The Influence of Age-Related Positivity Bias Effect in Emotional Language Comprehension

THE INFLUENCE OF AGE-RELATED POSITIVITY BIAS EFFECT IN EMOTIONAL LANGUAGE COMPREHENSION

by

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Final approval and acceptance of this dissertation is contingent upon the candidate's submission of the final copies of the dissertation to the Graduate College.

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Dedication

To my family, who have supported all of my life choices!

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Abstract

Older adults usually prioritize positive information over negative ones, termed as "positivity bias". For instance, when older and younger adults are given information about several models of a car, and are asked to choose a car, older adults tend to spend more time on positive than negative features, compared with younger adults. This age-related positivity bias could in turn influence readers' contextualized language use. However, it is unclear whether older adults still process and evaluate affective features of a word in isolation and in contexts the same way as younger adults do. In this dissertation, I examined whether and how the age-related positivity bias influences language processing from the three perspectives: visual word recognition, semantic/meaning update, and lexical prediction. Chapter 1 introduces the topic and provides a framework for understanding the relevant theories on the age-related positivity bias. Chapter 2 shows that at the single word level, older adults usually attend to low-arousing positive words first, and then regulate low-arousing negative meanings later. Chapter 3 shows that at the sentence level, older adults tend to update the affective-neural representations of a word with both positive and negative contexts. Chapter 4 shows that before an emotional word occurs, older adults predict both positive and negative meanings/features of a word equally likely. Finally, Chapter 5 presents a general conclusion for the dissertation as well as possible future directions.

Chapter 1. Introduction

People use language to express emotion and share their feelings every day. According to a study on emotion words (e.g., *happy*, *sad*), there are more negative emotion words than positive and neutral words in both English and Spanish (Schrauf & Sanchez, 2004), reflecting human's general tendency to attend to and allocate more cognitive resources to process negative linguistic information. It is unclear, however, how people represent and process emotional content in all words (e.g., *holiday*, *funeral*) across the lifespan. For one thing, there is evidence that when people get older, they tend to attend to and memorize more positive than negative information, termed as "positivity bias" (Mather & Carstensen, 2005). This age-related positivity bias is preserved even during the recent pandemic. For instance, sampled with a survey in April 2020 after the COVID outbreak, older adults still reported higher frequency and greater intensity of positive emotional experiences than negative ones, compared with younger adults (Carstensen et al., 2020). This suggested that older adults prioritized positive information in their life under high-stress situations. For another, aging has been associated with declining cognitive flexibility, an ability to acquire and update relevant information in the environment (Boone et al., 1993). This can in turn influence contextualized language use. Studies have found that older adults showed reduction in using prior semantic contexts to facilitate language processing (DeLong et al., 2014; Federmeier et al., 2010; Payne & Federmeier, 2017; Wlotko et al., 2012). However, emotional representations of a word can be changed in contexts. For instance, "*holiday*" becomes negative in the sentence "*holidays are stressful*", and "*visit*" could be pretty positive to older adults, while not so much, to younger adults. It is unclear how emotional information is processed and updated in different contexts in older adults.

My dissertation included three studies to investigate the age-related positivity bias at different levels of language processing. Study 1 examined how the age-related positivity bias depends on emotional arousal at the single word level. Study 2 investigated how age influences the update of affective representations of a word embedded in emotionally loaded contexts. Study 3 further investigated how age affects language prediction in emotionally ambiguous scenarios.

1.1. Psychological theories of the age-related positivity bias

The three studies in my dissertation tested the strength and vulnerability integration (SAVI) model (Charles, 2010) on whether and how the age-related positivity bias impacts the affective meaning of a word when, after, and before an emotional word actually occurs. The SAVI model posits that older adults have different strengths and vulnerabilities in emotional processing (Charles, 2010). Older adults show strengths in using different strategies such as attention deployment, appraisals, and behaviors to regulate negative emotions. This possibly results from the motivational shift in older adults to prioritize positive emotions due to constrained time horizons, despite the cognitive decline (Carstensen, 2006). However, when the emotional event is high-arousing, older adults show greater and/or more sustained emotional responses, attenuating their positivity bias (tested in Study 1). The SAVI model further hypothesized that the age-related positivity bias can depend on different stages of emotional experiences. That is, older adults usually use different strategies to regulate negative emotions *before* (tested in Study 3) or *after* (tested in Study 2) an emotional event. On the contrary, older adults' positivity bias is likely to be reduced *during* an emotional event, dependent on the emotional arousal, due to reduced physiological flexibility.

Evidence supporting the SAVI model comes from both behavioral and neuroimaging studies, but are restricted to pictures (c.f., Chapter 2/Appendix A: Introduction). Only an fMRI study compared the brain activity for positive and negative emotional words between younger and older adults (Leclerc & Kensinger, 2011). In this study, older adults showed greater medial prefrontal cortex activity for positive than for negative words. It was suggested that older adults use cognitive control to elaborate positive (vs. negative) meanings in words more. However, it is unclear whether and how positivity bias influences language representations at different stages of processing. On one hand, emotional representations of a word can be more malleable than those of a picture. For instance, reading the word "*blood*" can invoke different mental representations with varied emotional valence, such as a bloody situation, a scene of hospital, or just the red liquid pumping around the body, whereas seeing a picture of blood usually invokes rigid representations of blood. On the other hand, words can shape emotional representations of other visual stimuli (e.g., faces and pictures; c.f., Chapter 3/Appendix B: Introduction). These observations highlight the flexibility of emotional meanings in a word and how words impact one's mental representations of emotional experiences.

1.2. Cognitive linguistic theories of emotional meaning

To our knowledge, no linguistic theory touches upon the topic of emotional semantics (i.e., meaning processing) across the lifespan. Since all the three studies in my dissertation examined emotional meanings in words and sentences, it is important to survey cognitive and linguistic theories on emotion.

In cognitive linguistics, emotion is defined as a complex internally-represented knowledge system that interacts with cognitive systems including language (Schwarz-Friesel, 2015). Speakers can convey feelings or make judgments via explicit lexical items, such as emotion words (e.g., *happy*, *sad*) and emotional words (e.g., *sweet*, *revel*, *tyrant*), or via implied meaning in language (e.g., *Just got back my test, I got an F.*). To express a certain emotion, such as "*fear*", a speaker must have classified and identified the mental state or process as fear, which can be further characterized by three main attributes: value (positive or negative), intensity (strong or weak), and the duration. Listeners then extract emotional information represented as a network of conceptual schemes stored in memory. In other words, to evaluate the affective representation of a word, listeners need to make inferences of the surface linguistic form by activating world knowledge and/or prior emotion episodes, a process often referred to as "appraisal" by both systemic-functional linguists (Martin & White, 2003) and affective scientists (Ellsworth & Scherer, 2003). There are many appraisal theories, but in short, appraisal is considered as a mental evaluation process between language, situation, and emotion. It is operationally defined by dimensions including, but not limited to, intrinsic valence (positive or negative) and motivation (e.g., speaker goals and the perceiver's concerns).

Most linguistic appraisal theories focus on the evaluation of intrinsic valence of the stimulus alone, and few investigated how intrinsic valence of the stimulus can be influenced by individuals' different goals to prioritize negative or positive emotional experiences across the lifespan. For instance, Martin and White (2003) proposed that emotional meaning in language is referred to as affect, and a main factor to classify affect is whether the feelings conveyed through the linguistic stimulus (e.g., *snake*) are construed popularly by the culture as positive (e.g., *pleased*) or negative (e.g., *fearful*). It is important to consider individuals' different goals suggested in other appraisal theories in affective science, as culture-level representations of emotions may differ from individual-level representations.

The appraisal perspective on emotion is generally consistent with the constructionists' view of emotion in cognitive psychology (e.g., Barrett, 2011), as appraisal can be considered as evaluations of the mental content, based on the conceptual knowledge of emotion. However, one main difference between the constructionist view of emotion and appraisal is that the former focuses more on the conceptualization/categorization processes in generating emotional experiences. For instance, Barret and her colleagues proposed a conceptual act model of emotion in which emotions are events constructed by core affect and categorization (Barrett, 2011; Lindquist et al., 2012; Russell & Barrett, 1999). Core affect is a neurophysiological state that can be described with a continuous scale of valence and arousal. People use their conceptual knowledge of emotions, usually based on prior experiences or emotional episodes, to categorize their mental state. There can be a number of concepts for a certain emotion (e.g., anger), but which one to be called upon depends on the immediate situation, prior experiences, and the language serving as a contextual aid to stimulate such conceptual knowledge.

Such conceptualization/categorization process can be influenced by cognitive control, the ability to resolve competing knowledge or emotional representations in the mind (Barrett et al., 2004). People with high cognitive control may be better at suppressing the goal-irrelevant representations (i.e., emotional concepts) than those with low cognitive control. In addition, it is hypothesized that people with high cognitive control are better at integrating new information from the contexts into the existing emotional representations, in a flexible way. In contrast, individuals with low cognitive control rely more on the emotional representations stored in memory only.

Taken together, both the appraisal and constructionist view on emotion are based on human's conceptual knowledge of emotion that are learnt from past experiences or emotional episodes. Also, both views support a dimensional view of emotion with valence and arousal.

Additionally, appraisal theorists emphasize motivations or goals in evaluating emotional experiences, whereas constructionists highlight cognitive control in constructing emotional representations. However, motivations/goals and cognitive control ability can change across the lifespan. An unsolved issue is how emotional valence of a stimulus can be differently represented (i.e., via either construction or evaluation) across younger and older adults.

1.3. Overview of the dissertation

This dissertation aims to examine the affective neural representations of words in isolation and in contexts in younger and older adults. Specifically, I conducted three studies to investigate whether and how the age-related positivity bias impacts the retrieval (Study 1), updating (Study 2), and prediction (Study 3) of affective meanings of a word, in different stages of emotional word processing. My overarching hypothesis was that as people age, they prioritize positive meanings (Carstensen, 2006) during language processing. Furthermore, based on the SAVI model, this age-related positivity bias for constructing the affective representations of a word depends on word arousal *during* online word processing (Study 1), and occurs not only *after* the word of interest is embedded in context (Study 2), but also *before* encountering the word of interest (Study 3).

In Study 1/Chapter 2, I examined age differences in the comprehension of emotional words with varied valence and arousal. Specifically, I asked whether the age-related positivity bias effect depends on emotional arousal, during emotional word recognition. Based on the SAVI model, the two hypotheses were: Compared with younger adults, (1) older adults show a positivity bias to low-arousing words, but (2) a similar negativity bias to high-arousing words.

In Study 2/Chapter 3, I examined age-related positivity bias beyond words at the sentence level. Specifically, I asked how the affective representation of an emotional word is updated given emotionally loaded contexts. My two hypotheses were: (1) Positive (vs. negative) contexts should lead to more positive evaluations of both positive and negative topic words, in older adults. (2) In contrast, negative (vs. positive) contexts should lead to more negative evaluations of all topic words, regardless of topic word valence, in younger adults.

In Study 3/Chapter 4, I took a step further and investigated whether and how age-related positivity bias effect influences lexical prediction in emotionally ambiguous contexts. Specifically, I asked how emotional features of an upcoming word are predicted/pre-activated under emotionally ambiguous sentences. The hypothesis was that older adults would actively anticipate positive meanings in the emotionally ambiguous sentences, whereas younger adults are more likely to predict negative meanings

Across the three studies, I used electrophysiology (EEG) along with behavioral data to test both the affective and neural representations of words. EEG is a recording of electrical signals from the brain, representing the sum of neural activities from postsynaptic potentials. These signals can contain electrical activities associated with specific cognitive processes during experiments. For instance, multiple epochs of EEG extracted from the stimuli of the same category can form event-related potentials (ERPs). These ERPs can reflect neural processing of stimuli of a certain category. EEG provides good temporal resolution in measuring online neuronal activity, given that the focus of the current dissertation is on different temporal stages of word processing. In addition, EEG provides a good measure of the processing of the stimuli regarding some unconscious psychological constructs, e.g., semantic update or composition (Study 2) and lexical prediction (Study 3).

The current dissertation has both empirical and theoretical contributions on how age influences the neurocognitive processes of emotional language comprehension. Previous studies testing the SAVI model mainly focused on attention and memory processes with emotional pictures or single words (c.f., Chapter 2/Appendix A: Introduction). No studies, to our knowledge, investigated the SAVI model in language processes beyond the word level. My work thus provided empirical evidence on whether the SAVI model can be generalized and applied to language processes, where emotional experiences can be associated with different linguistic units including words (Study 1), sentences (Study 3), and short narratives (Study 2). Specifically, the findings can inform us how age influences visual word recognition (Study1), meaning update (Study 2), and lexical prediction (Study 3) of emotional words as follows.

Study 1: In terms of visual word recognition, a long debate has centered on the sequential vs. interactive view of visual word recognition (Carreiras et al., 2014). The sequential models (e.g., the dual route cascaded model; Coltheart et al., 2001) mainly posit that the processing of different linguistic representations (e.g., visual orthographical, phonological, and semantic) follows a strictly feedforward fashion. That is, the processing of higher-level representations such as phonology and semantics does not start until the lower-level representations (i.e., letter and orthographic-level representations) are activated. Such sequential view also suggests encapsulated and modular processing of linguistic representations at different levels, impenetrable from other cognitive or emotional processes. However, accumulating evidence has shown that emotional features such as valence can be represented in the brain underlying and/or interacting with semantic systems (Hinojosa et al., 2020). This supports an interactive activation view of visual word recognition (e.g., bimodal interactive activation model; Grainger & Holcomb, 2009), where different levels of linguistic representations are activated in parallel and interact with each other in a feed-back way. My Study 1 addresses this debate by considering linguistic, cognitive, and emotional processes simultaneously.

Study 2: In terms of affective meaning update, past research has found that older adults can track different emotional meanings in short narratives (Soederberg & Stine, 1995). For instance, when asked to read a paragraph about an unusual expedition trip during a vacation, older adults and younger adults both showed longer reading times to inconsistent target sentences (i.e., describing boredom emotion) than consistent ones (i.e., describing curiosity emotion). However, it is unclear whether and how other features of emotions such as emotional valence (i.e., positive and negative meanings) are updated in older adults. Additionally, updating affective meanings of a word depends on the combination of affective meanings of this word and its neighboring contexts. According to generative/formal semantic theories, such meaning composition should be linear. For instance, how the affective meaning of "*monster*" is updated in the sentence "*The monster is lovely.*" depends on the linear combination of affective meanings of both "*monster*" and "*lovely*". In this case, the updated affective meaning of "*monster*" is likely to be neutral, after averaging the positive feature of "*lovely*" and the negative feature of "*monster*". However, if the age-related positivity bias holds, the affective meaning update should not follow this linear function. Instead, older adults would put more weights to positive features than negative ones within a linguistic structure, leading to a non-linear combination of affective meanings. My Study 2 manipulated the emotional valence of topic words and context words to address the linear vs. non-linear view of affective meaning compositions.

Study 3: In terms of lexical prediction, older adults usually show declines in using prior contexts to predict non-affective features of upcoming words, and rely more on bottom-up input information (Payne & Silcox, 2019). However, few attempts were devoted to the investigation of affective meaning prediction in younger and older adults. Studies have found that clinical populations with social phobia and/or depression tended to predict more negative (vs. positive) features in the upcoming word followed by emotionally ambiguous sentences (Moser et al., 2012). This suggests that affective levels can influence emotional bias, which in turn influences affective meaning prediction. My Study 3 aimed to elucidate how healthy populations predict affective meanings/features across the lifespan, given the age-related emotional bias.

