So basically it is the square root transition rate distribution. In the Weibull distribution with  $\kappa = 3/2$ , the ratio between the standard deviation and the mean is approximately equal to 0.6789686932 and the line  $y = 0.6789686932 x$  runs nicely through the area of the point cloud where the density of the points is greatest. Now the variables  $K_2$  and  $K_3$  still play an important role in the coming into existence of the variables  $T_2$  and  $T_3$  respectively. Therefore, the regression of the standard deviation from  $T$  on the difference between the mean and the minimum of  $T$  is still determined by  $K$ . In the next section, the effect of  $K$  is taken into account by using linear regression analysis of  $T$  on  $K$ .



**Figure 3:** Regression plot of the standard deviation of  $T$  on the mean minus the minimum of  $T$  ( $x$ -axis:  $m - \min$ ,  $y$ -axis:  $s$ ).

**Regression analysis of  $T_2$  on  $K_2$  and of  $T_3$  on  $K_3$**

A regression analysis of  $T_2$  on  $K_2$  and of  $T_3$  on  $K_3$  was performed on a case by case basis. Each analysis was based on 25 observations. The correlation between  $T_2$  and  $K_2$  is indicated as  $r_2$  and between  $T_3$  and  $K_3$  as  $r_3$ . This yielded 450 correlations for each of type of correlation ( $r_2$  and  $r_3$ ). The frequency distributions of  $r_2$  and  $r_3$  are given in figures 4a and 4b. The mean, standard deviation, skewness and kurtosis of the correlation between  $T_2$  and  $K_2$  are respectively 0.483, 0.201, - 0.499 and - 0.137. For the correlation between  $T_3$  and  $K_3$ , those values were respectively 0.488, 0.219, - 0.785 and 0.407. It is clear that the distribution of both variables is skewed to the left. However,

when an exponential transformation was performed of the type  $r \rightarrow \exp(r)$ , both variables were normally distributed. The results of the Kolmogorov-Smirnov test with one sample were satisfactory. For each of the two correlations  $r_2$  and  $r_3$ , the test statistic was 0.027 and 0.051, respectively, with right tail probabilities equal to 0.799 and 0.111. The mean and standard deviation of  $\exp(r_2)$  were respectively equal to 1.653 and 0.317. For  $\exp(r_3)$  these values were respectively equal to 1.666 and 0.338. To check the null hypothesis of an underlying exponential distribution the square root of the mean square residual MSR of the linear regression of  $T_2$  on  $K_2$  was then plotted against the absolute value of the minimum residual score i.e.  $|MRS|$ . The same was done for the square root of MSR of the linear regression of  $T_3$  on  $K_3$ . The plots are shown in figure 5a and figure 5b respectively. In these graphs, too, the points are largely below the line  $y = x$ , and the line  $y = 0.6789686932 x$  also indicates that the Weibull distribution for  $\kappa = 3/2$  seems fairly applicable. The graphs clearly show that the scatter of the points is not entirely homoscedastic. Homoscedasticity can be obtained by taking the natural log (ln) transformation of the square root of MSR and the natural log transformation of the absolute value of MRS. Figure 6a and figure 6b show the graphs with the ln-transformations. In the Weibull distribution for  $\kappa = 3/2$ , one has  $\sigma = 0.6789686932 \mu$ . This implies that  $\ln \sigma = -0.3871802572 + \ln \mu$ . The Weibull distribution for  $\kappa = 3/2$  seems to hold up very well again. The distribution of the points clearly shows that homoscedasticity is now present.

