Cognitive Fatigue in Young, Middle-Aged, and Older Adults: A Response Time Distribution Approach

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Abstract

Cognitive fatigue arises after a long-lasting task, as attested by increases in reaction times (RTs). However, most studies have focused on young adults. Therefore, we investigated cognitive fatigue through changes in RT distributions in three age groups - young, middle-aged and older adults – during a 160-minute Stroop task. Task duration was divided into four blocks and the ex-Gaussian parameters (μ, σ, τ) were extracted from individual RT distributions in each time block for each item type. The results showed a significant Group effect on μ. Young adults had smaller μ values than the other two groups, meaning that middle-aged and older people performed the whole task slower than young adults. By contrast, τ showed no Group effect but increased with Time-on-Task in middle-aged people. Older adults did not show τ increase with Time-on-Task, which echoes studies showing some resistance to task monotony in this population. Globally, our results showed dissociated age and Time-on-Task effect on the ex-Gaussian parameters, confirming the relevance of this approach in the cognitive fatigue domain. We proposed here that cognitive fatigue affects only the decision component of response production, and that midlife may be a life stage with high sensitivity to cognitive fatigue.

***Keywords*:** Cognitive fatigue, Time-on-Task, Ex-Gaussian parameters, Middle-aged, Normal aging

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Statements and declarations

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All participants gave their informed consent to participate, and the study was approved by the Ethics Committee of the Faculty of Psychology and Educational Sciences of the University of Liège and was in accordance with the Declaration of Helsinki (1964).

Humans undergo constant demands until advanced age and cognitive fatigue has become one prevalent cause of accidents in everyday life as in the workplace (Dinges, 1995). Cognitive fatigue can be divided into two aspects: objective fatigue, which describes task performance declines (response times or accuracy), while subjective fatigue refers to perceived feelings such as weariness, effort, exhaustion, or aversion (Kluger et al., 2013; Lorist et al., 2000). Interestingly, cognitive fatigue may result either from cognitive overload or cognitive underload (May & Baldwin, 2009), meaning that not only very demanding, but also very unchallenging tasks lead to cognitive fatigue. The most frequently used methods to explore fatigue effects are Time-on-Task and probe approaches. In the Time-on-Task approach, cognitive fatigue is induced by continuously performing a long-lasting task, from 20 minutes to many hours. In the probe approach, studies assess the impact of performing a fatigue-inducing task (as compared to a control, non-fatiguing one) on subsequent performance or brain activity (Esposito et al., 2014; Persson et al., 2013). Up to now, most studies have focused on the young adult population while middle and older ages have been scarcely studied.

What Is Known in Young, Middle, and Older adults

Cognitively fatigued young adults consistently exhibit increased RTs and decreased accuracy (Boksem et al., 2005, 2006; Boksem & Tops, 2008), particularly in executive functions (see for example, Boksem et al., 2006; Lorist et al., 200, 2008, 2009; Hopstaken et al., 2015a, 2015b, 2016). Cognitive fatigue in young adults has also been associated with brain activity changes in fronto-parietal areas (e.g. Lim et al., 2016; Nakagawa et al., 2013), decreased deactivation in the default mode network (DMN; Gui et al., 2015; Lim et al., 2016), but also to a left-to-right shift in brain activations (Persson et al., 2013), suggesting the resort to “older-like” cerebral compensation (Park & Reuter-Lorenz, 2009).

It is now well established that normal aging triggers diminished cognitive functioning efficiency (e.g., Collette & Salmon, 2014; Crawford et al., 2000). Somewhat surprisingly, the few existing fatigue-related studies in older people did not systematically find evidence of behavioral decrease in older as compared to young adults (Arnau et al. 2017; Falkenstein et al., 2002; Philip et al., 1999; Terentjeviene et al., 2018; Wascher et al., 2016). This lack of evident age-related change has been explained by a better resistance to task monotony and higher motivation in older as compared to young adults. Nonetheless, Burke et al. (2018) used a 160-minute Stroop task in older people and found preserved accuracy but increased RTs with Time-on-Task, supporting the existence of a speed-accuracy tradeoff in older people (Salthouse, 1979).

Mild cognitive changes can be observed in the midlife period (Bielak et al., 2013; Park et al., 2013; Wolkorte et al., 2014) but to a much lesser extent than older people. Moreover, this 40- to 60-year-old population has to deal with cognitive challenges every day. However, very few studies have investigated cognitive fatigue at midlife. In two fMRI studies, Klaassen and colleagues (2014; Klaassen et al., 2016) had young and middle-aged males perform a control or a fatigue condition followed by an in-scanner memory task. The 2014 results showed higher dorsomedial prefrontal cortex activation in middle-aged than young adults in the control condition, whereas activation did not differ between groups in the fatigue condition. The 2016 results showed decreased activity in the anterior cingulate cortex from the control to the fatigue condition in middle-aged but not in young adults. In line with the CRUNCH hypothesis (Compensation-Related Utilization of Neural Circuits Hypothesis; Reuter-Lorenz & Cappell, 2008) linking aging to increased cerebral activity at lower task level (e.g., the control condition) but decreased activity at higher task demands (e.g., in the fatigue condition), these results suggested middle-aged resort to compensatory mechanism at lower task level than young people and reach the CRUNCH threshold more quickly. Otherwise, middle-aged have also been shown to act in an error-aversive manner when performing a long-lasting task (de Jong et al., 2018) and to preserve accuracy at the expense of slowed speed (de Jong et al., 2018; Wolkorte et al., 2014).

Ex-Gaussian Analysis of RT

Abovementioned studies indicate that middle-aged and older adults favor accuracy instead of speed during cognitively fatiguing tasks. Moreover, decreased processing speed has been consistently reported as a hallmark of normal aging (e.g., Salthouse, 1996, 2000), making the assessment of RT distributions relevant to catch age effects. However, a common issue is to determine the most appropriate measure. Studies investigating cognitive fatigue often compare the mean RT between different time blocks of a long-lasting task. However, RTs are rarely normally distributed but tend to be positively skewed (i.e., possess a right-tailed asymmetry) because of the extreme RTs made by the participant (Heathcote et al., 1991). Therefore, using means or medians as outcomes would lead to erroneous conclusions because central tendency measures are useful for symmetrical distributions only. According to Heathcote et al. (1991), a distributional analysis is the most appropriate way to describe RTs, and, among the various mathematical models, the ex-Gaussian distribution has proven to fit RT data very well (see also Dawson, 1988; Hohle, 1965; Schmiedek et al., 2007). The ex-Gaussian distribution is the convolution of the Gaussian and exponential distributions (Burbeck & Luce, 1982; Luce, 1986) and is characterized by three parameters: μ and σ, which are respectively the mean and the standard deviation of the Gaussian component and τ, which represents the mean and the standard deviation of the exponential component. Changes in μ reflects left or right shifts of the distribution, changes in σ reflects widening or narrowing of the distribution, and changes in τ represent changes in overall skewness of the distribution, namely a thickening of the right tail of the distribution, corresponding to extreme RTs made by the participant. The sum of μ and τ is equal to the mean. In other words, μ represents the mean of the distribution cleaned from its extreme values. Therefore, considering the mean can be misleading because an increase in τ can be counteracted by a decrease in μ. Likewise, two individuals may have the same mean even if they have two different RT distributions (Balota et al., 2008).

Functional Significance of the Ex-Gaussian Parameters

RTs would result from two successive components (Hohle, 1965; Luce, 1986): the time to make a decision about the response – the *decision component* – and the time to physically make the response – the *motor-transduction component*. RTs allocated to motor-transduction would be normally distributed (with a mean of μ and a standard deviation of σ), while RTs allocated to decision would be exponentially distributed (with a mean of τ; Dawson; 1988). Consequently, distributions following the ex-Gaussian function capture both transduction-motor and decision processes (Lacouture & Cousineau, 2008). Accordingly, studies have linked τ with control-decision processes (West et al., 2002) and with higher level cognitive functioning (Schmiedek et al., 2007).

Wang et al. (2014) assessed changes in the ex-Gaussian parameters using a long-lasting Stroop task in young adults. They found a significant increase in τ (but not μ nor σ) with Time-on-Task, which the authors interpreted as diminished cognitive control under cognitive fatigue. Though not bearing on cognitive fatigue, some studies explored age group differences on the ex-Gaussian parameters. However, no study has applied the ex-Gaussian approach to discriminate between age groups in the context of cognitive fatigue.

The Present Study

This study is aimed at investigating the effect of age (young, middle-aged, and older adults) on cognitive fatigue induced by a 160-minute Stroop task in which Time-on-Task effect is objectivized by changes in RT distributions in four 40-minute successive time blocks. We used the ex-Gaussian approach to determine which changes in the distribution of RTs [right-sided move (μ, related to motor-transduction processes) or increase in extreme RTs (τ, referring to decision processes)] are triggered by cognitive fatigue and how it varies as a function of age groups.

Age-Related Hypotheses

If previous studies are discrepant regarding age-related change on the ex-Gaussian parameters (Hoffman & Falkenstein, 2011; Moret-Tatay et al., 2017), they all converge to the absence of age effect on σ. Therefore, we hypothesized higher values of μ and τ but not σ in middle-aged and older people as compared to young people. Since aging is associated with decreases in executive abilities (Collette & Salmon, 2014; Crawford et al., 2000), we expected a Group by Item interaction, showing larger age-related increase in μ and τ parameters for Incongruent items as compared to Congruent and Neutral items.

Time-on-Task Related Hypotheses

τ characterizes the overall skewness or extreme RTs (Heathcote et al., 1991; Schmiedek et al., 2007) and is a relevant parameter to capture attention fluctuation (Schmiedek et al., 2007). We assume τ can be a good candidate to represent extreme RTs due to attention drops triggered by our long-lasting task. Therefore, we expect an overall Time-on-Task effect (Block effect) on τ but not on μ or σ (Wang et al., 2014). Moreover, τ increases have been hypothesized to relate to failures in higher level functions (Brewer, 2011; Unsworth et al., 2010). Therefore, Incongruent trials should increase τ given the additional time required for interference resolution. We thus expect the Time-on-Task by Item interaction to be significant, with Time-on-Task effect being more pronounced for Incongruent items as compared to Congruent or Neutral items.

