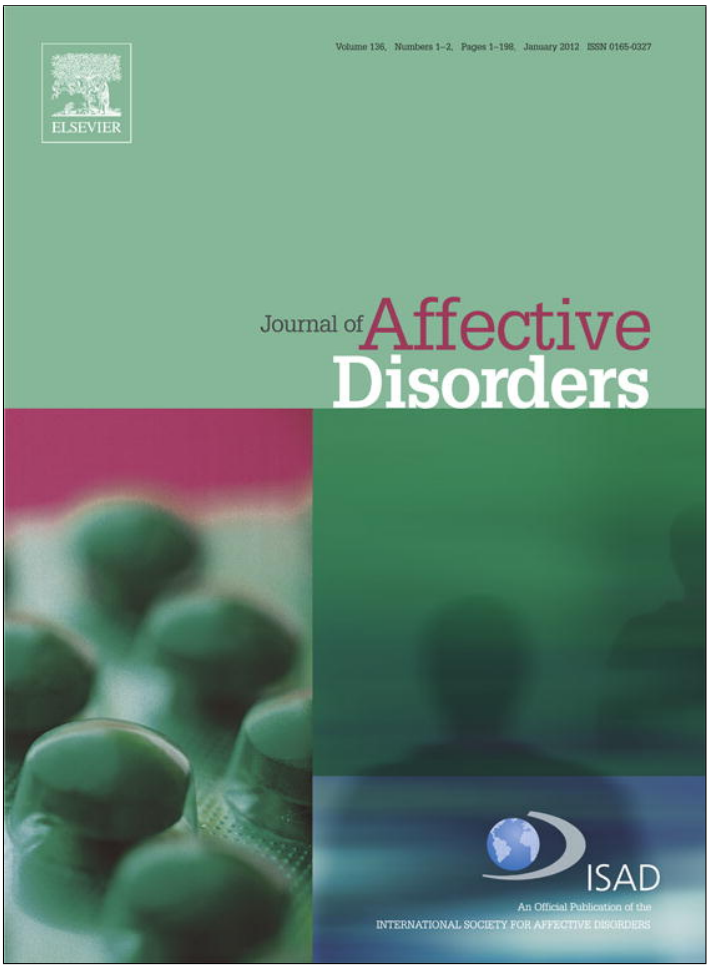

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Review

Time perception in depression: A meta-analysis

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ABSTRACT

Background: Depressive patients frequently report to perceive time as going by very slowly. Potential effects of depression on duration judgments have been investigated mostly by means of four different time perception tasks: *verbal time estimation*, *time production*, *time reproduction*, and *duration discrimination*. Ratings of the subjective *flow of time* have also been obtained.

Methods: By means of a classical random-effects meta-regression model and a robust variance estimation model, this meta-analysis aims at evaluating the inconsistent results from 16 previous studies on time perception in depression, representing data of 433 depressive patients and 485 healthy control subjects.

Results: Depressive patients perceive time as going by less quickly relative to control subjects ($g=0.66$, $p=0.033$). However, the analyses showed no significant effects of depression in the four time perception tasks. There was a trend towards inferior time discrimination performance in depression ($g=0.38$, $p=0.079$). The meta-regression also showed no significant effects of interval duration. Thus, the lack of effects of depression on timing does not depend on interval duration. However, for time production, there was a tendency towards overproduction of short and underproduction of long durations in depressive patients compared to healthy controls.

Limitations: Several aspects, such as influences of medication and the dopaminergic neurotransmitter system on time perception in depression, have not been investigated in sufficient detail yet and were therefore not addressed by this meta-analysis.

Conclusions: Depression has medium effects on the subjective flow of time whereas duration judgments basically remain unaffected.

Contents

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1. Introduction

Depressive patients frequently report to perceive time as passing by extremely slowly (Blewett, 1992; Ratcliffe, 2012; Straus, 1947). However, the question of whether time perception in the sense of judgments of defined time intervals is also affected by depression remains unresolved. We are faced with a large body of inconclusive and often contradictory findings. The present meta-analysis evaluates the existing literature on time perception in depression.

Over the last few decades, the potential effects of depression on time perception have been investigated empirically mostly by means of four different experimental tasks (see Msetfi et al., 2012 for a recent review). These tasks are (a) *verbal time estimation* (sometimes referred to as *'time estimation'*), where a time interval is presented, defined for instance by the inter-onset interval between two brief tones, and the subject gives an estimate in conventional time units like seconds (e.g., Bech, 1975; Bschor et al., 2004; Dilling and Rabin, 1967; Kitamura and Kumar, 1983), (b) *time production,* where the experimenter specifies a time interval in temporal units, and the subject produces this interval for example by pressing a button to mark the interval's beginning and end (e.g., Münzel et al., 1988; Tysk, 1984), (c) *time reproduction,* where a time interval is presented as in (a) and the subject produces a corresponding interval as in (b) (Mahlberg et al., 2008; Mundt et al., 1998), and (d) *duration discrimination*, where typically two time intervals of almost equal length are presented successively, and the subject selects the longer interval (Msetfi et al., 2012; Rammsayer, 1990; Sevigny et al., 2003). For tasks (a) to (c), most studies focused on the mean duration of the time estimates, or on deviations of the estimates from the veridical values. Thus, in terms of Fechner (1860), the studies compared the "constant error" between depressive patients and controls. For duration discrimination (task (d)), performance is often characterized in terms of the duration difference limen, defined as for example the difference in duration between the two presented time intervals that results in 75% correct responses. It should be noted that for tasks (a) to (c) a corresponding measure of sensitivity is provided by the standard deviation of the estimates or productions across several trials (Treisman, 1963). This corresponds to the "variable error" in terms of Fechner (1860). However, only few studies (e.g., Oberfeld et al., 2014) analyzed the variable error, and for this reason we restricted our meta-analysis to the mean duration of the time estimates (constant error) for tasks (a) to (c). Several studies additionally asked for ratings of the subjects' experience of the flow of time (task (e)), often by means of visual analogue scales (VAS; e.g., Bschor et al., 2004; Mundt et al., 1998; Oberfeld et al., 2014) or questionnaires (Bech, 1975; Münzel et al., 1988). On visual analogue scales, the subjects are asked to mark a point on a line where the endpoints represent a very slow and very fast subjective flow of time. Notably, these ratings differ from tasks (a) to (d) because the subjective flow of time is assessed rather than the perception or production of defined time intervals.

Occasionally, effects of depression on other than the five tasks listed above have been studied. For instance, Bolbecker et al. (2011) measured the timing abilities of depressive patients by means of a paced finger tapping task, and Oberfeld et al. (2014) studied time-to-contact estimates for approaching visual objects (cf. Regan and Gray, 2000). However, these additional tasks have not been investigated in more than two primary studies each, and were therefore not included in our meta-analysis.

In order to predict in which way depression might influence the performance on the experimental tasks, it seems sensible to consider the influential cognitive *pacemaker–accumulator models* of interval timing (Gibbon et al., 1984; Treisman, 1963). These models assume an *internal clock* consisting of a pacemaker emitting pulses and an accumulator (or counter) collecting these pulses. In *Scalar Expectancy Theory* (*SET*), which is one of the most prominent pacemaker–accumulator models (Gibbon et al., 1984; Meck, 1996), this clock device is integrated into an information processing framework that encompasses memory and decision stages. According to SET, as soon as a subject begins to process an interval, an attentionally modulated switch between pacemaker and accumulator closes. Therefore, the clock pulses emitted by the pacemaker can reach the accumulator, which starts to 'count' these pulses. The more pulses being accumulated, the longer the perceived length of an interval. This means that if the subject's clock runs faster, more pulses get accumulated within a specified interval, and therefore the interval is perceived as longer compared to a subject with a slower clock speed.

