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# Identifying the duration of emotional stimulus presentation for conscious versus subconscious perception via hierarchical drift diffusion models

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A B S T R A C T

To investigate subliminal priming effects, different durations for stimulus presentation are applied ranging from 8 to 30 ms. This study aims to select an optimal presentation span which leads to a subconscious processing.

40 healthy participants rated emotional faces (sad, neutral or happy expression) presented for 8.3 ms, 16.7 ms and 25 ms. Alongside subjective and objective stimulus awareness, task performance was estimated via hierarchical drift diffusion models.

Participants reported stimulus awareness in 65 % of the 25 ms trials, in 36 % of 16.7 ms trials, and in 2.5 % of 8.3 ms trials. Emotion-dependent responses were reflected in decreased performance (drift rates, accuracy) during sad trials. The detection rate (probability of making a correct response) during 8.3 ms was 12.2 % and slightly above chance level (33.333 % for three response options) during 16.7 ms trials (36.8 %).

The experiments suggest a presentation time of 16.7 ms as optimal for subconscious priming. An emotion-specific response was detected during 16.7 ms while the performance indicates a subconscious processing.

## 1. Introduction

A correct identification of emotions is an essential part of successful communication among humans. In fact, when perceiving our environment, we are processing a large number of emotional signals. To select relevant information, fast and correct perception and categorization are essential (Brosch et al., 2010). The human visual system can process visual stimuli in milliseconds (Thorpe et al., 1996). While extensive research has been conducted on visual perception, yet, the necessary duration to perceive a stimulus with awareness or process it without awareness is still controversial.

Unawareness can be defined via attentional and sensory perception [for a review on the terminology see (Tamietto & De Gelder, 2010)]. Attentional unawareness, where stimuli are not perceived consciously due to a lack of attention, can be induced by distracting

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attention, e.g. via a dual-task design (Axelrod et al., 2015). Sensory unawareness describes the phenomenon of a stimulus presentation below a detection threshold using a very brief (subliminal, typically below 30 ms) presentation time (Pessoa et al., 2005; Tamietto & De Gelder, 2010). When a stimulus is processed without awareness, we (as researchers) can obtain behavioral responses from participants that indicate whether stimuli have been subconsciously processed; these responses can be categorized into subjective and objective measures. As objective criteria, behavioral measures like performance accuracy and response time towards a specific stimulus can be obtained. According to Pessoa and colleagues (Pessoa, 2005), performance at chance level could be an objective criterion for unaware stimulus perception. The determination of chance level depends on the study design, which is in a two-choice paradigm with an equal frequency for both stimulus types 50 % and in a three-choice paradigm with an equal frequency for all three stimuli 33.333 %. Withal, individual subjective reports on whether the participants saw the stimulus depict a subjective criterion and can inform about an individual's self-perceived awareness of a stimulus (Pessoa, 2005).

Until today, several methods to study subconscious perception have been applied. This includes, amongst others, backward/forward masking, continuous flash suppression, binocular rivalry/fusion or change detection paradigms which lead to a large methodological heterogeneity (Axelrod et al., 2015; Esteves et al., 1994; Esteves & Öhman, 1993; Joormann et al., 2011; Killgore & Yurgelun-Todd, 2004; Stuhrmann et al., 2013; Victor et al., 2010; Yang et al., 2011; Zhang et al., 2016). Varying presentation time and stimulus material yielded inconsistent results concerning awareness and behavioral effects (for an overview of the display durations and stimuli used in studies investigating subconscious emotional stimulus processing, please see supplement 3). Until now, a major challenge in investigating the effect of subconscious stimuli has been determining the presentation time at which a stimulus is processed below conscious awareness.

Early studies applied backward masked paradigms to study subconscious processing, which included a brief stimulus presentation followed by a mask (Axelrod et al., 2015). These studies indicated that participants were not conscious of stimuli when the interval between the target onset and the masking stimulus was sufficiently brief, typically around 30 ms (Esteves et al., 1994; Whalen et al., 1998). However, the finding that 7 out of 11 healthy participants were able to detect fearful emotional faces at a presentation time of ≈ 33 ms during backward masking critically challenged the assumption that stimuli presented for 30 ms were perceived subconsciously (Pessoa et al., 2005). Studies used presentation times of 33 ms (Esteves et al., 1994; Pessoa et al., 2005; Whalen et al., 1998), 26 ms (Victor et al., 2010), 21 ms (De Pascalis et al., 2020), 20 ms (Zhang et al., 2020), 10 ms (Milders et al., 2008), 8 ms (Kiss & Eimer, 2008) or 7 ms (Flynn et al., 2017, note that target stimuli were not emotional expressions here). Yet, the majority of studies used a presentation time of 16.7 ms/17 ms to present images of emotional expressions (Hedger et al., 2019; Lojowska et al., 2019; Neath & Itier, 2014; Peng et al., 2017; Suslow et al., 2003; Zhang et al., 2016) and other stimulus material (words or grating orientation) (Cai et al., 2020; Lojowska et al., 2019) below conscious awareness. For an overview please see supplement 3.

In summary, subconscious perception most likely occurs between 7 ms and 30 ms, but study findings are not conclusive, yet. This may be a result of large inter-individual differences and small sample sizes, methodological differences in the task design, or the specific characteristic of the stimulus itself. Processing briefly presented material may not be equal across individuals. The investigation of inter-individual differences, for example comparing underlying neural processes of patients with mental disorders and healthy controls, has provided interesting insights on the process itself. Patients with major depressive disorder (MDD) showed a higher amygdala response when processing rapidly presented sad faces than healthy controls (HC), whereas HC showed a higher amygdala response during the perception of happy faces (Suslow et al., 2010). Similarly opposed group differences were shown for fearful versus happy faces (Whalen et al., 1998). These results show that it is important to control for psychiatric disorders or dimensional characteristics that can influence the perception of emotions. In the current study that tested detection differences of sad, neutral and happy faces, we therefore assessed. Participanté psychiatric history, including MDD, the presence of depressive symptoms and alexithymia. When stimuli are presented for a very brief time, they can affect behavior or neurophysiological signals, although participants report an inability to discriminate or detect the stimulus [for a review please see: (Axelrod et al., 2015; Tamietto & De Gelder, 2010)]. Event-related-potential (ERP) analyses revealed specific effects regarding fearful faces in comparison with neutral faces in healthy participants where an enhanced N2 was found only in subliminal trials (Kiss & Eimer, 2008). During the presentation of happy faces, HC exhibited larger N170 components and faster reaction times compared to MDD (Zhang et al., 2016). Additionally, the threshold for conscious perception of different emotional cues seems to differ. For example, individuals could discriminate happy expressions better than neutral, disgusted, or surprised expressions presented for 50 and 100 ms (Neath & Itier, 2014). The participants had the most difficulties in assigning fearful expressions presented for 50 and 100 ms (Neath & Itier, 2014).

Inconsistent study results could also be due to methodological limitations. The inter-study variance could be caused by many studies only applying accuracy as evaluation criterion. However, a consideration of accuracy alone does not fully reflect the complexity of the cognitive processes underlying decision-making such as attention and response selection which may contribute differently when shortening the presentation time. The present study aimed to evaluate the performance within a task not only via accuracy but also via drift rates within a decision-making process. Therefore there combination of reaction time (RT) and response accuracy can be used to inform a model which describes different parameters underlying psychological functions (Nishiguchi et al., 2019; Pitliya et al., 2022).

One model that quantifies complex internal processes during decision-making such as biases, motor-response time, decision times or general efficiency of information processing is a drift diffusion model (DDM) (Tavares et al., 2017). DDMs estimate the accumulation of information over time during a decision-making process until one of two responses are made (Kim et al., 2021; Mueller & Kuchinke, 2016; Pitliya et al., 2022). In a DDM, decision-evidence towards one of two response options can be estimated based on the respective reaction time and response accuracy. Therefore, the reaction process is separated into single variables describing the different influences on this cognitive processes. The DDM models decision-making processes in two-choice tasks. Each choice is represented as a response boundary. For example, two boundaries representing subjective decision "thresholds" (a) could be calculated for all "correct" responses in contrast to all responses which were "incorrect" during an emotion discrimination task. To reach this response-boundaries (correct or incorrect), a drift process has to tend towards one response option. This drift process starts with a "non-decision time" (t). Evidence accumulation is then represented via the "drift rate" (v) towards one response boundary (Ratcliff & Rouder, 1998; Wiecki et al., 2013).

The model is calculated based on the assumption that a response is made once enough information is collected to cross a subjective threshold (a). Depending on the amount of information needed, a threshold towards one or the other response boundary is higher or lower. A high threshold indicates a response made with more caution (Nishiguchi et al., 2019). This drift process starts at the "starting point" and can be shifted towards one response boundary representing a "bias" (z). Even before encountering specific stimuli, subjective biases towards one response are considered by varying the starting point of this decision process (bias).