More broadly, the current dissertation disentangled how age influences the construction and/or appraisal of emotions in language, by taking goal-dependent emotional bias, cognitive control, and affective levels into account. Most linguistic appraisal theories view the emotional meaning of a word as pretty rigid, based on only speakers' and writers' intended meanings. However, incorporating other appraisal and constructionist views of emotion, my hypothesis was that listeners and readers can also actively construct and shape the intended emotional meanings based on their goals (e.g., to meet increasing socio-emotional needs in old age) or states (e.g., affective levels), possibly via a top-down process (e.g., cognitive control). Specifically, I predicted that older adults would show a positivity bias in language processes across my three studies, especially for those who have high cognitive control, and high positive/low negative affect.

Chapter 2. Attention and regulation during emotional word comprehension in older adults: Evidence from event-related potentials and brain oscillations

Associated article:

Ku, L. C., Allen, J. J., & Lai, V. T. (2022). Attention and regulation during emotional word comprehension in older adults: Evidence from event-related potentials and brain oscillations. *Brain and Language*, *227*, 105086. https://doi.org/10.1016/j.bandl.2022.105086

For a copy of the published manuscript and associated works cited see Appendix A.

Abstract

Older adults often show a positivity bias effect during picture processing, focusing more on positive than negative information. It is unclear whether this positivity bias effect generalizes to language and whether arousal matters. The present study investigated how age affects emotional word comprehension with varied valence (positive, negative) and arousal (high, low). We recorded older and younger participants' brainwaves (EEG) while they read positive/negative and high/low-arousing words and pseudowords, and made word/non-word judgments. Older adults showed increased N400s and left frontal alpha decreases (300-450 ms) for low-arousing positive as compared to low-arousing negative words, suggesting an arousal-dependent positivity bias during lexical retrieval. Both age groups showed similar LPPs to negative words. Older adults further showed a larger mid-frontal theta increase (500-700 ms) than younger adults for low-arousing negative words, possibly indicating down-regulation of negative meanings of low-arousing words. Altogether, our data supported the strength and vulnerability integration model of aging.

Chapter 3. Context matters: Updating the affective representation of a word in younger and older adults

For a copy of the manuscript and associated works cited see Appendix B.

Abstract

Older adults often prioritize positive rather than negative information during word processing, termed as a positivity bias. However, it is unclear how older adults update affective (i.e., valence) representations of a word in context. The present study examined whether age-related positivity bias influences the update of valence representations of a word in different emotional contexts, in two experiments. In Experiment 1 (online), participants read positive and negative topic words in positive and negative contexts and rated the valence of the target word. The results showed that negative contexts biased the ratings more than positive ones, regardless of age, supporting a general negativity bias during valence evaluation. In Experiment 2 (EEG), another group of participants read positive and negative topic words in positive and negative contexts first, and then the same topic word again, and made valence judgment on the topic words. Compared with younger adults, older adults showed a larger P2 (180-300 ms) effect for positive topic words, regardless of context valence, suggesting their increased early attention to positive features of the topic words. At ~600 ms, younger adults showed a larger effect of late positive complex (LPC) for topic words in negative contexts, irrespective of topic valence, while older adults showed similar LPC effects across conditions. This suggests that younger adults update the valence representations of a word in negative (vs. positive) contexts more elaborately, whereas older adults do not. Our data supported a positivity bias in updating affective neural representations of a word in contexts in older adults.

Chapter 4. A reduced negativity bias in older adults: Predicting affective features of a word in emotionally ambiguous sentences

For a copy of the manuscript and associated works cited see Appendix C.

Abstract

Readers pre-activate linguistic features prior to encountering each word in a sentence. Language prediction studies usually examined concrete semantic features, such as animacy, but little focused on abstract features, such as emotional valence. The present study examined whether and how younger and older readers predict positive and negative features of a word in emotionally ambiguous sentences, using electroencephalogram (EEG). Participants first read the sentence primes that could have either a positive or a negative continuation, and actively predicted an outcome or explanation of the scenario described in the sentence prime. Then, participants made a similarity judgment between the target words (positive or negative) and their prior prediction. Younger readers showed a larger N400 for positive than negative target words, suggesting a greater mismatch between their internally predicted negative features and the externally presented positive features. This N400 effect was not present in older readers. Additionally, in both younger and older readers, negative target words elicited a larger late positivity than positive words. Such effect started earlier in older readers (~350 ms) and later in younger readers (~550 ms). This suggests that both younger and older readers made more efforts in processing negative features of the target words. Overall, our study supported a negativity bias in younger adults, and a reduced negativity bias in older adults during meaning prediction, which is consistent with the strength and vulnerability integration model of aging.

Chapter 5. Conclusion

In this dissertation, I have presented three studies to test how age-related positivity bias influences different aspects of language processing, including emotional word recognition (Study 1), the update of affective representations in sentence processing (Study 2), and affective meaning prediction in ambiguous contexts (Study 3). Generally, all my three studies supported the strength and vulnerability integration (SAVI) model: Older adults showed either a positivity or a reduced negativity bias before (Study 3) and after (Study 2) an emotional word occurs, and the positivity bias only occurred during (Study 1) the processing of low-arousing word. This further suggests that older adults use different attentional, appraisal, or regulation strategies in processing low-arousing meanings.

In Study 1, I examined how age affects the incremental processing of emotional words with varied valence (positive/negative) and arousal (high/low) in a visual word recognition paradigm. The results showed that older adults attend to low-arousing positive words at the word retrieval stage (N400) first, and then regulate low-arousing negative meanings downstream of processing (mid-frontal theta). In contrast, younger adults attend to all emotional words at the lexical retrieval stage (N400) and elaborate negative and high-arousing meanings more at the later stages (late positivity complex; LPC). Overall, Study 1 provided the first evidence indicating that emotional words, if they are low-arousing, are represented and evaluated differently in the brains of older and younger adults.

In Study 2, I examined whether age-related positivity bias influences the update of emotional representations of a word in different emotional contexts, in a web-based (behavioral) and an EEG experiment. In the web-based experiment, participants read and rated the valence of positive and negative topic words in positive and negative contexts (e.g., *The* <u>*pianist*</u> *had a new* *performance. Her skills were rusty.*). In the EEG experiment, another group of participants read and rated the same two-sentence vignettes, followed by the same topic word again (e.g., *The pianist practiced every day.*). The data in the web-based experiment showed that regardless of age, positive contexts biased the topic word evaluation toward stronger positive ratings, whereas negative contexts led to stronger negative ratings, compared with the topic words in isolation. This modulation effect was the strongest when the context was negative and the to-be-evaluated topic words were positive. This suggested that during the explicit evaluation (decision-making) stage, it is more difficult for younger and older adults to disengage from negative contexts, as negative contexts may attract more sustained attention. In the EEG experiment, I found that at ~200 ms (P2), regardless of context valence, younger adults quickly disengage from positive (vs. negative) topic words, while older adults attend to positive topic words more than younger adults. At ~600 ms (LPC), younger adults elaborate the emotional meaning of a word in negative (vs. positive) contexts, whereas older adults do so in both the positive and negative contexts. This suggested that older adults update their emotional representations with positive contents, but not younger adults. Overall, Study 2 suggested that neurally, age, word valence, and context valence conspire to update the affective representation of a word in context early on. However, at a later stage, age may not influence the update of affective representations of a word.

In Study 3, I examined how age-related positivity bias influences prediction of emotional features of an upcoming word in emotionally ambiguous sentences. Participants first read emotionally ambiguous sentence primes (e.g., *Mary received the exam results*) and for each sentence prime they actively imagined a possible interpretation while reading. They then read positive/negative target words (*pass/fail*), during which they needed to make a similarity judgment between the target word and their prior prediction. The results showed an N400 effect, larger for positive target words preceded by the emotionally ambiguous sentences than negative target words, in younger adults. There was no such N400 effect in older adults. This suggested that the younger adults found positive features unexpected, while the older adults did not. Overall, Study 3 indicated that younger adults predict more negative features of a word in an emotionally ambiguous sentence, as reflected by the reduced N400 to negative target words. Compared with younger adults, older adults predicted fewer negative features and possibly more positive features of a word in an emotionally ambiguous sentence, as shown by their null N400 effect and higher similarity ratings to positive (vs. negative) words.

To take a step further, these results can be combined in a finer-grained temporal scope of language processing (Figure 1). Compared with younger adults, older adults usually attend to positive contents and/or disengage from negative contents more, during (Study 1 & 3: N400 effects) and prior to (Study 2: P2 effects) the meaning retrieval stage. Later on, older adults start to attend to negative contents, after the meaning retrieval stage (Study 1 & 3: LPC effects; Study 2: web-based behavioral ratings and LPC effects). In contrast, younger adults showed a steady negativity bias prior to, during, and after the meaning retrieval stage. These results suggest that in retrieving emotional representations of a word, older adults are more likely to attend to positive meanings rather than negative meanings, if both are presented. After the emotional representations of a word are retrieved, older adults also start to elaborate or update negative meanings that are not attended to earlier. Figure 1 below showed a schematic overview of my findings in the three studies, adapted from the SAVI model (Charles, 2010). In the original SAVI model, an emotional event may last for seconds, hours, or even days. In the current expanded model, I narrowed down the temporal aspect of an emotional event to the millisecond level, to capture emotional experiences in reading emotional words and sentences.

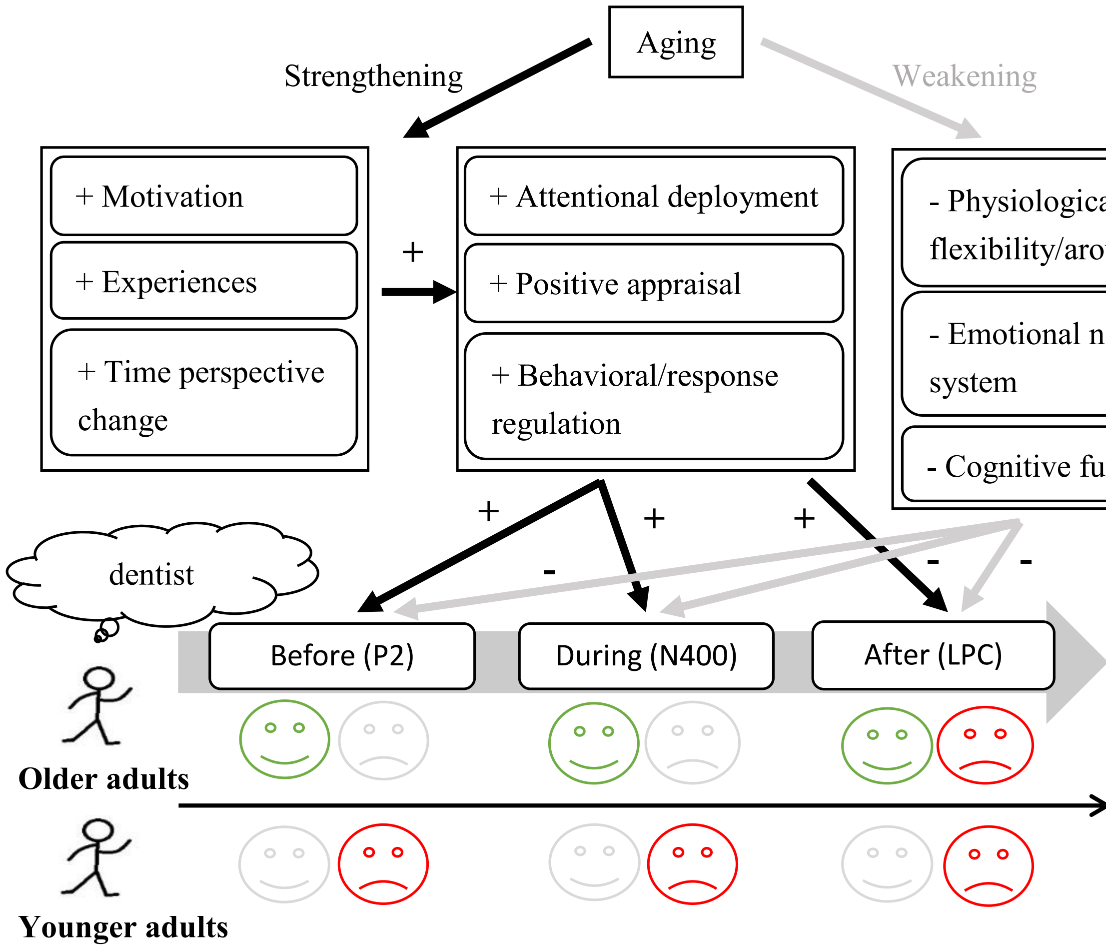

Figure 1. A temporal view of language processing based on different stages (before, during, and after) of meaning retrieval, as reflected by P2, N400, and late positivity complex (LPC) effects in the three studies of the current dissertation. The emotional bias in the different stages of meaning retrieval differs between older adults (top) and younger adults (bottom). The features attracting more attention are indicated in green (positive features) and red (negative features) faces, whereas the less attended features are shown in gray faces.

My findings provided empirical evidence to address the theoretical issues in visual word recognition, meaning update, and lexical prediction (c.f., Section 1.3). First, in terms of the sequential (modular) vs. interactive activation view of visual word recognition, Study 1 clearly supported the latter view, as emotion features of a word modulated the meaning retrieval process, as reflected by the N400 effects. In addition, such emotion effect on the semantic process was influenced by top-down processes such as cognitive ability/control. In Study 1, the N400 effect was reduced when the cognitive ability/control was held constant. Second, in terms of linear vs. non-linear view of affective meaning update, the behavioral data in Study 2 suggested that both younger and older adults put more weights to negative contents when evaluating the affective meaning of a word in emotional contexts. Consistent with Lüdtke and Jacobs' (2015) data in younger adults, Study 2 further extended their findings to older adults. Moreover, the ERP data in Study 2 suggested that younger and older adults update emotional representations of a word differently, based on the valence of this word and its context. Finally, in terms of affective lexical prediction, Study 3 suggested that affective features can be predicted just like non-affective features: In an active prediction paradigm, younger adults predict more negative meanings, whereas older adults do not.

From the perspective of constructionist views of emotion, my data suggest that older adults may select or attend to positive meanings and avoid negative ones, based on prior knowledge or emotional episodes, when reading emotional contents. Alternatively, according to the appraisal view of emotion, my data suggest that older adults may use more positive appraisal of emotions than younger adults when reading emotional contents. This suggests that traditional linguistic appraisal theories need to take readers (e.g., their goals, states, or stances, etc) into consideration in evaluating speaker meanings.

Specifically, there are two factors to influence readers in constructing or evaluating the emotional contents. The first one is cognitive control, as shown in my Study 1. Although Study 2 and Study 3 did not show an effect of cognitive control, it is noted that a non-verbal cognitive control task (i.e., Wisconsin Card Sorting Task) was used in Study 2, and a matched verbal cognitive control (i.e., category verbal fluency) was found between younger and older adults in Study 3, which may not truly reflect the relevance of verbal cognitive control or semantic control in older adults' positivity bias. My proposal is that older adults may use more cognitive control to suppress negative meanings and retrieve positive meanings of a word in constructing or evaluating the emotional contents. Another factor is readers' affective levels. Older adults across the three studies showed lower negative affect levels than younger adults, although there was no difference in positive affect levels across the age groups. Counterintuitively, lower negative affect levels were associated with larger ERP effects between negative and positive words, suggesting a stronger negativity bias (Study 1: preliminary analyses of LPC effects; Study 2: P2 and LPC effects). A possible reason is that high negative affect has often been linked to attenuated or "flat" emotional responses to both pleasant and unpleasant stimuli, reducing the ERP effects (Foti et al., 2010; Speed et al., 2015). Alternatively, older adults (also the low negative affect group) may show larger variances in ERP amplitudes, increasing the ERP effects.