Age by Time-on-Task Related Hypotheses

Since older people basically experience cognitive decline compared to young adults, we assumed a greater fatigue effect would be observed in this population. We expected a Group by Time-on-Task by Item interaction to be significant with τ increasing on all item types (Congruent, Neutral, and Incongruent) and more particularly on Incongruent items (i.e., the most demanding items) with Time-on-Task for older people, but only on Incongruent items in young people.

Regarding middle-aged people, a hypothesis is more difficult to establish given the very few existing studies. However, as this population shows relatively well-preserved cognitive resources, we hypothesize middle-aged adults to resist cognitive fatigue in a similar way to young adults, namely they would show increase in τ with Time-on-Task only on Incongruent items.

Method

Participants

Participants were recruited via social media, word-of-mouth and through a database of healthy volunteers available at the GIGA-CRC in vivo Imaging. All participants gave their informed consent to participate, and the study was approved by the Ethics Committee of the Faculty of Psychology and Educational Sciences of the University of Liège and was in accordance with the Declaration of Helsinki (1964). Participants included here were also used as control group in another study investigating the effects of breaks as a way to recover from fatigue (Gilsoul, Libertiaux & Collette, 2022).

Eighty-four participants (36 Young, 27 Middle-aged, and 21 Older adults) were screened for the following criteria: (1) no neurological, psychological, or psychiatric disorders; (2) no abusive consumption of alcohol or drugs; (3) no color blindness (Farnsworth, 1947) and no dyslexia; (4) free of depressive symptoms (CES-DS; Radloff, 1977), with a cut-off score of 17 for men and 23 for women; (5) being Caucasian and native French speakers; (6) older people had to be community dwelling and autonomous in everyday life; (7) no diagnosis of neurodegenerative disease or dementia. The cognitive status of middle-aged and older participants was checked with the Mattis-DRS (Mattis, 1976). Middle-aged and older participants scored above 129 (range 135–144), which constitutes the cut-off threshold for risk of dementia (Monsch et al., 1995). Finally, participants had normal or corrected-to-normal vision and hearing.

Participants were given a sleep-wake schedule to complete the week before the experiment and were required to follow a stable sleep-wake rhythm and to sleep for at least 6.5 to 8 hours the night before the experiment. All experiments started in the morning or in the afternoon. Participants were asked to refrain from consuming caffeine, psychoactive or energy drinks 24 hours before the experiment and to avoid engaging in intense cognitive activities before the experiment.

Following the application of these criteria, 15 participants were excluded, and 14 others were dismissed for technical reasons (see Supplemental Data). The final sample comprised 55 participants: 21 young (8 men, M_{Age} = 22.43 years; SD = 2.01; range 19–26), 17 middle-aged (7 men, M_{Age} = 50.47; SD = 6.37; range 39–59), and 17 older people (9 men; M_{Age} = 65.06; SD = 3.19; range 62–72).

Procedure

Induction of Cognitive Fatigue: the Stroop Task

A modified version of a computerized Stroop task (Stroop, 1935) was administered for 160 minutes without any break. Stimuli were displayed on a black background on a PC using MATLAB 2015 (Mathworks Inc., Sherborn, MA). Different words ("BLUE," "RED," "YELLOW," "GREEN") or the symbol "XXXX" appeared one at a time printed in color: blue, red, yellow, or green. The task comprised Congruent (C) items (i.e., the ink color is similar to the printed word), Incongruent (I) items (i.e., the ink color is not similar to the printed word), and Neutral (N) items (i.e., "XXXX" symbol printed in one of the four colors). Buffer Neutral (B) items were inserted after each I item. These items resemble Neutral (N) items but are not taken into account in statistical analyses since they are only used to eliminate an undesired negative priming effect (Tipper, 1985). N items always appear directly after a C item and do not possess any relationship with the latter. Participants are unable to distinguish between truly Neutral (N) and Buffer Neutral (B) items. Because self-paced tasks do not impose restriction on RT and may alter measure reliability (Burke et al., 2018), stimuli in our time-constrained design were presented for a fixed duration of maximum 2500 ms and were separated by a fixation cross for 500 ms. Participants had to react to the ink color of the presented stimuli as accurately and quickly as possible by pressing one out of four possible answer keys. Participants were allowed to train on the task until they were comfortable with it. They were tested individually in a room free of visual or auditory disturbance, in which the temperature was kept constant and the light set at 250 (±10) lux because the high illuminance has been found to be the most ergonomic (Hu et al., 2018).

To control for subjective fatigue level before and after the 160-minute Stroop task, participants filled the Karolinska Sleepiness Scale (KSS; Akerstedt & Gillberg, 1990; Kaida et al., 2006), which is a 9-point scale ranging from 1 (very alert) to 9 (very sleepy). They also rated their levels of demotivation, fatigue, and effort on visual analogue scales (VAS) from 0 to 100.

All other self-report questionnaires (CES-DS, Vocabulary level, EES, PSQI) were administered at the first visit (see Supplemental Information for a detailed description) when the sleep-wake schedule to complete was provided and inclusion criteria were checked (i.e., color blindness).

The Ex-Gaussian Distribution

Since RT data are rarely normally distributed but positively skewed (right-tailed), estimates like means and medians do not adequately describe RT distributions (Heathcote et al., 1991). Therefore, we fitted the ex-Gaussian distribution to individual RT distribution using an algorithm based on Nelder and Mead (1965) and a greedy approach (see Supplementary Material; free access on osf.io/8d7hb). The ex-Gaussian distribution results from the convolution of a Gaussian and an exponential distribution (Burbeck & Luce, 1982; Luce, 1986). Its probability density function (pdf) is given by the multiplication of the exponential function by the complementary error function (erfc), which is essentially the same as the cumulative density distribution of the Gaussian function and can be written as follows:

$$f(x;\mu;\sigma;\lambda) = \frac{\lambda}{2} e^{\frac{\lambda}{2}(2\mu+\lambda\sigma^2-2x)} erfc\left(\frac{\mu+\lambda\sigma^2-x}{\sqrt{2}\sigma}\right),$$

$$\text{where } erfc(x) = 1 - erf(x)$$

$$= \frac{2}{\sqrt{\pi}} \int_{x}^{\infty} e^{-t^2}\, dt.$$

μ and σ are respectively the mean and the standard deviation of the Gaussian component, and τ (i.e., $\frac{1}{\lambda}$) is both the mean and the standard deviation of the exponential component. μ and σ are localization and variability indicators, while τ corresponds to the right tail of the distribution (Lacouture & Cousineau, 2008). The mean and variance of an RT distribution can be expressed as a function of the three ex-Gaussian parameters. The mean of the distribution can be obtained by the sum of μ and τ, while the variance of the distribution is the sum of σ^2 and τ^2.

Demographic Data Analyses

Demographic data are presented in Table 1 and results of group comparisons are presented in Supplemental Information. Shortly, there is no difference between the three groups for vocabulary level, while depression status is higher in the Young than Middle-aged adults. Particularly relevant for the analyses, we do not observe group differences on Sleepiness or on Sleep quality. This equality on sleep-related variables is important in establishing that group differences found in our fatigue-inducing protocol cannot be explained by sleep disturbances.

[Insert Table 1]

Sensitivity Analyses

Sensitivity analyses were carried out with G*Power 3.1.7, given an α of .05 and a statistical power of .80. The analyses indicate that the minimum effect size our design was sufficiently sensitive to detect ranged between small and intermediate sizes, according to the exact measurement. It implies in turns that our design was also able to detect large effect sizes. A presentation of effect sizes associated with each measure of interest can be found in Supplemental Information.

Statistical Analyses

Subjective Cognitive Fatigue: KSS and VAS Scales

To test whether our protocol induced feelings of sleepiness, fatigue, demotivation and effort, paired sample t-tests were performed to compare subjective scales Before versus After inside each group (see Supplemental Information for description of normality assumptions). We adjusted the critical α to prevent Type 1 error by applying Bonferroni correction, leading to a corrected α of .0042 (12 comparisons).

To test whether changes in subjective feelings differed between the age groups, one-way ANOVAs were carried out on the ((After minus Before)/Before) scores. This index provided a relative score allowing better accounting for inter-individual changes as well as controlling for group differences in baseline subjective level. Since normality assumption was violated for each variable, we resorted to Kruskal-Wallis *H* test. We adjusted the critical α by applying Bonferroni correction, leading to a corrected α of .013 (4 comparisons).

Objective Cognitive Fatigue: the Stroop Task

Global Task Performance. A detailed presentation of the analyses can be found in Supplemental Information and Supplemental Table 1. Shortly, we performed two mixed ANOVAs implemented in the general context of linear mixed models in which the factors Group, Item, and the Group X Item interaction were predictors of mean RT and response accuracy, respectively. Participant was modelled as a random factor (i.e., varying intercept).

Analyses of Time-on-Task, Age Group, and Item Types on the Ex-Gaussian Parameters. Task duration was divided into four blocks of 40 minutes each, and we fitted the ex-Gaussian parameters (μ, σ, τ; see section ***The Ex-Gaussian Distribution*** for description of the parameters) to individual RT distributions in those four blocks separately for each item type (C, I, N). Only RTs to correct answers were taken into account. Post-error trials were removed from analysis to eliminate the slowdown effect in post-error responses (Heathcote et al., 1991). The 12 data sets (3 item types X 4 blocks) comprised at least 100 RT observations required to obtain stable estimates of the ex-Gaussian parameters (Heathcote et al., 1991).

We carried out three mixed models (i.e., one for each ex-Gaussian parameter: Model_μ, Model_σ, and Model_τ; see Supplemental Information for description of normality assumptions) comprising the following predictors: Group, Block as repeated measure, Item as repeated measures, and all interactions, with Education and Depression status as confounding variables (Supplemental Table 2). Participant variable was modelled as a random factor (i.e., varying intercept). Mixed models were performed using the *lme* function from the *nlme* statistical R package (Pinheiro et al., 2020). Significant effect in *lme* models were followed by post hoc tests with a probability value of $p < .05$ and Tukey's adjustment for multiple comparison of least square means using the *lsmeans* R package (Lenth, 2018).