Efficiency on information processing is represented by the speed of evidence accumulation (Nishiguchi et al., 2019). The stronger the relationship between accuracy and speed, the faster the drift rate towards one response specific threshold (a) (Roberts & Hutcherson, 2019). A higher drift rate (higher positive values) towards the upper boundary (correct response) can indicate faster and more accurate responses. Lower drift rate values can show slower responses and negative values represent a mean drift rate towards the lower boundary (incorrect responses) (Ratcliff & McKoon, 2008). This allows the comparison of the efficiency of emotion categorization (evidence accumulation efficiency e.g. drift rates) and the effects of varying presentation times on the decision-making process We hypothesize that emotions that are perceived consciously even at short presentation times may have higher drift rates while emotions that are perceived without awareness due to a fast backward masking may induce lower drift rates.

In this study, we show three emotional faces (happy, sad, and neutral) at four different presentation times (8.3 ms, 16.7 ms and 25 ms as potential subconscious, and 150 ms as a representation of conscious stimulus presentation). Lower drift rates towards correct responses, which are thus expected in trials with a brief presentation time, would suggest a lower processing efficiency. We hypothesize that with shorter presentation times the processing efficiency and therefore the drift rates decrease because of lower stimulus awareness and subsequently higher decision making insecurity. At shorter presentation times, the presented faces could potentially be processed only in parts which could lead to a more noisy decision process. Therefore, the extraction of drift rates during the decision-making process via DDM could give insights into processing steps of the presented emotional stimuli.

One key component of our perception is the attentional allocation. It refers to the way in which our attention is distributed and focused on specific stimuli and plays a critical role in determining which stimuli are selected for conscious processing (Pachur et al., 2018). As assumed by Nishiguchi and colleagues (Nishiguchi et al., 2019), the drift rate (v), the starting point (z) and a response threshold (a) is affected by attentional allocation to specific stimuli since attentional allocation could affect the efficiency of information processing (Jessen & Grossmann, 2020). Such biases may be expected when attention towards certain emotions differs. However, depending on the duration of stimulus presentation, it may be expected that an attentional bias has a larger or smaller effect on evidence accumulation. The accumulation process might be interrupted too early to make a certain decision hence reducing the steepness of the drift rate. Thus, more adequate attention could be needed for shortly presented emotional stimuli for precise decisions. Vice versa, assuming differences in attentional allocation, differences in the drift rates between emotions might be more pronounced at shorter presentation times.

Comparing such tendencies between different emotional categories may further elucidate if a specific emotion has an advantage of being perceived correctly at a certain presentation time.

Under the assumption that participants' decision processes are similar but never identical, a hierarchical drift diffusion model (HDDM) estimates these decision-making parameters simultaneously on an individual and group level (Wiecki et al., 2013). HDDMs provide a fast and flexible way to generate cognitive models for brain processes underlying decision-making via Bayesian parameter estimation. This can represent the complexity of cognitive decision-making more accurately than just considering accuracy alone (Pedersen & Frank, 2020; Wiecki et al., 2013). These intrinsic parameters influencing the decision-making process are estimated via the pooled analyses of raw reaction time data with HDDM. This enables to integrate individual drift rates into the measurement of task performance and thus could complement the pure consideration of accuracy as an objective measurement method for subconscious processing. By combining a drift rate analysis with the traditional accuracy analysis, we aim to add substantial information on subconscious stimulus processing and the decision-making process. In HDDM, the drift rate parameter specifically contributes to the understanding of the evidence accumulation process. Other parameters such as the non-decision time (t) primary reflect movement initiation and execution (Wiecki et al., 2013). In order to limit our model complexity, we thus focused only on estimating emotion and timing related drift rate parameters.

In the current study we aimed to test three different timing conditions for subconscious stimulus presentation below 30 ms (8.3 ms, 16.7 ms, 25 ms) applying subjective and objective measurements of awareness. These three timing durations were used based on previous literature suggesting that a presentation time below a detection threshold takes place below 30 ms (Pessoa et al., 2005; Tamietto & De Gelder, 2010). With a screen refresh rate of 120 Hz, we were able to display the stimuli either for 1 frame (8.3 ms), 2 frames (16.7 ms) or 3 frames (25 ms). In two experiments, participants were asked to classify emotional facial expressions presented for varying presentation times. The estimated processing efficiency should serve as an indication of whether the stimulus was perceived consciously, and which presentation time induces subconscious stimulus detection best. Taking subjective and individual perception differences into account, the study cohort in the second task was asked if they had been aware of the presented facial expression after every decision.

We expected that subjective awareness would increase with higher presentation times and processing efficiency would decrease with shorter presentation times. Subconsciousness was defined via a sensory awareness below chance level (33.333 % for three different stimulus categories).With the second task, we furthermore aimed to determine whether self-perceived awareness differs depending on the presented emotion. Assuming that attentional allocation may also support awareness, we assume that healthy participants report to be certain about an emotional expression to a higher degree if this emotion had an attentional advantage which is hypothesized for happy expressions (Svard et al., 2012). The prominence of visual characteristics in happy expressions such as significant alterations in the mouth configuration, including the display of an open mouth and teeth (Adolphs, 2004; Calvo & Marrero, 2009) could attribute to this superiority in happy face recognition.

## 2. Materials and methods

### 2.1. Participants

Subjects participated in either of two tasks. In task one 20 right-handed healthy subjects (8 male, 12 female) with a mean age of 26.550 years (Standard Deviation (SD) = 2.958) were investigated. In task two 20 right-handed healthy subjects (12 male, 8 female) with a mean age of 26.762 (SD = 3.038) years were tested.

All participants were screened for psychiatric disorders and other chronic or acute illnesses using the short form of the Structured Clinical Interview 5 for DSM Disorders (SCID-5) (Beesdo-Baum et al., 2019). To be included, participants had to be right-handed, between 18 and 50 years old and fluent in the German language. Additionally, subjects had to be free from chronic or acute illness as well as psychiatric disorders according to DSM-V (Falkai et al., 2018). The participants gave written informed consent according to the Declaration of Helsinki and were informed about the study before examination. Participants received compensation of 10 euro for completing task 1. Task 2 was completed without monetary compensation.

### 2.2. Questionnaires

To test for the influence of depressive symptoms, the Beck Depression Inventory (BDI-II) (Beck et al., 1996) was applied. Alexithymia symptoms were assessed using the Bermond-Vorst Alexithymia Questionnaire B (BVAQ-B) (Vorst & Bermond, 2001) (Table 1).

### 2.3. Procedure

Before inclusion, participants were screened for inclusion and exclusion criteria applying the short form of the SCID-5. Once included, participants were invited. Within one hour, participants first completed questionnaires and then accomplished the experimental task. The data were collected within one year (2021).

### 2.4. Experiment 1

In experiment one, a backward mask paradigm was used which provided masked stimulus presentation at different time levels. In line with previous studies, sad, happy, and neutral faces were presented (Stuhrmann et al., 2013; Suslow et al., 2010; Victor et al., 2010; Zhang et al., 2016). A total of 36 images (12 happy, 12 neutral, 12 sad) served as emotional stimuli. Pictures were gender balanced and taken from the FACES database (Ebner et al., 2010). Each image was presented 10 times at full opacity (PsychoPy settings for height "0.484" and width "0.4") against a grey background at the center of an LCD monitor (screen refresh rate = 120 Hz, 256 × 1440 resolution, 27 in., RGB) using the PsychoPy3 software (Peirce, 2007). A scrambled image created by Adobe Photoshop® served as a mask stimulus (see Fig. 1A).

At the beginning of each trial, a fixation cross appeared for 300 ms (36 frames) followed by the stimulus. This target could either be strongly masked (target duration was shorter than mask duration [8.3 ms, 16.7 ms or 25 ms followed by a mask for 41.6 ms]) or weakly masked (target duration was longer than mask duration [141.7 ms followed by a mask for 41.6 ms]). For the strongly masked stimuli (8.3 ms, 16.7 ms or 25 ms), the presentation time varied between blocks. Therefore, the strongly masked images were presented for 25 ms (3 frames) in the first block, for 16.7 ms (2 frames) in the second block and for 8.3 ms (1 frame) in the third block. In each block, the number of strongly and weakly masked trails (141.7 ms) were counterbalanced meaning 50 % of the trials in each block were strongly masked and the other half were weakly masked. Participants completed 3 blocks. Each block contained 120 trials of 50 % weakly and 50 % strongly masked stimuli which were fully randomized. The mask stimulus appeared always for 41.6 ms (5 frames) followed by a response phase of 1.5 s. A blank screen served as an inter-stimulus-interval (ISI) ranging between 1 and 2 s. Subjects completed 5 practice trials before starting the main task. The experimental design created an event related 4 × 3 factorial design (four timing conditions × three emotion conditions) which led to 12 different trial conditions. Participants indicated the stimulus emotion category only ("happy", "sad" or "neutral").

