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The temporal dynamics of attention: Thinking about oneself comes at a cost in sub-clinical depression but not in healthy participants

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Abstract
Self-relevant stimuli seem to automatically draw attention, but it is unclear whether this comes at a cost for processing subsequent stimuli, and whether the effect is depending on one's mental state (i.e. depression). To address this question, we performed two experiments. In Experiment 1, 45 participants were to report two words (T1 and T2) in an attentional blink (AB) paradigm. T1 was a personality characteristic varying in self-rated self-relevance, whereas T2 was a neutral word. A generalized linear mixed model (GLMM) was applied to compare the T1 and T2 accuracies when T1 was high or low self-relevant. A positive effect of self-relevance was found on T1, without observable carry-over effects on T2 performance. However, in Experiment 2, a GLMM applied on 93 participants showed that T1 self-relevance can affect T2, showing opposite effects depending on sub-clinical depression score. Our findings imply that people with low depression scores process self-relevant stimuli more efficiently, which is reflected in a reduced AB. In contrast, individuals with higher scores in depression demonstrated a difficulty to withdraw attention from self-relevant information, reflected in an increased AB. Our findings thus reveal that a processing advantage for highly self-relevant stimuli comes at either a subsequent cost or benefit in temporal attention depending on one's mental disposition.

Keywords Self-relevance · Attention · Attentional blink · Self-referential processing · Temporal attention · Depression

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Introduction

Hearing your name, seeing your own picture or spotting a car featuring the same color as your own car are all examples of self-relevant stimuli that quickly and automatically draw your attention. The relatively large impact of self-relevant stimuli on attention has already been known since the 1950s. Moray (Moray, 1959) demonstrated in his experimental work that mentioning the participant's own name is easily noticed even when attention is directed elsewhere, a phenomenon known as the 'Cocktail Party Effect'. A more recent study identified a self-advantage in decisions involving the correctness of an association between a shape and a person (Sui et al., 2012). Other studies likewise revealed a benefit in processing self-relevant information (Bargh & Pratto, 1986; Röer, & Cowan, 2021).

Interestingly, further studies point towards a paradoxical relation between attentional resource allocation and performance for self-relevant stimuli. Whereas one would expect that self-relevant information draws more attention than other information, a number of studies suggested that self-relevant information is processed with fewer rather than more attentional resources (Bargh, 1982; Tacikowski et al., 2017a, b). For instance, it has been demonstrated that reaction times to a secondary probe reaction task are shorter when the primary task involves self-related stimuli (Bargh, 1982). Additionally, a later study showed that participants were better able to combine self-related processing with a secondary task than 'other'-related processing, indicating that self-related processing requires fewer resources (Tacikowski et al., 2017a, b). Taken together, previous research on the processing of self-relevant stimuli has demonstrated several ways in which self-relevant information receives preferential treatment over information that is not self-relevant. Specifically, it appears to be more salient (Bargh & Pratto, 1986), it captures attention more strongly (Bola et al., 2021), and it is remembered better (Cunningham et al., 2008).

However, it remains unclear whether this preferential treatment is caused by the fact that 1) a self-relevant stimulus draws an increased amount of attention (Alexopoulos et al., 2012; Sui et al., 2012; Wang et al., 2021), or whether 2) it requires fewer processing resources (Bargh, 1982; Moray, 1959; Tacikowski et al., 2017a, b) and that it is processed more efficiently. In two experiments we aimed to address this by determining whether processing a self-relevant stimulus comes at cost or benefit for subsequent stimuli.

Given the conflicting evidence in the current literature, as well as the non-conclusive findings in our first experiment, in the second experiment we specifically focused on the role of individual differences in processing the self-relevant stimuli, as the effect might be substantially different depending on one's depression level. According to the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), one of the central symptoms of major depression is the tendency to have a negative view of self, including feelings of worthlessness and hopelessness (American Psychiatric Association, 2013) and there is general consensus that self-referential bias is associated with depression (Gronau et al., 2003; Nolen-Hoeksema et al., 2008; Kaiser et al., 2018; McIvor et al., 2021). For instance, previous studies suggested that people with depression tend to allocate relatively more attentional resources to self-relevant information than healthy controls (Figueroa et al., 2015; Nejad, et al., 2019). Depression thus seems a relevant factor to consider when studying the interaction between self-relevant information and temporal attention. Therefore, in Experiment 2, individual depression score was also measured.

In both experiments, the attentional blink (AB) paradigm was used to investigate the relationship between self-relevance and attention. For almost three decades the AB paradigm has been used intensively to study the temporal dynamics of attention in a variety of different fields (for a review, see Martens & Wyble, 2010), as it is well suited to assess the quickly occurring attentional effects of rapidly presented stimuli (Raymond et al., 1992). The AB refers to the finding that when two targets are to be identified, the second target (T2) is often missed when it is presented within 200–500 ms following the onset of the first target (T1). Germane to the current study, a number of studies have provided evidence that a more demanding T1 leads to a larger AB (e.g., Taatgen et al., 2009; Visser, 2007). It is assumed that T1 recruits attention in a way that hinders T2 consolidation when presented at close temporal proximity by either consuming all available resources or by employing the attentional resources to bias the competition in its favor causing a delay or conflict in processing subsequent information (Martens & Wyble, 2010). Consequently, an easily processed T1 should leave more attention resources available for T2, increasing its chance to be successfully reported. The paradigm should therefore be helpful in determining the attentional impact of self-relevant stimuli on processing subsequent information when the availability of resources is relatively low, simulating similar but less controlled situations in daily life.