Results

Subjective Cognitive Fatigue: KSS and VAS Results

All three groups reported significantly higher levels of sleepiness, demotivation, fatigue and effort after as compared to before the task (all *ps* below the corrected α of .0042; see Table 2), excepted for Middle-aged that did not report significantly higher level of demotivation After as compared to Before ($p = .06$).

There was no difference between groups in the development of subjective sleepiness, fatigue, demotivation, or effort ((Before-After/Before) scores; Table 3). Therefore, objective cognitive fatigue results from the Stroop task could not be explained by a difference in subjective feelings.

[Insert Tables 2 and 3]

Objective Cognitive Fatigue: Results of the Stroop Task

Global Task Performance

A detailed presentation of the results can be found in Supplemental Information and in Supplemental Table 1. Shortly, the mixed model on accuracy performance revealed that only Item type had a significant effect on the percentage of CR ($F(2,416) = 12.3$, $p < .001$). Post hoc tests showed that I items led to less CR than both C ($t(416) = 11.65$, $p < .001$, $d = .68$) and N items ($t(416) = -10.17$, $p < .001$, $d = .59$). The mixed model for overall mean RT for correct answers showed a main effect of Item type (*F*(2,

104) = 91.59, $p < .001$). Post hoc showed that I items were answered more slowly than C ($t(104) = -20.81$, $p < .001$, $d = 2.34$) and N ($t(104) = 15.98$, $p < .001$, $d = 2.02$) items. Also, N items were answered more slowly than C items ($t(104) = -4.83$, $p < .001$, $d = 1.13$). There was a main effect of Group ($F(2,52) = 8.14$, $p < .001$): both Middle-aged ($t(52) = -2.54$, $p = .037$, $d = .78$) and Older ($t(52) = -3.81$, $p = .001$, $d = 1.07$) groups answered slower overall than the Young group. There was no interaction ($F(4,104) = .51$, $p = .73$) between Group and Item type.

Time-on-Task, Age Group, and Item Types on the Ex-Gaussian Parameters.

Time-on-Task effects on the ex-Gaussian μ and τ parameters according to Group (Young, Middle-aged, Older) and Item type (C, I, N) are illustrated in Figures 1-2 and Supplemental Figure 1-6 and presented in Supplemental Table 2. Descriptive statistics reporting means (and *SD*) for μ and τ as a function of Group, Block, Item, and the Group X Block interaction are provided in Supplemental Tables 3-4.

μ Parameter. There was a significant effect of the educational level covariate ($F(1,51) = 7.28$, $p = .01$) on μ values. A correlation performed between these two variables was $r = -.22$, meaning that higher level of education was associated with lower μ values. After the statistical control of educational level and depression covariates, μ showed a significant effect of Group ($F(2,51) = 9.54$, $p < .001$). Post hoc tests showed that both Middle-aged ($M = 739.44$ ms, $SD = 140.36$) and Older ($M = 817.58$ ms, $SD = 209.99$) groups had higher μ values than the Young group ($M = 630.13$ ms, $SD = 102.38$, $t(51) = -2.82$, $p = .02$, $d = .9$ for Middle-aged; and $t(51) = -4.37$, $p < .001$, $d = 1.17$ for Older; see Supplemental Figure 1). However, the Block effect was not significant on μ (see Supplemental Figure 3). There was a significant effect of Item ($F(2,415) = 211.3$, $p < .001$). Post hoc tests showed that μ values for C items ($M = 660.23$ ms, $SD = 130.41$) were smaller than μ values for N items ($M = 697.22$ ms, $SD = 128.30$, $t(415) = -4.05$, $p < .001$, $d = .45$) but also than μ values for I items ($M = 808.12$ ms, $SD = 210.44$, $t(415) = -16.27$, $p < .001$, $d = .94$). μ values for N items were also smaller than I items ($t(415) = 12.22$, $p < .001$, $d = .85$; see

Supplemental Figure 5). Finally, there was no significant effect of the interactions (see Figure 1 for the Group x Block interaction effect).

τ Parameter. After the statistical control of covariates, the Group effect was not significant on τ (see Supplemental Figure 2). However, τ showed a significant effect of Block ($F(3,156) = 16.58$, $p < .001$). Post hoc tests showed that τ values were increased in the Block 4 ($M = 292.09$ ms, $SD = 147.05$) as compared to both the Block 1 ($M = 239.34$ ms, $SD = 114.79$, $t(156) = -4.15$, $p < .001$, $d = .35$) and the Block 2 ($M = 238.91$ ms, $SD = 123.25$, $t(156) = -4.26$, $p < .001$, $d = .37$; see Supplemental Figure 4). There was also a significant effect of Item type on τ ($F(2,415) = 40.10$, $p < .001$). Post hoc tests showed that τ values for I items ($M = 296.15$ ms, $SD = 141.72$) were higher than those of C items ($M = 240.45$ ms, $SD = 134.14$, $t(415) = -5.83$, $p < .001$, $d = .35$) and N items ($M = 240.27$ ms, $SD = 113.31$, $t(415) = 6.55$, $p < .001$, $d = .48$) while τ values for C and N items did not significantly differ from each other ($t(415) = -.26$, $p = .96$, $d = 0$; see Supplemental Figure 6). Finally, the Group X Block interaction was also significant on τ ($F(6,156) = 2.24$, $p = .04$). Post hoc tests showed that τ values in Block 4 ($M = 326.63$ ms, $SD = 161.37$) were significantly increased relative to both Block 1 ($M = 233.5$ ms, $SD = 86.02$, $t(156) = -4.54$, $p < .001$, $d = .69$) and Block 2 ($M = 223.3$ ms, $SD = 116.1$, $t(156) = -4.98$, $p < .001$, $d = .82$) only in the Middle-aged group while τ values of the Young and the Older groups did not significantly vary as a function of Block (see Figure 2).

[Insert Figure 1] **[Insert Figure 2]**

Discussion

This study aimed at determining age-related changes on cognitive fatigue assessed in a Time-on-Task paradigm. We administered a 160-minute Stroop task to young, middle-aged, and older adults and fitted the ex-Gaussian distribution to individual RT data in the four-time blocks for each item types (C, I, N). Globally, μ showed age-related changes while τ revealed a Block effect as well as a Group X Block interaction showing that middle-aged was the only group to increase its τ parameter with Time-on-Task. Our results indicate that the Ex-Gaussian parameters are impacted differently by age and Time-on-Task. All three age groups reported significantly higher subjective levels of sleepiness, demotivation, fatigue and effort after as compared to before the task, but these changes did not significantly differ between groups, showing that objective Time-on-Task cannot be explained by a variation in subjective feelings.

Global Task Performance

Interfering items led to less correct responses and were answered slower than both C and N items, which is in agreement with the Stroop literature (Heathcote et al., 1991; MacLeod & MacDonald, 2000). Both Middle-aged and Older groups responded slower than the Young group. However, there was no interaction between Group and Item type on mean RT. According to the inhibitory decline hypothesis (Hasher & Zacks, 1988), a larger slowdown in older people could have been expected, particularly for I items. However, older adults do not necessarily undergo inhibition impairments in the color Stroop task (see Rey-Mermet & Gade, 2018 for a meta-analysis). In addition, we used the Stroop task as a tool to induce cognitive fatigue but did not compute classic indices (e.g., Interference index = $I_{RT} - ((C_{RT} + N_{RT})/2)$) assessing specific Stroop effects. Consequently, we cannot rule out the possibility that age effect would have been revealed on such type of specific indices.

A Dissociation Between μ and τ: Age Versus Time-on-Task Effects

According to the literature, RTs comprise two components (Dawson, 1988; Hohle, 1965; Luce, 1986): the time to take a decision about the response – the *decision component* (represented by τ) – and the time to physically make the response – the *motor-transduction component* (represented by μ). Globally, our results seemed to show that Group and Time-on-Task effects on the ex-Gaussian parameters are dissociated.

As predicted, we found that μ undergone age differences. Values of μ were higher for the Middle-aged and Older groups than the Young group, meaning that both middle-aged and older adults answered slower than young adults. Increased μ in older ages was reported in previous studies (Moret-Tatay et al., 2017; Vasquez et al., 2018) and is consistent with the literature on speed slowdown in healthy aging (Salthouse, 1996, 2000). This result is also in agreement with many studies showing that age-related slowing is mostly due to an alteration in motor-related instead of decisional-related speed (e.g., Falkenstein et al., 2006; Roggeveen et al., 2007; see however Woods et al., 2015). By contrast, μ did not change with Time-on-Task, confirming the invariance of μ with the time spent on the task previously found in young participants (Wang et al., 2014) and further validating this result in other age groups.

τ did not show age-related changes, meaning that age was not linked to increasing extreme RTs. This was contrary to our expectations, but literature is controversial. Some studies report that τ discriminates between age groups (McAuley et al., 2006; Vasquez et al., 2018; West et al., 2002), while other do not show any age-related effect (Hoffman & Falkenstein, 2011; Myerson et al., 2007). Combining these results with findings concerning μ, our data indicate that healthy aging is more likely to influence the time required to perform the motor-transduction component of a response but not the time needed for the decisional component (Hohle, 1965; Luce, 1986).

τ increased with Time-on-Task, indicating increased extreme RTs with cognitive fatigue (Wang et al., 2014). As μ did not change with Time-on-Task, this result further suggests that cognitive fatigue does not influence the time to perform the motor-transduction process but influences well the time to take decision. From this result, it would be proposed that human errors and accidents under cognitive fatigue are mostly due to increased time for decision process (τ) while free-control decision processes (μ) remain unaffected. Accordingly, motor procedural sequence learning has already been shown to improve after a fatiguing task (Borragan et al., 2016).