**Table 1**
Descriptive Statistic of BDI-II and BVAQ-B Scores and age for task one and task two. For every experiment was N = 20. Given are mean, standard deviation (Std), minimal and maximal scores.

| Task 1 | Mean | Std. | Min. | Max. | Task 2 | Mean | Std. | Min. | Max. |
|---|---|---|---|---|---|---|---|---|---|
| BDI-II | 2.700 | 4.208 | 0 | 14 | *BDI-II* | 0.810 | 0.906 | 0 | 4 |
| BVAQ-B | 36.050 | 6.996 | 24 | 50 | *BVAQ-B* | 38.048 | 4.488 | 28 | 47 |


(caption on next page)

**Fig. 1.** Backward-masked paradigms. Images of happy, neutral and sad facial expressions, taken from the FACE database, were presented against a grey background of an LCD monitor (120 Hz refresh rate) using PsychoPy 3. A scrambled image served as mask stimulus. The target was presented either for 8.3 ms, 16.7 ms or 25 ms in strongly masked trials. In task 1 **(A)**, weakly masked trials were presented for 141.7 ms (17 frames). For the strongly masked target stimuli only, the presentation time varied between blocks. The target image was presented for 25 ms (3 frames) in the first block, for 16.7 ms (2 frames) in the second block and for 8.3 ms (1 frame) in the third block. Participants were asked to indicate the facial emotion of the target stimulus as fast and precisely as possible. In task 2 **(B),** weakly masked trials were presented for 150 ms (18 frames). Presentation times varied randomly between blocks. Participants were asked to indicate the facial emotion of the target stimulus as fast and precisely as possible. Additionally, subjects were asked to rate the subjective accuracy for indicating the face.

### 2.5. *Experiment 2*

The second experiment used a modified version of the task in experiment one. As one addition, after each stimulus presentation participants were asked to rate if the stimulus was visible ("yes", "no", "unsure") (see Fig. 1B). This served to assess a subjective component of stimulus perception. As another differentiation, weakly masked trials were presented for 150 ms, and all timing conditions were presented in randomized order regardless of the block number to avoid potential order effects.

In both experiments, participants rated the presented images via a button presses on a keyboard (7 = sad, 8 = neutral, 9 = happy, 7 = yes, 8 = no, 9 = unsure). To minimize the impact of response delay caused by movement, participants were instructed to keep their fingers in the same position for the responses on the emotion question and the following question about security.

### 2.6. *Data analysis*

#### 2.6.1. *Performance analysis*

Behavioral data were analyzed with GraphPad Prism version 9.3.1., GraphPad Software, San Diego, California USA, https://www.graphpad.com and RStudio (Team, 2020 https://www.rstudio.com). For all analyses, level of significance was set to α = 0.05. For post hoc comparisons corrections for multiple comparisons were applied. All scripts were uploaded on GitHub (https://github.com/JuliaSchraeder/SubconsciousTiming).

Normality distribution was checked with the Shapiro Wilk normality test (Shapiro & Wilk, 1965). Non-normality distributed data were analyzed by applying the Friedman's test (Marozzi, 2014). For post hoc tests a Dunn's correction was applied as recommended by the GraphPad software (Dunn, 1964).

For each task, mean accuracy was calculated individually for all time by emotion conditions. Descriptive statistics for main effects and condition by time categories were reported (see Tables 2 and 3).

#### 2.6.2. *Hierarchical drift diffusion model selection*

HDDMs were estimated collapsing data across both experiments. All HDDMs were assessed via the open-source Python-based software package HDDM (Wiecki et al., 2013). Estimation of posterior model parameter distribution was assessed via PyMC (Patil et al., 2010). Following the guideline described by Wiecki and colleagues (Wiecki et al., 2013), drift rates underlying decision-making were estimated via trial-by-trial response time data. The first step included the construction of a HDDM estimating group and subject parameters simultaneously at different hierarchies (Wiecki et al., 2013) where the estimation of individual parameters was constrained

**Table 2**
Descriptive Statistic of mean accuracy in task 1 for all emotion and timing conditions with mean, standard deviation, minimal and maximal values for task conditions.

| Mean Accuracy in % | Condition | Mean | Std. | Min. | Max. |
|---|---|---|---|---|---|
| Main effects | total trials | 80.400 | 5.963 | 71.880 | 92.690 |
| | happy | 87.640 | 7.295 | 74.140 | 97.200 |
| | sad | 64.310 | 12.130 | 47.900 | 96.000 |
| | neutral | 88.330 | 6.156 | 79.310 | 97.500 |
| | 8.3 ms | 49.330 | 23.760 | 28.570 | 100.000 |
| | 16.7 ms | 66.400 | 13.580 | 35.290 | 86.670 |
| | 25 ms | 79.430 | 8.705 | 62.710 | 93.880 |
| | 141.7 ms | 94.870 | 3.220 | 87.430 | 99.430 |
| Conditions | 8.3 ms happy | 45.330 | 32.830 | 7.143 | 100.000 |
| | 8.3 ms sad | 18.740 | 30.990 | 0.000 | 100.000 |
| | 8.3 ms neutral | 67.120 | 30.910 | 0.000 | 100.000 |
| | 16.7 ms happy | 81.310 | 25.910 | 12.500 | 100.000 |
| | 16.7 ms sad | 25.730 | 21.960 | 0.000 | 82.350 |
| | 16.7 ms neutral | 82.740 | 14.120 | 56.250 | 100.000 |
| | 25 ms happy | 94.410 | 5.483 | 84.210 | 100.000 |
| | 25 ms sad | 54.940 | 21.100 | 18.180 | 94.740 |
| | 25 ms neutral | 87.880 | 11.550 | 64.710 | 100.000 |
| | 141.7 ms happy | 98.850 | 1.421 | 95.080 | 100.000 |
| | 141.7 ms sad | 91.340 | 6.233 | 79.630 | 100.000 |
| | 141.7 ms neutral | 93.890 | 6.821 | 73.680 | 100.000 |

**Table 3**
Descriptive Statistic of mean accuracy in task 2 for all emotion and timing conditions with mean, standard deviation, minimal and maximal values for task conditions.

| Mean Accuracy in % | Condition | Mean | Std. | Min. | Max. |
|---|---|---|---|---|---|
| Main effects | total trials | 83.900 | 5.702 | 65.280 | 92.700 |
| | happy | 95.130 | 6.844 | 67.830 | 100.000 |
| | sad | 63.020 | 10.830 | 43.660 | 83.560 |
| | neutral | 91.460 | 10.520 | 54.550 | 100.000 |
| | 8.3 ms | 24.190 | 33.240 | 0.000 | 100.000 |
| | 16.7 ms | 74.740 | 9.887 | 54.320 | 93.850 |
| | 25 ms | 85.090 | 5.533 | 73.260 | 92.050 |
| | 150 ms | 93.030 | 3.892 | 84.150 | 100.000 |
| Conditions | 8.3 ms happy | 29.760 | 41.790 | 0.000 | 100.000 |
| | 8.3 ms sad | 3.811 | 10.210 | 0.000 | 40.000 |
| | 8.3 ms neutral | 20.690 | 36.020 | 0.000 | 100.000 |
| | 16.7 ms happy | 92.240 | 10.750 | 61.900 | 100.000 |
| | 16.7 ms sad | 26.040 | 22.020 | 0.000 | 81.250 |
| | 16.7 ms neutral | 86.590 | 14.800 | 45.000 | 100.000 |
| | 25 ms happy | 98.840 | 2.686 | 90.000 | 100.000 |
| | 25 ms sad | 57.310 | 19.920 | 12.500 | 87.500 |
| | 25 ms neutral | 93.050 | 11.700 | 51.720 | 100.000 |
| | 150 ms happy | 98.730 | 3.073 | 87.500 | 100.000 |
| | 150 ms sad | 86.530 | 9.640 | 63.640 | 100.000 |
| | 150 ms neutral | 96.000 | 8.104 | 64.290 | 100.000 |

by group-level distributions (Nilsson et al., 2011; Shiffrin et al., 2008).