Rather than having a single stimulus that is self-relevant (i.e. the participant's own name), we varied the self-relevance of the first target (a word) in an AB task using several personality characteristics. T2 performance (accuracy of reporting a neutral word) was measured as a function of T1 differing in self-relevance, while the time (lag) between the two targets was systematically varied. If self-relevance indeed modulates the AB, the direction of the modulation will provide support for either the first or the second prediction: If self-relevant stimuli require more resources, the AB should deepen, reflecting a cost. Alternatively, if self-relevant stimuli require fewer resources, the AB should become smaller, reflecting a benefit. Experiment 2 was based on the same idea, but included more participants, which allowed us to investigate whether individuals scoring either high or low on depression show the same or opposite effect of self-relevance on attention. We predicted that self-relevant words would have opposite effects on temporal attention as a function of depression score, with a reduced AB for people with low depression scores and an increased AB for people with higher depression scores.

Experiment 1

Materials & Methods

Participants

All 45 participants (33 female; *Mean age* = 20 years, *SEM* = 0.21) were Dutch students of the University of Groningen recruited from a subject pool. Participants had normal

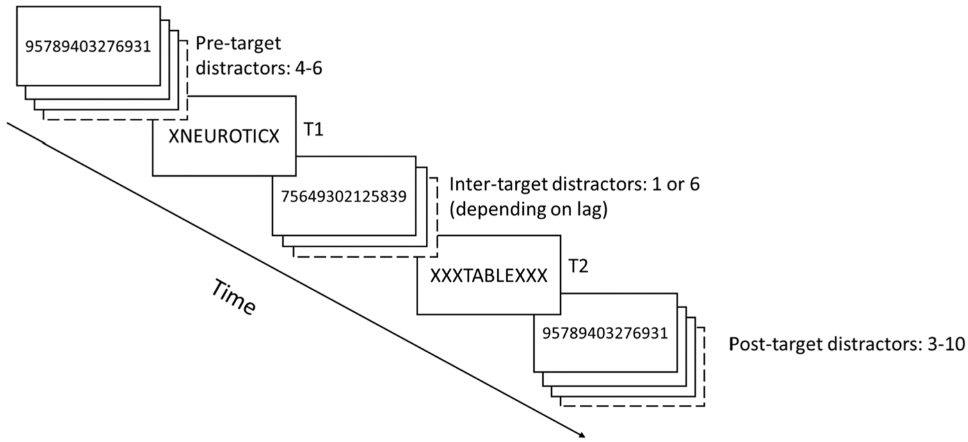

Fig. 1 Stimulus sequence of a trial in Experiment 1. Distractors were presented for 150 ms and targets for 150 ms subtracting the duration of the dynamic visual mask (as explained in the main text). T2 was randomly presented at Lag 2 or 7. At the end of every stream, participants were asked to report the identified words using a keyboard without time pressure

or corrected-to-normal vision. Ethical approval was acquired from the Ethical Committee Psychology of the University of Groningen, the Netherlands. In accordance to the declaration of Helsinki all of the participants signed an informed consent before taking part in the study. Participants received course credit for participation, which took approximately 60 min.

Stimuli and Procedure

Experiment 1 was conducted in the laboratories of the Department of Psychology at the University of Groningen, the Netherlands, and was run using E-Prime 2.0 software. The stimuli were presented on a 19-inch CRT monitor with a refresh rate of 100 Hz. Participants sat in front of a monitor, about 50 cm away from the screen. The stimuli were presented in black on a white background in the font ‘Courier New’ with font size 18. Participants responded by typing their answer on a keyboard. Experiment 1 contained a 45-min AB task and a 5 to 10-min word rating task.

At the start of the experiment, the participants received verbal instructions followed by more detailed instructions on the computer screen. The AB task consisted of a rapid serial visual presentation (RSVP) task in which two words were presented as targets amongst a sequential stream of 15 distractors, consisting of strings of 14 digits (see Fig. 1). The first target (T1) was randomly drawn without replacement from a list of 148 Dutch adjectives describing personality traits, such as “kalm” (calm), “oprecht” (Dutch for “sincere”) or “hebberig” (Dutch for “greedy”). These traits were taken from a study by Anderson (Anderson, 1968), in which 555 words for traits were tabled by the likableness from the most favorite to the least. We chose 74 words from the top of the list and 74 from the bottom of the list, with a comparable word length and frequency. The second target (T2) was a neutral noun, randomly drawn without replacement from another list of 148 nouns, e.g., “inhoud” (Dutch for “content”), “maand” (Dutch for “month”), or “zwaan” (Dutch for “swan”). The distractors consisted of strings of 14 random digits, excluding ‘0’ and ‘1’ (e.g. ‘38,574,936,848,582’). Target words were flanked by a number of ‘X’s such that each stimulus consisted of 14 characters in total.

Each trial started with a fixation cross. Participants pressed the spacebar to initiate the stimulus presentation 100 ms later. At the start of each block of trials, targets were presented with a duration of 140 ms, immediately followed by a 10-ms mask (an additional string of digits). In all trials, the total duration of the target and mask was 150 ms, thereby keeping the interval between target and distractor constant. However, after the first trial, target and mask durations were dynamically adjusted depending on performance in order to keep the task difficulty relatively constant and comparable within and across individuals, a previously done by a number of AB studies (e.g., Martens et al., 2009; Martens et al. 2010a; Martens et al. 2010b; Martens et al. 2010c; Martens et al. 2015; Shapiro et al., 2017). Specifically, on each trial, a running average of T1 accuracy was calculated. The target presentation was decreased by 10 ms and the mask duration was increased by 10 ms when the mean T1 accuracy became higher than 90%, whereas the target duration was increased by 10 ms and the mask duration decreased by 10 ms when the mean T1 performance dropped below 80%. A T1 accuracy of 80–90% is generally considered as an ideal difficulty to elicit the AB effect. That way it is neither too low (losing many trials when looking at T2|T1), nor too high (for a ceiling effect). Target durations could thus vary between 20 to 140 ms (*Mean* = 136 ms). T1 was always preceded by four to six distractors and followed by its mask, making its onset less predictable.