Absence of Group by Item and Time-on-Task by Item Interactions

The absence of Group x Item interaction was contrary to our hypothesis since it suggests that Item effects were similar between groups. Since normal aging is associated with decreased inhibitory processes (Hasher & Zacks, 1988), we expected greater age-related increase in μ and τ parameters for I items as compared to other items. However, as previously stated, older adults do not necessarily undergo inhibition impairments in the color Stroop task (see Rey-Mermet & Gade, 2018) or larger sensitivity to interference (Myerson et al., 2005; Verhaegen et al., 2005). Moreover, age-related cognitive abilities are influenced by cognitive reserve markers (Stern et al., 2003). In this regard, Van der Elst et al. (2006) found that age-related interference resolution during a Stroop task was influenced by the educational level. The statistical control of the educational level in our analyses can explain the absence of Group by Item interaction on μ and τ. Time-on-task was not more pronounced on I items, which we had hypothesized to be the most likely to suffer from fatigue. However, mental fatigue may result from cognitive overload triggered by item/task difficulty or cognitive underload triggered by monotony (May & Baldwin, 2009; see also Wascher et al., 2016). The repetitive nature and monotony of our protocol may have induced a global cognitive under-arousal (passive task-related fatigue; May & Baldwin, 2009) that similarly impacted the process of the three item types.

Cognitive Fatigue in Middle-Aged and Older Adults

Middle-aged participants generated significant increases in τ values (i.e., increases in extreme RT) with Time-on-Task, which may reflect the installation of cognitive fatigue particularly in this group. As indicated previously, the presence of large fatigue effects in middle-aged adults had been reported in two fMRI studies (Klaassen et al., 2014; Klaassen et al., 2016). The authors concluded from the different patterns of brain activity between groups (young, middle-aged) and conditions (fatigue, control) that middle-aged resort to compensatory mechanisms more quickly than young adults and also reach a state of neuronal resource exhaustion faster (CRUNCH hypothesis; Reuter-Lorenz & Cappell, 2008).

To explain middle-aged people's greater sensitivity to Time-on-Task, we propose this population have challenging lives and great responsibilities (see Office for National Statistics, 2016), likely inducing a less optimal daily cognitive state. Some studies report high stress levels in middle-age adults, sometimes considered as a “crisis” period (Lachman, 2004; see also Ulloa et al., 2013). Stress related to multiple rolesdemands and financial pressures is more prevalent in middle-age than at other adult life stages (Aldwin & Levenson, 2001; Almeida & Horn, 2004) and is negatively correlated with brain structure integrity (Echouffo-Tcheugui et al., 2018; Kokubun et al., 2018). Older people resisted cognitive fatigue better than middle-aged people, suggesting also that cognitive fatigue does not dramatically increase with age but instead affects people differentially as a function of life stages. Accordingly, future studies should investigate life conditions of middle-aged – personal, familial, job-related, financial, etc. –, which could be more fatiguing and stressing than in other age groups.

Given age-related decrease in cognitive efficiency (Collette & Salmon, 2014; Crawford et al., 2000), we hypothesized this group would be the most impacted by our fatigue-inducing task. However, older people did not experience cognitive fatigue more than young adults. An absence of fatigue effect is observed in some previous studies (Arnau et al., 2017; Terentjeviene et al., 2018; Wascher et al., 2016). In their ERP study, Staub et al. (2014) observed stable performance on a Go/No-Go task in parallel with stable engagement of proactive control with Time-on-Task in older adults, while young people experienced decrease in proactive control. Maintaining cognitive control over a long-lasting task depends on motivational aspects, which were greater in older than young adults. Wascher et al. (2016) suggested that increase in alpha activity in young people reflected attention withdrawal. Because cognitive fatigue in their study was essentially passive (May & Baldwin, 2009), the authors concluded that older people were better able to manage task monotony and declining motivation. Similarly, Terentjeviene et al. (2018) observed more signs of cognitive fatigue in young than in older adults after a 2-hour Go/No-Go task. RTs in the “Incorrect No-Go” condition increased with the time spent on the task only in the young group, which also experienced more subjective fatigue and steeper drops in motivation than older people. Therefore, our result seems to corroborate studies showing a certain resistance to cognitive fatigue in older people when a passive fatigue is triggered by a long-lasting repetitive task.

Although older adults did not perform worse than young adults, it is possible that age-related differences due to cognitive fatigue exist at the cerebral level. For example, in an fMRI Stroop task, Tam et al., (2015) found that longer RTs in older people were associated with greater activity in fronto-parietal attentional areas, which was interpreted as compensatory mechanisms. By contrast, longer RTs in younger adults were associated with greater activity in default mode network (DMN), suggesting mind wandering and reduced tolerance to monotony. Similarly, Arnau et al. (2017) did not find behavioral difference between young and older adults performing a fatiguing task. However, greater frontal theta power was found in older people, which was attributed to compensatory processes. By contrast, there was a saturation in occipital alpha in young adults, which was interpreted as management of task monotony. Therefore, we cannot rule out the possibility that preserved performance in older people with Time-on-Task was due to parallel cerebral compensatory mechanisms (Park & Reuter-Lorenz, 2009; Reuter-Lorenz & Cappell, 2008).

Limitations

The sample size was reduced due to strict exclusion criteria. However, regarding the cognitive fatigue literature, this sample remain in the standards, and we replicated Time-on-Task effect observed by Wang et al. (2014) that was based on fifteen participants. Sensitivity analyses were also reassuring since our design was sufficiently sensitive to detect effects between small and intermediate sizes.

We did not probe subjective fatigue at different time points during the task. By doing so, each assessment could have been correlated with the previous adjacent Block performance to test relationship between objective performance and subjective feelings but we did not adopt such a paradigm given the inherent undesired interruptions (potentially associated to fatigue recovery) needed to fill in subjective scales. We should also mention that we chose to divide task duration into four 40-min blocks to get a large data set and obtain trustful algorithm convergence. We cannot exclude that more subtle fatigue-related temporal effects occurred within each 40-minute time block. Finally, we can also not exclude that some degree of automatization for response-to-key mapping also takes place during Block 1, despite a training to the task was provided. However, the absence of significant difference between Block 1 and 2 seems to indicate that this effect, if present, would have minor influence on the pattern of results observed.

We have to mention usual difficulties in interpreting the results in term of cognitive fatigue. Cognitive fatigue effects can be challenged by alternative interpretations of the results: are performance decrements after a long-lasting task really attributable to cognitive fatigue or rather to task disengagement due to boredom or motivational aspects? Our significant Block effect on parameter τ as well as the significant Group X Block interaction on τ seem to show that fatigue induced by Time-on-Task influences the decision component (Hohle, 1965; see also Borragán et al., 2016). Certain authors have also suggested that participants' slowest responses would index executive control (Brewer, 2011; Unsworth et al., 2010). Given the Block effect on τ, we rather interpret Time-on-Task effect as being more likely to trigger executive control impairments rather than depending on motivational or personality factors. Of course, future studies are needed to clarify the exact nature of the declining process under long-lasting paradigms.

A final issue is the interpretation of the ex-Gaussian parameters in terms of cognitive processes. According to Brewer et al. (2017, p.4), parameters "should always be interpreted with caution because they simply reflect a decomposition of the response time distribution from a given participant within a given task and they do not reflect process-pure psychological mechanisms." Therefore, relation between cognitive processes and the ex-Gaussian parameters have to be interpreted as a function of the specific task context. We would interpret Time-on-Task effect as impacting executive process rather than motivational aspects, but we need replications across studies to confirm these interpretations.

Conclusion

Our study found evidence of increase in extreme RT (represented τ) as a function of Block, which may reflect the installation of cognitive fatigue with the time spent on the task. This result suggests that cognitive fatigue more particularly affects the decision component of response while the motor-transduction component remains unaffected. Interestingly, middle-aged adults were found to be the most sensitive to Time-on-Task as attested by significant increase in τ values, while older adults were not more affected than the other groups. This result can be explained by the fact that older adults are more resistant to task monotony, leading to similar behavioral performances between young and older people under passive task-related cognitive fatigue. Alternatively, midlife has been postulated to be a challenging life period that may induce higher sensitivity to cognitive fatigue. However, fMRI investigations would help reveal subtle age-related cerebral differences in the ways young and older people resist cognitive fatigue.

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Table 1

Demographic Data for the Three Age Groups

Variable	Young (*n* = 21)	Middle-aged (*n* = 17)	Older (*n* = 17)	Post Hoc	*p*	Effect size
				O vs Y	<.05	n.a.
Age (y)	22.43 (2.01)	50.47 (6.37)	65.06 (3.19)	O vs M	<.05	n.a.
				M vs Y	<.05	n.a.
Educational level (y)	14.29 (2.03)	13.35 (2.89)	11.35 (2.32)	O vs Y	.001	*d* = 1.36
				O vs M	.049	*d* = .76
Depression status	12.19 (3.59)	7.59 (5.60)	8.35 (5.96)	M vs Y	.019	*d* = 1
Mill Hill (% correct)	73.25 (14.47)	78.89 (11.59)	80.28 (13.02)	-	-	-
Sleepiness	7.10 (3.83)	7.24 (4.59)	7.71 (4.07)	-	-	-
Sleep quality	4.86 (2.10)	4 (2.72)	5.82 (2.94)	-	-	-
Mattis DRS score	-	141 (1.75)	141 (2.70)	-	-	-
Sex						
Males/Females	8/13	7/10	9/8			
Day Time						
Morning/Afternoon	12/9	12/5	9/8			
Chronotype[a]						
Morning	0	0	2			
Moderate Morning	5	10	9			

Neutral	12	5	6
Moderate Evening	3	2	0
Evening	1	0	0

Note. Values are shown as means (*SD*) except for Sex, Day Time, and Chronotype (count). Post hoc tests were computed to follow significant ANOVAs. O stands for Older; M stands for Middle-aged; Y stands for Young; n.a. stands for not available. [a] Horne and Ostberg Chronotype Questionnaire (Horne & Ostberg, 1976).