For simplicity, the conditions 141.7 ms and 150 ms were collapsed (weakly masked). The data of tasks one and two were pooled for further analyses to increase validity. A fixed probability for obtaining a RT outlier at 5 % was assumed. In total, three models were created assuming separate models for drift rate (v) estimation for:

i) emotion conditions (happy, sad, neutral)
ii) timing conditions (8.3 ms, 16.7 ms, 25 ms, 141.7/150 ms)
iii) all emotion × timing conditions (8.3 ms happy, 8.3 ms sad, 8.3 ms neutral, 16.7 ms happy, 16.7 ms sad, 16.7 ms neutral, 25 ms happy, 25 ms sad, 25 ms neutral, 141.7/150 ms happy, 141.7/150 ms sad, 141.7/150 ms neutral)

The starting point of the drift process towards one response was set to the maximum a-posterior value (MAP) estimated in each model (Wiecki et al., 2013). Bayesian inference was performed by drawing posterior samples using the Markov chain Monte Carlo Algorithm (MCMC) (Gamerman & Lopes, 2006). Model convergence was tested via the Gelman-Rubin statistic (Gelman & Rubin, 1992). For multiple runs of the same model, this test compares within-, and between-chain variance. Models with parameters close to 1 and < 1.02 were selected for further analysis since a parameter close to 1 indicates indistinguishability of the different chains (Wiecki et al., 2013). For most models specified here 100,000 samples were drawn while the first 500 samples were discarded (burned). To assess model convergence within the models including all twelve conditions, 100,000 samples and 500 burned were needed while only every fifth sample was kept (thin = 5).

### *2.6.3. General linear mixed model selection*

In order to explore fixed and random linear effects on (1) the correctness and (2) drift rates of responses across experiments, two generalized linear mixed models (GLMM) were estimated using the glmer function in the lme4 package for R (Bates, 2007; Team, 2013). Data were analyzed separately for task 1 and task 2. Due to similar results and matching statistical significance of effects in task 1 and task 2 (see supplement 2), we decided to collapse the datasets and present the results of a model including both datasets in the result section. A fixed factor for task number (task 1, task 2) was added to model potential differences based on the different task design.

*2.6.3.1. Model 1:.* To test possible experiment specific effects on subject's accuracy within the task, response correctness of every single trial served as dependent variable (correct; 1 = correct response, 0 = incorrect response), while stimulus timing (level) and stimulus emotion (stim) as well as the task number were set as repeated fixed factors (fixed effects). To remove variability in responses that were not directly associated to conditions of the experimental design, a random subject factor was added. The trial number was included as random slope (real_trial_number). During the model selection process, the number of included fixed effects and interactions was gradually increased. Due to bimodality of the dependent variable, the family link in this generalized linear mixed model was set to "binominal". An ANOVA was conducted to determine if the more complex model was significantly more effective in explaining the data than the simpler model (Bates et al., 2014).

Model1 <- glmer(correct ~ stim + level + task_number + (1 + real_trial_number| subj_idx), family= "binomial").

To estimate the probability of correct responses within one condition, the estimated logit values were back transformed into p-values [1/(1 + exp(logit))].

*2.6.3.2. Model 2:*. As an explorative analysis, effects of stimulus type and potential pathological symptoms (depression and alexithymia) on drift rates were evaluated in an additional model. Therefore, the mean approximated posterior distribution of drift rates estimated via HDDM served as dependent variable while total questionnaire scores (BDI, BVAQ) were used as fixed effects. During the model selection process, the amount of implemented fixed effects was gradually increased. To select the model fitting the data best, an ANOVA was used to test if more complex models were significantly more accurate than less complex models. In the winning model, age and gender were additionally implemented as fixed effects as well as the presented stimulus emotion. Since normally distributed data were assumed, the lmer function without a family link was used.

Model2 <- lmer(DriftRate ~ BDI + BVAQ + stim + age + gender + task_number + (1 | subj_idx))

All anonymized datasets and used analyses scripts can be downloaded via GitHub (https://github.com/JuliaSchraeder/SubconsciousTiming).

## 3. Results

### 3.1. Performance analysis task 1

Mean performance accuracy was significantly lower in sad trials compared to happy and neutral trials (sad vs happy: $p$ <.001, Z = 4.501; sad vs neutral: $p$ <.001, Z = 4.026) (see Fig. 2A).

Accuracy increased with longer stimulus presentation and accuracy in all strongly masked trials differed significantly from the accuracy during weakly masked trials (141.7 ms vs 25 ms: $p$ =.0015, Z = 3.769; 141.7 ms vs 16.7 ms: $p$ <.001, Z = 6.002; 141.7 ms vs 8.3 ms: $p$ <.001, Z = 6.661). In 8.3 ms trials accuracy was significantly lower than in 25 ms trials (25 ms vs 8.3 ms: $p$ =.035, Z = 2.891). Performance accuracy did not differ significantly between 8.3 ms and 16.7 ms trials (16.7 ms vs 8.3 ms: $p$ >.999, Z = 0.658), between 8.3 ms and 25 ms (8.3 ms vs 25 ms: $p$ =.035, Z = 2.891) or 16.7 ms and 25 ms trials (16.7 ms vs 25 ms: $p$ =.230, Z = 2.232) (for a visualization see Fig. 2A).

In all strongly masked timing conditions (8.3 ms, 16.7 ms, 25 ms) sad trials elicited a significantly lower accuracy compared to neutral trials (8.3 ms sad vs 8.3 ms neutral: $p$ =.008, Z = 3.421; 16.7 ms sad vs 16.7 ms neutral: $p$ =.002, Z = 3.815; 25 ms sad vs 25 ms neutral: $p$ =.043, Z = 2.916). In 141 ms trials no difference between emotions was observed (for a visualization see Fig. 2B).

### 3.2. Performance analysis task 2

In task two, mean performance accuracy was significantly lower in sad trials compared to happy and neutral trials (sad vs happy: $p$ <.001, Z = 6.002; sad vs neutral: $p$ <.001, Z = 5.05) (see Fig. 3A).

Similar to task 1, accuracy increased with longer stimulus presentation and accuracy in 16.7 ms and 8.3 ms strongly masked trials differed significantly from the accuracy in weakly masked trials (150 ms vs 16.7 ms: $p$ <.001, Z = 3.806; 150 ms vs 8.3 ms: $p$ <.001, Z = 6.148). However, in 150 ms and 25 ms trials, accuracy did not differ significantly (150 ms vs 25 ms: $p$ =.304, Z = 2.123). Again,

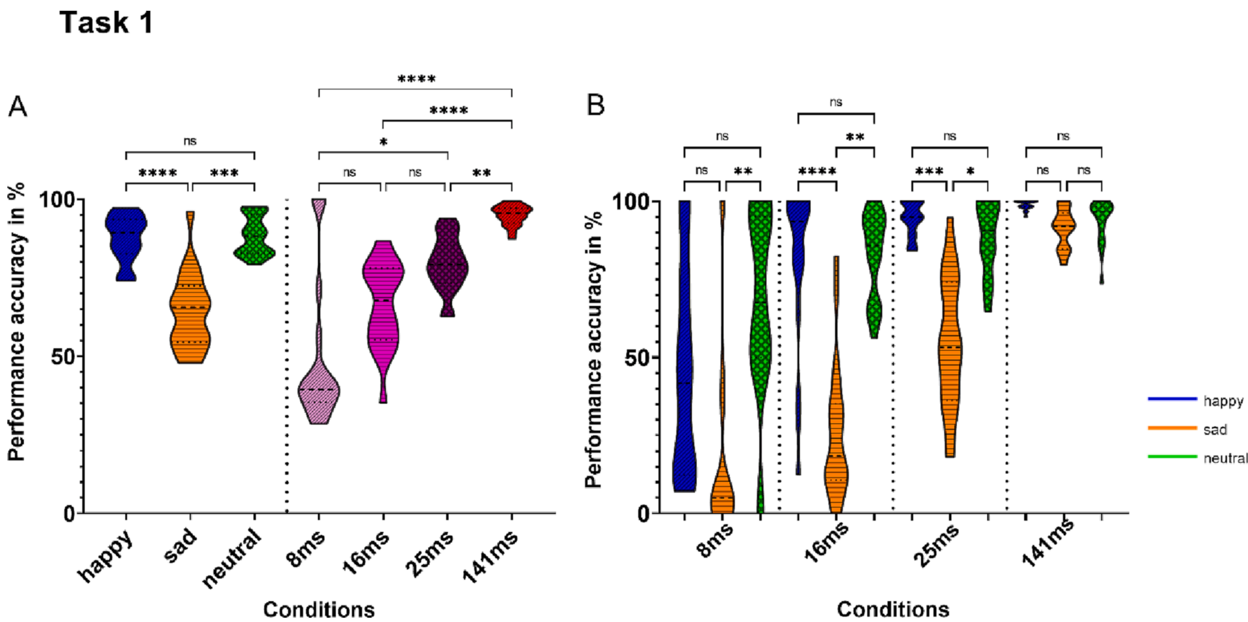


**Fig. 2.** Mean performance accuracy for task 1 in **(A)** main conditions (happy, sad, neutral, 8 ms, 16.7 ms,25 ms and 141.7 ms) and **(B)** every emotion per timing condition. Friedmańs test with significant codes for p-value: < 0.0001='****', < 0.001= '***', < 0.01= '**', < 0.05 = '*'. Non-significant= 'ns'.