In terms of this model, the observation that depressive patients frequently report to perceive time as going by less quickly can be explained by a faster running clock in depressive patients than in non-depressive controls. This assumption leads to precise predictions of performance differences between depressives and healthy control subjects in some of the interval timing tasks introduced above (Msetfi et al., 2012). For example, if the *verbal estimation* of a presented time interval in time units like seconds or minutes is required, according to the notion of an accelerated internal clock, the depressives accumulate more pulses during the presentation of the to-be-judged time interval, and hence produce higher estimates of the duration of the interval compared to control subjects. The opposite relation is predicted for a *production* task where the task is to produce an interval specified in time units, for example by marking its beginning and end by finger taps. If the internal clock runs at a faster pace, then the depressive patients should produce shorter intervals than the control subjects. According to the internal clock model, the subject starts to accumulate clock pulses at the first tap, and produces the second tap as soon as the accumulated number of pulses reaches a value (stored in long term memory) corresponding to for example "2 s". Due to the faster-running clock, the depressive patients should decide to mark the end of the interval at an earlier point in time than the control subjects. In a *reproduction* task, subjects are required to reproduce a previously presented time interval, for example by pressing a button to mark the interval's beginning and end. In contrast to *production* tasks, the interval is not specified in terms of time units but it is presented explicitly before the subject is asked to reproduce it. Here, a faster accumulation of pulses should affect

the representation of the interval to be timed as well as its reproduction. According to SET, the memory representation of the pulses accumulated during the presentation of the time interval, and the accumulation process during the production phase should be affected in the same way. Therefore, the clock speed should have no effect in a reproduction task, and therefore no differences between depressives and controls are to be expected. *Duration discrimination* tasks require the detection of small differences between two successively presented time intervals (two-interval task), or the comparison of a presented time interval with internal (memory) references, as for example in a temporal generalization task (cf. Grondin, 2010). At first glance, higher clock speed might provide higher temporal resolution capacity. If the clock period is not sufficiently smaller than the temporal interval that is to be judged (e.g., clock period of 1 s, interval duration 500 ms), then the accuracy in a duration discrimination task would indeed be impaired. Apart from this obvious relation, however, the effect of changes in the clock rate critically depends on the relation between the clock rate and the variance of the pulse counts. For example, it has been suggested that the internal clock is a Poisson process (Gibbon, 1992; Grondin, 2010), for which the mean count of pulses emitted during a given time interval is proportional to the variance of the pulse count. Thus, increasing the clock rate by, e.g., 50% would also increase the variability of the pulse count by 50%. For a duration discrimination task, the signal-detection theory measure of sensitivity, d', can be defined as the expected difference between the pulse counts during the longer and the shorter temporal interval, divided by the standard deviation of the pulse count (Green and Swets, 1966). For a Poisson-process clock, d' will increase with the square root of the clock rate. In other words, the discrimination performance should be superior with a higher clock rate. Thus, depressive patients should show higher sensitivity than controls.

If one considers the literature, for each of the different tasks, there is evidence for effects of depression on time perception, but also against such effects. Most studies did not focus on one task only but included a variety of tasks and interval durations (e.g., milliseconds, seconds, minutes). Verbal time estimation has been studied frequently. However, the results are not conclusive for this task: While some studies provide clear evidence for a systematic overestimation in depressive patients compared to healthy control subjects at several interval durations (e.g., Kitamura and Kumar, 1983; Kornbrot et al., 2013; Wyrick and Wyrick, 1977), compatible with an increased clock speed in depression, others reported mixed results (Biermann et al., 2011; Bschor et al., 2004) or even opposite effects (underestimation in depressives relative to controls) at certain interval durations (Tysk, 1984). Similarly, the effects in production tasks are discussed controversially. Beside statistically significant results in favor of the 'faster clock in depressives-assumption' (underproduction in depressives) (Bschor et al., 2004; Mundt et al., 1998), several studies did not find differences in the produced interval lengths between depressives and controls (Kitamura and Kumar, 1983; Tysk, 1984). Moreover, Münzel et al. (1988) and Kornbrot et al. (2013) reported overproduction in a depressive group. In the case of interval discrimination, the results are also mixed (Gil et al., 2009; Msetfi et al., 2012; Sevigny et al., 2003), with tendencies towards lower discrimination thresholds, i.e., higher temporal sensitivity in control subjects (Rammsayer, 1990). With regard to time reproduction (Mahlberg et al., 2008; Mundt et al., 1998; Oberfeld et al., 2014) and time experience (Bech, 1975; Kitamura and Kumar, 1982; Münzel et al., 1988; Oberfeld et al., 2014; Wyrick and Wyrick, 1977), similar inconsistent results can be found.

Taken together, when qualitatively reviewing the existing literature on the topic, one has to conclude that the empirical evidence for or against effects of depression in the different interval timing tasks is mixed. It is therefore difficult to answer the question of whether the would-be common clinical phenomenon of a subjective slowing of the flow of time in depressives is accompanied by systematic effects on time perception in terms of interval timing. One of the potential origins of the indecisive body of literature is the limited statistical power of each single study. Owing to the usual problems in recruiting large numbers of patients, each study investigated only a rather small sample of depressive patients. The meta-analytic approach used in the present study allows overcoming this limitation by combining information from multiple studies.

Apart from issues of statistical power, the inconsistency of the empirical findings could also be due to methodological heterogeneity of the studies, owing for example to the use of different tasks (e.g., verbal estimation versus production) and/or different time intervals (e.g., milliseconds versus minutes). For example, the demands in terms of motor activity clearly differ between the tasks. While production and reproduction tasks require timed motor responses, time estimation, duration discrimination, and judgment of the flow of time (time experience) do not. Also, memory processes are involved differently depending on the particular task. Time production and time estimation require the subject to refer to (long term) memory representations of the intervals to be timed. In time reproduction and discrimination tasks, however, the information necessary for doing the task is presented within a given trial, or within the experimental block, so that these tasks are likely to depend on short-term memory or sensory memory rather than on long-term memory. Moreover, it is important to consider that production and estimation, for example, produce opposite effects if the internal clock is accelerated. Therefore, deviations of the estimates from the veridical values on the two different tasks should not be pooled directly. Another crucial aspect might be the interval duration. There is evidence that different timing mechanisms are involved depending on the length of the interval to be timed (Bangert et al., 2011; Grondin, 2012; Lewis and Miall, 2003). Processing of intervals in the range of milliseconds is assumed to be based mainly on sensory mechanisms while cognitive factors like attention and memory become more important in the interval range above one second (e.g., Grondin, 2010). Hence, possible effects of depression on interval timing might depend on the time intervals used.

To answer the question of whether differences in time perception between depressive patients and controls depend on the task and on the interval duration, which might explain some portion of the seemingly contradictory findings, we analyzed the existing studies according to the experimental task and to the interval duration. We defined four interval duration ranges: ultra short: <1 s, short: 1 s to 10 s, medium: 10 s to 10 min, and long >10 min.

2. Method

2.1. Search strategies and study selection

We searched for relevant studies in Web of Science. The primary key words were 'depression' and 'timing' or 'time'. Additional studies were identified by including the references listed in the studies found in Web of Science, and by considering the studies that cited the resulting body of literature, again using Web of Science. Moreover, based on an email list from the "International Conference on Timing and Time Perception" (held at Corfu in April 2014), we sent calls for unpublished data on the topic to more than 100 researchers in the field of timing and time perception. Additionally, we contacted the authors of previous papers on depression and time perception as far as current email addresses were available. This iterative literature search strategy yielded 39 articles addressing time perception in depression, with 31 papers reporting empirical data (see Appendix A.1).

For the meta-analyses, we selected studies according to the following four criteria.

Criterion 1: The studies had to provide data from a group of depressive patients as well as a control group consisting of healthy adults only. Because healthy subjects also tend to produce systematic errors in interval timing tasks (e.g., Wearden and Lejeune, 2008), it is uninformative to simply compare judgments of depressive subjects, for example verbal time estimates, to the veridical values of the presented time intervals. Hence, for studies that tested depressive subjects only (e.g., Mezey and Cohen, 1961), it is not possible to decide whether the reported deviations of the time estimates from the veridical values are specifically related to depression. Therefore, systematic comparisons between depressive subjects and healthy control subjects on the single study level are required.

Criterion 2: Depressives had to be either diagnosed by means of standard diagnostic criteria (DSM or ICD), or had to be assigned to a depressive group based on a depression inventory like Hamilton's Rating Scale for Depression (HRS) (Hamilton, 1960) or the Beck depression inventory (BDI) (Beck et al., 1961).