Table 2

Changes in Subjective Fatigue Scales Within Each Group

		KSS		VAS Motivation		VAS Fatigue		VAS Effort	
		Before	After	Before	After	Before	After	Before	After
Young	Raw scores	4.1 (1.84)	6.1 (2.28)	35.82 (16.97)	55.32 (19.76)	40.32 (16.28)	58.73 (15.23)	34.05 (18.84)	65.53 (17.28)
	Statistic	$t = -3.94$		$T = 20.0$		$t = -5.62$		$t = -6.47$	
	p values	<.001***		<.001***		<.001***		<.001***	
	d	.86		.90		1.23		1.41	
Middle-aged	Raw scores	2.35 (1.66)	5.65 (2.6)	22.05 (21.93)	36.21 (23.07)	25.28 (21.57)	52.45 (28.44)	29.37 (22.69)	55.1 (24.53)
	Statistic	$t = -5.56$		$T = 22.5$		$t = -4.79$		$t = -3.41$	
	p values	<.001***		.06		<.001***		.004**	
	d	1.35		.67		1.16		.83	
Older	Raw scores	2 (.87)	4.29 (2.66)	17.25 (13.46)	39.99 (29.52)	25.75 (16.59)	44.76 (20.56)	28.17 (16.79)	57.16 (22.34)
	Statistic	$t = -3.87$		$T = 12.0$		$t = -4.31$		$t = -4.32$	
	p values	.001**		.004**		<.001***		<.001***	
	d	.94		.81		1.05		1.05	

Note. Results of t-tests for paired samples contrasting KSS and VAS scores Before and After the Stroop test in each group; Raw scores represent the raw mean scores Before and After in each group on a 9-point scale for the KSS and as a percentage for the VAS; *t* stands for Student t-test; *T* stands for the Wilcoxon signed-rank test.

KSS = Karolinska Sleepiness Scale; VAS = Visual Analogue Scale

**p* < .05; ***p* < .01; ****p* < .001

Table 3

Changes in Subjective Fatigue Between the Three Groups

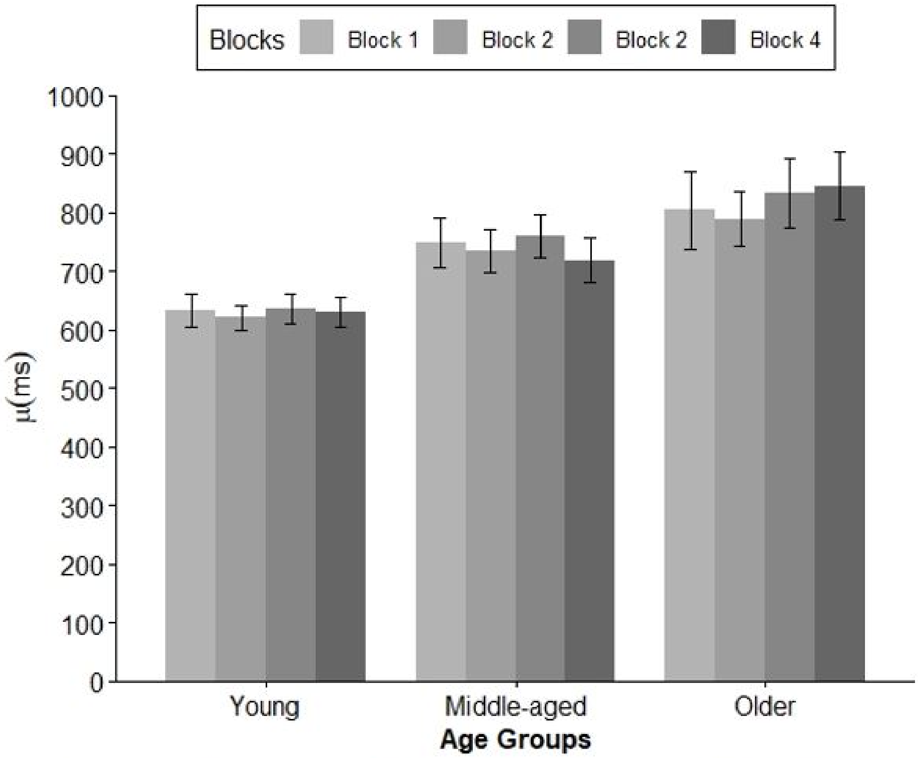
	Mean Index			*H* values	*p* values	η^2_H
	Young	Middle-aged	Older			
KSS	-0.85	-2.22	-1.41	4.78	.09	.05
VAS Motivation	-3.04	-12.67	-17.4	.37	.83	-.03
VAS Fatigue	-0.79	-10.52	-8.77	1.91	.38	-.002
VAS Effort	-2.61	-13.06	-8.51	.02	.99	-.04

Note. Results of single factor ANOVAs performed on Index scores between the three age groups. Mean Index in each group represents the difference between the Before score and the After score divided by the Before score on a 9-point scale for the KSS and as a percentage for the VAS; *H* values are reported for Kruskal-Wallis test. VAS = Visual Analogue Scale

*p < .05; **p < .01; ***p < .001

Figure 1

Time-on-Task as a Function of Group on the Ex-Gaussian Parameter μ

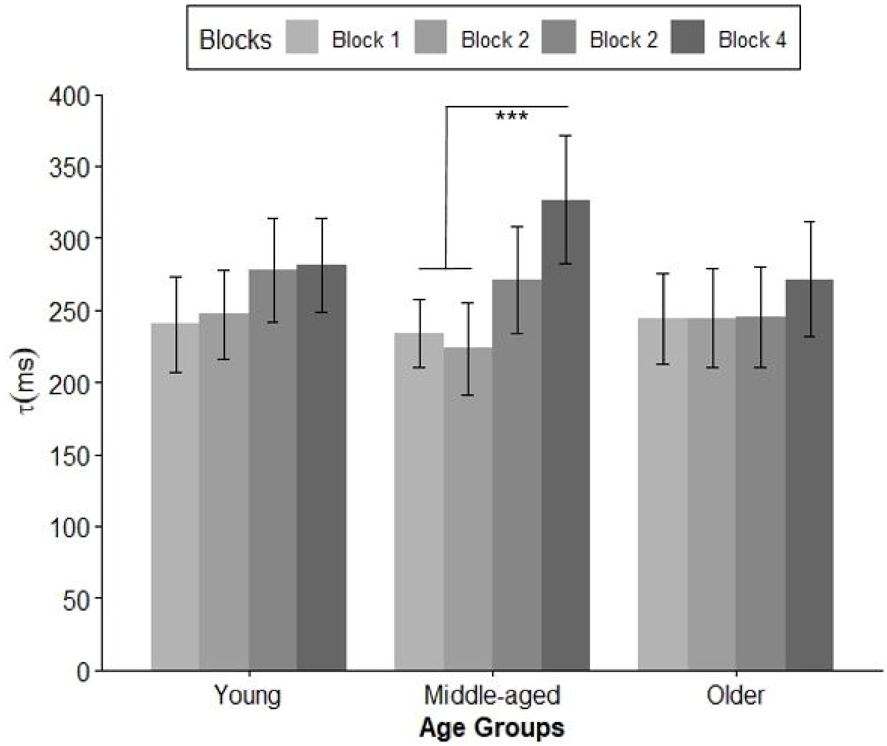


Note. Bars represent the mean of μ in the time Blocks (color shaded from Block 1 to Block 4) as a function of the age Groups. Error bars are 95% confidence intervals of the mean; ms stands for milliseconds.

*p < .05 **p < .01 ***p < .001

Figure 2

Time-on-Task as a Function of Group on the Ex-Gaussian Parameter τ



Note. Bars represent the mean of τ in the time Blocks (color shaded from Block 1 to Block 4) as a function of the age Groups. Error bars are 95% confidence intervals of the mean; ms stands for milliseconds.

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

Supplemental Material

Exclusion participants

Two young women and 2 young men were excluded because they were not native French speakers (i.e. native German speakers). The other 11 participants (2 young women, 2 young men, 2 middle-aged women, 2 middle-aged men, and 3 older women) were excluded for at least one of the following reasons: not respecting the required sleep quantity the night before the experiment, scoring higher than the threshold score on the CES-DS (Radloff, 1977), or taking medication for restless-legs syndrome, which is likely to interfere with optimal cognitive functioning. Moreover, 11 participants (1 young woman, 3 young men, 3 middle-aged women, 3 middle-aged men, and 1 older woman) were excluded because of computer problems/technical issues or incorrect use of the keyboard responses. Finally, three young men were excluded because they gave up or asked for a break during the task.

Description of the self-report questionnaires

The **CES-DS** (Center for Epidemiologic Studies-Depression Scale ; Radloff, 1977) is a validated questionnaire assesses severity of depressive symptoms. The scale consists of a self-administered questionnaire with 20 items to be completed according to mood over the last seven days. The frequency of symptoms is assessed using a Likert scale ranging from 0 (never, very rarely) to 3 (frequently, all the time). The sum of response to all items give a global score for severity of depressive symptoms.

The **Mill Hill scale** (Deltour, 1993) is a verbal task assessing crystallized intelligence linked to lexical knowledge (i.e., vocabulary). This task is made of 33 items. For each item, participants had to determine, among six possibilities, the semantically nearest word of a given target word. The score is the total number of correct answers.

The **EES** (Epworth Sleepiness Scale; Johns, 1991) is a questionnaire estimating the subjective level of sleep during the day. The subject reads eight different daily situations are presented and the participant determines the probability of falling asleep for each situation on a 4-point Likert scale. The total score corresponds to the addition of score for the eight situations.

The **PSQI** (Pittsburgh Sleep Quality Index; Buysse et al., 1989 is a validated questionnaire assesses sleep quality and disturbances over a 1-month interval. 19 individual items generate seven "component" scores: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medication, and daytime dysfunction. The sum of all components gives access to a global score of perceived sleep quality.