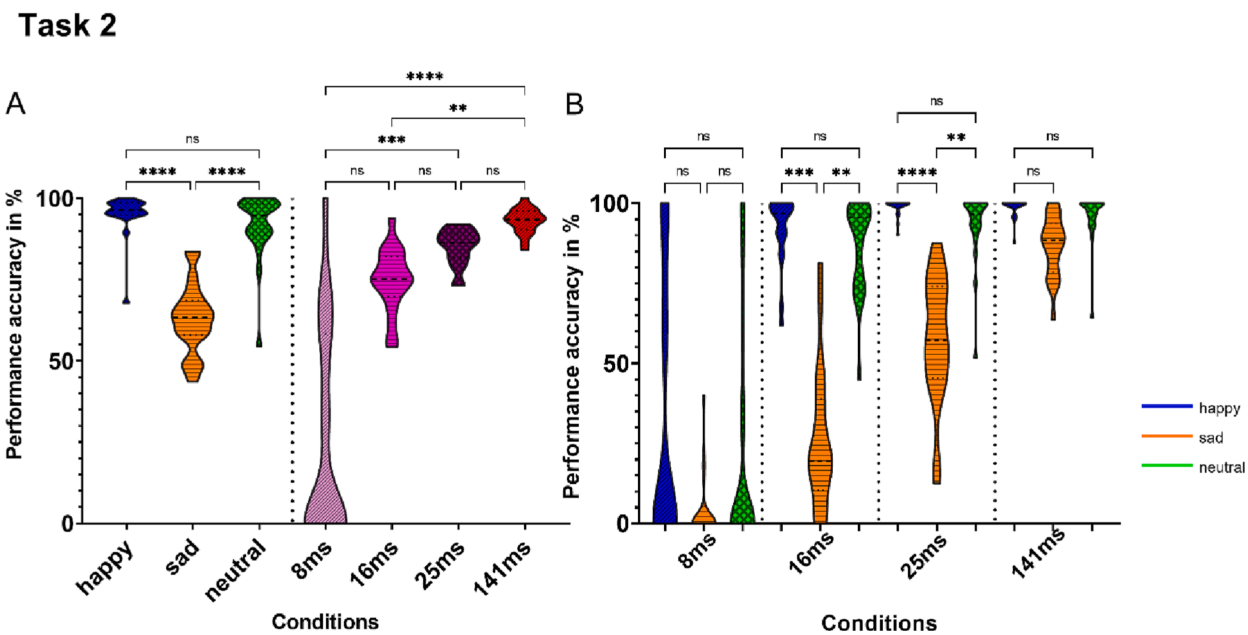


**Fig. 3.** Mean performance accuracy for task 2 in **(A)** main conditions (happy, sad, neutral, 8 ms, 16.7 ms,25 ms and 141.7 ms) and **(B)** every emotion per timing condition. Friedmańs test with significant codes for p-value: < 0.0001='****', < 0.001= '***', < 0.01= '**', < 0.05 = '*'. Non-significant= 'ns'.

accuracy in 8.3 ms trials was significantly lower than in 25 ms trials (25 ms vs 8.3 ms: $p$ <.001, Z = 4.026). Performance accuracy did not differ significantly between 8.3 ms and 16.7 ms trials (16.7 ms vs 8.3 ms: $p$ =.173, Z = 2.342), between 8.3 ms and 25 ms (8.3 ms vs 25 ms: $p$ <.001, Z = 4.026) or between 16.7 ms and 25 ms trials (16.7 ms vs 25 ms: $p$ =.831, Z = 1.683) (for a visualization see Fig. 3A).

In strongly masked timing conditions (16.7 and 25 ms trials) sad stimuli elicited a significantly lower accuracy compared to neutral trials (16.7 ms sad vs 16.7 ms neutral: $p$ =.008, Z = 3.377; 25 ms sad vs 25 ms neutral: $p$ =.004, Z = 3.552) while in 150 ms and 8.3 ms

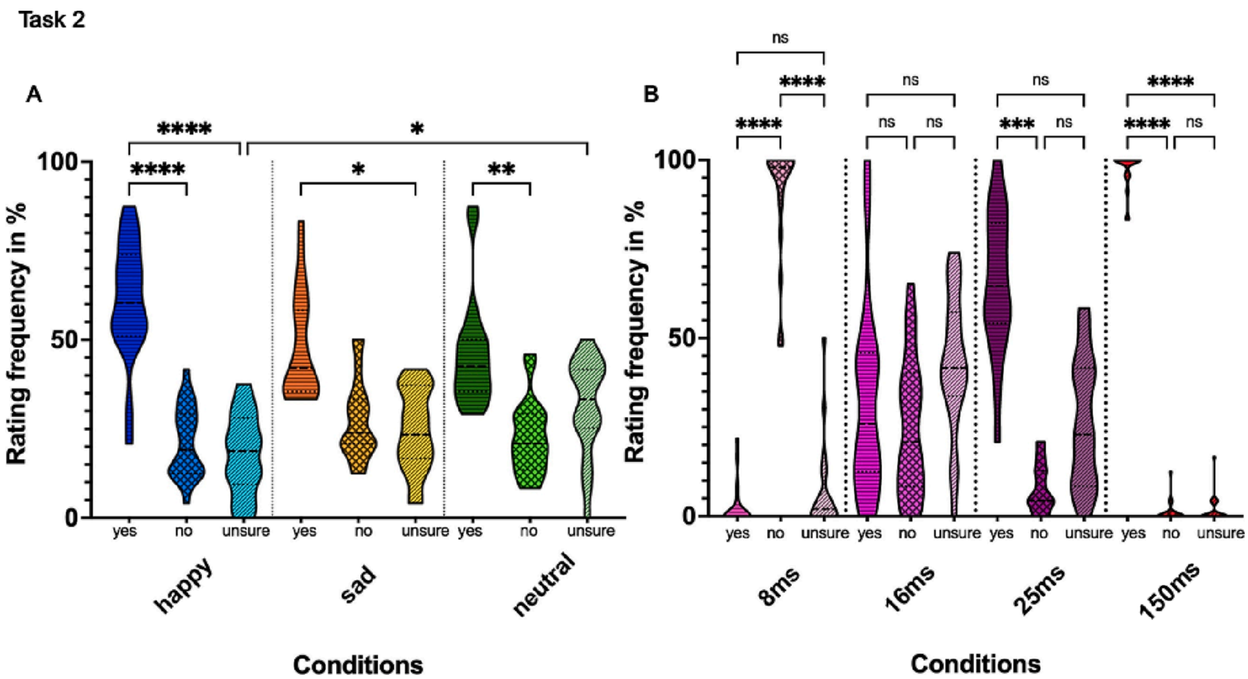


**Fig. 4.** Subjective awareness rating in task 3 for happy, sad, neutral trials **(A)** and all timing conditions **(B)**. Frequency of rating "yes", the stimulus was rated as "seen", "unsure" for rating insecure visual perception and "no" for no reported visual stimulus perception. Friedmańs test with significant codes for p-value: < 0.0001='****', < 0.001= '***', < 0.01= '**', < 0.05 = '*'. Non-significant= 'ns'.

trials, no difference between emotions was observed (for a visualization see Fig. 3B).

### 3.3. Subjective awareness

In total, neutral trials were rated significantly more often as "unsure" compared to happy trials (happy unsure vs neutral unsure $p$ =.027, Z = 3.175). Therefore, happy trials were rated with greater certainty than neutral trials (see Fig. 4A for rating differences between stimulus emotions).

The certainty of stimulus awareness significantly increased with rising presentation duration (see Fig. 4B "yes" conditions). Most weakly masked trials were evaluated as seen (96.67 %, for all total rating frequencies see Table 4) (150 ms yes vs 150 ms no p <.001, Z = 7.937; 150 ms yes vs 150 ms unsure p <.001, Z = 7.74). In 25 ms trials most trials were rated as consciously perceived (65.01 %). In 16.7 ms trials, all three response options were used equally (see Fig. 4B) while in 8.3 ms trials, 91.20 % of the trials were rated as "not seen" (8.3 ms yes vs 8.3 ms no $p$ <.001, Z = 7.082; 8.3 ms no vs 8.3 ms unsure $p$ <.001, Z = 6.052).