There are some limitations for the current dissertation. First, it is beyond the scope for these studies to answer which regulation strategies (e.g., meaning selection, attention deployment, cognitive appraisal) older readers used in the three studies. Future studies can manipulate participants' attention or appraisal strategies to tease apart the regulation mechanisms that older adults use in language comprehension. Second, older adults' positivity bias was influenced by cognitive ability/control in Study 1, but not in Study 2 and 3. Future studies should recruit a more heterogeneous sample with a careful measure of verbal cognitive control/semantic control to elucidate its impact on older adults' positivity bias in language processing. Third, our data showed that older adults' positivity bias only occurred in a simple non-emotional task in Study 1 (lexical decisions; N400 effects), but turned into a reduced negativity bias with a more complex or emotional task in Study 2 (valence judgment; LPC effects) and Study 3 (active prediction and similarity judgment; N400 effects). Future studies can also adopt a simpler, non-emotional task during meaning update (Study 2) and lexical prediction (Study 3) to investigate whether the task loads impact older adults' positivity bias. Lastly, the enrichment of the neural resources in older adults may be modulated by factors including bi-/multilingualism and intellectual activity (Reuter-Lorenz & Park, 2014). Future studies can examine, for example, how bilingual elders or frequent reading will influence the dynamics of neural networks during emotional language processing.

Altogether, this dissertation provides neural evidence to call for incorporating reader characteristics (i.e., age) in the neurocognitive model of affective language processing, and establishes a link between linguistics, psychology, and cognitive neuroscience. Also, previous research on affective norms and sentiment analyses mostly focused on younger adults. The current data call for more age-sensitive affective norms and sentiment analyses. In broader applications, these findings have implications for the possibility that reading emotional texts may help older adults regulate emotion. This may in turn be used in language-based emotion intervention in healthy aging.

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Appendix A.

Attention and regulation during emotional word comprehension in older adults: Evidence from event-related potentials and brain oscillations

RUNNING TITLE: Age differences in emotional word processing

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Abstract

Older adults often show a positivity bias effect during picture processing, focusing more on positive than negative information. It is unclear whether this positivity bias effect generalizes to language and whether arousal matters. The present study investigated how age affects emotional word comprehension with varied valence (positive, negative) and arousal (high, low). We recorded older and younger participants' brainwaves (EEG) while they read positive/negative and high/low-arousing words and pseudowords, and made word/non-word judgments. Older adults showed increased N400s and left frontal alpha decreases (300-450 ms) for low-arousing positive as compared to low-arousing negative words, suggesting an arousal-dependent positivity bias during lexical retrieval. Both age groups showed similar LPPs to negative words. Older adults further showed a larger mid-frontal theta increase (500-700 ms) than younger adults for low-arousing negative words, possibly indicating down-regulation of negative meanings of low-arousing words. Altogether, our data supported the strength and vulnerability integration model of aging.

Keywords: Aging, Emotional words, Positivity bias effect, Event-related potentials, Theta oscillations, Alpha oscillations

1. Introduction

Do older adults comprehend emotional language differently from younger adults? Some behavioral studies have shown that older adults have greater attention to and better memory for positive stimuli than negative ones, termed as the positivity bias effect (Reed et al., 2014). In contrast, others showed that older adults have reduced attention or memory for negative stimuli over positive ones, reflecting a reduced negativity bias effect (Grühn et al., 2007; Jacques et al., 2010). Most of these studies examined emotional faces and scenes in attention or memory paradigms (e.g., Charles et al., 2003; Isaacowitz et al., 2006a, 2006b; Mather & Carstensen, 2003, 2005). The present study examined how older adults perceive positive and negative content in language.

1.1. Theoretical frameworks for the age-related positivity bias effect

There are three theories regarding the positivity bias effect in older adults (Carstensen & DeLiema, 2018). According to the socioemotional selectivity theory (SST) (Carstensen, 2006), older people's time horizons about the future become increasingly constrained, which alters their motivation, priorities, and goals. As such, their social goals may shift from acquiring information or meeting new people, to the search for emotional meaning, regulation, and satisfaction (Reed & Carstenson, 2012). The SST theory thus argues for a more top-down, controlled shift in attentional resources toward goal-relevant (i.e., positive) stimuli in older individuals. The cognitive control hypothesis (CCH) (Nashiro et al., 2012) argues that older adults' preference for emotional well-being results from their increased devotion of cognitive resources to emotion regulation. Empirically, supporting CCH, older adults had more medial prefrontal cortex (mPFC) activity for positive pictures than negative ones, when they were deeply engaged in the task (Ritchey et al., 2011). Older adults also showed increased amygdala-mPFC or amygdala-anterior cingulate cortex (ACC) functional coupling during various tasks, including rest, free viewing, and actively down-regulating negative pictures (Jacques et al., 2010; Sakaki, Nga, & Mather, 2013; Sakaki, Yoo, et al., 2016; Urry et al., 2006).

The strength and vulnerability integration (SAVI) model posits that the positivity bias effect in older adults can be modulated by the intensity of emotion (i.e. arousal), and the stages of the emotional experience (i.e. before, during, or after the event, Charles, 2010). For low-arousing events, older adults show the strengths in using attentional, appraisal, or behavioral strategies to regulate negative events, leading to a more positive emotional experience (i.e., a positivity bias). In contrast, for high-arousing events, older adults show the vulnerability in modulating high levels of physiological arousal of both positive and negative emotions efficiently, due to reduced physiological flexibility (e.g., slow physiological arousal or responses). This usually leads to a similar level of intensity (i.e., no positivity bias) when older and younger adults experience high-arousing events. Evidence supporting the SAVI model comes from both behavioral and neuroimaging studies. Behaviorally, older adults often rated low-arousing negative pictures as being less unpleasant, and low-arousing positive pictures as more pleasant, compared with younger adults (Streubel & Kunzmann, 2011). Low-arousing negative stimuli were also recalled less than arousal-matched positive stimuli in older adults (Kensinger, 2008). For high-arousing stimuli, negative pictures were rated more unpleasant by older than by younger adults. However, in terms of memory recall and stimulus detection, equal performance was often found between high-arousing negative and positive stimuli (Kensinger, 2008; Mather & Knight, 2006). Neurally, low-arousing negative stimuli engage more controlled processes, while high-arousing negative stimuli capture attention more automatically (Dolan, 2002; Kensinger & Corkin, 2004; Knight et al., 2007;

Mather & Knight, 2005). When viewing low-arousing negative pictures, older adults showed decreased amygdala activity accompanied by increased ventral ACC activity, compared with younger adults (Dolcos et al., 2014). In addition, older adults' increased ventral ACC/ventromedial prefrontal cortex (vmPFC) activity was associated with reduced ratings for low arousing negative pictures. In contrast, both younger and older adults recruited similar amygdala activity in response to high-arousing negative pictures. In our view, the abovementioned literature is consistent with an emotion regulation account of emotion processing: older adults may activate top-down emotion regulation strategies to dampen the physiological arousal processes, but only with low-arousing stimuli.

Summing up, the SST model draws on behavioral but not neural evidence, whereas the CCH model draws on neural but not behavioral evidence. Neither SST nor CCH examined arousal. The SAVI model examines arousal, but there are only a few studies (3 behavioral studies and 1 fMRI study). In addition, those studies focus on pictures, not language. It is unclear if and how arousal modulates older adults' positivity bias effect during word comprehension.

1.2. Neural processing of the age-related positivity effect in emotional word/picture processing

To date, few studies have examined the neural processing of the age-related positivity effect in language comprehension. One fMRI study (Leclerc & Kensinger, 2011) compared the brain activation for emotional pictures and words between younger (18-35 years) and older adults (64-81 years). In a semantic judgment task, older adults showed greater mPFC activity for positive than for negative words, and greater amygdala activity for positive than for negative pictures, compared with younger adults. The authors associated the mPFC activation with cognitive control for positivity bias. Specifically, older adults elaborate the verbal stimuli more, possibly in a selfreferential fashion, as the mPFC activity is associated with emotional aspects of text processing, social information (i.e., self vs. other), and emotion memory (Ferstl et al., 2005; Gutchess et al., 2007). The study thus highlighted the differences between pictures and words: Pictures elicit emotional response more automatically, while words require controlled and elaborative processing. We thus reviewed the event-related potential (ERP) studies below to show when the age-related positivity bias effect influences the processing stream of emotional stimuli.

In ERP studies using emotional pictures, older adults' positivity bias effect is associated with the late positive potential (LPP, Kisley et al., 2007; Mathieu et al., 2014; Wood & Kisley, 2006). The LPP in picture studies is a positive-going brainwave peaking between 400 and 900 ms after the picture onset, with a centro-parietal scalp distribution. In younger adults, some found that both positive and negative pictures elicited larger LPPs than neutral ones (Cuthbert et al., 2000; Schupp et al., 2000), associating the LPP with re-allocation of attention to emotional content. Others found that negative pictures elicited larger LPPs than positive ones (Foti et al., 2009; Wood & Kisley, 2006), associating the LPP with a negativity bias in younger adults who typically zoom in to negative information. In older adults (56-81 years), such picture LPP effect was smaller, albeit still statistically significant (Kisley et al., 2007; Wood & Kisley, 2006). Kisley and colleagues argued that this suggests that older adults used emotion regulation to reduce the negativity bias. This is consistent with the idea that older adults have a reduced negativity bias, which might be thought of as the "weak" form of the positivity bias.

While no ERP study of words examined the positivity bias effect in older adults, there are many ERP studies of emotional words in younger adults, which can inform us about relevant ERP correlates: the early posterior negativity (EPN), N400, LPP, and sustained slow positivity (SSP). Emotional words (both positive and negative) usually elicit a larger EPN (200-300 ms) than neutral words, which is linked to an initial arousal-driven, automatic processing of emotional stimuli (Hinojosa et al., 2010; Palazova et al., 2011; Recio et al., 2014; Sass et al., 2010; Schacht & Sommer, 2009a). A few studies further found that emotional words (positive and/or negative) elicit a reduced, frontal N400 (300-500 ms) compared with neutral words (Kanske & Kotz, 2007). Because N400 reflects semantic retrieval effort, the reduced N400 reflects a facilitation of semantic retrieval due to the emotional content (Ku et al., 2020). Emotional words also often elicit a larger LPP than neutral words, albeit with a peak between 400 and 750 ms, earlier than pictures (Hinojosa et al., 2010; Kanske & Kotz, 2007; Schacht & Sommer, 2009a). While these earlier studies showed no LPP difference between positive and negative words, recent studies found a larger LPP for negative relative to positive words in both evaluative and lexical decision tasks (Delaney-Busch et al., 2016; Ku et al., 2020), indicative of a negativity bias in younger adults. Some studies additionally reported a long-lasting SSP from 700-1000 ms for emotional (versus neutral) words, with a centro-parietal scalp distribution (Citron et al., 2013; Dillon et al., 2006). Both the LPP and SSP effects in word studies have been linked to both elaborative processing and sustained attention to emotional content, without a clear functional dissociation.

To summarize, the one fMRI finding suggests that older adults devoted more effort in processing positive words, supporting a positivity bias. The ERP findings from pictures suggest that older adults reduced their emotional responses to negative pictures, also consistent with a positivity bias. However, it remains unknown how the age-related positivity bias influences different stages in emotional word processing.

1.3. The time-frequency representations (TFRs) of emotional word processing

While the ERP captures the time-locked activity that is phase-locked, the TFR additionally captures time-locked activity that is either phase-locked or non-phase-locked which has been associated with cognitive functions (Bastiaansen et al., 2012). Like the ERP literature, much of the EEG TFR emotion research has focused on pictures and less on words. Studies using pictures have reported effects in the delta (0.5–3.5 Hz), theta (4–7 Hz), alpha (8-13 Hz), beta (14-30 Hz), and gamma (>30 Hz) -bands (De Cesarei & Codispoti, 2011; Güntekin & Başar, 2014; Güntekin & Tülay, 2014; Schubring & Schupp, 2019). Specifically, negative pictures elicited increased beta and gamma responses compared to positive and neutral ones in early time windows (100-250 ms; valence effect). High-arousing (both positive and negative) pictures elicited increased delta and theta responses compared to low-arousing (neutral) stimuli in later time windows (200-1000 ms; arousal effect). While high-frequency oscillations such as beta and gamma are argued to reflect emotional integration between top-down and bottom-up information, low-frequency oscillations in the delta band reflect the perception and updating of emotionally salient stimuli, usually with pictures of high arousal (Güntekin & Başar, 2016; Knyazev, 2007, 2012). Particularly, theta has also been linked to top-down control processes (Cavanagh & Frank, 2014). For instance, successful emotion regulation using cognitive reappraisal increased the mid-frontal theta power (Ertl et al., 2013). Researchers have associated theta oscillations of different topographical distributions with memory, attention, and emotion processes.

Studies using word stimuli have predominately focused on the theta band. Semantically rich words (e.g., nouns and verbs) often elicited an increased temporo-parietal theta compared with semantically lean words (e.g., prepositions) or pseudowords (e.g., *thaft*) around 300-500 ms after word onsets, reflecting the retrieval of lexical-semantic information (Bastiaansen & Hagoort, 2006; Bastiaansen et al., 2005; Marinkovic et al., 2012). In emotional words specifically, in younger adults, the theta power changes have been reported in both early and late time windows. Kryuchkova et al. (2012) found that words with intermediate danger ratings (4-6 on an 8-point scale) showed a mid-frontal theta increase, but not words with low danger ratings, in an early time window from 150-350 ms after word onsets. They suggested that the theta increase reflects cortical processes initiated by subcortical routes due to flight or fight responses to information in danger word. Sulpizio et al. (2020) found a trend of temporo-parietal theta desynchronization to negative words relative to neutral words in a later time window from 500-1500 ms. They suggested that the theta desynchronization reflects attentional demand due to the emotional significance of the words.

Not every electrophysiological study of emotional language in younger adults reported theta oscillations. Using magnetoencephalography (MEG), Hirata et al. (2007) found decreased beta and low gamma (30-60 Hz) power for reading emotional (vs. neutral) words passively during the 1-second period after word onsets over the ACC, left inferior frontal gyurs (IFG), and left middle frontal gyrus (MFG). These authors attributed the results to emotion processing (ACC) and processing of emotional connotations during reading (left IFG/MFG). They did not distinguish the functional significance of beta and low gamma separately. Also not reporting theta, Wang and Bastiaansen (2014) found only sustained alpha desynchronization for the emotional (vs. neutral) words during 500-1000 ms after word onsets in a color detection task. The authors argued that the decreased alpha for emotional words indicated sustained attention towards the emotional content, while the increased alpha indicated released attention after the initial semantic analysis. Our interpretation of the inconsistent theta results is that these studies used words with different arousal ratings and different tasks. After converting the arousal scores from these studies to a 9-point scale, we found that arousal values for emotional words in the studies without a theta activity were lower than those with a (trend of) theta activity (e.g., no arousal ratings in Hirata et al., 2007, 5.42-5.56

in Wang & Bastiaansen, 2014, and 6.45 in Sulpizio et al., 2020). Additionally, tasks that require retrieving semantic/emotional features in words (e.g., valence judgment tasks) may capture more attention than those that do not probe semantic/emotional contents (e.g., silent reading and color detection tasks), thus leading to the change in theta oscillations.