Criterion 3: The report of sample sizes, means, and standard deviations or t/F values of the response measures had to be sufficiently detailed in order to compute effect sizes (Hedges' g) and their variance. If this was not the case, we contacted the authors of the original study for papers published after 1990. Only one author (Kornbrot et al., 2013) kindly provided additional statistics necessary for our meta-analysis.

Criterion 4: At least one of the five common tasks (a) to (e) listed above had to be used.

Only 15 of the 31 empirical studies met these four criteria and were considered for further analyses (Bschor et al., 2004; Gil and Droit-Volet, 2009; Kitamura and Kumar, 1982, 1983; Kornbrot et al., 2013; Mahlberg et al., 2008; Mioni et al., submitted; Msetfi et al., 2012; Mundt et al., 1998; Münzel et al., 1988; Oberfeld et al., 2014; Rammsayer, 1990; Sevigny et al., 2003; Tysk, 1984; Wyrick and Wyrick, 1977) (see also Appendix A.1). Data from Kitamura and Kumar (1982, 1983) are based on the same sample. However, the two studies focused on different tasks (1982: time experience; 1983: time estimation and production) and for practical reasons they will be listed as two separate studies. Msetfi et al. (2012) reported two experiments investigating independent samples of subjects. Therefore, in the analyses, their first and second experiment were treated as two separate studies, resulting in a total of 16 independent studies entering the analyses.

2.2. Description of studies

The 16 studies included in this meta-analysis provided data from a total of 918 subjects (433 depressive patients and 485 healthy controls). The median publication year was 2003 (range: 1977 to 2014). Studies were conducted in Great Britain ($n=5$), Germany ($n=6$), France ($n=1$), Italy ($n=1$), Sweden ($n=1$), USA ($n=1$), and Canada ($n=1$).

Most patients (52.12%) were diagnosed according to DMS-III, DSM-IV, or ICD-9 criteria. 36.03% of the subjects in the patient group were assigned based on a BDI score. A minority of depressive subjects (17.55%) was diagnosed/assigned based on a "Present State Examination" and a questionnaire on "Depressive Mood" (Kitamura and Kumar, 1982, 1983), or according to the Multiple Affect Adjective Check List (MAACL) (Wyrick and Wyrick, 1977). Some patients were under medication, others not. The exact number of medicated subjects was not reported in most of the primary studies, and only one study reported separate data for subjects on and off medication (Oberfeld et al., 2014).

Supplementary Table 1 provides an overview of study-specific criteria for group assignment, diagnostics, and potential (drug) treatment of patients. Also, data on age and gender are presented as far as reported by the primary studies.

2.3. Preprocessing

Some studies reported separate results for patient groups suffering from different subtypes of depression, for example major depression with melancholia, major depression without melancholia, neurotic depression, etc. (e.g., Kitamura and Kumar, 1982; Tysk, 1984). Due to the inhomogeneity of diagnostic criteria (DSM-III, DSM-IV, ICD-9, BDI score, etc.), the small number of studies focusing on particular subtypes of depression, and the aim of the present meta-analysis to answer the question whether depression as such influences time perception, we decided to aggregate data from the different patient groups within those studies. Therefore, if multiple patient groups had been tested, for each response measure we computed weighted averages of the means and standard deviations with weights proportional to the number of subjects in the respective subgroup.

To ensure the comparability of effect size measures from the different studies, further preprocessing was required. With regard to judgments of time experience, the questionnaire scale for assessing the flow of time in Münzel et al. (1988) (1 indicating fast and 5 indicating slow) had to be inverted in order to be comparable to the scale used by Kitamura and Kumar (1982) and Wyrick and Wyrick (1977) (1 indicating slow and 5 indicating fast). The VAS measure used by Mundt et al. (1998) was also inverted in order to be comparable to the measures used by Bschor et al. (2004) and Oberfeld et al. (2014). Hence, for all judgments of time experience, higher values indicated a quicker flow of time. In the case of discrimination tasks, Rammsayer (1990) and Msetfi et al. (2012) reported the mean duration discrimination threshold with smaller values indicating higher sensitivity while Sevigny et al. (2003) analyzed the percentage of correct responses with larger values indicating higher sensitivity. For Sevigny et al. (2003), we multiplied the effect size measure by -1 in order to analyze comparable measures for all discrimination tasks.

2.4. Effect size estimates

Based on the reported means, standard deviations and sample sizes for depressive groups (M_d, SD_d, n_d) and control groups (M_c, SD_c, n_c), we calculated Hedges' g as an effect size index, which is an estimate of the standardized mean difference between the two groups. According to Hedges and Olkin (1985), g is defined as

$$g = \frac{M_d - M_c}{s}, \tag{1}$$

where s is the pooled sample standard deviation,

$$s = \sqrt{\frac{(n_d-1)SD_d^2 + (n_c-1)SD_c^2}{n_d+n_c-2}}. \tag{2}$$

According to Hofmann et al. (2010), the magnitude of g may be interpreted based on the conventions for the common effect size estimator d (small: ≥ 0.2; medium: ≥ 0.5; large: ≥ 0.8) (Cohen, 1988).

For Wyrick and Wyrick (1977), because means and standard deviations were not reported, g was calculated based on the presented F values and sample sizes (Rosnow and Rosenthal, 1996),

$$g = \sqrt{F\frac{n_d+n_c}{n_d n_c}\frac{n_d+n_c}{n_d+n_c-2}} \tag{3}$$

Following the recommendation by Normand (1999), we did not consider the bias correction factor $J(m)$ proposed by Hedges and Olkin (1985), which yields somewhat smaller effect size estimates.

The asymptotic variance of g is (Hedges and Olkin, 1985)

$$Var(g) = \frac{n_d + n_c}{n_d n_c} \frac{g^2}{2(n_d + n_c)} \quad (4)$$

Following the preprocessing explained above, one value of g (and $Var(g)$) was computed for each pair of means reported in the selected studies, that is, for each combination of sample, task, and interval duration (see Supplementary Table 2).

For some of the tasks, the g values were multiplied by -1 so that positive values of g reported in our analyses indicate overestimation in time estimation tasks (a), underproduction in time production tasks (b), over-reproduction in temporal reproduction tasks (c), lower discrimination performance in duration discrimination tasks (d), and a reduced speed of the flow of time in time experience tasks (e) in depressive subjects relative to control subjects. Thus, for all tasks, positive effect sizes represent the effects of depression that are typically expected in the literature.

It should be noted that for tasks (a) to (c), different response measures were reported by the primary studies. Performance was analyzed in terms of the mean time estimates, the deviation of the estimates from the veridical values (constant error), the constant error divided by the veridical value (relative error), or the ratio between the estimated value and the veridical value. As all of these measures are linear transformations of each other, the effect size estimates according to Eqs. (1) and (3) are not affected by the choice of the response measure in the primary studies.

3. Results

As pointed out above, the effects of depression on the different time perception tasks (time estimation, production, reproduction, discrimination and experience) are not necessarily identical. For instance, the internal clock model predicts opposite effects of an accelerated or decelerated internal clock in a verbal estimation and a production task, and predicts no effects of depression in a time reproduction task. Therefore, we decided to differentiate between data provided by the five different tasks (time estimation vs. production vs. reproduction vs. discrimination vs. experience). In addition, we considered different interval duration ranges (ultra short: <1 s, short: 1 s to 10 s, medium: 10 s to 10 min, long: >10 min) as a possible source of variance in the interval timing tasks (not including time experience, for reasons explained above).

3.1. Pooled effect size estimates per task

The aim of the first step of analysis was to determine one pooled effect size estimator for each of the five tasks. We used two different meta-analytic approaches.

In the first approach, possible effects of depression on task performance were analyzed by fitting a classical random effects meta-regression model (van Houwelingen et al., 2002). On the level of single studies, in cases where several effect sizes were available for the same sample, task and interval range, for example because different intervals within the same interval range had been studied, we first computed the arithmetic mean of the g-values, and then computed the asymptotic variance for the mean value according to Eq. (1) or Eq. (3) and Eq. (4), respectively. The column labeled J in Appendix A.2 specifies the number of pairs of means for depressives versus controls reported for the same sample, task and interval range, each corresponding to one effect size (g). If the sample sizes reported within a combination of sample, task and range differed between for example time intervals, owing most likely to dropout (e.g., Kitamura and Kumar, 1983; time estimation), we averaged the sample sizes when computing $Var(g)$. These analysis steps provided one value of g and its variance for each combination of sample, task and interval range (see Appendix A.2).