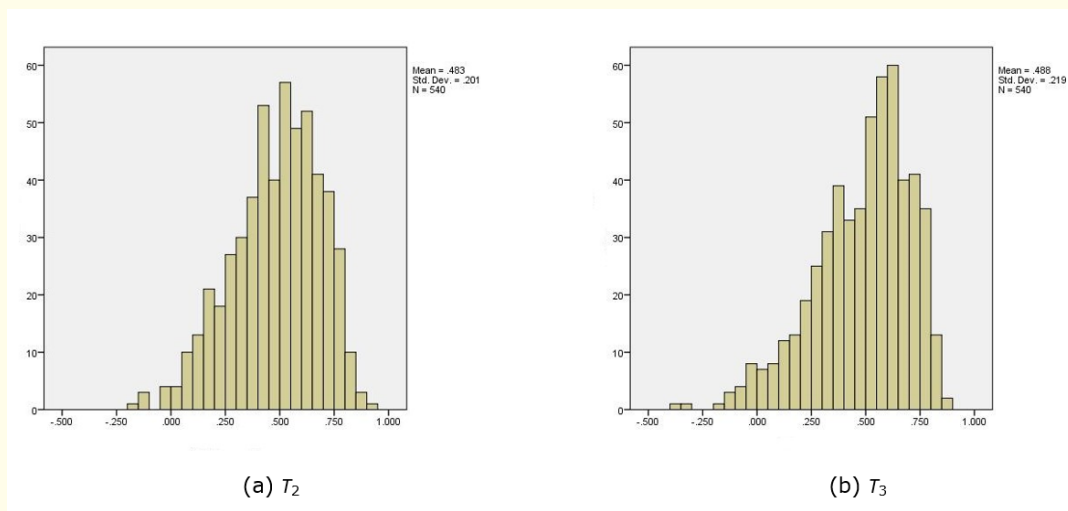


Figure 4: Frequency distribution of  $r_2$  and  $r_3$  (x-axis:  $r$ , y-axis: frequency).