The duration of T2 and its mask were always the same as that of T1 and its mask on any given trial. On 50% of the trials, T2 followed T1 after one distractor (Lag 2) while on the other half of the trials it followed after six distractors (lag 7). In the Lag 2 condition, the time interval between the onset of T1 and T2 was 300 ms, during which the AB is commonly found to be maximal. In the Lag 7 condition, the interval between the onset of T1 and T2 was 900 ms, during which any target interference as reflected in the AB should be absent. Depending on the lag (the position of T2 relative to T1 in the stream) and the number of distractors preceding T1, T2 was followed by 3 to 10 distractors, such that the stream always contained 17 items (plus the target masks). After presentation of the stream, participants were prompted to report both target words in the same order as they appeared on the screen using the computer keyboard. In case that they were unable to report one of the words they were instructed to leave the response field empty or take a guess. On average, participants left the response field empty in 8% of the trials in Experiment 1.

After reading and receiving oral instructions, every participant completed 18 practice trials in which they received feedback about their performance. The stimuli in this practice block were drawn from the same 148 character traits as in the experimental trials. Subsequently, the participants performed 198 experimental trials without feedback, with a break after every 50 trials.

Typo Correction

We adapted a semi-automatically examining method for typographical errors using the software 'R' and the package 'Data.table'(version 1.10. 4–3) (Dowle & Srinivasan, 2017). The first step of the response correction consisted of an automatic comparison of each letter position in a string of a word. Possible typos were identified by comparing every letter of the response of the participant (e.g., 'zwan') with the letters at the exact same position and the positions before and after the letter in question of the correct response (e.g. 'zwaan', meaning 'swan'). If the typed letter was not at any of these locations, the letter was counted as incorrect. If two or fewer letters were counted as incorrect, it was flagged as a possible typo and further checked in the second step. The second step consisted of the manual review of the possible typos by comparing the response to the original correct answer. If it was clear that a typo had indeed been made, the response was then confirmed to be correct rather than incorrect and analyzed as such. A total of 1633 typos were detected and corrected (6% of the total responses).

Word Rating Task

Following completion of the AB task, a word rating task was given, in which all character traits that had served as T1 in the AB task were randomly presented once, one by one. Participants were instructed to indicate how relevant a presented characteristic was to themselves. These self-relevancy ratings were given on a scale of '1' to '5', '1' referring to a low relevance and '5' referring to a high relevance.

For the self-relevance rating task, traits rated with 1 or 2 were categorized as low self-relevant, traits rated with 3 were categorized as neutral, and words rated with 4 or 5 were categorized as highly self-relevant. An important advantage of this approach is that the degree of self-relevance for each stimulus was determined on an individual basis.

Statistical Design

The experiment had Lag (2 and 7) and Self-relevance (high, neutral, and low, described in the next section) as within-subjects independent variables, and accuracy (%) of T1 and T2 as dependent variables. Data was analyzed using the software 'R' (version 4.0.2). Generalized linear mixed models (GLMM) were fitted in R studio software (Version 1.1.463) using the function 'glme' in the package 'lmerTest' (Version 3.1–2) (Kuznetsova et al., 2015). Generalized linear models (GLM) were fitted using function 'lmer' in the package 'lmerTest'.

Results and Discussion

Distribution of Self-Relevance Ratings

Participants rated all character traits regarding self-relevance in the word rating task at the end of the session. The distribution of the ratings of all the participants is normally distributed according to a Q-Q plot, and is provided in the supplementary materials. The average self-relevance rating was 2.74 (SD = 1.31).

T1 Accuracy

Task performance of T1 and T2 given correct report of T1 (T2|T1) is depicted in Fig. 2. A GLMM was fitted on T1. To test whether a certain variable was a significant predictor of T1 accuracy, self-relevance level, lag, and their interaction were added to the model as the fixed factors, the subject-specific intercepts and word length of T1 were added as random factor, T1 accuracy was the dependent variable. Word Length was added as a random effect because it could form a possible confound (Olson, Chun, & Anderson, 2001). The duration of the targets was also added as a random effect because the varying duration may also influence perceptual identification of targets. Moreover, to obtain sufficient experimental trials, we randomly repeated 50 of the stimuli. To rule out the potential influence of such repetitions, we included the number of times a specific stimulus was presented as a random effect ('T1/T2 presentation count'). Our final model considered all the main effects and interactions: Model = glmer (T1Acc ~ Self_Relevance*

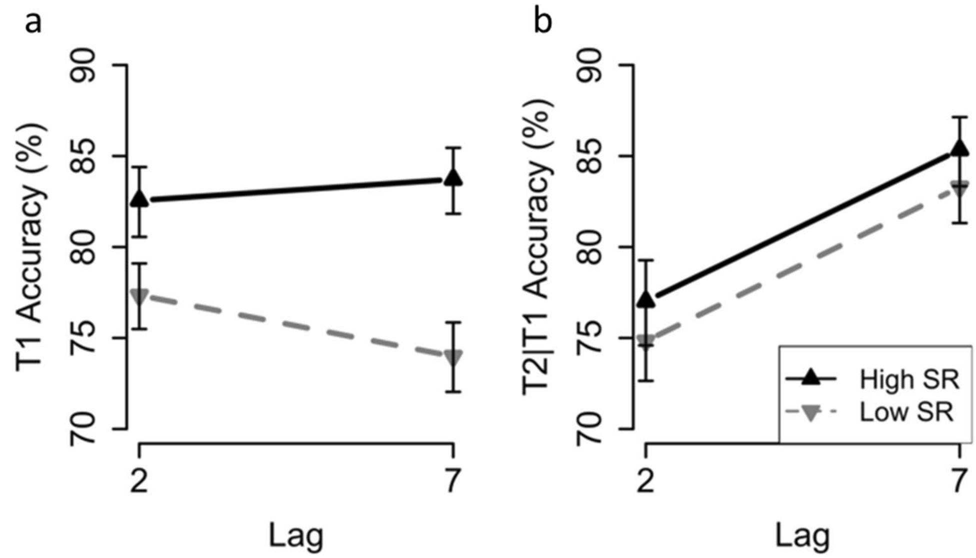

Fig. 2 T1 accuracy (panel **a**) and T2 accuracy given correctly reported T1 (panel **b**) as a function of Lag and T1 self-relevance. Solid lines represent the T1 and T2|T1 mean accuracy in high self-relevant T1 condition while the dotted lines represent T1 and T2|T1 accuracy in the low self-relevant T1 condition. Error bars reflect standard error of the mean according to the Agresti-Coull method (Agresti & Coull, 1998)