The interval range was entered as an effect-coded rather than continuous covariate because we are not aware of any argument that the effects of depression should be linearly related to the interval duration. This corresponds to the analyses in the original studies where the interval duration was analyzed as a within- or between-subjects factor in ANOVAs (e.g., Kornbrot et al., 2013; Oberfeld et al., 2014).

Using the SAS PROC MIXED procedure (Littell et al., 2006), for each task, the meta-regression model provided an intercept value that represents an effect size estimate of depression. It also provided a Type 3 test for the effect of interval duration. The degrees of freedom were calculated according to Kenward and Roger (1997). The PROC MIXED script used in our analysis is provided in Appendix B.1

As an alternative approach, we considered a recent robust variance estimation approach that provides an advanced meta-regression method to handle dependent effect sizes (Hedges et al., 2010). In our meta-analysis, most primary studies reported several effect sizes for the same task, for example because different time intervals had been studied. These effect sizes cannot be assumed to be independent because they had been obtained from the same sample of subjects. However, the classical meta-regression model explained above does not explicitly account for these potential dependencies. To identify potential resulting biases in the pooled effect size estimates, we additionally calculated effect size estimates based on the robust variance estimation approach (Hedges et al., 2010) using the SPSS ROBUST macro by Tanner-Smith and Tipton (2014) and compared these results to those from the classical meta-regression model (van Houwelingen et al., 2002). The analyses using the robust variance estimation approach were based on the data as reported in Supplementary Table 2. Thus, the effect sizes for each combination of sample, task, and interval duration as reported by the primary studies were entered in the analysis, without first computing an average effect size per interval range as for the classical random-effects meta-regression model. The interval range was included as an effect-coded covariate, just as in the classical meta-regression model. The method by Hedges et al. (2010) requires the specification of the (common) correlation ρ between the effect sizes in the different conditions. As no evidence concerning the to be expected correlation was available, we set ρ to 0.8, following Hedges et al. (2010). All analyses were repeated with ρ set to 0.0, but this resulted in only very minor changes in the estimated effects sizes, variances, and p-values.

For each of the five tasks, Table 1 presents the pooled effect size estimates and t-statistics based on (a) the classical meta-regression model and (b) the robust variance estimation approach.

Yielding similar or even identical (time experience) results, both regression models did not indicate statistically significant effects of depression on task performance in any of the interval timing tasks. However, a significant effect of medium size in time experience tasks indicated a reduced speed of the passage of time in depressive subjects. In addition, the random-effects meta-regression indicated a marginally significant, small detrimental effect of depression on discrimination performance, but this effect was clearly non-significant in the robust variance estimation analysis.

3.2. Meta-regression analysis on the effect of interval range for each task

The aim of the second step of the analysis was to determine for each interval timing task (estimation, production, reproduction, and discrimination) whether the effect sizes differed between the time interval ranges (ultra short, short, medium, long). Time experience measures were not included in this step because, as pointed out in

Table 1
Pooled effect size estimates per task. The table shows results from the random-effects meta-regression model and the robust variance estimation approach.

Task	*N* ind. samples	Classical random-effects meta-regression									Robust variance estimation meta-analysis						
		N effect sizes	θ	CI_L	CI_U	*t*	*df*	*p*	τ^2	SE_{τ^2}	p_{τ^2}	*N* effect sizes	θ	CI_L	CI_U	*t*	*df*	*p*
Estimation	7	19	0.16	−0.22	0.54	0.93	13.7	0.370	0.24	0.12	.028	53	0.15	−0.41	0.71	0.86	3	0.454
Production	8	16	0.04	−0.28	0.37	0.29	11.8	0.778	0.10	0.08	.218	28	0.03	−0.48	0.54	0.87	4	0.866
Reproduction	4	8	0.14	−0.30	0.57	0.81	5	0.455	0.12	0.13	.184	13	0.15	−3.44	3.74	0.52	1	0.695
Discrimination	5	8	0.38	−0.06	0.82	2.11	6	0.079	0.15	0.12	.107	9	0.41	−0.19	1.02	2.18	3	0.117
Experience	6	6	0.66*	0.08	1.24	2.93	5	0.033	0.22	0.19	.261	13	0.66*	0.08	1.23	2.29	5	0.033

Note: "*N* ind. samples": number of single studies/independent samples (i.e., the sample size on level 1). "*N* effect sizes": number of single effect sizes that were entered into the corresponding model (i.e., the sample size on level 2). θ: pooled effect size estimate. CI_L and CI_U are the lower and upper bounds of the 95% confidence interval, respectively, and *t*, *df*, and *p* refer to a test of θ against 0. τ^2: estimate of the inter-study variance. SE_{τ^2}: standard error of τ^2. p_{τ^2} refers to a test of τ^2 against 0. "*"indicates statistically significant effects ($p < .05$).

Table 2
List of studies covering the different combinations of task and interval range.

	Ultra short (< 1 s)	Short (1–10 s)	Medium (10 s–10 min)	Long (> 10 min)
Estimation	Oberfeld et al. (2014)	Wyrick and Wyrick (1977) Kitamura and Kumar (1983) Tysk (1984) Bschor et al. (2004) Kornbrot et al. (2013) Oberfeld et al. (2014)	Wyrick and Wyrick (1977) Kitamura and Kumar (1983) Tysk (1984) Münzel et al. (1988) Bschor et al. (2004) Kornbrot et al. (2013) Oberfeld et al. (2014)	Wyrick and Wyrick (1977) Kitamura and Kumar (1983) Münzel et al. (1988) Bschor et al. (2004) Oberfeld et al. (2014)
Production	Oberfeld et al. (2014) Mioni et al. (submitted)	Tysk (1984) Münzel et al. (1988) Mundt et al. (1998) Bschor et al. (2004) Oberfeld et al. (2014) Kornbrot et al. (2013)	Tysk (1984) Münzel et al. (1988) Mundt et al. (1998) Bschor et al. (2004) Oberfeld et al. (2014) Kornbrot et al. (2013)	Kitamura and Kumar (1983)
Reproduction	Oberfeld et al. (2014) Mioni et al. (submitted)	Mahlberg et al. (2008) Oberfeld et al. (2014) Mioni et al. (submitted)	Mundt et al. (1998) Mahlberg et al. (2008) Oberfeld et al. (2014)	
Discrimination	Rammsayer (1990) Sevigny et al. (2003) Gil and Droit-Volet (2009) Msetfi et al. (2012) *exp.1* Msetfi et al. (2012) *exp.2*	Sevigny et al. (2003) Msetfi et al. (2012) *exp.1* Msetfi et al. (2012) *exp.2*		

Section 1, the concept of interval duration does not apply to this type of task. It has to be noted that for some tasks data are available for a few interval ranges only (see Table 2). The tasks which were studied most frequently are verbal estimation and time production, in particular in the interval ranges short and medium.

The effect of interval range on the effect size (i.e., on the difference between depressives and controls) was analyzed by fitting the random effects meta-regression model introduced above (van Houwelingen et al., 2002) per task, again using the SAS PROC MIXED procedure, and again based on the data presented in Appendix A.2, that is, averaged effect sizes and variances per sample, task and interval range. Because SAS PROC MIXED computes Type 3 tests only for dummy-coded, but not for effect-coded covariates, a slightly different SAS syntax was used (see Appendix B.2). The meta-regression models also provided least-squares means as estimators of effect size per interval range and task. These estimates represent predicted population marginal means, based on the estimated fixed-effects parameters (Littell et al., 2006). Results are presented in Fig. 1 and Table 3.

Note that although the robust variance estimation approach (Hedges et al., 2010) can be used for meta-regression, at present it is not possible to compute Type 3 tests for the effects of a categorical covariate within this procedure (Elizabeth Tipton, personal communication, November 2014).