Demographic data analyses

Single factor ANOVAs were performed on Educational level, Depression status (CES-DS; Radloff, 1977), Vocabulary level (Mill Hill; Deltour, 1993), Sleepiness (Epworth Somnolence Scale (EES); Johns, 1991) and Sleep quality (Pittsburgh Sleep Quality Index (PSQI); Buysse et al., 1989) using the aov function from the stats R package (R Core). Significant parametric ANOVAs were followed by post hoc adjusted by Tukey for multiple comparisons of least square means using the lsmeans R package (Lenth, 2018) to test which groups statistically differed from one another. Assumptions of normality as well as variance homogeneity were tested in each cell for each single factor ANOVA. Homogeneity of variance was met for each ANOVA but normality was violated for Sleep Quality. For this variable, we resorted to Kruskal-Wallis H test (rank-based non parametric one-way ANOVA). Effect sizes for Kruskal-Wallis tests were computed according to the formula $\eta 2H = (H-k+1)/(n-k)$ where H is the Kruskal-Wallis H-test statistic, k is the number of groups, and n is the total number of observations (Tomczak & Tomczak, 2014). Non-parametric post hoc analyses following Kruskal-Wallis tests were performed with the kruskalmc function from the pgirmess R package (Giraudoux et al., 2018) but do not have related effect size index.

A single factor ANOVA showed a significant effect on the Educational level ($F(2, 52) = 7.10$, $p = .002$, $\eta^2 = .21$). Post hoc tests demonstrated that the Young ($p = .001$) and the Middle-aged ($p = .049$) groups had a higher Educational level than the Older group. The ANOVA performed on Vocabulary level did not show any statistical difference between the three groups ($F(2, 52) = 1.54$, $p = .22$, $\eta^2 = .06$). Another one-way ANOVA showed a significant effect on Depression status ($F(2, 52) = 4.63$, $p = .01$, $\eta^2 = .15$). Post hoc tests revealed that the Young group ($p = .019$) scored higher than the Middle-aged group. Two other single factor ANOVAs showed that the three groups did not differ from each other on Sleepiness ($F(2, 52) = .11$, $p = .90$, $\eta^2 = .004$) or on Sleep quality ($H(2) = 4.89$, $p = .09$, $\eta^2_H = .06$).

A chi-squared (χ^2) test showed that the sex distribution did not differ between the three groups (*Pearson* $\chi^2 = .90$, $p = .64$, $\phi = .13$). Another χ^2 test performed between groups and the testing time during the day was also not significant (*Pearson* $\chi^2 = 1.22$, $p = .54$, $\phi = .15$), meaning that the sessions (morning or afternoon) were well balanced between groups. We also report the distribution of the chronotype (Horne & Ostberg, 1976) as a function of the age groups. We did not perform a chi-squared test between chronotype and age groups because the assumption of having at least one observation by cell was violated.

Sensitivity analyses

The minimum effect size we can detect given an α of .05 and a statistical power of .80 is detailed below for all measurements.

For subjective scales (see below), paired t-test have been performed. Regarding paired t-tests in the Young group, given a total sample size of 21, we were able to detect effect size of $d = .64$, which is an intermediate effect size. Similarly, regarding paired t-tests in the Middle-aged and Older groups, given a total sample size of 17, we were able to detect effect size of *d* = .72, which is an intermediate effect size.

For global task performance as well as ex-Gaussian parameter analyses, linear mixed models were performed (see below). Regarding the between effect (Group effect), with a total sample size of 55 and three groups, we were able to detect effect size of *f* = .34 which corresponds to an η^2 = .10 and is an intermediate effect size. Regarding our first within effect (Block effect), given a total sample size of 55, and four repeated measurements, we were able to detect effect size of *f* = .16 which corresponds to an η^2 = .025 and represents a small effect size. Regarding our second within factor effect (Item effect), given a total sample size of 55 and three repeated measurements, we were able to detect effect size of *f* = .17, which corresponds to an η^2 = .028 and is a small effect size. Regarding the first within-between interaction (Group X Block), given a total sample size of 55, three groups and four repeated measurements, we were able to detect effect size of *f* = .18, which corresponds to an η^2 = .03 and is a small effect size. Regarding the second within-between interaction (Group X Item), given a total sample size of 55, three groups and three repeated measurements, we were able to detect effect size of *f* = .19 which corresponds to an η^2 = .035 and represents a small effect size. Regarding the third within-between interaction (Group X Block X Item), given a total sample size of 55, three groups and twelve (4X3) repeated measurements, we were able to detect effect size of *f* = .13 corresponding to an η^2 = .02 which is a small effect size.

Normality assumption

Subjective cognitive fatigue: KSS and VAS Scales. Normality assumption on the distribution of the scores of difference (score After – score Before) were tested for each scale. If the assumption of normality on these scores of difference was respected, we resorted to Student t-test for paired sample (denoted *t* in Table 2); if not, we resorted to the non-parametric Wilcoxon signed-rank tests for paired samples (denoted *T* in Table 2).

Analyses of Ex-Gaussian parameters. Assumptions for application of mixed models (no multicollinearity, homogeneity of residual variance, and normally distributed residual scores) were also checked. Those assumptions were met for Model_μ and Model_τ but Model_σ strongly violated the assumption of homogeneity of residual variance even after correction attempts. Therefore, we report results on Model σ in Supplemental Table 5 as purely informative extra data.

Global Stroop Task Performance

We report the mean number of items used on the entire task (i.e., only correctly answered items) as well as among the three Item types (C, I, N). Percentage of correct responses (CR), incorrect responses (IR) and non-responses (NR) on the entire task are also reported. We performed a mixed ANOVA implemented in the general context of linear mixed models in which the percentage of CR was explained by Group, Block as repeated measure, Item as repeated measure, and all interactions. Participant was modelled as a random factor (i.e., varying intercept). Descriptive statistics on the percentage of CR as a function of Group, Block, and Item are given in Supplemental Table 1. To test classical Stroop effects we performed another mixed model in which the factors Group, Item, and the Group X Item interaction were predictors of mean RT.

The mean number of items used per participant on the entire task was 2,290 (*SD* = 56) and is distributed among the three Item types as follows: 776 (*SD* = 13) C items, 757 (*SD* = 33) I items, and 757 (*SD* = 14) N items. Percentage of CR on the entire task was 97.04% (*SD* = 3.01), percentage of IR was 2.07% (*SD* = 2.11), and percentage of NR was 0.78% (*SD* = 1.48). Percentage of CR is distributed among the three Item types as follows: 98% (*SD* = 2.14) for C items, 95.46% (*SD* = 4.64) for I items, and 97.66% (*SD* = 2.48) for N items; among Groups as follows: 96.91% (*SD* = 3.51) for Young, 97.01% (*SD* = 3.20) for Middle-aged, and 97.24% (*SD* = 3.66) for Older; and through Blocks as follows: 97.19% (*SD* = 3.69) in Block 1, 97.55% (*SD* = 2.78) in Block 2, 97.03% (*SD* = 3.45) in Block 3, and 96.38% (*SD* =

3.77) in Block 4. The mixed model revealed that only Item had a significant effect on the percentage of CR (F(2,416) = 12.3, p < .001). Post hoc tests showed that I items led to less CR than both C (t(416) = 11.65, p < .001, d = .68) and N items (t(416) = -10.17, p < .001, d = .59). All descriptive statistics of accuracy for the Group X Block X Item interaction are provided in Supplemental Table 1.

The overall mean RT for correct answers is 972.99 ms (*SD* = 188.61) and is distributed among the three Item types as follows: 893.03 ms (*SD* = 154.7) for C items, 1086.78 ms (*SD* = 193.33) for I items, and 939.16 ms (*SD* = 160.81) for N items; and among Groups as follows: 877.88 ms (*SD* = 134.95) for Young, 1001 ms (*SD* = 173.66) for Middle-aged, and 1062.48 ms (*SD* = 208.74) for Older. In agreement with the literature (Heathcote et al., 1991), the mixed model showed a main effect of Item type (F(2, 104) = 91.59, p < .001). Post hoc showed that I items were answered more slowly than C (t(104) = -20.81, p < .001, d = 2.34) and N (t(104) = 15.98, p < .001, d = 2.02) items. Also, N items were answered more slowly than C items (t(104) = -4.83, p < .001, d = 1.13). There was a main effect of Group (F(2,52) = 8.14, p < .001): both Middle-aged (t(52) = -2.54, p = .037, d = .78) and Older (t(52) = -3.81, p = .001, d = 1.07) groups answered slower overall than the Young group. There was no interaction (F(4,104) = .51, p = .73) between Group and Item type.

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Supplementary Material

Finding the Best-Fitting Ex-Gaussian Parameters: An Algorithm Based on Nelder and Mead (1965) and the Greedy Approach

To paraphrase Lacouture and Cousineau (2008), to find the values of a probability function that best represent the ex-Gaussian function, an iterative approach known as *maximum likelihood estimation* allows the best-fitting parameters to be estimated. Given a data set and a probability density function (pdf) with specific parameter values, the likelihood value (LogL criterion) provides an indication of the goodness of fit between the data and the function. Among the available techniques, the simplex algorithm is often used for fitting the ex-Gaussian parameters because it is robust (Cousineau et al., 2004; Lacouture & Cousineau, 2008). The simplex algorithm implemented in the DISTRIB Toolbox in MATLAB by Lacouture and Cousineau (2008) works as follows: the LogL criterion defines a hypersurface in a multi-parameter space. Starting with predetermined parameter values, the simplex method uses the steepest gradient on the hypersurface to determine how the parameter values should be changed to increase the LogL. The algorithm follows an iterative procedure until a minimum on the error surface is found. The steepest gradient corresponds to the steepest slope on the hypersurface and allows a minimum of the function to be found (see Lacouture & Cousineau, 2008, for more details). However, if the error surface is not smooth enough or if the search falls into a local minimum (i.e., a region on the error surface that provides a minimum that is not a global minimum of the function), the parameter search with the simplex method may fail to converge (Lacouture & Cousineau, 2008).

Dawson (1988) proposed a program based on the simplex method described by NeIder and Mead (1965). The basic simplex technique consists in moving and deforming a closed hypersurface with N+1 vertices in an N-dimensional parameter space. The simplex is simply a tetrahedron (or a triangle) in 3D (or in 2D) space. This iterative procedure is repeated until the simplex converges on the function minimum. The advantage of the Nelder-Mead (1965) algorithm is that it does not require computation of the gradient, which can be difficult to compute for some applications.