Lag + (1|Subject) + (1|WordLengthT1) + (1|T1Duration) + (1|T1 presentation count) + (1|T2 presentation count), family = 'binomial', data = DataExp1). The model converged successfully, and showed a significant fixed effect of self-relevance, such that the low self-relevant words had a significantly lower accuracy (*Mean* = 67.9%, *SEM* = 0.02) than the highly self-relevant words (*Mean* = 75.7%, *SEM* = 0.02), effect size = 0.53, $p < 0.001$, SE = 0.10, $z = 5.50$, AIC = 7792.92, 1-β > 0.95; post-hoc power tested by G-power (Faul, Erdfelder, Buchner, & Lang, 2009). No other significant effects were found (all $ps > 0.05$).

T2|T1 Accuracy

A GLMM was also fitted on T2|T1 accuracy. To test whether a certain variable was a significant predictor of T2|T1 accuracy, self-relevance level, lag, and their interaction were added to the model as the fixed factors, the subject-specific intercepts, word length of T2 (as described above), duration of T1 (as described above) and T1/T2 presentation count (as described above) were added as random factor, T2|T1 accuracy was the dependent variable. We used a full model that considered all the main effects and interactions of self-relevancy level and Lag: model = glmer (T2onT1 ACC ~ SR * Lag + (1|Subject) + (1|Word Length T2) + (1|T1Duration) + (1|T1 presentation count) + (1|T2 presentation count), family = 'binomial', data = DataExp1). The model converged successfully, and showed a significant fixed effect of Lag, such that when T2 appeared within the attentional blink period (Lag 2, *Mean* = 76.0%, *SEM* = 0.01) accuracy was significantly lower than when presented at Lag 7 (*Mean* = 84.4%, *SEM* = 0.01), effect size = 0.12, $p < 0.001$, SE = 0.03, $z = 3.95$, AIC = 6214.55, 1-β > 0.95, post-hoc power tested by G-power**.** No other significant effects were found (all $ps > 0.05$).

AB Magnitude

To specifically study the relative decrement in performance at Lag 2 due to the AB, AB magnitude was calculated as T2|T1 accuracy at Lag 2 relative to T2|T1 accuracy at lag 7 using this formula: AB magnitude = ((T2|T1long—T2|T1short)/ T2|T1Long) * 100%. A linear regression model was used to test whether self-relevance level predicted AB magnitude. Self-relevance was included as a fixed factor and subject intercept was included as a random factor. However, because only a single AB magnitude can be calculated per participant per condition (two in total), the model did not have enough data to reliably estimate the random intercept per subject. Therefore, we ran a *t*-test with Self-relevance as a within-subject factor on AB magnitude, which is equivalent to a model without any random factors, only including Self-relevance as a fixed factor. The results showed no significant difference in AB magnitude between high and low Self-relevance, $p = 0.95$, $t(44) = 0.06$.

In summary, the results of Experiment 1 showed increased performance for highly self-relevant words, suggesting that highly self-relevant stimuli are either processed more efficiently, or draw additional attention, leading to higher T1 accuracy. However, self-relevance level showed no influence on AB magnitude. The benefit of processing a self-relevant word processing seems to come at neither cost nor benefit for processing subsequent information (T2).

However, a remaining possibility is that carry-over effects on T2 are obscured if there is a benefit for some participants, but a cost for others, perhaps as a function of individual mood or mental state. To investigate this possibility directly, in Experiment 2, we recruited two groups of participants that either scored relatively high or low on sub-clinical depression level, predicting that processing self-relevant words has opposite effects on temporal attention as a function of depression score.

Experiment 2

Materials & Methods

Participants

Participants in Experiment 2 were recruited from a large group of students ($n = 978$) from Shenzhen University in China. One hundred of them were selected for the present study (65 females, *Mean* age = 19.9 years, *SEM* = 0.17), depending on their score on the Beck Depression Inventory-Short Form [BDI-SF; (Beck & Beck, 1972; Hautzinger et al., 1994)], measured prior to the experiment (pretest) via an online link. Participants had normal or corrected-to-normal vision. All who finished the BDI-SF online were paid 5 Chinese yuan.

The BDI-SF is a valid and effective instrument for detecting moderate and severe depression. It has been demonstrated to have a comparable level of internal consistency (coefficient alphas) to the long version of the BDI which contains 21 items (Beck et al., 1988). For screening purposes, a 9/10 cut-off score is indicated (Furlanetto et al., 2005). This means that participants with a BDI-SF score lower than 10 do not consistently report symptoms of depression, while those having a BDI-SF score higher or equal to 10 report mild-to-moderate symptoms of depression. Based on their scores, we invited 100 participants who scored either relatively high or low on the BDI-SF approximate one week after the first BDI-SF test. In order to ensure that their scores were still valid at the time of the experiment, they were tested again shortly before to the experiment, again via an online link. Seven participants were excluded because of an inconsistent BDI-SF score in pre- and post- BDI-SF test. Fifty-two participants were subsequently assigned to the Non-depressed group, with both pre-test and post-test BDI-SF score lower than 10 (thirty-nine females; *Mean* age = 20 years, *SEM* = 0.22), and another 41 participants were assigned to the Depressed group with both pre-test and post-test BDI-SF score higher than 10 (twenty-six females; *Mean* age = 19.7 years, *SEM* = 0.08). The ages in the two groups showed no significant difference, $t\,(91) > 0.45$. A chi-square analysis revealed no differences in gender and handedness between the two groups either, (gender: $\chi 2\ (1,\ 93) = 1.46$, $p = 0.26$; handedness: $\chi 2\ (1,\ 93) = 0.52$, $p > 0.47$, post-hoc power $1\text{-}\beta > 0.90$). The experiment was approved by the ethical committee psychology of the Shenzhen University, China. In accordance to the declaration of Helsinki all participants had given written consent prior to the experiment. Participants were paid 50 Chinese yuan for participation, which took approximately 60 min.