Overall, despite the mixed findings in the EEG TFR research, an emergent pattern is that theta oscillations are sensitive to the emotional content of single words, and that they occur in tasks that tap into language processing. Alpha oscillations are more related to general attention towards emotional contents.

1.4. The present study

The current study investigated whether age affects the incremental processing of emotional words, by taking both the valence and arousal dimensions of emotion into consideration. We focused on older adults between 60 and 75 years of age, as a previous cross-sectional study suggested that negative emotions level off at around the age of 60 (Stacey & Gatz, 1991). Participants performed a lexical decision task (LDT). We chose to use the LDT, because a word/nonword decision can be made without too much semantic demand and past literature indicates that cognitively demanding or explicitly evaluative tasks could attenuate the positivity bias effect in older adults (Mather, 2006; Reed et al., 2014). Using EEG, we also sought to learn more about whether older adults show more or differential brain regions in comparison to younger adults during emotional word processing.

Our predictions for the ERPs are as follows: Based on the SAVI model, older adults would show a positivity bias (c.f., Leclerc & Kensinger, 2011) or a reduced negativity bias (c.f., Kisley et al., 2007; Wood & Kisley, 2006) in processing words with a low level of physiological arousal.

We thus predicted that if the positivity bias holds, older adults would have larger LPPs than younger adults in recognizing low-arousing positive (LP) words. Alternatively, if the reduced negativity bias holds, older adults could show attenuated LPPs in recognizing low-arousing negative (LN) words compared with younger adults. By contrast, due to inconsistent literature on high-arousing stimuli, we expected that processing high-arousing words could lead to similar emotional responses across age groups, with larger LPPs and/or SSPs to negative (vs. positive) words to replicate the negativity bias often found in younger adults (e.g., Citron et al. 2013). We also expected to replicate the reduced N400s to emotional (vs. neutral) words, at least in younger adults (Ku et al., 2020), and that older adults would show a decrease in N400 amplitudes in general compared with younger adults (Kutas & Iragui, 1998).

For the time-frequency analysis, if different levels of emotional arousal capture attention differently in the lexical decision task, then words of different arousal should show different theta/alpha oscillatory patterns. We decided to focus on theta, because theta has been associated with lexical semantic processing (300-500 ms, temporo-parietally distributed), attention to emotion contents (>500 ms, temporo-parietally distributed), and emotion regulation (mid-frontally distributed). We also analyzed alpha, as it indicates general attention processing. Due to mixed findings in past literature (e.g., early theta increase in Kryuchkova et al., 2012; late theta decrease in Sulpizio et al., 2020), we did not have specific predictions for the directionality and latency of the theta activity between high-arousing and low-arousing words. As for alpha, we predicted that high-arousing words would show an alpha desynchronization at a later stage, based on Wang and Bastiaansen (2014). Based on the SAVI model, we further predicted that if the positivity bias holds, older adults would have an increased theta and/or decreased alpha compared with younger adults in recognizing LP words at a later stage to reflect increased attention to LP contents. Alternatively, if the reduced negativity bias holds, in recognizing LN words, older adults would show an decreased theta and/or increased alpha to reflect decreased attention to LN contents, and/or an increased mid-frontal theta to reflect top-down regulatory processes. For high-arousing words, similar theta/alpha activity was expected across the two age groups.

2. Methods

2.1. Participants

Fifty-six younger (33 females, mean age ± SD = 18.64 ± 1.02 years, range = 18-24 years) and 45 older (25 females, mean age ± SD = 67.36 ± 4.4 years, range = 60-75 years) adults participated in the experiment. The full characteristics of the participants are available in Table 1. The younger participants were undergraduate students recruited from the psychology subject pool and received course credits. The older adults were recruited on the university campus, senior community centers, and via online/newspaper advertisements, and received $20. All the participants were right-handed, native English speakers, with normal or corrected-to-normal vision. None had neurological disorders, psychiatric illness, and were on psychoactive medications likely to modulate emotional processes (e.g. anti-depressants), based on self-report. All gave informed consents in accordance with the local ethics committee prior to participation.

Participants' current mood was measured by the Beck Depression Index – second edition (Beck et al., 1996). The BDI-II measures levels of depression with 21 questions, each of the questions answered on a 4-point scale ranging from 0 to 3 based on severity of each item. The total BDI-II score of our participants ranges from 0 to 26. Three younger and one older participants were excluded due to a total BDI-II score larger than 14, the cutoff score for borderline depression. The remaining participants in both the age groups were non-depressed. In addition, each participant had a minimum score of 27 on the Mini-Mental State Examination (MMSE) (Folstein et al., 1975), which indicated no cognitive impairment. They also completed the Digit Symbol Substitution Task (DSST) (Wechsler, 1997) as a general assessment of cognitive functions such as motor speed, attention, visuoperceptual functions, working memory, and executive functions (Jaeger, 2018).

Two younger and 6 older participants were excluded due to their low task performance (i.e. accuracy < 50% in any condition). Thirteen younger and 3 older adults were excluded due to insufficient trials (< 50%) after artifact rejection of the EEG data. Three younger adults were also excluded due to equipment errors. The characteristics of the remaining participants are summarized in Table 1A.

2.2. Materials

The stimuli consisted of 180 words, including 36 high-arousing positive (HP) (e.g. *winner*), 36 low-arousing positive (LP) (e.g. *grandpa*), 36 high-arousing negative (HN) (e.g. *pain*), 36 low-arousing negative (LN) (e.g. *trash*), and 36 neutral (e.g. *teeth*) words. The characteristics of the word stimuli are presented in Table 2.

Words were selected from the affective norms for English words (Warriner et al., 2013). In this norm, subjective ratings of valence and arousal are measured with 9-point Likert scales (1 = *unhappy* to 9 = *happy*; 1 = *calm* to 9 = *aroused*). On average, positive words scored higher on valence ratings than neutral words, followed by negative words (all p values < .001). There is no valence differences for HP vs. LP words (p = .988), nor for HN vs. LN words (p = .752). For arousal ratings, HP words were rated with higher scores than LP words, and so is the case for negative words (all p values < .001). No arousal differences between HP and HN words, nor between LP and LN words were found (all *p* values > .9). The neutral words had the same level of arousal as other low-arousing valenced words (both *p* values > .1). To avoid age differences in the ratings, valence and arousal ratings were carefully matched in each condition between younger and older adults (all *p* values > .09), based on the same norms.

Word concreteness ($F(4, 175) = 0.697$, $p = .595$), imageability ($F(4, 175) = 1.633$, $p = .168$), and familiarity ($F(4, 175) = 1.421$, $p = .229$) were matched across the five word types, based on the Glasgow norms (Scott et al., 2018). Seven-point Likert type scales were used for the ratings of concreteness (1 = *very abstract* to 7 = *very concrete*), imageability (1 = *very unimageable* to 7 = *very imageable*), and familiarity (1 = *very unfamiliar* to 7 = *very familiar*). Other word properties including word length ($F(4, 175) = 1.653$, $p = .163$), word frequency (in log) ($F(4, 175) = 1.897$, $p = .113$), orthographic neighborhood sizes (F(4 175) = 1.16, p = .33), and numbers of phonemes ($F(4, 175) = 1.726$, $p = .146$) and syllables ($F(4, 175) = 1.078$, $p = .369$) were also matched, based on the SUBTLEX-US corpus (Brysbaert et al., 2012) and the English Lexicon Project database (Balota et al., 2007).

An additional 180 pseudowords (e.g. *thack*) were selected from the ARC non-word database (Rastle et al., 2002), with the length ranging between 4-9 letters. Pseudowords are non-existent words following the orthographic and phonological rules in English. The length in letters of pseudowords and words was matched ($t(320.35) = 1.257$, $p = .21$). All the 360 words and pseudowords were divided into four lists. Each list consists of 45 words (9 words for each word type) and 45 pseudowords. The stimulus order in each list was pseudo-randomized such that no more than three consecutive trials came from the same word type. The list order was counterbalanced with participants' number.

2.3. Procedure

Participants first completed a questionnaire about their language use and health condition. An elastic cap mounted with 64-channel Ag/AgCl electrodes was then fitted on the participant's head. After the EEG capping procedure, the participant was taken to a sound-proofed booth and seated at a desk facing a computer screen 80-100 cm in front of them. The stimuli were presented visually in a white font (Font: Courier New; Point size: 20) against a black background via E-prime 3.0 software (Psychology Software Tools, Inc.).

An example trial is illustrated in Figure 1. Each trial started with a central fixation cross for 500 ms, followed by a blank screen for 200 ms. Then, a target stimulus appeared and remained on the screen with a length-dependent duration between 260 and 420 ms. Participants were instructed to read the word carefully and silently. A question mark then came up at the center of the screen after a 500-ms blank. When cued by the question mark, participants needed to decide whether the stimulus is a meaningful word as accurately as possible, by pressing the YES or NO button on a response box. The button configuration (left or right) was counterbalanced across participants. After the response, a "blink or continue" screen would appear following a 300-ms blank so that participants could rest their eyes or take a quick break in a self-paced way.

Before the formal experiment, participants did eight practice trials to familiarize themselves with the procedure. The session of the experiment were divided into four blocks, with a short break between blocks. Each block lasted for 6-7 minutes, and the entire EEG session lasted for about 30 minutes.

2.4. EEG acquisition

The electroencephalogram (EEG) was recorded from 64 electrodes placed on an electrode cap arranged in the 10-10 system (actiCAP, Brain Products GmBH). The scalp EEGs were recorded with a sampling rate of 500 Hz and referenced to vertex during online recording (actiCHamp, Brain Products GmBH). A forehead electrode served as the ground. To avoid impulse artifacts, the online low pass filter was set to 140Hz and the high pass filter was set as DC recording. The electrode impedance was kept below 10 kΩ.

2.5. ERP analysis

EEG recordings were processed offline with the EEGLAB toolbox (Delorme & Makeig, 2004) and the ERPLAB plugins (Lopez-Calderon & Luck, 2014) implemented in Matlab (Mathwork Inc.). For the ERP analysis, the EEG data were first bandpass filtered with frequency values set as 0.1-30 Hz. Data were re-referenced to the average of both mastoids (i.e. TP9 and TP10). Then, the continuous EEG data were epoched by setting the interval as 200 ms before and 1000 ms after the stimulus onset, using the pre-stimulus interval of -200 to 0 ms as the baseline correction. Eye blinks and movements were identified using an independent component analysis (ICA) with the runica algorithm implemented in EEGLAB, and were corrected from the ERP data by visual inspection of the component time courses. Trials contaminated with artifacts due to body movements, excessive noises due to fatigue, or peak deflection exceeding ±75 mV were rejected. The average trial acceptance rates were 81.57% for younger adults and 82.73% for older adults. No difference was found between groups ($t(44) = -0.368$, $p = .72$). Finally, the ERP data were averaged across the younger and older participants for each word type and pseudowords.

2.6. Time-frequency analysis

A bandpass filter with frequency values set as 0.1-50 Hz was applied to the raw EEG data. Then, the filtered data were re-referenced to the average of both mastoids and re-epoched from -700 before to 1500 ms after the stimulus onset, with a 200 ms pre-stimulus baseline. To address the issue that short epochs could be contaminated by edge artifacts, the epoched EEG data from each trial and electrode were reversed and concatenated to both ends of the trial, making the epoch three times as long (Cohen, 2014). Trials contaminated with artifacts were corrected with the same ICA procedure, and rejected with the same standard as in the ERP analysis (section 2.5). The number of trials included in the time-frequency analysis for each participant was the same as those in the ERP analyses, but not the identical epochs after pre-processing.

The time-frequency representations (TFRs) of power were computed using the Matlab toolbox Fieldtrip (Oostenveld et al., 2011). Each TFR of the single trial EEG data was constructed by using a 5-cycle complex Morlet wavelet for frequencies logarithmically-spaced from 2 to 30 Hz in 25 steps. The wavelet was applied to single trials with a duration equivalent to -2.9 before to 3.7 seconds after the word onset due to the reflected data on either end. The result was downsampled to yield a value every 10 ms. After acquiring the TFR of single trials, the power estimates over single trials were averaged for each word type respectively and across the participants. The resulting subject-averaged power changes for the neutral words were subtracted from those for the other four word types respectively, so as to elucidate power changes related to emotional word processing (without contamination of motor responses). The power changes were calculated with the 200 ms pre-stimulus baseline interval, and expressed in plots with dB scaling after discarding the reflected portion of the data.

2.7. Statistical analysis

For the behavioral data, the mean accuracy of words and controls (pseudowords) were entered into a two-way repeated-measures ANOVA with the factors of Lexicality (word, pseudoword) and Age (younger, older). To examine differences across experimental conditions, we conducted a two-way repeated-measures ANOVA with the factors of 5 Word Type (HN, LN, HP, LP, neutral) and 2 Age (younger, older). The reaction times were not analyzed, because a delayed response of the lexical decision was adopted to avoid motor artifacts caused by button pressing.

Mean ERP amplitudes were exported from 300-450 ms, 500-700 ms, and 700-900 ms post-stimulus based on the above-mentioned literature as well as visual inspection. A three-way mixed-design ANOVA of 5 Word type (HN, LN, HP, LP, neutral) x 3 Anteriority (frontal, central, parietal) x 2 Age (young, old) was conducted in each time window. Guided by visual inspection of the ERP waveforms and past literature on emotion processing and regulation (Cuthbert et al., 2000; Hajcak et al., 2010; Moser et al., 2014; Shafir et al., 2015), mean ERP amplitudes were averaged over three electrodes from each of the three regions of interest: frontal (F1, Fz, F2), central (C1, Cz, C2), and parietal (P1, Pz, P2) sites. When the sphericity assumption was violated, the Greenhouse-Geisser correction was applied. The alpha levels were set as 0.05 for all statistic tests. To correct multiple comparisons, the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995) was applied by setting a false discovery rate as 0.05. Only significant main effects or interactions involving Word Type and/or Age were reported.

For the TFR data, a non-parametric permutation test with the maximum-statistic based method was used to compare the contrasts of interest (Maris & Oostenveld, 2007). Guided by the visual inspection of the TFRs, past TFR/ERP studies on (emotional) word processing (Bastiaansen & Hagoort, 2005; Citron et al., 2013), and current ERP results, the TFR data were averaged within the theta band (4-6.5 Hz) and alpha band (8-12 Hz) in 300-450 ms, 500-700 ms, and 700-900 ms post-stimulus time windows, and entered into the permutation test respectively. To start with, a simple dependent-samples t-test was performed on the TF space of interest for each channel data point. A null distribution was then created, which assumes no power difference between the word types. The previous two steps were repeated for 1000 times by randomly assigning the conditions in subjects, and a t-statistic was computed for each randomization. Finally, the t-statistics of the observed data were compared to the null distribution, and the proportion of t-statistics larger or smaller than the observed ones was calculated. These p-values were thresholded by taking the max statistical value (i.e. t values) across the TF space of interest on each iteration to ensure that the expected proportion of falsely rejected hypotheses was less than 5%. The permutation tests were conducted by comparing two word types each time at the first-level. Once the channels that showed a difference between the word types were identified, the subject means were extracted from these channels (as regions of interest) and time windows (as time of interest), and further entered into a second-level permutation test on the two age groups (N = 23 subjects each group), with the participants' DSST scores included as a control variable (randomization = 1000 times, $p < .05$, maximum-statistic correction). To explore age differences on emotional word processing, the permutation tests were also conducted by contrasting the two age groups for each word type across each time window and frequency band respectively.