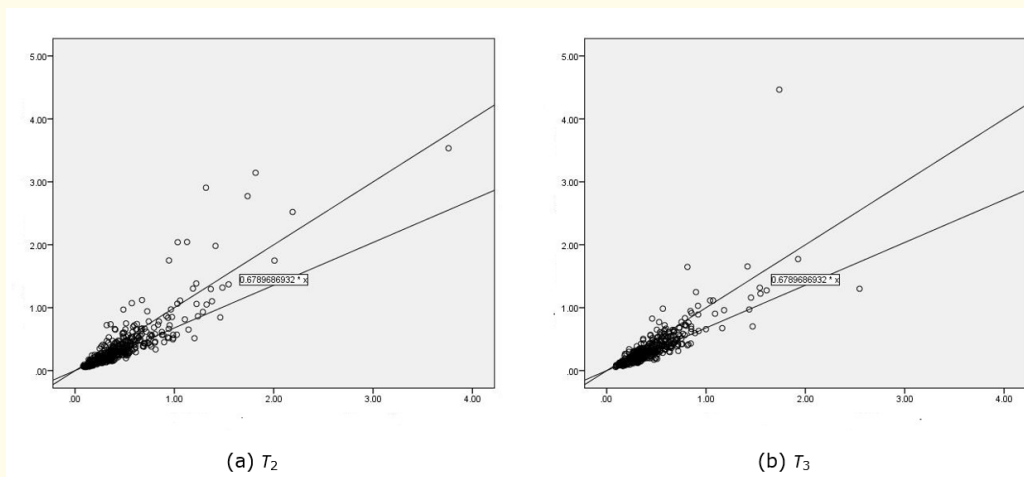
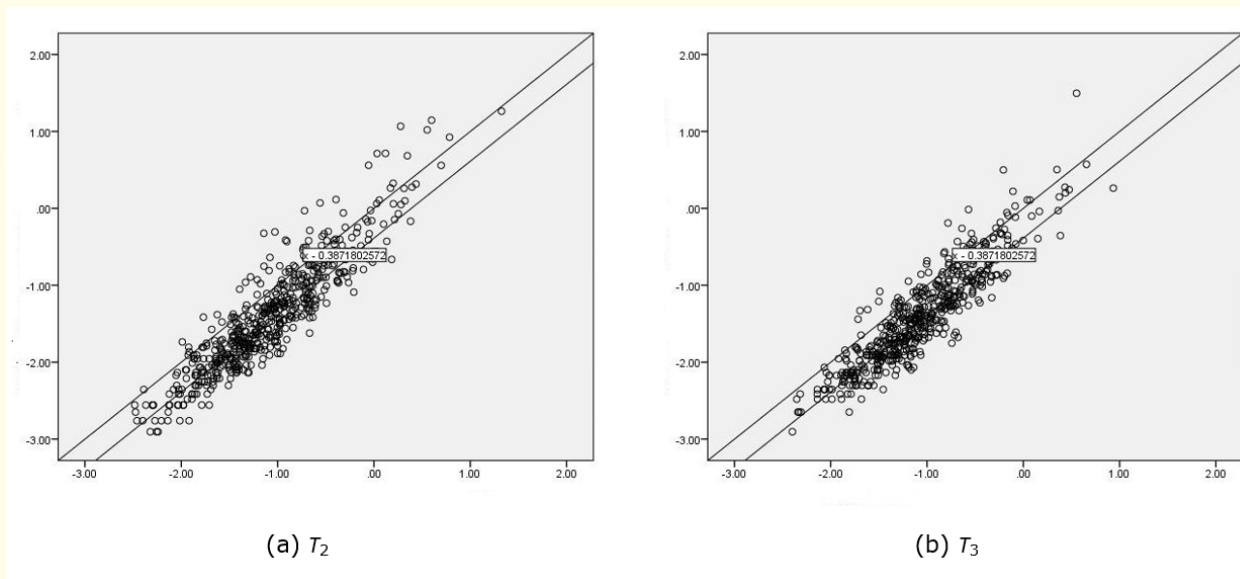
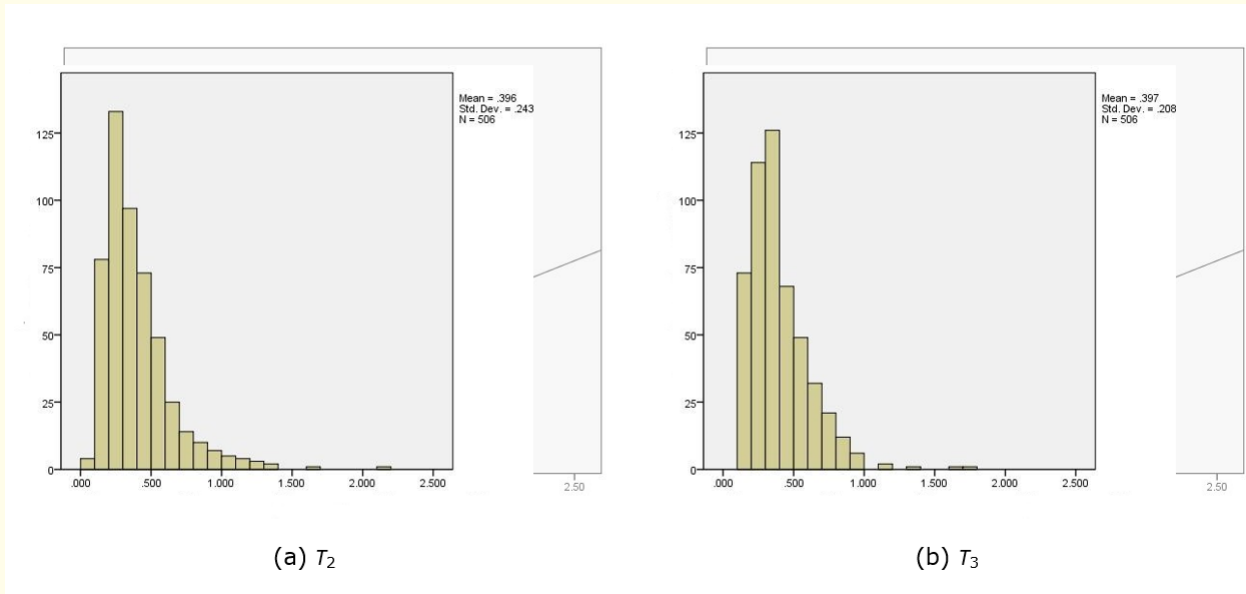