Stimuli and Procedure

Experiment 2 was conducted using E-prime 3 software on a 19-inch CRT monitor with a refresh rate of 100 Hz. Participants sat in front of a monitor, about 70 cm away from the screen. The stimuli were presented in black on a white background in the font 'Song' with font size 18. Participants responded by giving their answers using a computer keyboard.

Experiment 2 contained an AB task and a word rating task, and the settings were comparable to those of Experiment 1. The main difference between Experiment 1 and 2 was that all stimuli were presented in Chinese both in the AB task and the word rating task. In the AB task, the targets were Chinese characters and the distracters were the digits 0 to 9, written in Chinese. The targets were flanked by the neutral character "的", which does not have a particular meaning in Chinese, to keep the length of the stimuli the same throughout the experiment. Similar to Experiment 1, T1 was always drawn without replacement from a word list of 150 (two more than in Experiment 1) adjective words describing character traits, originating from a study by Anderson (Anderson, 1968) and translated into Chinese. After all 150 words had been presented once, 60 words were randomly selected without replacement and presented for a second time. T2 was a noun of a neutral object, and was also chosen without replacement from a list of 150 Chinese nouns. Sixty words were randomly selected without replacement and presented for a second time, once the list of 150 words was exhausted. After presentation of the stream, participants were asked to type the "pinyin"[1] of the two targets in the same order they were presented. In case that they were unable to report one of the words they were instructed to leave the response field empty or take a guess. On average, participants left the response field empty in 7% of all trials in Experiment 2.

In the subsequent word rating task, similar to Experiment 1, participants were asked to rate each word that had been presented as T1 in the AB task in terms of self-relevance level from '1' to '5'. The participants performed 210 AB trials with an additional 12 practice trials and a total of 150 word rating trials.

[1] Pinyin, is the official Romanization system for Standard Chinese in mainland China and to some extent in Taiwan. It is normally written using Chinese characters. Pinyin can be used to spell Chinese names and words in languages written with the Latin alphabet and also in certain computer input methods to enter Chinese characters.

Typo Correction

Due to the particular characteristics of Chinese, the responses typed in by the participants were manually checked for typos by three native Chinese speakers, each of them having an A-level Putonghua certificate[2] and naïve as to the design and goals of the study. Only responses that were marked as incorrect needed to be checked. A word initially marked as incorrect would be relabeled as correct when two of the raters judged that a typo had been made. A total of 3062 typos were detected and corrected (10% of total responses).

Statistical Design

This experiment had Lag (2 and 7) and Self-relevance (high, neutral, and low, described in the next section) as within-subjects independent variables and Group (High/Low depression) as a between-subject independent variable, with accuracy of T1 and T2 (%) as dependent variables. Data was analyzed using the software 'R' (version 4.0.2). GLMM were fitted in R studio software (Version 1.1.463) using the function 'glme' in the package 'lmerTest' (Version 3.1–2) (Kuznetsova et al., 2015). Generalized linear models (LMM) were fitted using function 'lmer' in the package 'lmerTest'. The interactions were analyzed using a post-hoc package 'emmeans' in R (Lenth et al., 2018).

Results

Distribution of Self-Relevance Ratings

Participants rated all character traits regarding self-relevance in the word rating task at the end of the session. The distribution of the ratings of all the participants is normal distributed according to a Q-Q plot, as provided in the supplementary materials. The average self-relevance rating was 2.79 (*SEM* = 0.02).

T1 Accuracy

The accuracy of T1 identification was analyzed with a GLMM. To test whether a variable predicted T1 accuracy, we constructed a model including self-relevance level, lag and group as fixed factors, the subject-specific intercepts, duration of T1 (as described above) and T1/T2 presentation count (as described above) were added as random factor. Firstly, we used a full model that considered all the main effects and interactions of self-relevancy level and Lag: Model1 = glmer (T1acc ~ SR* Lag* Group + (1|Subject) + (1|T1Duration) + (1|T1 presentation count) + (1|T2 presentation count), family = 'binomial', data = DataExp2). However, the model failed to converge even when we increased the number of iterations of the model to 20,000. Secondly, we built a model that only considered the main effects first: Model2 = glmer (T1acc ~ SR + Lag + Group + (1|Subject) + (1|T1Duration) + (1|T1 presentation count) + (1|T2 presentation count), family = 'binomial', data = DataExp2). The model converged successfully, and showed a significant fixed-effect of self-relevance, effect size = 0.13, $p = 0.001$, SE = 0.05, z = -2.59, AIC = 15,468.87, 1-β > 0.95, post-hoc power tested by G-power. As shown in Fig. 3, the model revealed that the accuracy of high self-relevant words was significantly higher (*Mean* = 83.1%, $SEM = 8*10^{-4}$) than for low-self relevant words (*Mean* = 85.7%, $SEM = 6*10^{-4}$). The effects of lag and group were not significant (all $ps > 0.06$). To detect whether the interactions between self-relevance, lag and group were significant, we used an ANOVA () function to compare Model1 and Model2. The results showed that there was no significant difference between Model1 and model2, indicating that the interactions were not significant and did not contribute to the prediction of T1 accuracy.