Because there is evidence that cognitive ability in older adults influences their responses to emotional pictures (Foster et al., 2013), we used a two-step approach to make sure that we could attribute the observed ERP and TFA results (if there are any) to age, and not to cognitive ability. First, we selected a subset of participants whose DSST scores were matched (N=23 each group). Participants' characteristics are summarized in Table 1B. Second, we conducted an additional three-way mixed-design ANCOVA of 5 Word type (high-arousing negative, low-arousing negative, high-arousing positive, low-arousing positive, neutral) x 3 Anteriority (frontal, central, parietal) x 2 Age (young, old) with the DSST scores included as the covariate. Only significant effects or interactions involving Word type and/or Age were reported below.

3. Results

3.1. Behavioral results

The accuracy results are summarized in Figure 2. There was a main effect of Lexicality ($F(1, 44) = 21.99$, $p < .001$, $\eta_p^2 = 0.333$). In both older and younger adults, words were more accurately recognized than pseudowords (Word: 98.02 ± 3.73%, Pseudoword: 95.15 ±5.03%). There was also a main effect of age ($F(1, 44) = 9.567$, $p = .003$, $\eta_p^2 = 0.179$). The older adults had an overall higher accuracy of lexical decisions over the younger adults (Older adults: 98.20 ± 0.97%, Younger adults: 95.00 ± 4.94%). There was no interaction between Lexicality and Age ($F(1, 44) = 3.502$, $p = .068$, $\eta_p^2 = .074$).

Word type matters (Figure 2). There were a main effect of Word Type ($F(4, 176) = 3.397$, $p = .011$, $\eta_p^2 = 0.072$) and a marginal effect of Age ($F(1, 44) = 3.894$, $p = .055$, $\eta_p^2 = 0.81$). Older adults tended to recognize all the words more accurately than younger adults (Older adults: 99.07 ± 0.94%, Younger adults: 96.97 ± 5.03%). Regardless of age, there was a trend that all the negative and all the high-arousing words were recognized as more accurately than neutral words (HN words: 98.50 ± 3.64%, LN words: 98.17 ± 4.36%, HP words: 98.54 ± 2.84% vs. Neutral words: 97.72 ± 4.60%; all p values = .05-.075). No Word Type x Age interaction was found ($F(4, 176) = 1.987$, $p = .098$, $\eta_p^2 = 0.043$).

3.2. ERP results

The grand averaged ERP waveforms based on 23 subjects each group with the matched DSST scores between groups are shown in Figures 3 and 4. In both the groups, there were clear visual N1 and P2 complexes, indicating normal early visual processing. In younger adults, all five word types showed prominent deflections starting from 300 ms, identified as N400s, late positive potentials (LPPs), and sustained slow positivities (SSPs). In older adults, the LN words elicited larger positivities at ~500 ms, compared with the other word types.

3.2.1. N400 (300-450 ms)

In the 300-450 ms time window, the results showed a main Age effect ($F(1, 44) = 13.341$, $p = .001$, $\eta^2 = 0.233$), an Age x Anteriority interaction ($F(2, 88) = 21.333$, $p < .001$, $\eta^2 = 0.327$), and a trend of three-way interaction of Word type x Age x Anteriority ($F(8, 352) = 2.195$, $p = .050$, $\eta^2 = 0.050$). Further comparisons revealed that in younger adults, there was an interaction of Word type x Anteriority ($F(8, 176) = 3.689$, $p = .006$, $\eta^2 = 0.144$). Younger adults showed a trend of a larger frontal N400 for neutral than for positive words ($p = .053$) and also a trend of a larger frontal N400 for neutral than for negative words ($p = .065$), irrespective of word arousal. In older adults, there was a widespread main effect of Word type ($F(4, 88) = 3.620$, $p = .009$, $\eta^2 = 0.141$): the LP words elicited a larger N400 than the LN words in older adults ($p = .020$). A main effect of Word type was also found ($F(4, 122) = 3.122$, $p = .016$, $\eta^2 = 0.066$). However, the post-hoc comparisons did not show any significant N400 differences across word types (all p values > .063). After controlling for the DSST scores, the three-way interaction disappeared ($F(8, 344) = 2.093$, $p = .072$), yet the Age effect ($F(1, 43) = 12.369$, $p = .001$, $\eta^2 = 0.223$) and Age x Anteriority interaction ($F(2, 86) = 22.188$, $p < .001$, $\eta^2 = 0.340$) remained significant: Older adults had a smaller N400 than younger adults in both the frontal and central sites (both p values < .015). This suggested that the observed Word type by Age interaction could still be affected by the residual differences of the DSST performance between the two age groups in the matched subsets.

3.2.2. Late positive potentials (500-700 ms) and sustained slow positivities (700-900 ms)

To statistically understand if the patterns of results differ between the 500-700 and 700-900 time windows, we carried out a four-way mixed-design ANOVA of 2 Time (500-700 ms, 700-900 ms) x 5 Word type (HN, LN, HP, LP, neutral) x 3 Anteriority (frontal, central, parietal) x 2 Age (young, old) on the subset of data (N = 23 subjects each group). We found that time interacted with all variables: Time x Word type x Anteriority ($F(8, 352) = 3.108$, $p = .016$, $\eta^2 = 0.066$), Time x Word type x Age ($F(4, 176) = 2.817$, $p = .032$, $\eta^2 = 0.060$), and Time x Anteriority x Age ($F(2, 88) = 6.273$, $p = .008$, $\eta^2 = 0.125$). This suggests that the patterns of results in these two time windows differ.

Focusing on the 500-700 ms time window, we found a main Age effect ($F(1, 44) = 10.097$, $p = .003$, $\eta^2 = 0.187$) and an Age x Anteriority interaction ($F(2, 88) = 46.603$, $p < .001$, $\eta^2 = 0.514$). Older adults had a larger LPP than younger adults in both the frontal ($t(44) = -5.568$, $p < .001$) and central sites ($t(44) = -2.332$, $p = .024$), regardless of the word types. There was also a main effect of Word Type ($F(4, 176) = 5.654$, $p < .001$, $\eta^2 = 0.114$). Regardless of age, the HN words elicited a larger LPP than the LP words ($p < .01$). Additionally, the LN words showed a larger LPP than all the positive and neutral words ($p < .01$). After controlling for the DSST scores, the Age effect ($F(1, 43) = 9.477$, $p = .004$, $\eta^2 = 0.181$) and Age x Anteriority interaction ($F(2, 86) = 42.024$, $p < .001$, $\eta^2 = 0.494$) remained significant, but the effect of Word type disappeared ($F(4, 172) = 1.810$, $p = .129$).

In the 700-900 ms time window, we found an Age x Anteriority interaction ($F(2, 88) = 27.033$, $p < .001$, $\eta^2 = 0.381$). Older adults had a larger LPP than younger adults in the frontal sites ($t(44) = -4.216$, $p < .001$), regardless of the word types. There was also an interaction of Word type x Anteriority ($F(8, 352) = 2.301$, $p = .050$, $\eta^2 = 0.050$). Further comparisons showed that the LN words continued to elicit an SSP compared with the LP words ($p = .04$), with the effect restricted to the frontal sites. After controlling for the DSST scores, the Age x Anteriority interaction ($F(2, 86) = 26.096$, $p < .001$, $\eta^2 = 0.378$) remained significant, but the Word type x Anteriority interaction disappeared ($F(8, 344) = .396$, $p = .923$).

3.3. TFR results

3.3.1. Theta waves (4-6.5 Hz)

Accessing word type effects combined across younger and older adults, the permutation tests revealed an enhanced theta power only in the 500-700 ms time window for the LN words compared with the LP words, at the left frontal sites ($p < .05$) (Figure 5).

Based on our a-prior prediction of theta difference between younger and older adults, we directly compared the groups. There was a stronger theta decrease in the 700-900 ms time window for younger than older adults, for the HN and LP words, respectively, at the left temporal-parietal sites ($p < .05$), although the effects may not be robust, spanning fewer than 3 adjacent electrodes (Figure 5C).

3.3.2. Alpha waves (8-12 Hz)

In the 300-450 ms time window, the permutation tests revealed an enhanced alpha power for the LN words compared with the LP words at the left frontal sites, in both the age groups (p

< .05) (Figure 6). The alpha increase between these two word types was significantly larger for younger than older adults at the left frontal sites ($p < .05$) (Figure 7). In both the age groups, the alpha power also increased for the HN words compared with the LP words at the right frontal sites in the same time window (Figure 6D).

In direct comparison between the groups, there was a stronger alpha decrease in the 700-900 ms time window, for younger than older adults, for the HN and HP words, respectively, at the left temporal-parietal sites ($p < .05$) (Figure 6C).

4. Discussion

The current study investigated how age affects the comprehension of emotional words with varying valence (positive, negative) and arousal (high, low) in a visual word recognition paradigm. We found age affected word processing in both the lexical/semantic retrieval and later elaboration stage. Consistent with the SAVI model, older adults showed a positivity bias only when recognizing low-arousing (vs. high-arousing) words. In the 300-450 ms time window, older adults showed increased N400s for low-arousing positive (LP) words relative to low-arousing negative (LN) words, whereas younger adults showed a trend of attenuated frontal N400s for emotional relative to neutral words. Older adults also showed a weaker left frontal alpha (8-12 Hz) increase than younger adults for the LN (vs. LP) words. In the 500-700 ms time window, older adults showed a larger mid-frontal theta increase than younger adults for LN words. In the 700-900 ms time window, the exploratory analyses showed a stronger alpha decrease for high-arousing negative (HN) and high-arousing positive (HP) words in younger than older adults.

4.1. Lexical/semantic retrieval: N400 effects

Our ERP N400 results suggest that older adults prefer positive over negative information in language, but only when such information is low-arousing, consistent with the SAVI model (c.f., Introduction). In ERP research of language, N400 has been associated with the ease of word retrieval from the semantic memory (Lau et al., 2008). Emotional words often showed an attenuated N400, compared to neutral words. The widely accepted interpretation is that emotional content facilitates word retrieval (Imbir et al., 2016; Ku et al., 2020; Palazova et al., 2011; Recio et al., 2014; Sass et al., 2010). Our younger adult group showed exactly this, although with a marginal significance, which may reflect lower power due to the smaller sample size (N=23) included in the cognitive-ability-matched participants. In older adults, the LP words showed enhanced N400s relative to the LN words, reflecting the effort to retrieve more meanings from the LP words. That is, low-arousing positive information can pose more difficulty for older adults during lexical retrieval, possibly due to their up-regulation for low-arousing positive information. In the time-frequency representations (TFRs), younger adults showed a larger alpha increase in the LN (vs. LP) words in comparison to older adults (300-450 ms). There are two possible interpretations of alpha: affective attention and inhibition. Based on the attention account of alpha, older adults devoted more attentional resources to the LP words during the word retrieval stage than younger adults, supporting arousal modulation of the positivity bias effect. Alternatively, the LN words may elicit (emotionally) conflicting information that is more difficult to process than words activating non-conflicting information (i.e., HN words) (Citron et al., 2013). When information of different valence and arousal is combined in a single word, high arousal facilitated evaluations of negative words and interfered with evaluations of positive words, while low arousal interfered with those of negative words and facilitated those of positive words (Dillon et al., 2006). According to the inhibition–timing hypothesis (Klimesch et al., 2007), an alpha event-related desynchronization (ERD) reflects a release of inhibition related to cortical activation, whereas an alpha event-related synchronization (ERS) suggests increased inhibitory control. We thus argued that the "conflicting" information in our LN words may lead to an alpha ERS, suggesting an inhibition to the conflicting or irrelevant information in the words. In this regard, the larger alpha increase found for younger than older adults may indicate older adults' decreased inhibition to the "conflicting" information in the LN words, possibly due to their physiological decline. Additionally, both the age groups with matched DSST scores showed a larger alpha ERS (300-450 ms) in the HN words than the LP words. Following the account of approach-withdrawal motivation, our data could suggest that withdrawal information (i.e., HN words) is linked to a suppression of attention during word retrieval, whereas approaching information (i.e., LP words) implies an increased attention in the same stage, after controlling for participants' general cognitive ability. Taken together, negative words, regardless of arousal, generated higher alpha increase in our study. We speculated that this could support "affective tuning" in which negative emotions narrow or constrict one's attentional and/or cognitive scope, leading to increased inhibition of brain processes (Fredrickson, 2004).

Topographically, the alpha activity in the N400 time frame seemed prominent at the right frontal/parietal regions in the LN and LP words in older adults (Figure 6B), albeit not statistically significant. This scalp distribution is consistent with a recent meta-analysis (Hoffman & Morcom, 2018). They found that older adults showed a reduced activity in the left hemisphere semantic network, but an increased activity in the right frontal and parietal regions, during lexical and semantic tasks, suggesting a shift from semantic-specific to domain-general neural resources in later life.

4.2. Semantic elaboration and sustained attention: LPP and SSP effects

In contrast to our prediction, age did not modulate LPP effects in emotional words. Irrespective of age, the LPPs were larger for HN than for LP words, and were larger for LN than for HP, LP, and neutral words. These findings are in line with the negativity bias effect often seen in younger adults during emotional word processing (Delaney-Busch et al., 2016; Kanske & Kotz, 2007; Schacht & Sommer, 2009b) and emotional sentence processing (Delaney-Busch & Kuperberg, 2013; Fields & Kuperberg, 2012; Holt et al., 2009). Although we should not interpret too much about null effects, the lack of age modulation on the emotional word LPP effect is likely due to our control of DSST scores between the two age groups. In our matched subsets, older adults have as generally good cognitive ability as younger adults given the high sensitivity of the DSST to cognitive deficits (Jaeger, 2018). Foster et al. (2013) found that age differences on emotional processing are mainly driven by cognitive abilities including cognitive control: Cognitive functioning performance was positively correlated with posterior LPP amplitudes (450-650 ms) for negative pictures. The authors argued that people with higher cognitive abilities are more likely to devote more neural resources to negative pictures, as reflected by the enhanced LPP. They may also be better in regulating negative emotions, possibly as reflected by an attenuated LPP in a later time window which was not analyzed in their study. In contrast, people with lower cognitive abilities may have difficulty processing negative pictures, attenuating both the earlier and later LPP effects. This highlights the mediating role of cognitive abilities rather than age per se in explaining variances in our late ERP effects.

In the TFRs in the same LPP time window, the LN words showed a larger left frontal theta increase than the LP words. Theta activity in the fronto-temporal regions has been associated with the retrieval of lexical-semantic information, albeit in an earlier time window (i.e., 300-500 ms, Bastiaansen & Hagoort, 2006; Bastiaansen et al., 2005). This means that low-arousing and negative information in LN words together may lead to elaborative meaning processing as compared to low-arousing positive information in LP words. It is possible that our younger and older adults re-evaluated negative meanings, especially with low arousal, following a suppression of attention to either (1) the word as a whole, or (2) the conflicting information in the word, in the N400 time window. An alternative interpretation for the enhanced theta is an emotion regulation account. For instance, Ertl et al. (2013) found an enhanced mid-frontal theta power (4-5 Hz) during cognitive reappraisal of negative emotions in pictures with the sources localized to the left middle/inferior frontal gyrus. This indicated that both the age groups in our study made similar efforts in down-regulating low-arousing negative emotions than they did with high-arousing ones. However, a closer look at the topography of theta activity across different word types and age groups (Figure 5) indicated that older adults showed a larger mid-frontal theta increase for the LN rather than the LP words compared with younger adults. This is confirmed by a planned comparison of the mid-frontal theta (i.e., the averaged power of AFz, Fz, and FCz channels) with permutation tests on both the age groups for each word type in the same LPP time window ($p < .05$). We thus postulated that mildly negative emotions can be down-regulated via top-down processes in healthy elders, possibly via meaning elaboration. This partially supports the SAVI model, and a "weak" version of the positivity bias effect.