For no task, the Type 3 test indicated a significant influence of the covariate interval range on the effect of depression on task performance (time estimation: $F(3, 13.5)=0.78$, $p=0.525$; time production: $F(3, 11.4)=2.85$, $p=0.085$; temporal reproduction: $F(2, 5)=2.06$, $p=0.223$; duration discrimination: $F(1, 6)=1.68$, $p=0.243$). However, for time production, there was a tendency towards overproduction of short and underproduction of long durations in depressive patients.

The least-squares means (Table 3) showed marginally significant effects of medium size for verbal time estimation at long intervals (depressives overestimated time intervals) and duration discrimination at short intervals (depressives discriminated less accurately). For time production and time reproduction, no significant or marginally significant results were obtained for any interval range.

In summary, the meta-regression showed no strong effects of interval range. Thus, the lack of significant effects of depression in Step 1 cannot be attributed to effects of depression on time perception differing between interval durations ranging from the sub-second range to minutes.

3.3. Outlier-corrected results

In the third step, for each task, we used regression diagnostics to identify outlying data. Following the recommendations by Viechtbauer and Cheung (2010), we analyzed the externally studentized residuals (also called the studentized deleted residuals) and the DFFITS index proposed by Belsley et al. (1980) as a measure of the influence of an observation. Following Belsley et al. (1980), externally studentized residuals with an absolute value exceeding 1.96, or an absolute DFFITS value exceeding $2\sqrt{p/n}$,

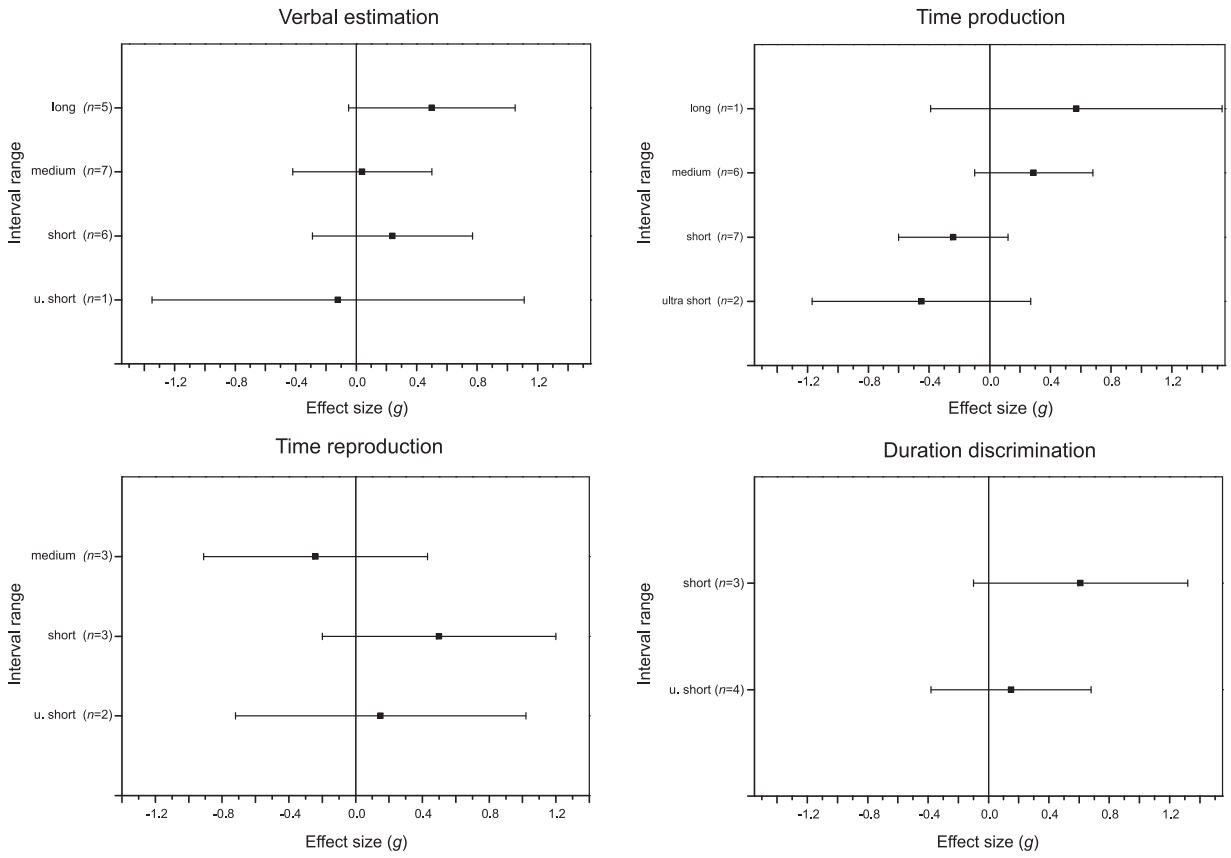

Fig. 1. Pooled effect sizes per combination of task and time interval range. Effect size estimates and corresponding 95% confidence intervals as provided by least-squares means (marginal means) in the meta-regression analysis. Each data point represents one interval range, with the number of studies indicated by the values in parentheses. Each panel represents one task.

Table 3
Estimated effect sizes (θ_{LSM}) per combination of task and interval range, as provided by least-squares means computed in the classical random effects meta-regression model.

Task	Interval range	*N* studies	θ_{LSM}	CI_L	CI_U	*t*	*df*	*p*
Estimation								
	Ultra short	*1*	*−0.12*	*−1.35*	*1.11*	*0.21*	*14.0*	*0.834*
	Short	6	0.24	−0.29	0.77	0.98	13.3	0.344
	Medium	7	0.04	−0.42	0.50	0.87	12.8	0.871
	Long	5	0.50†	−0.05	1.05	1.97	13.6	0.070
Production								
	Ultra short	2	−0.45	−1.18	0.27	1.36	12.0	0.200
	Short	7	−0.24	−0.60	0.12	1.47	10.2	0.173
	Medium	6	0.29	−0.10	0.68	1.69	9.8	0.123
	Long	*1*	*0.57*	*−0.39*	*1.53*	*1.31*	*11.2*	*0.217*
Reproduction								
	Ultra short	2	0.15	−0.72	1.03	0.45	5	0.669
	Short	3	0.50	−0.20	1.19	1.83	5	0.127
	Medium	3	−0.24	−0.91	0.43	0.93	4.8	0.398
Discrimination								
	Ultra short	5	0.15	−0.38	0.67	0.68	6	0.521
	Short	3	0.61†	−0.09	1.32	2.12	6	0.078

Note: †Indicates statistically marginal significant results ($p < .1$). Categories including data from one single study only are indicated by italics.

where *n* is the number of effect sizes analyzed in the model, and *p* is the number of levels of the covariate (interval range), were defined as outliers. For the time estimation task, the data in the long interval range provided by Oberfeld et al. (2014) ($g = -0.33$) and Wyrick and Wyrick (1977) ($g = 2.11$) were identified as outliers. Excluding these data points from the analyses yielded a pooled effect size estimate for the time estimation task of $g = 0.11$ ($p = 0.334$), which is slightly smaller than the value based on the analysis including the two outliers (Table 1). With the two outliers excluded, the effect of interval range remained statistically insignificant, $F(3, 11.9) = 0.78$, $p = 0.530$, indicating no differences in comparison to the analysis that included the outliers. The least-squares mean in the long interval range dropped from $g = 0.50$ (cf. Table 3) to $g = 0.28$ ($p = 0.175$).

For the time production task, one effect size of 0.85 for the medium interval range reported by Bschor et al. (2004) was identified as an outlier. Its exclusion resulted in an even reduced pooled effect size estimate ($g = 0.017$, $p = 0.91$), and no significant effect of interval range, $F(3, 9.55) = 2.34$, $p = 0.14$.

For time discrimination, one effect size of 0.95 for the ultra-short interval range reported by Rammsayer (1990) was identified as an outlier. Its exclusion resulted in a reduced pooled effect size estimate ($g = 0.18$, $p = 0.29$), and no significant effect of interval range, $F(1, 2.14) = 8.55$, $p = 0.17$. The outlier-corrected predicted marginal means (θ_{LSM}) were −0.12 ($SE = 0.13$; $p = 0.500$) and 0.48 ($SE = 0.16$; $p = 0.172$) for the ultra short and short interval range, respectively.