T2|T1 Accuracy

T2|T1 accuracy is depicted in the Fig. 4a and b. A binomial GLMM was also fitted on T2|T1 accuracy. To test whether a certain variable was a significant predictor of T2|T1 accuracy, self-relevance level, lag, group, and their interaction were added to the model as the fixed factors, the subject-specific intercepts, duration of T1 (as described above) and T1/T2 presentation count (as described above) were added as random factor, T2|T1 accuracy was the dependent variable: Model = glmer (T2onT1ACC ~ SR*Lag*Group + (1|Subject) + (1|T1Duration) + (1|T1 presentation count) + (1|T2 presentation count), family = 'binomial', data = DataExp2). The model converged successfully, and the results showed a significant fixed effect of Lag, such that performance was significantly lower at lag 2 (*Mean* = 75.1%, *SEM* = 0.01) than at lag 7 (*Mean* = 85.8%, *SEM* = 0.01), effect size = 0.48, $p < 0.001$, SE = 0.10, $z = 4.84$, AIC = 15,559.50, 1-β > 0.95, post-hoc power tested by G-power. No other significant fixed effects were found (all $ps > 0.05$). Importantly, the interaction between self-relevant level, lag and group was a significant predictor of T2|T1 accuracy. We performed a post-hoc analysis on the interaction and found that, in the Non-depressed group, when T2 appeared at lag 2, high self-relevant T1s (*Mean* = 78.2%, *SEM* = 0.02) led to marginally significant better performance than low

[2] A-level is the highest level of the Putonghua language proficiency test, with a score of 92 or higher out of 100. The test assesses pronunciation, intonation, natural intonation and smooth expression during reading and free conversation.

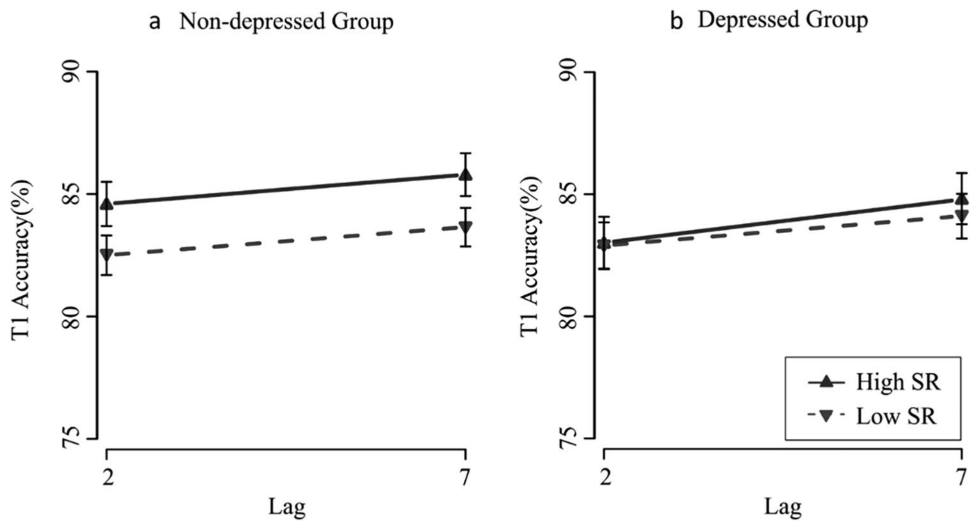

Fig. 3 T1 accuracy as a function of Lag and Self-relevancy in the Non-depressed (**a**) and Depressed group (**b**), respectively. Solid lines represent T1 accuracy for high self-relevant words while the dotted lines represent the T1 accuracy for low self-relevant words. Error bars reflect standard error of the mean

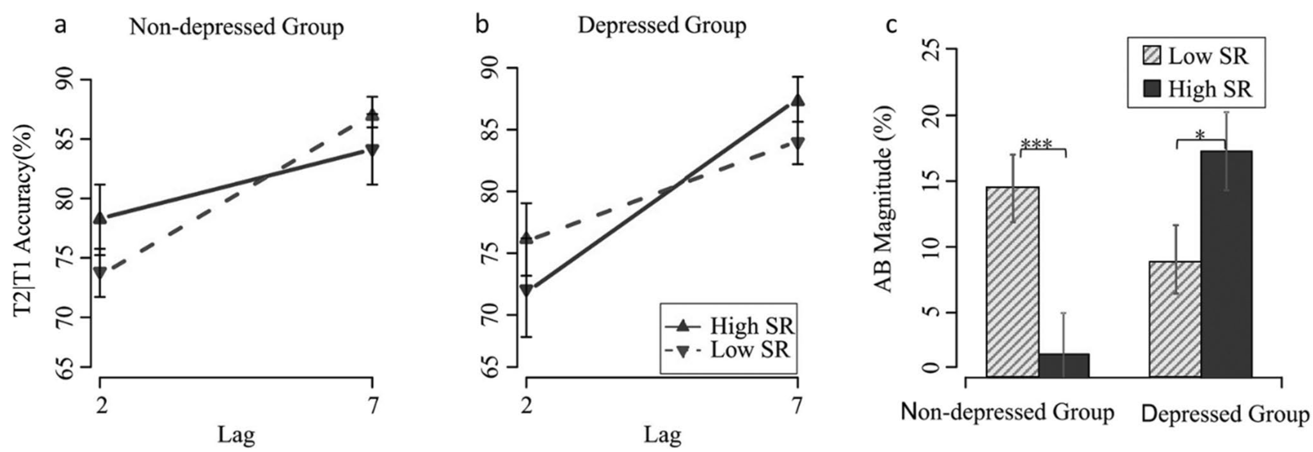

Fig. 4 Panel **a** and **b**: T2|T1 accuracy given correctly reported T1 as a function of Lag and T1 Self-relevance for the Non-depressed group and Depressed group, respectively. Solid lines represent T2|T1 accuracy following high self-relevant words while the dotted lines represent T2|T1 accuracy following low self-relevant words. Panel **c**: The AB magnitude for the Non-depressed and Depressed group, respectively. Error bars reflect standard error of the mean. *** $p < 0.001$; * $p < 0.05$

self-relevant T1s (*Mean* = 73.8%, *SEM* = 0.02), t (91) = 3.70, $p = 0.057$. At lag 7, high self-relevant T1s (*Mean* = 84.2%, *SEM* = 0.01) led to significantly worse performance than low self-relevant T1s (*Mean* = 87.3%, *SEM* = 0.01), t (91) = 4.70, $p = 0.03$. For the Depressed group, the pattern of results was reversed. Although not significant, performance seemed to be worse following high self-relevant T1s (*Mean* = 72.3%, *SEM* = 0.03) compared to low self-relevant T1s (*Mean* = 76.2%, *SEM* = 0.02) when T2 appeared at lag 2, $t(91) = 2.22$, $p = 0.14$, and performance was significantly better following high self-relevant T1s (*Mean* = 87.6%, *SEM* = 0.02) compared to low self-relevant T1s (*Mean* = 84.0%, *SEM* = 0.01) when T2 appeared at lag 7, $t(91) = 4.71$, $p = 0.03$.