Figure 5: Regression plot of the square root of the mean square residual on the absolute value of the minimum residual score (x-axis: absolute value of MRS, y-axis: square root of MSR)

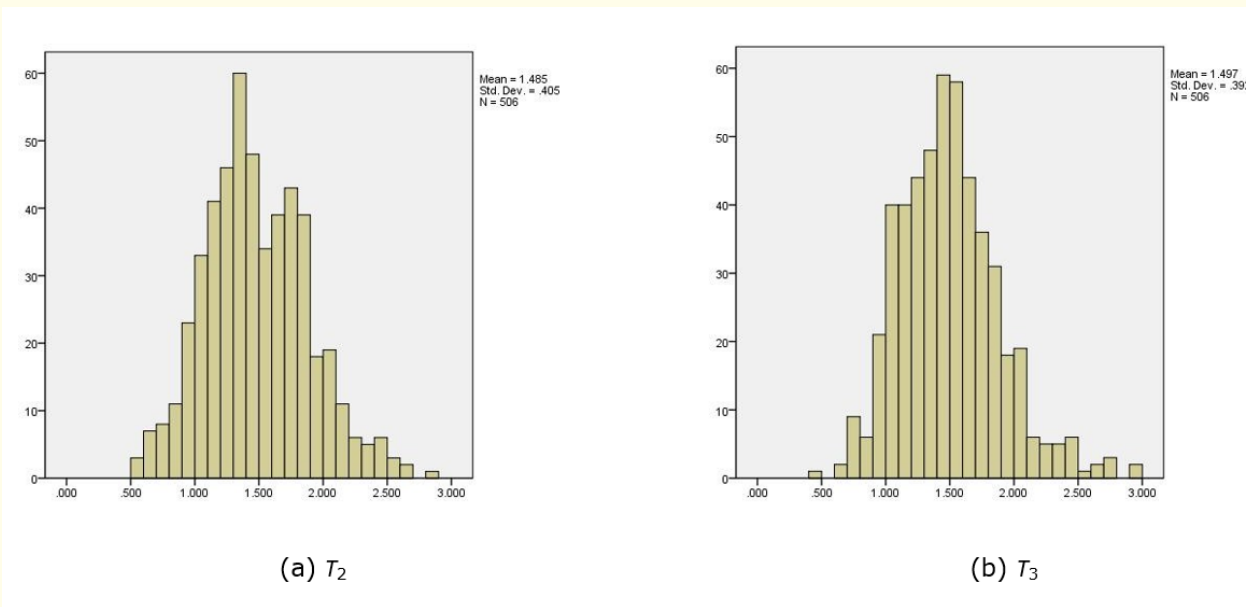


**Figure 6:** Regression plot of the natural logarithm of the square root of the mean square residual on the natural logarithm of the absolute value of the minimum residual score (x-axis: In absolute value of MRS, y-axis: In square root of MSR)

It was suggested above, assuming a one-parameter Weibull distribution, that the distribution with  $\kappa = 3/2$  might best explain the observed scatter plots. To double check this explanation, it was decided to estimate the parameters  $\lambda$  and  $\kappa$  on a case by case basis based on the statistics |MRS| and MSR and then check if the average of the estimate of  $\kappa$  would be close to  $3/2$ . If there was a one-parameter Weibull distribution with  $\kappa = 3/2$  underlying the response times, one would also expect that the estimated  $\kappa$  based on response times  $T_2$  should not be correlated with the estimated  $\kappa$  based on response times  $T_3$ . Indeed, if there were systematic differences in  $\kappa$ , there would also be a significant non-correlation between the estimated  $\kappa_2$  and the estimated  $\kappa_3$ . On Wikipedia, in the article entitled Weibull distribution, one can find expressions for the Mean and Variance in terms of  $k$  and  $\lambda$ . This allows two equations to be made, each with two unknowns. When one substitutes  $k$  for  $\kappa$  and then solves the two equations for  $\kappa$  and  $\lambda$ , one obtains expressions for  $\kappa$  and  $\lambda$  in terms of the Mean and Variance. Mean and Variance were replaced by |MRS| and MSR and finally a numerical solution for  $\lambda$  and  $\kappa$  was found, using the fsolve command of Maple release 2015.1. In 21 of the cases the estimated value of  $\kappa_2$  was negative. In 17 of the cases the estimated value of  $\kappa_3$  was negative. In 4 cases, both the estimated value of  $\kappa_2$  and the estimated value of  $\kappa_3$  were negative. For the calculation of the graphs and the calculation of the various statistics, the 34 cases in which the estimated value of  $\kappa_2$  or the estimated value of  $\kappa_3$  were negative were not included. Graphs of the frequency distributions of the estimated  $\lambda$  based on the response times  $T_2$  and  $T_3$  are shown in figures 7a and 7b and graphs of the frequency distributions of the estimated  $\kappa$  based on the response times  $T_2$  and  $T_3$  are shown in figures 8a and 8b. The mean and standard deviation of the estimated value of  $\kappa_2$  is equal to 1.485 ( $N=506$ ) and 0.405, respectively. The mean and standard deviation of the estimated value of  $\kappa_3$  is equal to 1.497 ( $N = 506$ ) and 0.392, respectively. The means are very close to the expected value of a random variable, which has a Weibull distribution with  $\kappa = 3/2$ . The correlation between the estimated value of  $\kappa_2$  and the estimated value of  $\kappa_3$  is equal to 0.086 with a two-tailed significance of  $p = 0.052$ . The correlation is very low, which is to be expected if one assumes that  $\kappa$  across cases is a constant. The two-tailed probability is significant at the 0.05 level, but this result can be easily obtained if the number of observations is quite large.



**Figure 7:** Frequency distributions of the estimated  $\lambda$  based on response times  $T_2$  and the estimated  $\lambda$  based on response times  $T_3$  (x-axis: estimated  $\lambda$ , y-axis: frequency).