For all statistical comparisons please see supplement 2.

### 3.4. Hddm

Weakly masked trials led to high estimated posterior drift rates (v) (see Fig. 5B) compared to strongly masked trials. The drift rates underlying decision-making in these trials were greater than in all strongly masked trials [P(25 ms/16.7 ms/8.3 ms < weakly masked) > 0.999]. With increasing presentation times, drift rates increased [P(8.3 ms > 16.7 ms > 25 ms > weakly masked)] (for all comparisons see supplement 1 tab. 1). A negative mean drift rate was estimated only in 8.3 ms trials (see Fig. 5B).

Trials with happy stimuli elicited a greater posterior probability of drift rates than sad and neutral trials. Sad trials produced a lower posterior drift rate than neutral trials [P(happy > sad/neutral) > 0.999, P(neutral > sad) > 0.999] (see Fig. 5A).

The mean emotion specific responses (mean drift rates) are illustrated in Fig. 5C where mean drift rates for every emotion are plotted to see the task specific effects on the drift process of decision-making. The drift curve was steeper for than for neutral and sad conditions. The mean timing specific responses (mean drift rates) are illustrated in Fig. 5D. The drift curves were steeper with longer presentation duration. In 8.3 ms trials the drift rate was negative.

The interaction effects between all timing × emotion conditions are presented in Fig. 6. In all timing conditions, sad trials led to the lowest drift rates [**8.3 ms:** P(happy/neutral > sad) > 0.999; **16.7 ms:** P(happy/neutral > sad) > 0.999; **25 ms:** P(happy/neutral > sad) > 0.999; **141/150 ms:** P(happy/neutral > sad) > 0.999] (Fig. 6 A, B, C, D). Mean drift rates of sad and happy trials were negative in 8.3 ms trials (Fig. 6 A). In 16.7 ms trials, mean drift rates were negative during sad stimulus presentation (Fig. 6B).

Happy trials elicited the highest drift rates in all timing conditions [**16.7 ms:** P(sad < happy) > 0.999, P(neutral < happy) = 0.961; **25 ms:** P(sad/neutral < happy) > 0.999; **141/150 ms:** P(sad/neutral < happy) > 0.999] except during 8.3 ms trials where neutral trials elicited higher drift rates [**8.3 ms:** P(happy > sad) > 0.999, P(happy > neutral) = 0] (see Fig. 6 A, B, C, D).

Mean drift rates increased with longer stimulus duration in all emotion conditions [**happy:** P(25 ms/16.7 ms/8.3 ms < weakly masked) > 0.999; **sad:** P(25 ms/16.7 ms/8.3 ms < weakly masked) > 0.989; **neutral:** P(25 ms/16.7 ms/8.3 ms < weakly masked) > 0.974] (see Fig. 6. E, F, G).

### 3.5. Glmm

The separate analyses for task 1 and 2 can be found in supplement 2. The here reported results arise from analyses with the collapsed datasets. There was a significant effect of the stimulus emotion on response correctness. Compared to neutral stimuli, sad stimuli were identified correctly less often ($p$ <.001); happy stimuli on the other hand more often ($p$ <.001). Additionally, shorter stimulus presentation was associated with more errors ($p$ <.001). A significant effect of presentation time showed that the 8.3 ms stimulus timing was associated to the lowest number of correct responses compared to all other presentation times (see Table 5 for all fixed effects).

The probability to respond correctly was increased with longer presentation times and was around chance level for 16.7 ms trials (for all probabilities see Table 6).

In comparison to neutral stimuli, the presentation of sad faces led to negative effects on drift rates ($p$ <.001) (see Table 7 for all fixed effects on drift rate). The task number (task 1) had a significant positive effect on the drift rate ($p$ =.012). Potential pathological

**Table 4**
Frequency (%) of rating a stimulus as seen, not seen or insecure (yes, no, unsure) for every emotion and timing condition.

| Condition | yes | unsure | no |
|---|---|---|---|
| sad | 45.313 | 21.748 | 32.939 |
| neutral | 46.518 | 23.238 | 30.243 |
| happy | 59.030 | 13.249 | 27.722 |
| 8.3 ms | 2.594 | 6.204 | 91.201 |
| 16.7 ms | 36.113 | 40.056 | 23.831 |
| 25 ms | 65.011 | 29.289 | 5.700 |
| 150 ms | 96.670 | 2.386 | 0.943 |

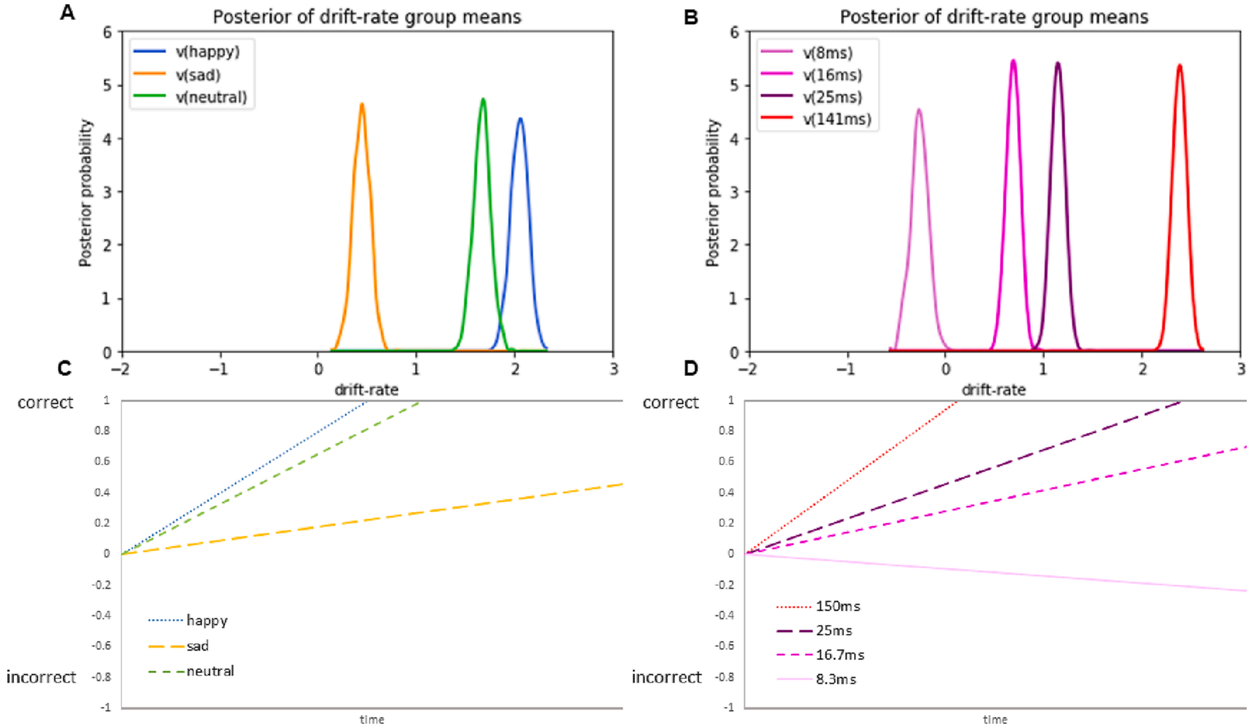


**Fig. 5.** Posterior density plot of drift-rate group means for emotion conditions (model i) **(A)** and stimulus timing (model ii) **(B).** High drift-rates and thus faster and more accurate responses are most likely during happy and weakly masked trials and less likely during sad and strongly masked trials (8 ms). **(C)**: Plot of mean drift rates for happy, neutral and sad trials (mean drift rate happy = 2.032, neutral = 1.661, sad = 0.46) over time (model i). (**D**): Plot of mean drift rates for weakly masked trials and all strongly masked timing conditions over time (model ii) (8.3 ms, 16.7 ms and 25 ms) (mean drift rate weakly masked trials = 2.356, 25 ms = 1.144, 16.7 ms = 0.67, 8.3 ms = -0.235.

symptoms had no significant effect on the drift rate (BDI: $p$ =.642, BVAQ: $p$ =.2).

## 4. Discussion

We tested the processing of subconscious emotional facial stimuli in three different timing conditions below 30 ms (strongly masked) using a backward mask paradigm, comparing it to weakly masked emotional stimuli. We aimed to understand the decision process discriminating emotional stimuli depending on the presentation time and potential influence factors. Furthermore, we tested which presentation time can lead to an unaware processing of the emotion-specific information.