AB Magnitude

AB magnitude is shown in Fig. 4c to further clarify this interaction between self-relevancy, depression, and the attentional blink. Given only a single AB magnitude can be calculated per participant per condition (two in total), the linear regression model method would not have enough data to reliably estimate the random intercept per subject. Therefore, we ran an ANOVA analysis with the self-relevance level of T1 (High/Low) as within-subject factor and Group (Non-depressed/Depressed) as a between-subject factor. The results showed that the interaction between Self-relevance level and Group is significant, $p < 0.10^{-5}$, F (1, 91) = 20.73, $\eta^2 = 0.19$, 1-β > 0.95, post-hoc power tested

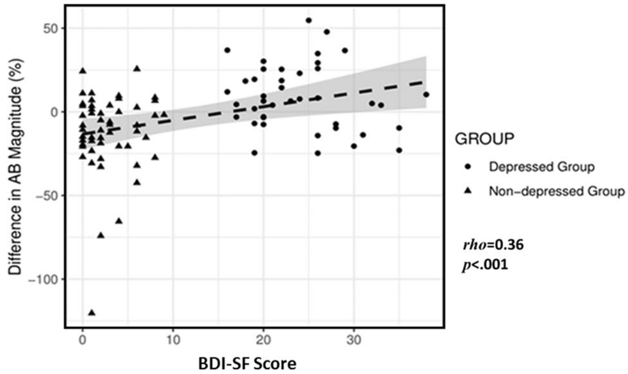

Fig. 5 Correlation between individual BDI-SF scores and difference in AB magnitude for both groups. AB magnitude difference was calculated by subtracting the AB magnitude in the low self-relevance condition from the high self-relevance condition. The line represents the linear relationship and the shadow represents the 99% confidence interval

by G-power with $\alpha = 0.05$. Performing a post-hoc analysis, we further found that the AB was substantially smaller in the Non-depressed group, following a high self-relevant T1 (low self-relevant T1: *Mean* = 14.5%, *SEM* = 0.03; high self-relevant T1: *Mean* = 1.8%, *SEM* = 0.05), $t\,(91) = -4.10$, $p < 0.001$. In contrast, in the Depressed group, AB magnitude was significantly larger when T1 was highly self-relevant (low self-relevant T1: *Mean* = 8.7%, *SEM* = 0.03; high self-relevant T1: *Mean* = 17.3%, *SEM* = 0.03), $t\,(91) = 2.45$, $p = 0.02$.

The Interaction Between Depression, Ab Magnitude, and Self-Relevance

Lastly, we wanted to investigate whether depression scores correlate with the relative impact of self-relevance on AB magnitude, at an individual level. We calculated the relative impact by subtracting the AB magnitude in the low self-relevance condition from the high self-relevance condition, for each individual. We found a significant correlation between the relative impact of self-relevance on the AB as a function of BDI-SF score, $p < 0.001$, $rho = 0.36$, $1\text{-}\beta > 0.95$, post-hoc power tested by G-power with $\alpha = 0.05$. It should be noted that the BDI-SF scores were cut off by the high/low depression criteria. To overcome the non-normalized distribution of BDI-SF scores, we used a non-parametric permutation test on the Spearman correlation coefficient to obtain the *p*-value, which can fulfill the assumption about normal distribution. As shown in Fig. 5, depression level correlated significantly ($p < 0.001$) with the relative difference of AB following either a high or low self-relevant T1. In the permutation test, we randomly permuted the pairs of data (depression score and relative self-relevance impact), and calculated the Spearman correlation coefficient (*rho* value) for each pair of the random data, repeating this procedure for 10,000 times to get a distribution of random rho value. We compared the original rho value to the distribution. The *p*-value was calculated by this formula: *p*-value = P (|rho random data| ≥ |rho original data|) (DiCiccio & Romano, 2017; Stelmach, 2012).

Taken together, our results suggest that a highly self-relevant word can have a positive impact on temporal attention for a subsequently presented neutral word for individuals scoring low on depression. However, the opposite pattern is true for individuals scoring relatively high on depression: a highly self-relevant word (T1) comes at a cost rather than benefit for identifying a subsequent word (T2) when presented shortly after the first word. Our correlational analysis moreover suggests that the more depressed a person is, the bigger the negative impact of a highly self-relevant T1 on temporal attention for T2.

Discussion

In the current study we assessed the relationship between attention and self-relevance by addressing two research questions: 1) does processing self-relevant stimuli come at a cost or benefit for subsequent stimuli and 2) is the processing of self-relevant stimuli modulated by the mental state (e.g., depression). Our results confirmed that there is a benefit to identify self-relevant words, which was reflected in increased accuracy. In two experiments, we found that self-relevant personality words are more easily processed and perceived when presented as the first of two targets in an AB paradigm. This finding is in line with previous studies that have shown the self-advantage and extends this literature by showing that the advantage also holds true for character traits that vary in self-relevance on an individual basis.

Although we did not observe any carry-over effects of this self-advantage on the processing of a second neutral target word in Experiment 1, in the second experiment we found convincing evidence that processing a self-relevant word can either come at a cost or benefit for identifying subsequent stimuli, depending on the presence of depressive symptoms. Whereas people scoring relatively high on depression seem to be stuck on processing the self-relevant word, indicated by a larger AB magnitude, people scoring relatively low on depression showed a smaller AB magnitude, suggesting an increased efficiency in processing the highly self-relevant stimulus. Possible explanations for this pattern of results are further discussed below.