Regarding the word type effect on LPPs, our data further showed that the negativity bias effect depends on word arousal. For high-arousing words, the larger LPPs for the HN relative to LP words indicated elaborative processing of negative contents, possibly due to enhanced motivational salience for withdrawal (relative to approach) information. For low-arousing words, the larger LPPs in the LN words relative to all the positive and neutral words further suggested that negative information, regardless of arousal, attracted elaborative processing. Recent studies showed that how arousal and valence impact word processing can depend on task demands. For instance, Bayer et al. (2013) compared the processing of German emotional nouns in a lexical decision task (LDT) and a reading task. High-arousing words elicited larger LPP amplitudes (420-630 ms) than low-arousing words in the LDT rather than the reading task. In contrast, using the LDT, Citron et al. (2013) did not find a valence or arousal effect on the LPP (430-650 ms), but a trend of interaction of valence and arousal on the SSP (650-1000 ms) when participants read English emotional words of different word categories (i.e., nouns, adjectives, and verbs). The authors argued that this may suggest differential processing for straightforward approach-withdrawal system (LP and HN words in this case) and "conflicting" approach-withdrawal system (HP and LN words). More recently, Delaney-Busch et al. (2016) found an arousal effect in a semantic categorization task (i.e. to judge if the word referred to an animal). High-arousing words elicited larger LPPs (500-800 ms) than low-arousing words. Regardless of word arousal, LPP amplitudes were larger for unpleasant words than pleasant words, followed by neutral words in a valence categorization task. We thus argued that how valence and arousal contribute to the LPP may depend on task and the emotional dimension that the task is focused on. In this regard, our data showed that our lexical decision task successfully directed people's attention toward both the valence and arousal aspects of words.

We did not find an age difference on the SSP effect (700-900 ms). Both the age groups elicited a larger SSP for the LN than the LP words. There are two possible interpretations of the SSP effect: attention vs. regulation. From the attention account, it is possible that the low-arousing negative information attracted sustained attention for meaning resolution than the arousal-matched yet positive information. From the regulation account, our participants may regulate the negative emotions only in the low-arousing words, irrespective of age when cognitive abilities are matched. Past studies have associated increased late positivity (400-1,000 ms) with more cognitive resources for down-regulating negative information in pictures in younger adults (Baur et al., 2015; Langeslag & Surti, 2017). Partially supporting the SAVI model, the enhanced SSP may thus reflect increased efforts to down-regulate the low-arousing negative (vs. positive) contents in people with average cognitive abilities. However, due to a lack of explicit regulation instructions in the current task, one needs to take caution in interpreting these SSP effects. Future studies are needed to further distinguish the functional significance between LPP and SSP effects.

In the TFR analyses in the 700-900 ms time window, age differences were found in the alpha band for the HN and HP words, with a more robust effect in the HN words. Specifically, younger adults showed a stronger posterior alpha ERD in the HN (and possibly HP) words than older adults. This is consistent with the past findings that (high) emotionally arousing information led to an alpha decrease in younger adults, in a late time window (~600-1000 ms) across different tasks, such as the passive viewing and categorization tasks (Schubring & Schupp, 2019), and the color detection task (Wang & Bastiaansen, 2014). It is likely that high arousing information (1) attracts more sustained attention, or (2) reflects greater cortical inhibition due to emotion regulation, than low-arousing information in younger adults, but not that much in older adults due to physiological decline.

In terms of topographical differences, older adults showed a frontal distribution of late/sustained positivity, consistent with the PASA model where a posterior-anterior shift in the brain takes place as a person ages (Davis et al., 2007). For instance, it is found that the P300 effect shifts from posterior to anterior regions in older adults. This reflects their need to maintain a top-down control to achieve the same task performance compared with younger adults (O’Connell et al., 2012). In support of this, our data showed that older adults had actually higher accuracy rates of lexical decisions for all the word types (including the pseudowords) than younger adults. Previous studies found that the P300 effect reflected decision making and context-updating in stimulus processing, often with the oddball paradigm (van Dinteren et al., 2014). We obtained similar distributions of the late positivities in our study, with a different task that particularly taps into emotional word processing. In this regard, older adults may use more cognitive resources as a compensatory mechanism to achieve a better task performance than younger adults during visual word recognition. However, these topographical differences should be interpreted carefully due to the poor spatial resolution of the scalp EEG.

4.3. Limitations and future directions

There are a number of limitations and future directions. First, although we only included minimally-depressive participants into the analyses based on the BDI-II scores, younger adults still showed a slightly higher BDI-II score than older adults. This means that older adults generally felt slightly more positive than younger adults did when they filled out the questionnaire two weeks before the EEG experiment. It is thus possible that the positivity bias we found in older adults may be due to their recent positive affect, rather than a long-term trait affect. Second, later ERP effects in general are more likely to be affected by task demands. We chose to use the LDT, because it does not require explicit evaluation or elaborative processing. Future studies can use tasks that require some elaborative processing, yet are not too demanding, such as a semantic relatedness task. Third, although we strictly matched the orthographic and lexical/semantic properties of our word stimuli, it still remains unclear at which level of word processing (e.g., orthographic or lexical/semantic) the age-related positivity bias occurs. Future studies can manipulate each of these variables, e.g., word frequency, to pinpoint the processing level in which the age-related positivity bias occurs. Finally, our data on the N400 effect showed that the age differences across word types could partly be explained by the DSST performance, even though the DSST scores were carefully matched between the two age groups. Future studies should further examine how cognitive ability affects the age-related positivity bias.

5. Conclusions

In the current study, we examined how age affects positivity bias in language, and whether that depends on emotional arousal of words. Our data supported the SAVI model in that older adults attend to low-arousing positive meanings initially, yet elaborate low-arousing negative meanings more at the later stages of word processing. In contrast, younger adults attend to and elaborate negative and high-arousing meanings more at the later stages. The present study indicates that future studies on emotional word processing should take age differences into account. In addition, although emotional words are generally considered as less arousing than emotional pictures, we found the evidence that it may be difficult for older adults to regulate meanings in high-arousing (vs. low-arousing) words. More importantly, given that the same word may elicit different emotional experiences across older adults, our data suggest that older adults' positivity bias may be a ubiquitous phenomenon, despite their various life experiences and/or frequency of exposure.

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Table 1. Participant characteristics

A. All participants (N=35 each group)

Mean (SD)	Younger adults	Older adults	*t*	*p*
N	35	35	N/A	N/A
Age	18.77 (1.14)	67.66 (4.46)	N/A	N/A
Sex	M: 14, F: 21	M: 17, F: 18	N/A	N/A
BDI-II	5.23 (4.12)	3.54 (2.75)	2.015	.048
MMSE	29.31 (0.90)	29.54 (1.46)	-0.788	.434
DSST	65.91 (10.23)	50.80 (10.67)	6.05	< .001

B. Participants matched for the DSST scores (N=23 each group)

Mean (SD)	Younger adults	Older adults	*t*	*p*
N	23	23	N/A	N/A
Age	18.65 (0.89)	67.26 (4.19)	N/A	N/A
Sex	M: 9, F: 14	M: 7, F: 16	N/A	N/A
BDI-II	5.23 (4.12)	3.54 (2.75)	2.056	.047
MMSE	29.22 (1.00)	29.52 (1.90)	-1.087	.283
DSST	60.78 (8.51)	56.52 (7.73)	1.778	.082

Table 2. Stimulus characteristics

Mean (SD)	High-arousing negative	Low-arousing negative	High-arousing positive	Low-arousing positive	Neutral
Valence	2.64 (0.45)	2.81 (0.49)	7.27 (0.38)	7.19 (0.39)	5.01 (0.08)
Younger	2.76 (0.45)	2.83 (0.49)	7.37 (0.38)	7.13 (0.39)	5.05 (0.33)
Older	2.50 (0.58)	2.77 (0.70)	7.20 (0.53)	7.30 (0.53)	5.00 (0.29)
Arousal	5.91 (0.46)	3.97 (0.48)	5.86 (0.38)	3.96 (0.57)	3.70 (0.44)
Younger	5.85 (0.65)	3.84 (0.62)	6.01 (0.46)	3.99 (0.69)	3.72 (0.68)
Older	5.95 (0.62)	4.04 (0.62)	5.77 (0.68)	3.91 (0.72)	3.63 (0.50)
Concreteness	4.68 (1.31)	4.52 (1.52)	4.54 (1.29)	4.93 (1.44)	4.90 (1.37)
Imageability	4.99 (1.06)	4.72 (1.37)	5.19 (1.09)	5.36 (1.21)	4.80 (1.48)
Familiarity	5.40 (0.57)	5.32 (0.54)	5.57 (0.62)	5.60 (0.59)	5.47 (0.64)
Length	6.64 (1.69)	6.06 (1.26)	6.64 (1.40)	6.00 (1.35)	6.22 (1.49)
Frequency	2.75 (0.52)	2.58 (0.52)	2.85 (0.46)	2.74 (0.53)	2.58 (0.49)
No. of phonemes	5.22 (1.61)	4.75 (1.30)	5.58 (1.36)	5.06 (1.26)	5.36 (1.62)
No. of syllables	2.06 (0.82)	1.89 (0.71)	2.14 (0.68)	1.83 (0.70)	2.08 (0.87)

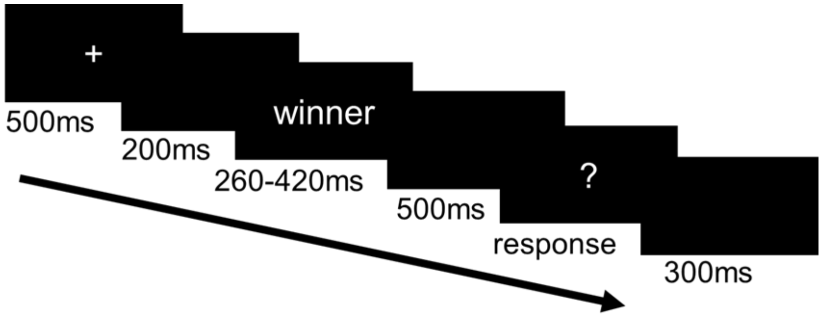

Figure 1. An example trial in the lexical decision task

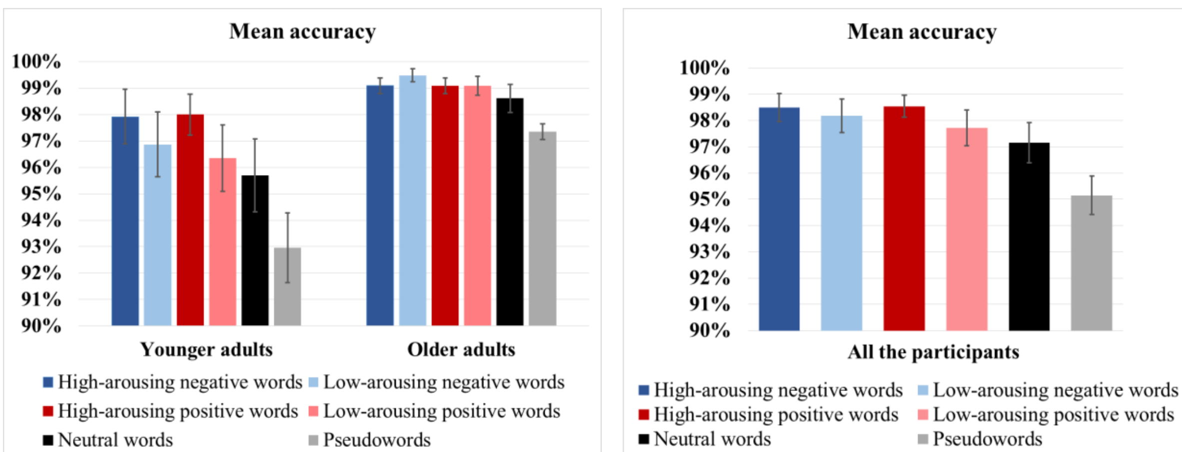

Figure 2. Accuracies (in percentage) for the younger and older participants (Panel A; N=23 for each group) and for all the participants (Panel B, total N =46)

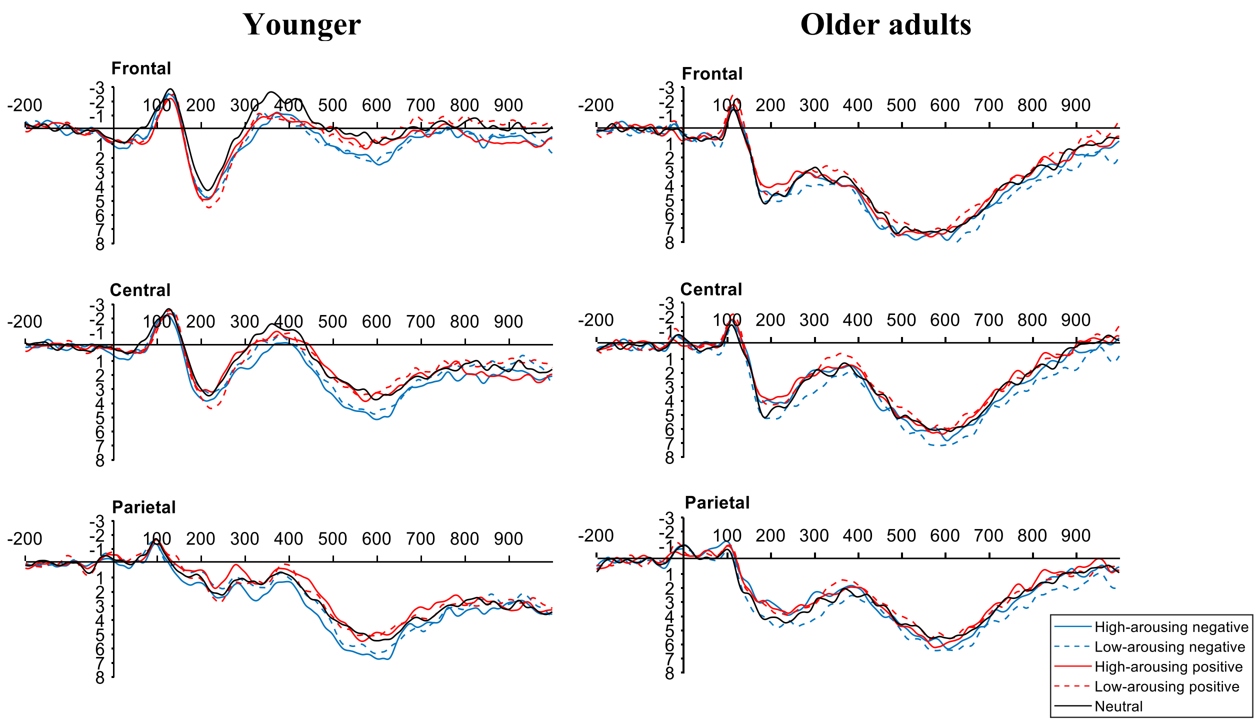

Figure 3. Grand averaged ERP waveforms (N=23 each group with matched DSST scores) for high-arousing negative (solid blue line), low-arousing negative (dashed blue line), high-arousing positive (solid red line), low-arousing positive (dashed red line), and neutral (black line) words at frontal, central, and parietal scalp regions for younger adults (left panel) and older adults (right panel)