Moreover, to increase our chance of finding the global optimum, we coupled the Nelder-Mead algorithm with a greedy approach: we initialized the Nelder-Mead procedure with different starting points and kept only the best result. This approach is time-consuming but can easily be parallelized on a standard current computer. Our algorithm is available on osf.io/8d7hb.

References

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Supplemental Tables

Supplemental Table 1

Global Accuracy as a Function of the Group by Block by Item Interaction

		Percentage of Correct Responses (CR)			
		Min	Max	*M*	*SD*
Young					
Block 1	C	94.97	100.00	98.66	1.28
	I	83.92	100.00	95.46	3.96
	N	93.78	100.00	98.20	1.82
Block 2	C	92.96	100.00	98.05	1.92
	I	86.43	100.00	95.78	4.01
	N	92.82	99.49	97.94	1.55
Block 3	C	90.95	100.00	98.30	2.12
	I	83.92	100.00	95.53	4.59
	N	93.30	100.00	97.55	2.13
Block 4	C	85.86	100.00	97.11	3.15
	I	82.83	99.49	94.14	4.93
	N	78.87	100.00	96.17	4.85
Middle-aged					
Block 1	C	91.46	100.00	98.55	2.06
	I	81.22	98.99	95.39	4.26
	N	93.78	100.00	98.54	1.77
Block 2	C	93.40	100.00	98.12	1.94
	I	91.96	100.00	96.80	2.91
	N	94.30	100.00	97.81	1.77
Block 3	C	92.96	99.49	97.60	2.09
	I	81.73	99.50	95.03	5.23
	N	91.75	100.00	97.36	2.73
Block 4	C	90.91	99.50	96.93	2.80
	I	87.94	100.00	95.37	3.89
	N	89.64	100.00	96.63	3.10

Supplemental Table 1

Global Accuracy as a Function of the Group by Block by Item Interaction

Older					
Block 1	C	89.95	100.00	97.80	2.41
	I	70.56	99.50	93.93	7.19
	N	93.81	100.00	98.05	1.78
Block 2	C	96.45	100.00	98.78	1.24
	I	78.89	100.00	96.39	4.82
	N	95.85	100.00	98.51	1.31
Block 3	C	93.94	100.00	98.34	1.82
	I	79.29	100.00	95.87	4.87
	N	92.27	100.00	97.67	2.07
Block 4	C	94.92	100.00	97.74	1.75
	I	80.81	99.50	96.06	4.71
	N	94.85	100.00	97.69	1.78

Note. C stands for Congruent; I stands for Incongruent; N stands for Neutral.

Supplemental Table 2

Linear Mixed Models on the Ex-Gaussian Parameters μ and τ

	DF		*F*	*p*	DF		*F*	*p*
	Num.	Den.			Num.	Den.		
			μ				τ	
Educational level	1	51	7.28	.01 *	1	51	.34	.56
CES-DS	1	415	3.4	.07	1	415	.04	.84
Group	2	51	9.54	<.001***	2	51	.64	.53
Block	3	156	2.12	.1	3	156	16.58	<.001***
Item	2	415	211.3	<.001***	2	415	40.10	<.001***
Group : Block	6	156	1.67	.13	6	156	2.24	.04*
Group : Item	4	415	1.53	.19	4	415	2.39	.05
Block : Item	6	415	.9	.49	6	415	.78	.58
Group : Block : Item	12	415	.42	.96	12	415	1.02	.43

Supplemental Table 2

Linear Mixed Models on the Ex-Gaussian Parameters μ and τ

Note. Results of the *lme* models to determine the effect of Group, Block, Item as well as the interactions on μ and τ with Educational level and Depression (CES-DS) as confounds.

**p* < .05 ***p* < .01 ****p* < .001

Supplemental Table 3

Descriptive Statistics of μ and τ as a Function of Group, Block, and Item.

Variable	μ		τ	
	M	*SD*	*M*	*SD*
Group				
Young	630.13	102.38	261.51	135.76
Middle-aged	739.44	140.36	263.57	133.32
Older	817.58	209.99	251.20	128.54
Block				
Block 1	721.49	187.34	239.34	114.79
Block 2	707.30	148.78	238.91	123.25
Block 3	734.58	175.66	265.49	137.28
Block 4	724.07	176.77	292.09	147.05
Item				
Congruent	660.23	130.41	240.45	134.14
Incongruent	808.12	210.44	296.15	141.72
Neutral	697.22	128.30	240.27	113.31

Supplemental Table 4

Descriptive Statistics of μ and τ as a Function of the Group by Block interaction

Variable	μ		τ	
	M	*SD*	*M*	*SD*
Young				
Block 1	633.99	113.27	240.35	134.79
Block 2	620.27	88.43	246.98	127.28
Block 3	635.43	107.16	277.73	146.14
Block 4	630.84	100.76	280.98	132.54
Middle-aged				
Block 1	747.18	153.27	233.50	86.02
Block 2	733.36	135.68	223.30	116.10
Block 3	759.17	130.76	270.84	136.25
Block 4	718.07	141.52	326.63	161.37
Older				
Block 1	803.88	241.82	243.94	115.04
Block 2	788.75	165.83	244.54	126.07
Block 3	832.46	217.02	245.02	126.97
Block 4	845.22	209.55	271.29	145.90

Supplemental Table 5

Linear Mixed Model on the Ex-Gaussian Parameter σ

	DF		*F*	*p*
	Num.	Den.		
			σ	
Education	1	51	7.78	.01*
CES-DS	1	413	4.10	.04*
Group	2	51	.44	.65
Block	3	156	1.24	.3
Item	2	413	25.84	<.001***
Group : Block	6	156	1.5	.18
Group : Item	4	413	1.44	.22
Block : Item	6	413	.9	.5
Group : Block : Item	12	413	.65	.8

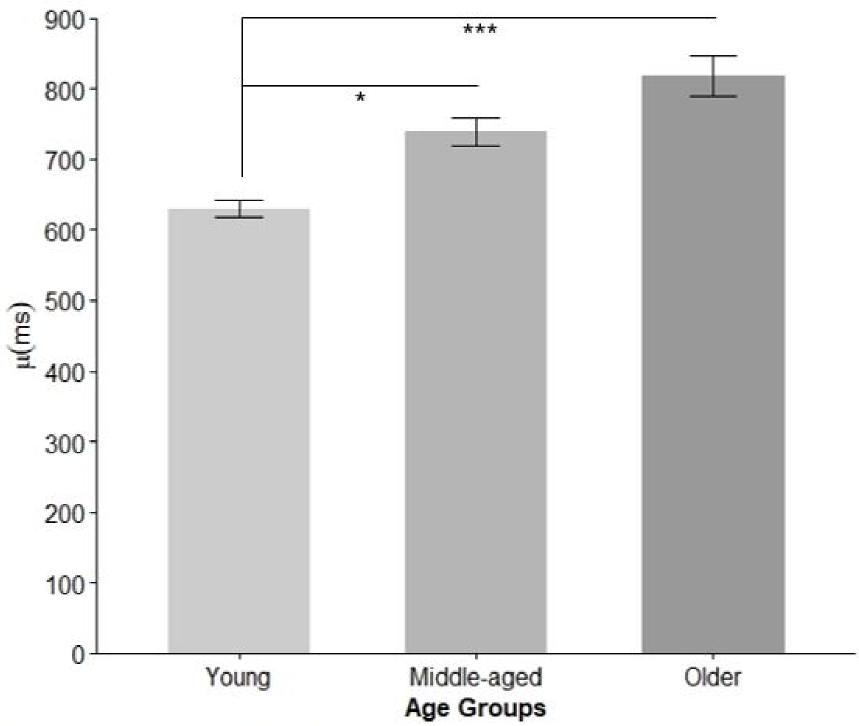
Note. Results of the *lme* model to determine the effect of Group, Block, Item as well as the interactions on σ with Educational level and Depression as confounds. These results are purely extra information that are not interpreted in the paper because of homoscedasticity violation.

$^*p < .05$ $^{**}p < .01$ $^{***}p < .001$

Supplemental Figures

Supplemental Figure 1

Group Effect on the Ex-Gaussian Parameter μ

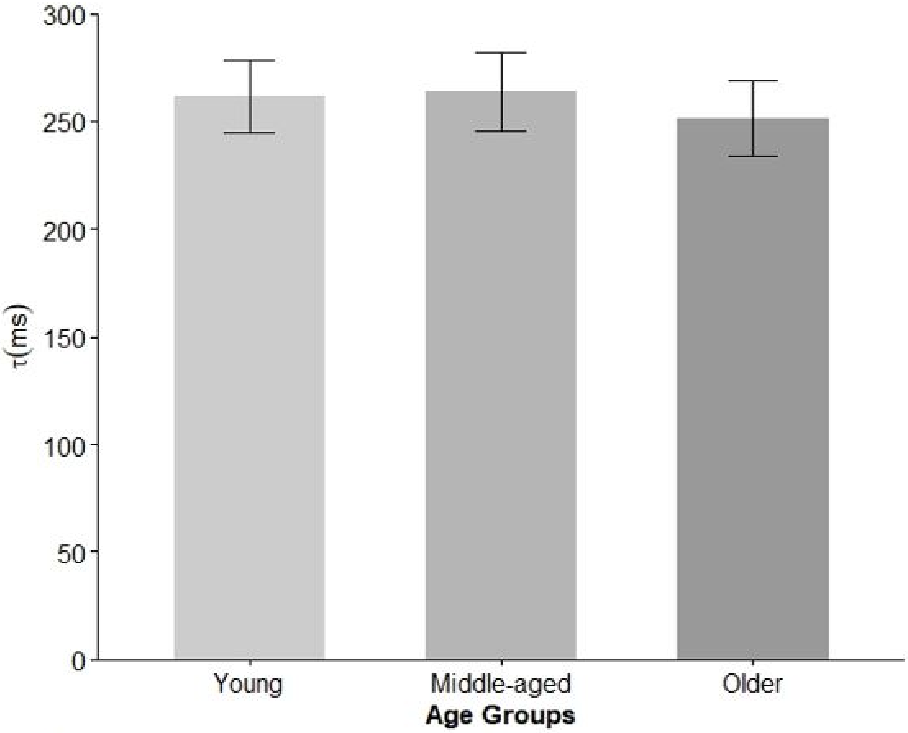


Note. Bars represent the mean of μ in Young, Middle-aged, and Older groups (color shaded from Young to Older). Error bars are 95% confidence intervals of the mean; ms stands for milliseconds.