Previously, opposite findings have been found regarding the relationship between self-relevance and attentional resource deployment. In some cases, studies showed attentional capture by self-relevant stimuli (Alexopoulos et al., 2012; Gronau, et al., 2003; Ruz & Lupianez, 2002; Sui et al., 2015), while other studies demonstrated more efficient processing for self-relevant stimuli (Bargh, 1982; Moray, 1959; Tacikowski et al., 2017a, b). We argued that each of these two possibilities would lead to a different outcome when tested in the AB paradigm. We tested this by presenting a self-relevant word (T1) and assessed the time-course of subsequent attention when participants were to identify a neutral word (T2) when presented at different lags following T1.

Unexpectedly we did not find a significant effect of self-relevance on T2 performance in Experiment 1. On the one hand this result might indicate the absence of any carry-over effect, but on the other hand an interaction between self-relevancy and temporal attention may exist that is dependent on one's emotional state. More specifically, individuals scoring relatively high on a depression symptom scale might process self-relevant trait characteristics differently than individuals scoring low on a depression symptom scale, with opposite effects on temporal attention. That is, it is possible that individuals scoring high on depression might be mostly drawn to negative words, while individuals scoring low on depression might be inclined to associate more positive than negative trait characteristics to one self. They might be relatively efficient in processing positive words requiring few resources, while a negative word that is considered as highly self-relevant might draw substantially more attentional resources. Such opposing effects may well cancel each other out, possibly contributing to the pattern of results in Experiment 1, including the lack of an interaction between self-relevancy and temporal attention.

Given these initial findings and the conflicting pattern of results reported in the literature, we specifically focused on the role of individual differences in a second experiment. We selected two groups of participants, each scoring either relatively high or low on depression. As predicted, an effect of self-relevance on temporal attention for T2 was revealed that was modulated by the level of depressive symptoms. For those who scored relatively high on depression symptoms, a larger AB magnitude was observed, while for those who scored relatively low on depression, a reduced AB magnitude was found, following a highly self-relevant T1. These results suggest that for individuals reporting mild-to-moderate symptoms of depression, self-relevant information captures more attentional resources.

These findings are in line with previous studies showing that depressed people have an attentional bias to self-relevant stimuli and show a difficulty to disengage attention from self-relevant (especially negative) words (Koster et al., 2011), which supported the self-focused model of depression (Ingram, 1990). For the participants not reporting any symptoms of depression, highly self-relevant words seemed to be processed more efficiently, leaving more attention available to identify the second target. At the individual level, additional evidence was provided by a correlational analysis that demonstrated the relative attentional impact (either positive or negative) of a self-relevant T1 on T2 performance as a function of depression level. This matches with a previous study demonstrating that emotional disorders can lead to a relative loss of attentional control, such that patients with both social anxiety disorder and depression showed a relatively large attentional blink (Morrison et al., 2016).

In Experiment 2 of the present study, though no difference was found between participants with high or low depression score in general AB magnitude, importantly, it was found that AB magnitude increased following the presentation of a self-relevant T1. A related but opposite effect was found in an AB study (Romens et al., 2011) that manipulated the valence of T2 for individuals with negative cognitive styles, a bias for negative thinking that is often observed in depressed patients (Gibb, et al., 2001; Robinson & Alloy, 2003). They reported a reduction in AB magnitude when T2 (rather than T1) consisted of negative words, suggesting an increase in the allocation of attention for such stimuli. Our findings suggest that these stimuli are not merely processed with priority or increased efficiency, but that this preference for processing self-relevant (presumably negative) stimuli comes at a cost for processing other subsequently presented stimuli, thus clarifying how the interaction between self-relevant information and temporal attentional is modulated by (sub-clinical) depression level.

Cultural Differences

Previous studies have shown cultural differences in self-representation, such that Western adults utilize the medial prefrontal cortex to represent only the individual self, while Chinese adults use the same brain area to represent both the individual self and close others. One explanation by Markus and Kitayama (1991) is that Western cultures emphasize self-identity while the Chinese culture more strongly emphasizes social connections. In consideration of individual differences, we asked participants to rate the self-relevance of all presented words in order to obtain a measure of self-relevancy for each word and individual. We are therefore optimistic that any such cultural differences did not strongly influence the current results. That is, in both experiments similar results were obtained such that highly self-relevant words led to a higher identification accuracy than low self-relevant words. Carry-over effects on a subsequently presented T2 were only found when depression level was taken into account (Experiment 2). Given that Experiment 2 only included Chinese participants though, future studies that specifically focus on cultural differences would nevertheless be helpful in order to confirm the generalizability of our current findings.

Conclusion

Our findings thus shed light on the previously paradoxical relation between the temporal dynamics of attention and self-related processing: Depending on one's mental disposition, a processing advantage for highly self-relevant material comes at either a subsequent cost or benefit in temporal attention.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12144-022-02994-3.

Author Contributions Jing Wang: Conceived and designed the study; Collected the data of experiment2; Performed the data analysis; Wrote the paper; Revised the paper.

Corné Hoekstra: Collected the data of experiment1; Performed part of the data analysis; Wrote the paper.

Stefanie Enriquez-Geppert: Revised the paper critically for important intellectual content.

Yuejia Luo: Revised the paper; Funding support.

André Aleman: Revised the paper critically for important intellectual content.

Sander Martens: Conceived and designed the experiments; Revised the paper critically for important intellectual content.

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Data Availability All data in this study are available upon request by contact with the corresponding author, in consideration of data protection, a formal data sharing agreement is needed when the data is requested.

Code Availability The data in this study was analyzed by custom code in matlab. It is available upon request by contact with the corresponding author.

Declarations

Conflict of Interest All authors declare that they have no conflict of interest.

Ethical Approval 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.

Consent for Publication Consent for publication was obtained from all individual participants included in the study.

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