For the time reproduction task and the subjective flow of time, no outliers were identified.

4. Discussion

The objective of this meta-analysis was to evaluate whether time perception in terms of judgments of temporal intervals on the one hand and judgments of the subjective flow of time on the other hand is altered in depression. In a first step, pooled effect size estimates were computed for each of the five different types of tasks that have been used in the literature to investigate time

perception in depressives: verbal time estimation, time production, time reproduction, duration discrimination, and time experience (subjective flow of time). In a second step of analysis, we investigated whether possible effects of depression on time perception depend on the interval durations (e.g., sub-second versus minute range) that had to be judged by the subjects. Using a meta-regression approach, we considered interval duration as a covariate, which might influence the effect of depression on time perception in the interval timing tasks (not time experience) and could explain some of the between study variance.

Our analyses provided no evidence for effects of depression on time interval judgments. Verbal estimation, production, reproduction, and discrimination of time intervals did not significantly differ between depressives and control subject. However, effects of depression on judgments of the flow of time were statistically significant and medium in size ($g=0.66$). Thus, the results confirm the notion of a reduced speed of the flow of time in depressive subjects and, at the same time, suggest that this impression is not tantamount to a change in the ability to judge the duration of time intervals.

The meta-regression using interval range as a covariate (Step 2) showed that differences in interval durations cannot explain the heterogeneity of the single study results or the lack of significant results in the time perception tasks in this meta-analysis. For none of the four tasks, interval range had a significant influence on potential effects of depression on time perception. Only in the production task, there was a tendency towards overproduction of short and underproduction of long durations in depressive patients compared to a healthy control group. And, in the cases of long range verbal estimation and short range duration discrimination, least-squares means indicated medium and marginally significant effects of depression. Here, depressive subjects tended to overestimate the time intervals, and to discriminate time intervals less precisely compared to control subjects. However, even these marginal effects would be further reduced when taking corrections for multiple testing and our exclusion of outliers into account.

Partly, the data on time perception in depression are in line with the predictions of the *pacemaker–accumulator models* (Gibbon et al., 1984; Treisman, 1963). Judging time as going by less quickly is compatible with a faster running internal clock in depressive subjects. As discussed above, the null effects of depression in reproduction and duration discrimination tasks are also predicted by the internal clock model. However, the lack of significant group differences in the context of verbal estimation and production tasks is not in favor of this assumption. Thus, to some extent, the inconsistencies in the empirical findings remain and even meta-analyzed data do not fully support the hypothesis of a faster running internal clock in depressive patients.

Moreover, it has to be noted that even the few statistically significant and marginally significant results have to be viewed cautiously due to several reasons. First, we used the uncorrected (slightly biased) effect size estimator *g*. According to Hedges and Olkin (1985), *g* is biased towards overestimation of effects especially when effects and sample sizes are small. At least the problem of small effect sizes has to be considered in our analysis, indicating that the effect of depression on time perception might be even smaller in the depressive population than in our aggregated sample. Second, the analyses included multiple testing because we computed pooled effect sizes separately for each of the five tasks. On an appropriately adjusted α-level (Hochberg, 1988), no effect would have reached statistical significance. Third, publication bias may have caused an overestimation of effect size in our analysis. We did not attempt to provide quantitative estimates of publication bias or to correct for its estimated influence (cf. Sutton and Higgins, 2008) because given the small number of primary studies in our view there is insufficient information for doing these analyses. However, we sent calls for unpublished data on the topic to more than 100 researches in the field of timing and time perception and received only one additional set of data (Mioni et al., submitted). For this reason, we do not assume a substantial amount of unpublished data on the topic.

Beside these limitations suggesting a potential overestimation of effect sizes in the analyses, the fact that some of the studies included depressive patients who were on medication or in psychotherapy might have led to an underestimation of effect sizes. The small number of studies that were included in the analysis, and the failure of most studies to provide detailed information concerning the number of subjects under medication, did not allow controlling for possible effects of medication and psychotherapy. Half of the studies (see Supplementary Table 1) reported that at least some of their patients were medicated or in psychotherapy. Needless to say, medication and psychotherapy are applied in order to reduce depressive symptoms. Therefore, possible effects of depression on time perception might also decline in subjects that are under medication or in psychotherapy. Hence, the inclusion of depressive patients that received some sort of therapy probably led to an underestimation of the pooled effect sizes reported in this meta-analysis. Unfortunately, it was not possible to include medication status as a covariate, because only our own study (Oberfeld et al., 2014) analyzed the effects of depression on time perception separately for patients on and off medication. In the latter study, there was no significant effect of medication status. In addition, for the studies that administered a depression inventory like the BDI (e.g., Gil and Droit-Volet, 2009; Kornbrot et al., 2013; Msetfi et al., 2012; Oberfeld et al., 2014; Sevigny et al., 2003), the BDI scores provide information about the severity of depression on the day of testing. In our own study (Oberfeld et al., 2014), there were no significant correlations between the BDI score and the different time perception measures. Thus, individual differences in the severity of depression, which might have been due to medication or psychotherapy, do not appear to explain the weak effects of depression on time perception.

Based on the foregoing arguments, we conclude that the pooled effect sizes reported in this meta-analysis are more likely to overestimate than to underestimate the effects of depression on time perception on the population level.

A general issue for this meta-analysis was the heterogeneity of diagnostic criteria (DSM, ICD, BDI score etc.) and their modifications over time (e.g., DSM-III vs. DSM-IV). This factor might have led to inconsistencies in group assignment between the different studies. For instance, some subjects that were assigned to the control group in one study might have been classified as depressives in another study that used different criteria for group assignment. In order to minimize this potential problem, future research should consider group assignments based on BDI scores or using the BDI score as a continuous variable. This would provide a consistent quantitative measure of the severity of depression, facilitating the comparison between studies.

With regard to future research, our review of the literature identified several additionally aspects that have not yet been investigated sufficiently and which therefore were not evaluated in our meta-analysis. For example, some of the mechanisms that are considered to be responsible for alterations in clock rate not only in depressive subjects are changes in neurotransmitter systems. In the context of interval timing in the seconds-to-minutes range, the internal clock appears to depend on the level of dopaminergic activity (Meck, 1996, 2005; Rammsayer, 1990). Evidence from animal as well as human research suggests that decreased dopaminergic activity is related to a deceleration of clock speed (underestimation of time intervals) while increased dopamine levels usually cause opposite effects (e.g., Cheng et al., 2007; Jones and Jahanshahi, 2009; Rammsayer, 1993; Wiener et al., 2014). In depressive patients, abnormalities in neurotransmitter systems are observed frequently (Leonard, 2014; Werner

and Covenas, 2010). In particular, dopamine levels are typically decreased in depression, but with large inter-individual variability (Ebert and Lammers, 1997; Kapur and Mann, 1992; Yadid and Friedman, 2008). Thus, effects of depression on time perception might be mediated by dopamine levels and therefore vary between different patients or subtypes of depression. It would be interesting to consider direct measures of dopamine level in future studies in order to shed more light on the role of alterations in neurotransmitter systems in time perception in clinical populations.

In this context, additional research on patients in manic and mixed states (bipolar disorders) is also needed. For example, in contrast to major depression, which is often associated with slowed thinking (e.g., Marazziti et al., 2010), patients in manic and mixed states typically report racing thoughts (sometimes referred to as tachypsychia) (Benazzi and Akiskal, 2003; Geller et al., 2002). These opposing symptoms might be related differently to alterations in clock speed. Bschor et al. (2004), for example, provide evidence for an accelerated passage of subjective time in manic patients compared to a control group and a major depressive group. In order to reduce noise in the data from depressive patients, future studies should distinguish between the different subgroups of depression according to recent classifications. Moreover, ratings on the subjective flow of time can be improved by additionally assessing boredom ratings. This might help (depressive) subjects in understanding questions on the passage of time correctly, and can prevent them from confusing the concepts of time passage and boredom.