**Figure 8:** Frequency distributions of the estimated  $\kappa$  based on response times  $T_2$  and the estimated  $\kappa$  based on response times  $T_3$  (x-axis: estimated  $\kappa$ , y-axis: frequency).



One could use the estimated value of  $\lambda$  as a possible score for the test. But the figures 7a and 7b clearly show that the estimated value of  $\lambda$  is not normally distributed. However, a natural log-transformation of the estimated value of  $\lambda$  appears to be normally distributed. The one-sample Kolmogorov-Smirnov statistics for the natural-log of the estimated value of  $\lambda_2$  and the natural-log of the estimated value of  $\lambda_3$  are respectively equal to 0.023 and 0.031 with two-tailed significances equal to 0.954 and 0.701. The internal consistency of these two measures was determined by calculating the correlation between them. The correlation was equal to 0.715 (N = 506). For individuals 7 to 16 years old, the correlation between the natural-log of the estimated value of  $\lambda_2$  and age was equal to -0.483 (N = 370) and the correlation between the natural-log of the estimated value of  $\lambda_3$  and age equal to -0.509 (N = 370) and the correlation between the natural-log of the estimated value of  $\lambda_3$  and age equal to -0.509 (N = 370). To obtain an idea of the reliability of age measured in years, the correlation was calculated between the age measured in years and the age measured in days, specific for the group with ages ranging from 7 to 16 years. This correlation was equal to 0.974. Now if the age measured in days is considered the true score and the age measured in years as the observed score, the reliability of the age measured in years is  $0.974^2 = 0.949$  according to the classical test theory [9]. With the help of the well-known formula for the correction for attenuation (see Wikipedia), it is now possible to calculate the true correlation between ln the estimated value of  $\lambda_2$  and age measured in years. This correlation is equal to -0.586. The true correlation between ln the estimated value of  $\lambda_2$  and age measured in years is equal to -0.618. These values are usually found when it comes to correlations between intelligence- and attention test scores and age.

## Discussion and Conclusion

Since the publication of the inhibition theory in Smit and van der Ven [6] the authors have tried to find empirical evidence for the actual existence of inhibition as a driving force for the observed response times. Now, after 25 years, it has finally been possible to report at least some evidence of the real existence of inhibition. The analysis was based on the default version of the Attention Concentration Test and only response times were used, which elapsed between two consecutive target button clicks. Had there not been an underlying inhibition process, these response times would have had a shifted exponential distribution, but the null hypothesis of a shifted exponential distribution clearly had to be rejected in favor of a hypothesis in which the transition rate increases (and therefore does not decrease). An increasing transition rate corresponds to a decreasing inhibition during periods of distraction. Within general inhibition theory, it is believed that a response time is actually composed of a series of alternating periods of real attention and distraction. It has been stated that with very short response times it can be reasonably assumed that there is always about one distraction period. According to the inhibition theory, the inhibition will decrease during this distraction period and thus the transition rate to switch to an attention period will increase. In the Weibull distribution, the transition rate increases when  $\kappa$  is greater than one. Therefore, the Weibull distribution with  $\kappa$  greater than one is consistent with the fact that the ratio of the square root of the mean square residual to the absolute value of the shortest residual score is almost always smaller than one. In the Weibull distribution, the transition rate has a value of zero for  $t = 0$  when  $\kappa$  is greater than one. A possible inhibition model that is consistent with this is a model in which, during each individual attention period, the time lasts until the inhibition has reached a fixed maximum value. At the beginning of each individual distraction period, the inhibition then has the same maximum value that the inhibition has at the end of the preceding attention period and that value then corresponds to a transition rate equal to zero. Actually, the way of explaining the response time behavior in terms of the inhibition concept is consistent with the natural science approach. This is fully in line with Herbart's approach: **The lawfulness of the human mind (German: Geist) is exactly the same as that of the starry sky ([10], p. 373).** According to Jahoda [11]: **Herbart conceived Vorstellungen as embodying Newtonian-type 'forces', with motions capable of being represented by sets of equations which lay at the heart of his mathematical psychology. Accordingly, he viewed them as existing in two modes, mechanics and statics. Mechanics referred to the forces being capable of producing motions of several different types, the simplest being that Vorstellungen can rise above the threshold of consciousness or sink below it over periods of time ([11], p.558).** Moving from a state of distraction into a state of attention corresponds exactly with Herbart's idea of a Vorstellung rising above the threshold.

### Data Availability

The author declares that the main data supporting the finding of this study are available upon request.

### Competing Interests

The author declares no competing interests.

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