All three timing conditions below 30 ms elicited a decision pattern different from the pattern during weakly masked trials. Therefore, the decision process during trials with short presentation times was distinct from that trials where sensory and attentional awareness was present. Whether the reduced processing efficiency within the trials below 30 ms is due to a lack of attention, a non-visibility or subconscious visibility of the stimulus is discussed subsequently. Importantly, based on a detailed analysis of performance measures, a presentation time of 16.7 ms (compared to 8.3 ms and 25 ms) was found to be most suitable to affect performance at a non-conscious level using emotional stimuli in backward masking tasks. Emotional discrimination performance differed regarding emotions both on the conscious and subconscious level in an analogous manner. This effect was stable in all subconscious timing conditions except 8.3 ms.

The HDDM yielded a higher drift rate towards a correct response for happy stimuli compared to neutral or sad trials. Considering that high drift rates produce fast and accurate responses (Pedersen & Frank, 2020), decisions on happy faces were more precise than decisions on sad faces. A prioritization to process happy facial details is well-known. Healthy participants without mood disturbances are inclined to focus/bias their attention towards positive information, e.g., happy facial expressions compared to sad/negative information (Gotlib et al., 2004; Kellough et al., 2008; Nummenmaa & Calvo, 2015). Consistent with this, happy faces are better recognized and show an advantage during early processing over other emotional faces (Svard et al., 2012). This recognition advantage could be due to more salient visual features such as an open mouth in happy facial expressions (Calvo & Marrero, 2009). While, sad and neutral emotional expressions have similar visual features (Calvo & Marrero, 2009) they induced highly different drift rate patterns in our study. Therefore, we hypothesize that additional factors are important when it comes to emotion-dependent processing. Eye-tracking studies have shown that directed attention can influence which facial expression can be discriminated more easily. Such attentional advantages may even differ between population groups (Kaiser et al., 2015). Healthy participants often demonstrate better recognition of happy faces while depressed patients show a faster responses towards masked negative emotional cues (Disner et al.,

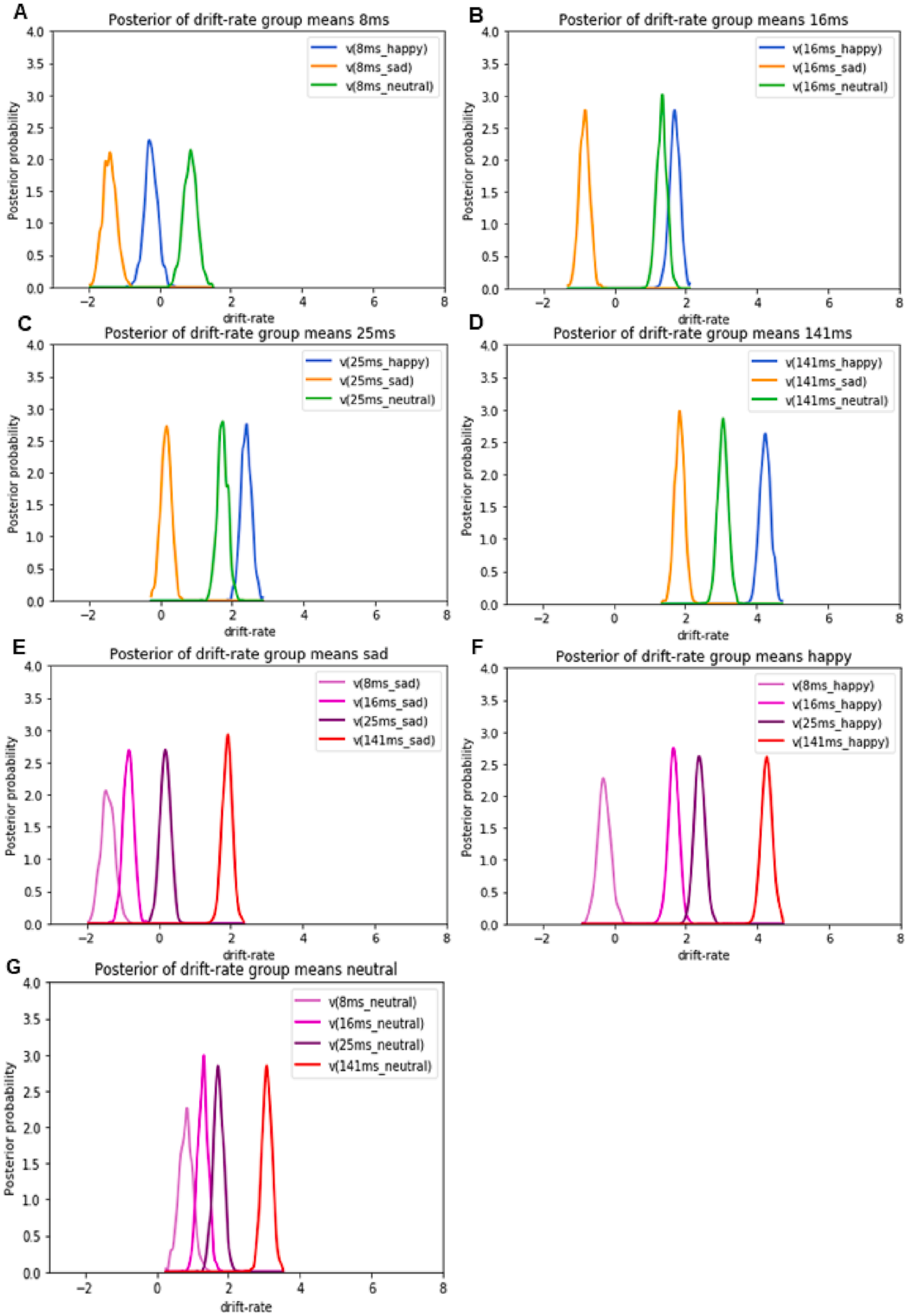


**Fig. 6.** Posterior density plot of drift-rate group means for all emotion × timing conditions (model iii). Mean drift rates for all emotion conditions per timing **(A)** 8.3 ms happy, 8.3 ms sad, 8.3 ms neutral, **(B)** 16.7 ms happy, 16.7 ms sad, 16.7 ms neutral, **(C)** 25 ms happy, 25 ms sad, 25 ms neutral **(D)** 141.7/150 ms happy, 141.7/150 ms sad, 141.7/150 ms neutral and all timing conditions per emotion: **(E)** sad **(F)** happy **(G)** neutral. High drift-rates and thus faster and more accurate responses are most likely during happy trials in all timing conditions except 8.3 ms. Mean drift rates are low during sad trials in all timing conditions. Mean drift rates increase with longer stimulus duration in all emotion conditions.

**Table 5**
Random and Fixed Effects estimated via "Model 1" with response correctness as dependent variable including stimulus timing (level) and stimulus emotion (stim) and task number (task_number) as fixed factors as well as a random subject factor and trial number as random slope. Family link was set to "binominal".

| **Random effects:** | | | | |
|---|---|---|---|---|
| Groups | Name | Variance | Std. Dev. | Corr |
| subj_idx | (Intercept) | 0.294 | 0.543 | |
| | real_trial_number | $1.565e^{6}$ | 0.001 | −0.740 |
| Number of observations: 11439, groups: subj_idx, 40 | | | | |
| **Fixed effects:** | | | | |
| | Estimate | Std. Error | t value | Pr(>\|z\|) |
| Level 8.3 ms | −1.974 | 0.070 | −28.117 | < 0.001 *** |
| Level 16.7 ms | -0.542 | 0.049 | −10.907 | < 0.001 *** |
| Level 25 ms | 0.464 | 0.0561 | 8.262 | < 0.001 *** |
| Stim happy | 0.873 | 0.048 | 18.183 | < 0.001 *** |
| Stim sad | −1.598 | 0.045 | −35.607 | < 0.001 *** |
| Task 1 | -0.088 | 0.072 | −1.214 | 0.225 |

(AIC = 7481.5; BIC = 7555.0).
Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1.

**Table 6**
Estimated logits from model 1 and transformed probability of making correct responses in different timing conditions.

| Condition | logit | Probability of making a correct response |
|---|---|---|
| Weakly masked | 2.053 | 0.886 |
| 25 ms | 0.464 | 0.614 |
| 16.7 ms | -0.542 | 0.368 |
| 8.3 ms | −1.974 | 0.122 |

**Table 7**
Random and Fixed Effects estimated via "Model 2" with mean drift-rates as dependent variable including stimulus emotion, BDI and BVAQ scores, age and gender and task number as fixed effects.

| **Random effects:** | | | | | |
|---|---|---|---|---|---|
| Groups | Name | | Variance | Std. Dev. | |
| Subj_idx | (Intercept) | | 0.032 | 0.179 | |
| | Residual | | 0.171 | 0.414 | |
| Number of observations: 120, groups: subj_idx, 40 | | | | | |
| **Fixed effects:** | | | | | |
| | Estimate | Std. Error | df | t value | Pr(>\|t\|) |
| BDI | 0.015 | 0.032 | 34 | 0.469 | 0.642 |
| BVAQ | 0.015 | 0.012 | 34 | 1.308 | 0.200 |
| Stim happy | 0.646 | 0.053 | 78 | 12.090 | < 0.001 *** |
| Stim sad | -0.919 | 0.053 | 78 | −17.214 | < 0.001 *** |
| Age | 0.032 | 0.017 | 34 | 1.876 | 0.069 |
| Gender female | 0.034 | 0.051 | 34 | 0.661 | 0.513 |
| Task 1 | 0.272 | 0.102 | 34 | 2.670 | 0.012 * |

(AIC = 157.99; BIC = 185.86).
Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1.