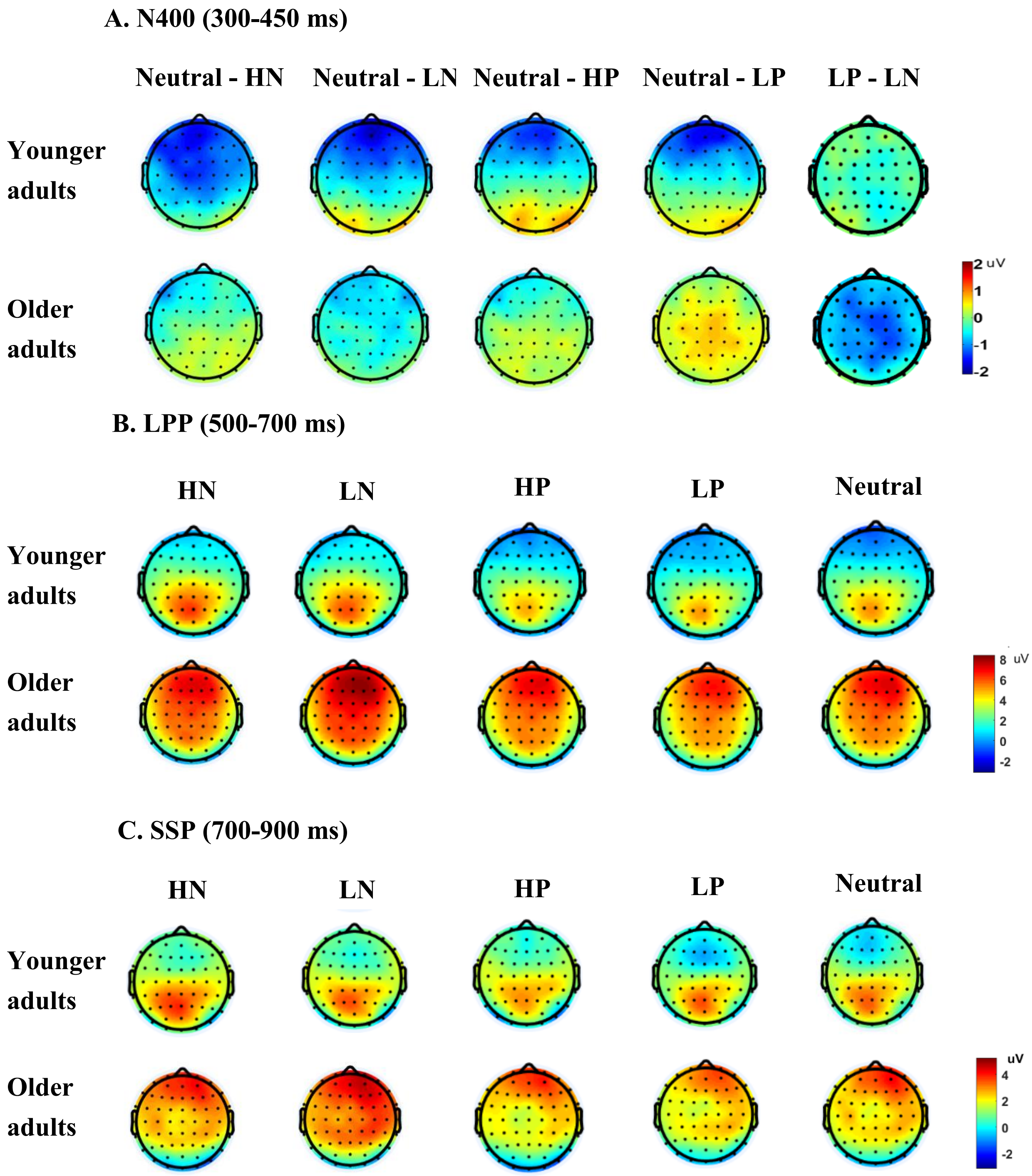

Figure 4. The topographies of the N400 effects, obtained by subtracting each type of emotional words from the neutral words (panel A), the LPP in each of the word types (panel B), the SSP in each of the word types (panel C), in younger and older adults with matched DSST scores.

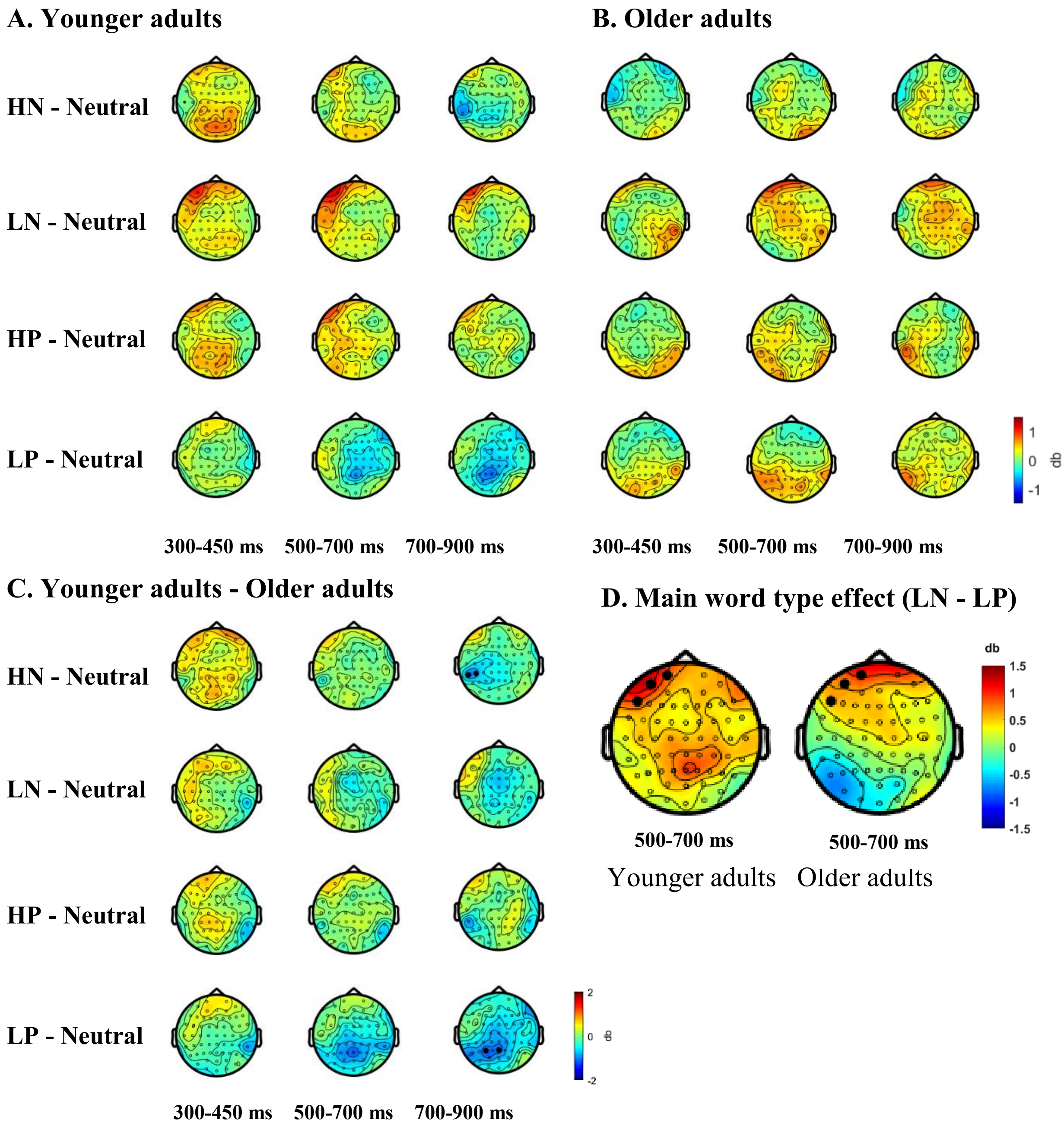

Figure 5. The spatial distribution of the theta (4-6.5 Hz) power differences between emotional words and neutral words in the 300-450 ms, 500-700 ms, and 700-900 ms post word onsets in (A) Younger adults, (B) Older adults, (C) Younger adults vs. Older adults. (D) Difference scalp topographies of the frontal theta increase (500-700 ms) in younger (left) and older adults (right). Channels with the statistically thresholded difference ($p < .05$) are highlighted in black dots in the scalp maps. HN: High-arousing negative words, LN: Low-arousing negative words, HP: High-arousing positive words, LP: Low-arousing positive words

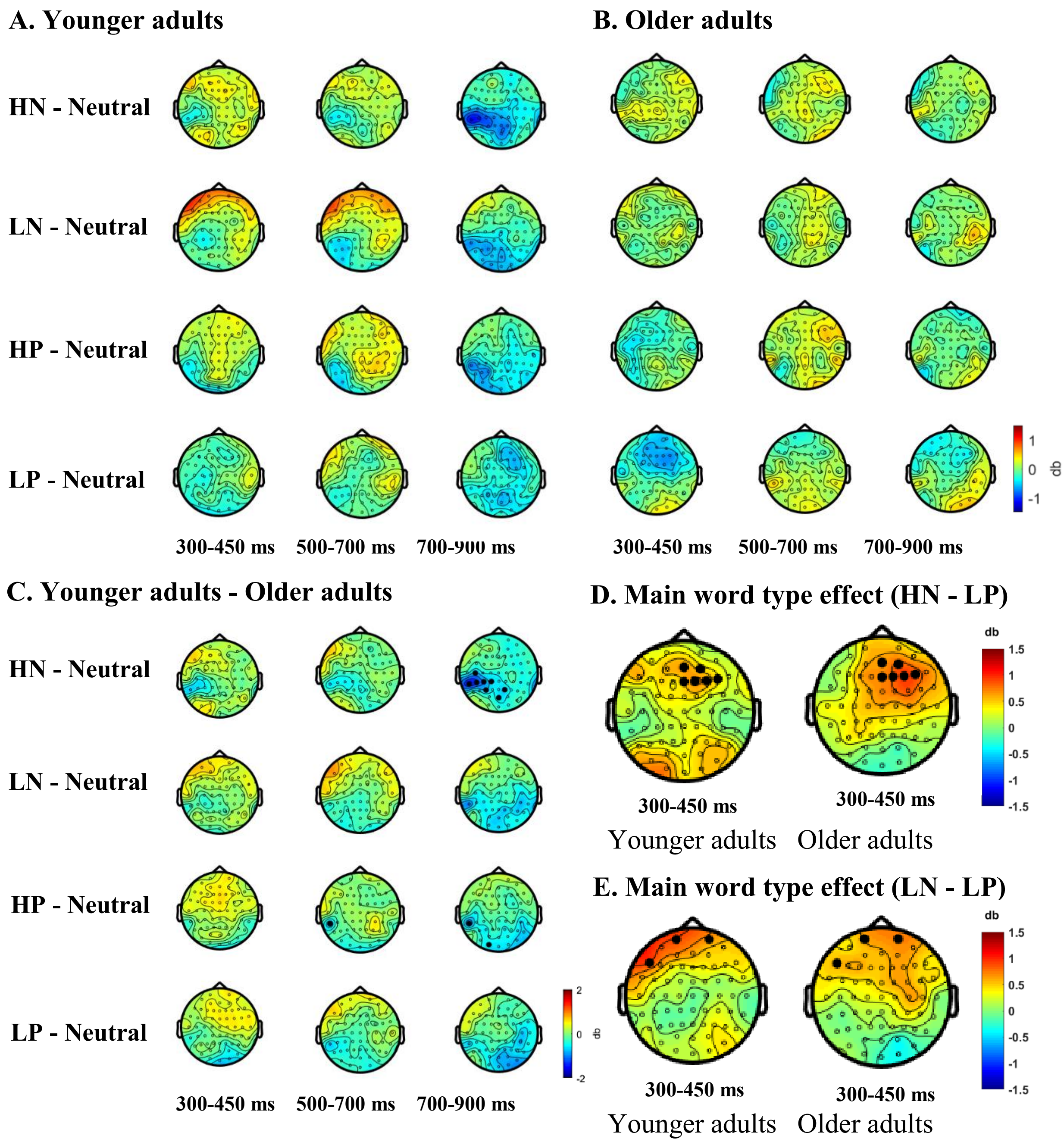

Figure 6. The spatial distribution of the alpha (8-12 Hz) power differences between emotional words and neutral words in the 300-450 ms, 500-700 ms, and 700-900 ms post word onsets in (A) Younger adults, (B) Older adults, (C) Younger adults vs. Older adults. Difference scalp topographies of the frontal alpha increase (300-450 ms) for the (D) HN-LP contrast and (E) LN-LP contrast, in younger and older adults. Channels with the statistically thresholded difference ($p < .05$) are highlighted in black dots in the scalp maps. HN: High-arousing negative words, LN: Low-arousing negative words, HP: High-arousing positive words, LP: Low-arousing positive words

low-arousing negative minus low-arousing positive

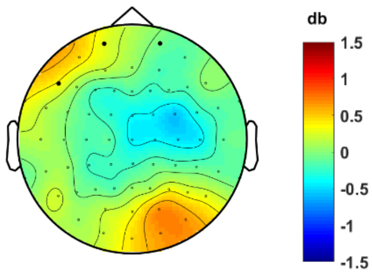

Figure 7. The spatial distribution of the alpha (8-12 Hz) power differences between younger vs. older adults for significant word type contrasts in the 300-450 ms time frame. Channels with the statistically thresholded difference ($p < .05$) are highlighted in black dots in the scalp map.

Appendix B.

Context matters: Updating the affective representation of a word in younger and older adults

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Abstract

Older adults often prioritize positive rather than negative information during word processing, termed as a positivity bias. However, it is unclear how older adults update affective representations of a word in context. The present study examined whether age-related positivity bias influences the update of affective representations of a word in different emotional contexts, in two experiments. In Experiment 1 (web-based), participants read positive and negative topic words in positive and negative contexts and rated the valence of the topic word. The results showed that negative contexts biased the ratings more than positive ones, regardless of age, supporting a general negativity bias during valence evaluation. In Experiment 2 (EEG), another group of participants read positive and negative topic words in positive and negative contexts first, and then the same topic word again, and made valence judgment on the topic words. Compared with younger adults, older adults showed a larger P2 (180-300 ms) effect for positive topic words, regardless of context valence, suggesting their increased early attention to positive features of the topic words in contexts. At ~600 ms, younger adults showed a larger late positive complex (LPC) for topic words in negative contexts, irrespective of topic valence, while older adults showed similar LPC effects across all the conditions. This suggests that younger adults update the affective representations of a word in negative (vs. positive) contexts, whereas older adults do so in both positive and negative contexts. Our data supported a positivity bias in updating affective neural representations of a word in contexts in older adults.

.