Another interesting aspect would be to focus on possible influences of the modality in which the stimuli to be timed are presented. In the primary studies analyzed here, temporal intervals were presented either visually or acoustically. The question whether the processing of visual stimuli is affected more strongly by depression than the processing of acoustic stimuli or vice versa remains unaddressed so far. Future research might consider modality as a covariate of time perception in clinical populations. In healthy subjects, there is evidence for differences in the temporal processing of visual vs. acoustic stimuli. Compared to visually marked time intervals, intervals of the same duration presented in the auditory modality are perceived as being longer (Goldstone and Lhamon, 1974; Wearden et al., 1998). Moreover, sensitivity to time is higher when intervals are presented acoustically, i.e., temporal judgments are less variable than for visually presented time intervals (Grondin, 2010; Grondin and McAuley, 2009). Accordingly, effects of depression on time perception might be easier to detect when the tasks involve auditory rather than visual stimuli.

Additionally, for time estimation tasks, it is crucial to differentiate between prospective and retrospective judgments (cf. Grondin, 2010), which has not been done systematically in the context of depression and time perception. In the prospective paradigm, the subject is informed about the task to estimate a presented time interval. Here, the subject explicitly focuses attention on the temporal task. In the retrospective paradigm, the subject is uninformed about the time estimation task. For example, a participant is asked at the end of the experiment how much time had elapsed since the beginning of the experiment, without having been informed previously that such an estimate would be required. In this case, the subject did not focus attention on time. In contrast to prospective judgments, the task to give a retrospective estimate is less attention-related and more memory demanding (e.g., Brown, 2008; Grondin, 2010). There is evidence indicating systematical differences between prospective and retrospective estimation paradigms (for a meta-analytic review see Block and Zakay, 1997), with prospective judgments being longer and less variable than retrospective judgments. Regarding possible effects of depression on time estimation, prospective and retrospective judgments might be affected differently indicating whether attentional (prospective) processes or/and memory-related (retrospective) processes of temporal information processing are altered in depression. Due to the fact that only few studies could be included in this meta-analysis, further covariates as for example the estimation paradigm (prospective vs. retrospective) could not be considered in the analysis. Inspection of the studies, however, indicated differences between results from one study including retrospective judgments (Münzel et al., 1988) and another study including prospective judgments (Bschor et al., 2004), with a trend towards larger effects in the context of retrospective (memory-related) judgments (more overestimation in depressives). However, in three out of four studies that actually tested both types of judgments within the same sample (Kitamura and Kumar, 1983; Oberfeld et al., 2014; Tysk, 1984; Wyrick and Wyrick, 1977), no systematic differences between retrospective and prospective estimates are evident. Only Wyrick and Wyrick (1977) reported larger effects for retrospective than for prospective judgments.

Taken together, the results of our meta-analysis indicate that judgments of time intervals are not affected systematically by depression. However, the notion of a reduced speed of the flow of time in depression has been confirmed. This also emphasizes the importance of a clear distinction between judgments on the flow of time and estimates of precisely defined time intervals (for a discussion see Oberfeld et al., 2014). Our review also shows that several aspects have not yet been investigated in sufficient detail in the context of time perception in depression and might be addressed by future research. These aspects include the role of the dopaminergic neurotransmitter system, influences of different subtypes of depression, potential influences of stimulus modality, and specific task-related characteristics like prospective versus retrospective time estimation. The effect sizes provided by our meta-analyses may be used for selecting appropriate sample sizes in future experiments.

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Conflict of interest

The authors declare no conflicts of interest.

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Appendix A. Supporting information

Supplementary data (Supplementary Tables 1 and 2) associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jad.2014.12.057.

Appendix A.1

Results of the literature search. Studies were considered for further analyses only if all of the four inclusion criteria (see Section 2.1) were met. Studies included in the meta-analysis are indicated by bold font.

See Table A1.

Table A1

Study	Empirical study?	Patient and control group?	Sufficient statistical information?	Comment	Relevant tasks?	Inclusion?
Straus (1947)	No					No
Dubois (1954)	No					No
Mezey and Cohen (1961)	Yes	No (dep. before and after recovery)	Yes		Yes	No
Bojanovsky (1965)	Yes	No (psychogenic vs. endo. dep.)	No	(*M* and imprecise *p* only)	Yes	No
Dilling and Rabin (1967)	Yes	Yes	No	(No *SD/SE or t/F values*)	Yes	No
Lehmann (1967)	No					No
Bojanovsky and Tölle (1973)	Yes	No (neurotic vs. endo. dep.)	No	(*M* and imprecise *p* only)	Yes	No
Grinkeret al. (1973)	Yes	Yes	No	(No numerical *M/SD,* only figure, no *t/F* values, imprecise *p* only)	Yes	No
Bech (1975)	Yes	Yes	No	(*Mean and range, no SD* and imprecise *p* only)	Yes	No
Wyrick and Wyrick (1977)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Kitamura and Kumar (1982)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Kitamura and Kumar (1983)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Tysk (1984)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Richter and Benzenhofer (1985)	Yes	No (case study)	Yes		Yes	No
Tysk (1984)	Yes	No (dep. longitudinal)	No	(*r* and imprecise *p* only)	Yes	No
Hawkinset al. (1988)	Yes	No	Yes		Yes	No
Münzel et al. (1988)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Kuhs et al. (1989)	Yes	Yes	No	(*M* and imprecise *p* only)	Yes	No
Rammsayer (1990)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Watt (1991)	Yes	No	Yes		Yes	No
Blewett (1992)	Yes	No (depressives only)	Yes		Yes	No
Nosachev (1992)	Yes	Yes	No	(Measure of dispersion reported, but not specified whether SE, SD etc.)	Yes	No
Mundt et al. (1998)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Lemke et al. (1999)	Yes	Yes	Yes		No (movement analysis)	No
Sevigny et al. (2003)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Bschor et al. (2004)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Meck (2005)	No (review)					No
Grondin et al. (2006)	No (review)					No
Mahlberg et al. (2008)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Gil and Droit-Volet (2009)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Biermann et al. (2011)	Yes	No	Yes		Yes	No
Bolbecker et al. (2011)	Yes	Yes	Yes		No (f. tapping)	No
Gallagher (2012)	No (review)					No
Msetfi et al. (2012)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Ratcliffe (2012)	No (review)					No
Droit-Volet (2013)	No (review)					
Kornbrot et al. (2013)	**Yes**	**Yes**	**Yes**	**Author provided the raw data**	**Yes**	**Yes**
Oberfeld et al. (2014)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**
Mioni et al. (submitted)	**Yes**	**Yes**	**Yes**		**Yes**	**Yes**

Note. dep.=depression/depressive patients; f. tapping=finger tapping task; endo.=endogenous; SD=standard deviation; SE=standard error.

Appendix A.2

Averaged effect sizes (g) and effect size variances ($Var\ g$), number of reported means (J), and corresponding 95% confidence intervals per combination of sample, task and interval range. J denotes the number of effects sizes on which the average g is based on.

See Table A2.

Appendix B. SAS syntax used in the meta-analyses

Appendix B.1. SAS syntax for the classical random-effects meta-regression model used to compute the pooled effect size estimates per task

This meta-regression model was applied separately for each task. In the example, the data for the time production task are analyzed. The data set time_depression_TimeProduction contains one effect size estimate (variable g_i) for each combination of study and interval range (variable `intervalRange`). Each of these combinations was treated as a separate study, indicated by a unique value of the variable `studyNo`. The interval range was analyzed as a categorical covariate, using effect-coding via the indicator variables `e1` to `e3`, so that the estimated intercept corresponds to the pooled effect size estimate (θ). SAS syntax based on van Houwelingen et al. (2002).

```
data time_depression_TimeProductionEC;
  set time_depression_TimeProduction;
  if intervalRange="large" then
    do;
      e1=1;e2=0;e3=0;
    end;
  else if intervalRange="medium" then
    do;
      e1=0;e2=1;e3=0;
```