2011; Zhang et al., 2016). The latter also show a hyperactive brain responses during masked sad trials compared to healthy controls (Victor et al., 2010).

Subthreshold characteristics of alexithymia or depression had no influence on the subconscious processing of emotions in our healthy sample. Which and how other individual differences including pathologies contribute to modifications in subconscious perceptual thresholds remains to be investigated.

In our study, the drift rate and thus the efficiency of information accumulation decreased with briefer stimulus presentation. At 8.3 ms trials the effect that happy faces are processed more efficiently disappeared. Here, neutral images were processed most efficient while a negative mean drift rate in sad and happy trials indicated an average drift rate towards the lower boundary (incorrect). One possible explanation for this loss of prioritization is that the stimuli were no longer perceived. A stimulus presentation of 8.3 ms could be too brief to even detect stimulus appearance and therefore may prohibit an effect even at a subconscious level. It is not surprising that conscious awareness was not given in most trials during this condition. Investigating the influence of presentation times on processing facial emotional details therefore shows that emotion-dependent differences in drift rates and accuracy exist during all presentation times. Even though we hypothesized that differences in the drift rates in recognizing emotions might be lower if the presentation times are shorter, as more accurate attention may be required to correctly identify emotional stimuli that are presented shortly our results did not support this.

Comparing the performance between the two tasks, we found that decision performance was higher in task 1 than in task 2. We assume that this might be an artifact of an additional decision participants had to make in task 2. They first had to decide on the presented stimulus emotion and second on how certain they were in their responses towards the decision. The higher complexity in task 2 could therefore have led to a performance decrease. Additionally, the trials in task 2 were also randomized between blocks, not only within the blocks. Consequently, participants could prepare to the stimulus duration in task 1 which may have facilitated attention allocation in this task. In both tasks, a long presentation around 150 ms may be interpreted as fully consciously processed stimulus, according to the performance data and subjective ratings.

The emotion classification performance within both cohorts suggests a better recognition of happy faces compared to sad or neutral faces as reflected by task performance measures (accuracy and drift rates). This very-well known finding has been reported in numerous studies (Victor et al., 2010; Zhang et al., 2016). Indeed, GLMM estimation of stimulus emotion effects on response correctness showed that happy stimuli influence response correctness positively while sad stimuli reduce response correctness. This leads to the assumption that not only the stimulus presentation time, but the presented stimulus emotion influences the performance within the tasks.

Shorter presentation times led to a different pattern (accuracy and drift rates) indicating emotion-specific differences in accuracy and evidence accumulation efficiency. Sad stimuli produced a lower accuracy in 25 ms and 16.7 ms masked trials compared to neutral and happy stimuli. This effect disappears in in conscious trials. Additionally, emotion-specific accuracy varied during 8.3 ms trials in the first cohort but not in the second cohort which suggests inconsistency potentially based on the combination of weak effects due to high variance and small sample sizes within a cohort as observed in many previous studies. Contrary to previous findings, we found a performance accuracy below chance level in all 8.3 ms trials of both cohorts. In a small study of 14 healthy participants, performance accuracy was at chance level during emotion classification with a subliminal presentation of 8.3 ms (using neutral and fearful faces) (Kiss & Eimer, 2008). Our results of subjective measures agree more with a previous finding reporting that such shortly presented stimuli are subjectively rated as “not perceived” (Flynn et al., 2017). We conclude that a stimulus presentation time around 8 ms could be too short to be perceived at all.

We discovered that most of the trials with a presentation time of 25 ms were evaluated as aware and the performance accuracy within the two tasks was up to 85 %. Thus, a stimulus presentation of 25 ms could be too long to induce subconscious emotion processing. A probability of making a correct response of 62 %, which is highly above chance level of 33.333 %, underpins this assumption. Though, during 16.7 ms trials, a probability of making a correct response marginally above chance level was found (see Table 6), where participants were mostly unsure about discriminating the presented image. This is in line with previous studies where 9 of 11 participants were not able to consciously detect fearful faces during a 17 ms presentation time (Pessoa et al., 2005) and where participants were unaware of happy, sad and neutral face presentation at a duration of 16.7 ms (Suslow et al., 2003).

In conclusion, The presentation time to be used within a backward masking paradigm depends on the research question. If a stimulus should induce a perception without awareness and without causing emotion specific effects on a detectable behavioral level, 8.3 ms could be a suitable presentation time. However, this might result in instable response patterns. A probability of making a correct response around chance level while observing an emotion-specific response accuracy and processing efficiency indicates emotion processing at a subconscious level in 16.7 ms trials. Since not only the drift rate differed between emotions but also the accuracy differed, we conclude that, even largely unaware, the stimuli induced behavioral measurable responses at a presentation time of 16.7 ms. Above this time (e.g., 25 ms) the stimulus presentation deliberately leads to conscious facial emotion recognition.

### *4.1. Limitations*

A higher sample size with a wider age range could strengthen our results and reduce inconsistencies found in accuracy during 8.3 ms trials between the first and second cohort in this study. The design of the task elicited only 20–30 trials for the HDDM evaluation of the calculation of the interaction effects. Although the HDDM analysis is suitable for a calculation with a lower trial numbers (Wiecki et al., 2013), a lower precision could be assumed in this model (Voss et al., 2013). Furthermore, these results are only representative for a young healthy sample. For constraints of generality, this study targets a young, healthy population. Due to the fixed frame rate of the screen of 120 Hz, only three presentation times below 30 ms could be evaluated. With a screen with a higher frame rate, more presentation times could be examined potentially revealing a more specified ideal presentation time. Due to a programming error the duration of weakly masked trials was unintentionally increased from 141.7 ms to 150 ms in the second task. Both 141.7 ms and 150 ms trials are processed fully consciously. Furthermore, used stimuli were limited to the emotions “happy”, “sad”, and “neutral”. Using fearful and surprise faces would diversify individuals’ responses to different emotional stimuli.

## 5. Conclusion, Implications, and outlook

Our results showed that a presentation time of 16.7 ms is most suitable to present emotional stimuli on a subconscious level. While a stimulus presentation for 8.3 ms is too short to allow a discrimination between emotions, an emotion classification is still possible at

16.7 ms presentation time while the performance and probability of correct responses indicates subconscious processing. During 25 ms trials, conscious stimulus processing could not be excluded. In addition, the results fit into previous findings that healthy participants identify happy stimuli more accurate than neutral or sad faces.

Subconscious stimulus processing using 16.7 ms presentations is an interesting target for neurophysiological measurements like EEG or MRT, since it could give insight into which brain regions are critically involved in the early phase of emotion processing before conscious awareness occurs (bottom-up pathway) and how these brain responses are linked to subsequent conscious cognitive processes (top-down pathway). By identifying 16.7 ms as a suitable display duration for subconscious stimulus presentation, other studies, e.g. neuroimaging studies, may use this time to design priming tasks and to test different emotional stimuli without the need to evaluate the presentation time for subconscious image presentation again.

Additional Information

Used scripts and datasets can be found on GitHub (https://github.com/JuliaSchraeder/SubconsciousTiming).

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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**Compliance with Ethical Standards**

**Research Involving Human Participants**

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

**Informed consent**

Informed consent was obtained from all individual participants included in the study.

**Public Significance Statement**

Our results highlight 16.7 ms as the optimal duration for subconscious processing of the emotion-based stimuli. We believe that our findings are highly interesting for researchers interested in understanding human perception and its boundaries. Moreover, our findings are likely of great interest for readers from clinical research fields in which emotion dependent responses are commonly observed.

**Ethics and Data Availability Statement**

This study was approved by the ethics committee of the medical faculty of RWTH Aachen University. The form will be made available as a registration option on Open Science Framework (https://osf.io/bfrky/). All anonymized datasets and used analyses scripts can be downloaded on GitHub (https://github.com/JuliaSchraeder/SubconsciousTiming).

## Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.concog.2023.103493.

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