*p < .05 **p < .01 ***p < .001

Supplemental Figure 2

Group Effect on the Ex-Gaussian Parameter τ

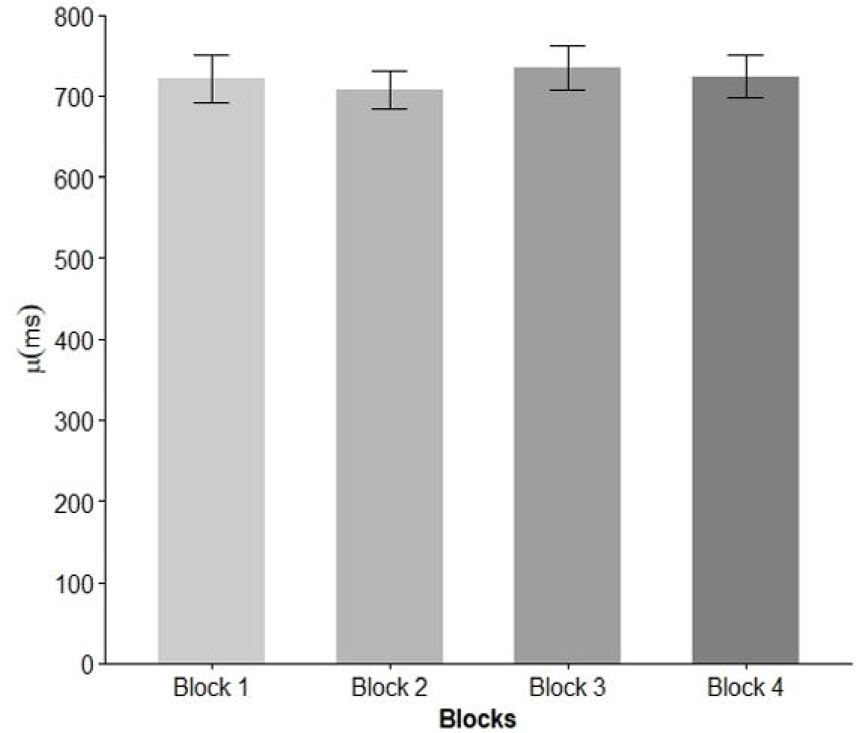


Note. Bars represent the mean of τ in Young, Middle-aged, and Older groups (color shaded from Young to Older). Error bars are 95% confidence intervals of the mean; ms stands for milliseconds.

*p < .05 **p < .01 ***p < .001

Supplemental Figure 3

Time-on-Task Effect on the Ex-Gaussian Parameter μ

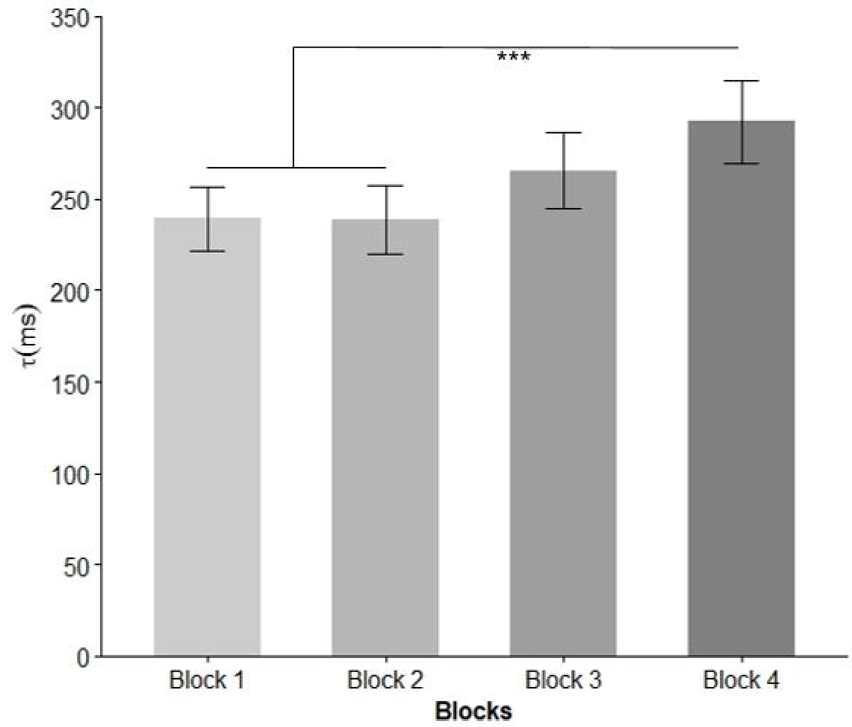


Note. Bars represent the mean of μ in Block 1, Block 2, Block 3, and Block 4 (color shaded from Block 1 to Block 4). Error bars are 95% confidence intervals of the mean; ms stands for milliseconds.

*p < .05 **p < .01 ***p < .001

Supplemental Figure 4

Time-on-Task Effect on the Ex-Gaussian Parameter τ

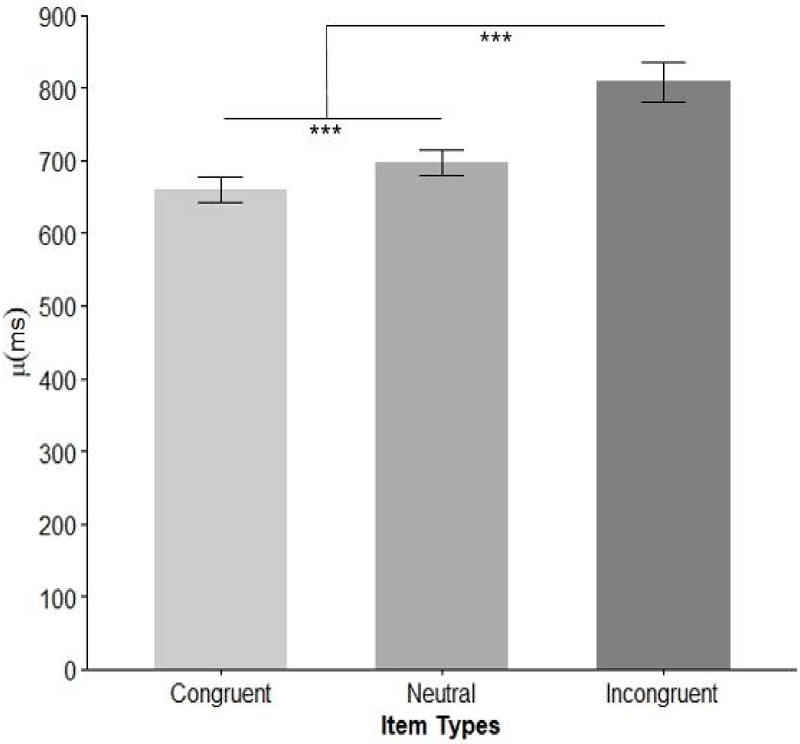


Note. Bars represent the mean of τ in Block 1, Block 2, Block 3, and Block 4 (color shaded from Block 1 to Block 4). Error bars are 95% confidence intervals of the mean; ms stands for milliseconds.

*p < .05 **p < .01 ***p < .001

Supplemental Figure 5

Item Effect on the Ex-Gaussian Parameter μ

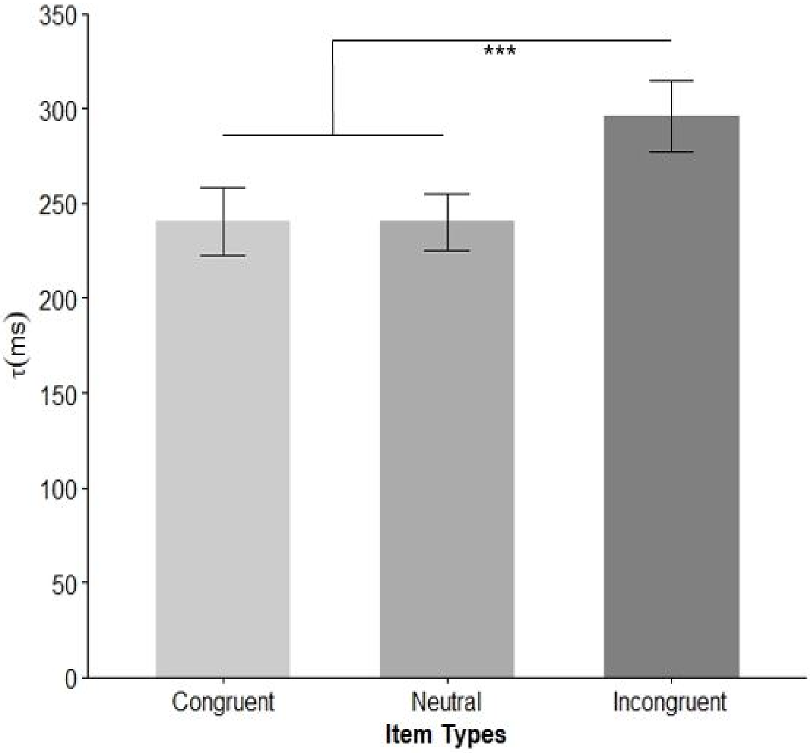


Note. Bars represent the mean of μ for Congruent, Neutral, and Incongruent items (color shaded from Congruent to Incongruent). Error bars are 95% confidence intervals of the mean; ms stands for milliseconds.

*p < .05 **p < .01 ***p < .001

Supplemental Figure 6

Item Effect on the Ex-Gaussian Parameter τ



Note. Bars represent the mean of τ for Congruent, Neutral, and Incongruent items (color shaded from Congruent to Incongruent). Error bars are 95% confidence intervals of the mean; ms stands for milliseconds.

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$