Table A2

Study	Task	Interval range	J	g	$Var(g)$	CI_L	CI_U
Wyrick and Wyrick (1977)	Est	Short	2	0.14	0.12	−0.37	0.64
		Medium	4	0.42	0.24	−0.09	0.93
		Long	2	2.11	0.03	1.48	2.75
Kitamura and Kumar (1983)	Est	Short	6	0.53	0.09	−0.06	1.13
		Medium	12	0.53	0.09	−0.06	1.13
		Long	6	0.20	0.09	−0.39	0.79
	Pro	Long	3	0.57	0.09	−0.02	1.17
Tysk (1984)	Est	Short	1	0.44	0.05	−0.02	0.89
		Medium	3	−0.03	0.05	−0.48	0.42
	Pro	Short	1	0.27	0.05	−0.72	0.19
		Medium	2	−0.19	0.05	−0.26	0.64
Münzel et al. (1988)	Est	Medium	3	0.38	0.08	−0.19	0.95
		Long	1	0.00	0.08	−0.57	0.57
	Pro	Short	3	−0.08	0.08	−0.65	0.48
		Medium	1	0.37	0.08	−0.20	0.94
Rammsayer (1990)	Dis	U short	1	0.95	0.05	0.52	1.37
Mundt et al. (1998)	Pro	Short	1	−0.13	0.09	−0.72	0.47
		Medium	3	0.74	0.10	0.13	1.35
	Rep	Medium	4	−0.48	0.09	−1.08	0.12
Sevigny et al. (2003)	Dis	Short	2	0.25	0.12	0.42	0.92
		U short	1	0.75	0.12	0.06	1.44
Bschor et al. (2004)	Est	Short	1	0.00	0.06	−0.50	0.49
		Medium	2	−0.28	0.06	−0.77	0.22
		Long	1	0.59	0.07	0.09	1.10
	Pro	Short	1	−0.39	0.06	−0.89	0.11
		Medium	2	0.84	0.07	0.32	1.35
Mahlberg et al. (2008)	Rep	Short	2	1.03	0.08	0.49	1.58
		Medium	1	0.09	0.07	−0.43	0.60
Gil and Droit-Volet (2009)	Dis	U short	1	−0.17	0.08	−0.71	0.37
Msetfi et al. (2012) *exp. 1*	Dis	U short	1	−0.28	0.11	−0.93	0.38
		Short	1	0.84	0.12	0.16	1.52
Msetfi et al. (2012) *exp. 2*	Dis	U short	1	−0.14	0.05	−0.59	0.30
		Short	1	0.34	0.05	−0.10	0.79
Kornbrot et al. (2013)	Est	Short	1	−0.40	0.10	−1.01	0.21
	Pro	Medium	4	−0.68	0.10	−1.30	−0.06
		Short	1	−0.71	0.10	−1.33	−0.08
		Medium	4	−0.67	0.10	−1.29	−0.05
Oberfeld et al. (2014)	Est	U short	1	−0.12	0.09	−0.71	0.47
		Short	1	0.27	0.09	−0.32	0.87
		Medium	1	−0.12	0.09	−0.71	0.47
		Long	1	−0.33	0.09	−0.93	0.26
	Pro	U short	1	0.01	0.09	−0.58	0.60
		Short	1	0.20	0.09	−0.39	0.80
		Medium	1	0.21	0.09	−0.38	0.80
	Rep	U short	1	−0.10	0.09	−0.69	0.50
		Short	1	−0.09	0.09	−0.68	0.51
		Medium	1	−0.37	0.09	−0.97	0.23
Mioni et al. (submitted)	Pro	U short	1	−1.09	0.16	−1.88	−0.30
		Short	2	−0.33	0.14	−1.08	0.41
	Rep	U short	1	0.47	0.15	−0.28	1.22
		Short	2	0.50	0.15	−0.25	1.25

Note: Est: verbal time estimation; Pro: time production; Rep: time reproduction; Dis: duration discrimination; "U short": ultra short.

```
  end;
else if intervalRange="short" then
  do;
    e1=0;e2=0;e3=1;
  end;
else if intervalRange="ultra_sh" then
  do;
    e1=-1;e2=-1;e3=-1;
  end;
  run;
proc mixed
data=time_depression_TimeProductionEC
order=data method=REML covtest NOBOUND; /*Option
COVTEST provides a test for heterogeneity. Option
'NOBOUND' is used to prevent a non positive definite
estimated R matrix, which often happens if the
between-study variance is close to 0*/
    class studyNo; /*Classification variable
studyNo contains the study number*/
    model g_i=e1 e2 e3
/outp=time_depression_TProdout s ddfm=KR CL;
/*g_i is the effect size estimate. The model
contains an intercept and the three indicator
variables representing the effect-coded
covariate (interval range). Degrees of freedom
computed according to Kenward and Roger (1997).
Option 's': print fixed effects estimates. Option
'outp': save estimates in new data set. Option
'CL': print confidence limits for the estimated
parameters*/
    random int /subject=studyNo G s; /*Random
intercept model, intercept allowed to vary between
studies.
Option 's': print random effects estimates.
Option 'G': print G matrix*/
    repeated /group=studyNo type=VC R; /*Each
study has its own variance. Covariance matrix R has
type
"variance components" (Wolfinger, 1993). Option
'R': print estimated R matrix */
    parms (2) (.0919) (.0691) (.1006) (.0848)
(.0966) (.0914) (.0526) (.0647) (.1012) (.1441)
(.0838) (.0918) (.0914) (.0528) (.1627) (.0909)
/eqcons=2 to 17; /*List of parameters: contains a
starting value for the between study variance
(first entry) and the variances (Var(g_i)) for each
study (see Appendix A.2), which should be kept fixed
(Option 'eqcons')*/
  run;
```

In the SAS output, the row "Intercept" in Table "Solution for Fixed Effects" provides the estimate of the population effect size θ and its standard error. Row "Intercept" in table "Covariance Parameter Estimates" provides the estimate of the inter-study variance τ^2 and a test for homogeneity of the single-study means.

Appendix B.2. SAS syntax for the random effects meta-regression model used to compute Type 3 tests for the effects of the covariate interval range

This analysis uses the same model as in Appendix B.1, but with dummy-coded rather than effect-coded covariate.

```
proc mixed data=time_depression_TimeProductionEC
  order=data method=REML covtest NOBOUND;
  /* Option COVTEST provides a test for
  heterogeneity. Option 'NOBOUND' is used to prevent
  a non positive definite estimated R matrix, which
  often happens if the between-study variance is
  close to 0.*/
    class studyNo intervalRange; /* Classification
  variable studyNo contains the study number,
  variable intervalRange specifies the interval
  range */
    model g_i=intervalRange
  /outp=time_depression_TProdout s ddfm=KR CL;
  /* g_i is the effect size estimate. The model
  contains an intercept and the dummy-coded variable
  representing the covariate (interval range).
  Degrees of freedom computed according to Kenward
  and Roger (1997).Option 's': print fixed effects
  estimates. Option 'outp': save estimates in new
  data set. Option 'CL': print confidence limits for
  the estimated parameters */
    random int /subject=studyNo G s; /* Random
  intercept model, intercept allowed to vary between
  studies. Option 's': print random effects
  estimates. Option 'G': print G matrix */
    repeated /group=studyNo type=VC R; /* Each
  study has its own variance. Covariance matrix R has
  type "variance components" (Wolfinger, 1993).
  Option 'R': print estimated R matrix */
    parms (2) (.0919) (.0691) (.1006) (.0848)
  (.0966) (.0914) (.0526) (.0647) (.1012) (.1441)
  (.0838) (.0918) (.0914) (.0528) (.1627) (.0909)
  /eqcons=2 to 17; /* List of parameters: contains a
  starting value for the between study variance
  (first entry) and the variances (Var(g_i)) for each
  study (see Appendix A.2), which should be kept fixed
  (Option 'eqcons')*/
    lsmeans intervalRange / adjdfe=row; /* This
  provides least-squares estimates (marginal
  means) of the effect size per level of the
  classification variable intervalRange, plus
  confidence intervals. Option 'adjdfe': use Kenward
  & Roger degrees-of-freedom specific for each level
  of intervalRange */
run;
```

In the SAS output, the table "Type 3 Tests of Fixed Effects" displays the test for an effect of the covariate (interval range). Row "Intercept" in table "Covariance Parameter Estimates" provides the estimate of the inter-study variance τ^2 and a test for homogeneity of the single-study means.

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