Keywords: Affective representations, emotional contexts, aging, P2, LPC

Introduction

Do younger and older adults differ in their processing of positive or negative meanings in different sentential contexts? Consider, for example, the word "*monster*". "*Monster*" in the sentence "*The monster looks scary to the children.*" typically connotes negative meanings. It can further imply a threat or danger that needs to be attended to on top of other information in the sentence. However, when combined with a different sentential context such as "*The monster looks funny to the children.*", "*monster*" becomes less negative or even mildly positive in one's mental representation. For long, studies have debated about whether positive or negative information is processed more attentively in emotional word processing (Kauschke et al., 2019), termed as positivity or negativity bias. These processing bias based on emotional valence (i.e., positive or negative) may depend on age. For instance, empirical evidence has revealed that younger adults often show a negativity bias during word and sentence processing (Delaney-Busch et al., 2016; Delaney-Busch & Kuperberg, 2013). In the present study, we investigated whether and how these age-dependent emotional bias influences the update of affective representations of a word in emotionally loaded contexts, by using an explicit valence judgment task and event-related potentials (ERPs).

Words can serve as linguistic cues that activate a variety of conceptual representations of not only objects and events, but also emotions (Hinojosa et al., 2020; Lupyan & Bergen, 2016). According to the early theory of constructed emotions, emotions are events constructed by core affect and categorization (Russell & Barrett, 1999). Core affect is a neurophysiological state that can be measured by the continuous scale of valence (positive vs. negative) and arousal (high vs. low). Emotional experiences come from prototypical emotional episode (i.e., prior knowledge) and the categorization the affective state, usually with the aid of linguistic contexts, to stimulate such emotional episode or knowledge. The categorization of these affective states and their representations can be highly context-dependent. For instance, behaviorally, it was reported that in judging a morphed face with an equal blend of happiness and angry, participants reported the face to be angrier if it is paired up with the word "angry" (Halberstadt & Niedenthal, 2001). Neurally, when reading sentences with (vs. without) fearful contents prior to a neutral scene, participants showed increased brain activation in the right anterior temporal pole, possibly suggesting the binding of emotional information across the visual and linguistic information (Willems et al., 2011). Additionally, a greater activation in the amygdala, an area commonly associated with emotion processing, was found when the same neutral scene was viewed later, without being paired with the fear-inducing sentence. This indicated the retention and impact of emotional information in linguistic contexts on the neutral visual information. These studies showed that emotional words and sentences can shape or update how one perceives and represents emotions in face or visual stimuli. However, few attempts have been made to examine the influence of linguistic contexts on the processing of word stimuli, considering the relationship between a word and its affective representations may not be, due to the arbitrariness of the word, as hardwired as that between a scene or face and its implied emotions.

Critically, age may play a role in different contextualized language use during word processing. From the aspect of language processing, studies have suggested an age-related reduction in the capacity to anticipate or integrate upcoming information with the prior context, such as the pre-activation of possible semantic features and/or specific lexical items (Federmeier et al., 2010; Wlotko et al., 2012). This age-related reduction was further found to be mediated by older adults' cognitive performance, particularly cognitive control (Dave et al., 2018; Federmeier et al., 2010). From the aspect of emotion processing, older adults show the ability to track different emotional information (e.g., curiosity) in stories, and accordingly update their mental representation of the described state of affairs (i.e., situational models), as younger adults (Soederberg & Stine, 1995). However, it is unclear whether older readers can track emotional information based on emotional valence of the contexts. These mixed findings suggested a dichotomy between non-emotional vs. emotional contextualized language use in older adults. That is, older adults may still use emotional, but not necessarily non-emotional, contexts to update their affective representations of a word. An unresolved question is whether differently valenced contexts can be used to update the affective representations of a word similarly across younger and older adults, given the age-related emotional bias.

Emotional bias in language processing across younger and older adults

According to the automatic vigilance hypothesis (AVH; Pratto & John, 1991), humans tended to attend to negative information for evolutionary reasons, termed as negativity bias, as it threatens perceivers' well-being and thus needs to be detected, attended to, and avoided rapidly (Dijksterhuis & Aarts, 2003; Estes & Verges, 2008; Kuperman et al., 2014). Supporting evidence of the AVH comes mainly from lexical decision, valence judgment, and naming tasks. Generally, negative words showed slower lexical decisions, slower word naming, yet faster valence judgment, compared with arousal-matched positive words. In addition, in a color-word Stroop task using positive (e.g., *sincere*) and negative (e.g., *hostile*) words (Pratto & John, 1991), undergraduate participants named the color of the negative words more slowly than that of positive ones, regardless of word arousal levels. These studies showed that negative information attracts either prolonged attention in language tasks, or heightened attention in emotional tasks, mostly in younger adults. However, a recent meta-review suggested that the negativity bias may be age-dependent (Reed et al., 2014). Older adults aged between 60 and 75 often showed greater attention to, or better memory for, positive stimuli than negative ones, i.e., a positivity bias, compared with younger adults. This can be explained by the socioemotional selectivity theory (SST; Carstensen, 2006): Due to constrained time horizons, when people grow older, they tend to re-prioritize positive information to achieve emotional well-being in their life, despite declining cognitive control. Studies supporting the SST comes mainly from memory and production tasks (Mikels & Shuster, 2016; Shamaskin et al., 2010). For instance, in a surprise recognition task of positively and negatively framed health-related texts (e.g., *Research shows that people who regularly check their cholesterol levels have an increased/decreased chance of recognizing their risks for other related health issues.*), older adults recalled more positive texts with a higher accuracy, compared with negative texts (Shamaskin et al., 2010). These studies mostly indicated a link between emotional bias and the processes after the activation of lexical-semantic representations (e.g., decision making or response execution). It is unclear whether emotional bias also influences the activations and updates of lexical-semantic representations during word processing. To complement the above-mentioned behavioral studies, we reviewed the ERP studies below that elucidated the processing of lexical-semantic representations of a word in isolation and in context, with better temporal information.

ERP correlates of the processing of emotional words in isolation

For younger adults, many studies on single word processing have revealed emotion effects on both early and late ERP components: the early posterior negativity (EPN), P2, N400, and the late positive complex/component (LPC). Emotional words, both positive and negative, often elicit a larger EPN, than neutral words (Citron et al., 2013; Herbert et al., 2008; Hinojosa et al., 2010;

Kissler et al., 2009; Palazova et al., 2011; Recio et al., 2014; Schacht & Sommer, 2009a, 2009b; Scott et al., 2009). The EPN usually occurs around 200-300 ms after word onsets at temporal-occipital brain regions, and is associated with an arousal-driven, automatic processing of emotional features in the stimuli. A few studies reported a larger EPN to positive words (usually low- or moderately-arousing) than negative ones, suggesting a positivity bias in the initial stage of affective feature processing (Hinojosa et al., 2010; Palazova et al., 2011; Recio et al., 2014). In the similar time window, some studies found a larger P2 to emotional (both positive and negative) than neutral words (Kanske & Kotz, 2007; Schacht & Sommer, 2009b). The P2 effect is linked to the same functional significance as the EPN effect, albeit with a more fronto-central distribution. Like the EPN effects, positive words sometimes elicit a larger P2 than negative words (Kanske & Kotz, 2007). Downward the processing stream, a less commonly seen component is the N400, which peaks around 300-500 ms after word onsets with an anterior distribution. Emotional words, regardless of valence, often elicit a reduced N400 than neutral words (Kanske & Kotz, 2007; Ku et al., 2020; Palazova et al., 2011; Sass et al., 2010). The reduced N400 effect is related to a facilitation of semantic retrieval due to affective features of the word, as the N400 is typically associated with semantic retrieval efforts. Additionally, many studies reported a larger LPC to emotional words than neutral words (Hinojosa et al., 2010; Kanske & Kotz, 2007; Ku et al., 2020; Schacht & Sommer, 2009a). The LPC usually peaks around 450-800 ms after word onsets, with a centro-parietal distribution. Related to a broad P3 family, the LPC effect reflects an elaborative processing and attention reallocation towards affective features in the stimuli. Notably, the LPC effect can be modulated by word concreteness, word categories (i.e., adjectives, verbs, and nouns), and task types (Delaney-Busch et al., 2016; Kanske & Kotz, 2007; Palazova et al., 2011; Recio et al., 2014). When words are highly concrete, or an explicit emotion task (e.g., valence judgment) is adopted, negative words usually elicit a larger LPC than arousal-matched positive words. Also, this negativity bias could be shifted to a positivity bias when the words are adjectives, compared with nouns or verbs.

In older adults, only a study, to our knowledge, examined the age-related emotional bias in emotional word processing. In a lexical decision task, Ku and colleagues (2022) manipulated the word valence (positive, negative) and arousal (high, low), and found a larger N400 to low-arousing positive words than arousal-matched negative ones in older (but not younger) adults. Compared with younger adults, older adults also showed a higher mid-frontal theta (4-6.5 Hz; 500-700 ms) activity in response to low-arousing negative words, in a follow-up time-frequency analysis. The authors interpreted the enhanced N400 as an arousal-dependent positivity bias in older adults when retrieving the affective representations of a word. As the mid-frontal theta reflects cognitive inhibition or emotion regulation, the increased mid-frontal theta activity could suggest older adults' down-regulation of low-arousing negative features of the word. This, to our view, supports an arousal-dependent positivity bias in older adults after affective representations of a word are retrieved.

ERP correlates of the processing of emotional words in sentential contexts

At sentence-level processing, past ERP studies mainly focused on younger adults (Cao et al., 2019; Chou et al., 2020; Delaney-Busch & Kuperberg, 2013; Ding et al., 2016; Holt et al., 2009; León et al., 2010; Martín-Loeches et al., 2012; Moreno & Rivera, 2014; Moreno & Vázquez, 2011). In terms of word-level emotion effects, negative words in contexts, regardless of context congruency, elicited a larger LPC than positive words in contexts, suggesting a negativity bias (Delaney-Busch & Kuperberg, 2013; Fields & Kuperberg, 2012; Holt et al., 2009). In terms of context congruency, the findings so far suggest that incongruent emotional content increases the depth of semantic analysis. For instance, Holt et al. (2009) examined emotional words with features either congruent or incongruent with its neutral sentential context (e.g., *Stephen owned a lot of nineteenth century art. Everyone knew that he* <u>*bought*</u>*/*<u>*loved*</u>*/*<u>*forged*</u> *paintings of old masters.*). The emotionally incongruent words (both *forged* and *loved*) elicited a larger N400 than the congruent words (*bought*), suggesting a deeper semantic analysis. Likewise, Moreno and colleagues (2011, 2014) set up emotional expectation through context (e.g., *There was nothing special about the episode and it turned out to be very…*<u>*boring*</u>*/*<u>*interesting*</u>.). In addition to the N400, they reported a post-N400 frontal positivity (PNP) to emotionally incongruent (vs. congruent) target words. The authors argued that the PNP effect reflects the effort needed to override a lexical prediction built up by the affective features in the preceding context. Recently, Chou et al. (2020) manipulated both context constraint via valence (emotionally-biased vs. emotionally unbiased) and target word valence (emotional vs. neutral) in a coherent judgment task. Neutral target words in emotionally-biased context elicited a larger P2 and LPC effect than those in emotionally unbiased contexts. Both the P2 and LPC effects were associated with the effect of emotional contexts in updating the lexical representations of the neutral target words.

To summarize, the ERP studies on single words and sentences indicated that younger adults often attend to negative features of a word, in a post-lexical stage, as reflected by the enhanced LPC to negative (vs. positive) words. Furthermore, the sentence ERP studies reflect two stages in processing emotionally incongruent content in sentences, in younger adults: (1) The P2/N400 effects reflect the detection and/or semantic processing of incongruent affective features of a word based on context, and (2) the PNP/LPC effects indicate the update of affective representations of the same word due to emotional incongruency built up by context.

However, two questions still remain. First, most ERP studies did not distinguish positive vs. negative features in the emotional contexts, which poses a question of whether there is emotional bias from the context effects. Second, even if a few studies did manipulate context valence (e.g., Moreno & Rivera, 2014), it is unclear how younger adults and older adults track and update emotional representations of a (same) word in plausible contexts. Most ERP studies used the violation paradigm, i.e., presenting implausible target words combined with prior contexts, which cannot truly reflect the possible update of emotional representations of a word before and after contexts. The only relevant study we found, if not none, is a behavioral study that examined the updating of affective representations of a sentence, and focused again on only younger adults (Lüdtke & Jacobs, 2015). Younger adults rated the sentence "*The grandpa is lonely.*" as equally negative as "*The burglar is lonely.*", even though the topic word "*grandpa*" was positive based on the affective norms (Vo et al., 2009). The authors suggested that this reflects a negativity bias in younger adults when updating the affective representation of a sentence.

The present study

To answer the above questions, here we investigated (1) whether younger and older adults update affective representations of an emotional word in the same affective context differently, and (2) how affective neural representations of a word change depending on emotional valence of contexts. We created three-sentence vignettes by manipulating emotional valence of topic words (positive, negative) and contexts (positive, negative). Most ERP studies examined the affective representations of a single word in contexts by measuring emotional responses of the word per se. Unlike past studies, we compared affective representations between the first and second occurrence of a topic word in younger and older adults, i.e., before and after emotional contexts update the affective representation of the topic word. We employed valence judgment tasks in both a web-based and an EEG experiment to track participants' update of affective and neural representations of an emotional word, respectively. Our overarching hypothesis was that emotional valence of the contexts affects affective representations of the topic words. We further hypothesized that if the AVH holds, negative (vs. positive) contexts should lead to more negative evaluations of all topic words, regardless of topic word valence. In contrast, if the SST holds, positive (vs. negative) contexts should lead to more positive evaluations of both positive and negative topic words. If neither holds, the very same word before and after positive and negative emotional contexts should show the same valence evaluation.

Experiment 1

Experiment 1 tested whether younger and older adults update affective representations of an emotional topic word in the same affective context differently, using a valence evaluation task. We predicted an age-dependent context effect: Based on the AVH, younger adults would rate both the positive and negative topic words in negative contexts as similarly negative, consistent with a negativity bias. In contrast, based on the SST, older adults would rate both the positive and negative topic words in positive contexts as similarly positive, consistent with a positivity bias.

Methods

Participants

Sixty younger (36 females, 1 non-binary, 1 unspecified sex, mean age ± SD = 19.7 ± 2.4 years, range = 18-30 years) and 43 older (24 females, mean age ± SD = 65.4 ± 3.8 years, range = 60-73 years) adults participated in the experiment. Participants were recruited from either the psychology subject pool for course credits, or via Prolific and online advertisements and received \$7.5. All the participants were native English speakers currently living in the U.S., with normal or corrected-to-normal vision. None had language-related disorders, mental illness, and were on psychoactive medications likely to modulate emotional processes (e.g. anti-depressants), based on self-report. All gave informed consents in accordance with the local ethics committee prior to participation.

We ensured that participants in both the age groups were non-depressed using the Beck Depression Index – second edition (BDI-II; Beck et al., 1996). Sixteen younger and two older participants were excluded due to a total BDI-II score larger than 14, the cutoff score for borderline depression. To examine the influence of affective traits on emotional word processing (Ku et al., 2020), participants completed the Positive and Negative Affect Schedule – trait version (PANAS; Watson et al., 1988), which includes two self-reported subscales for positive affect (PA) and negative affect (NA), respectively. Each participant indicated the level one generally feels this way to 20 items, each on a 5-point scale (1 = *not at all* to 5 = *extremely*).

Additionally, all the participants had Mini-Mental State Examination (MMSE; Folstein et al., 1975) scores of greater than 27, which indicated no cognitive impairment. To examine the effect of cognitive ability on the positivity bias (Ku et al., 2022), participants completed the Digit Symbol Substitution Task (DSST) (Wechsler, 1997) as a general assessment of cognitive functions (Jaeger, 2018), and an abbreviated version of the Wisconsin Card Sorting Test (WCST) that specifically probes cognitive control, especially for inhibition (Greve, 2001).

For the data analysis, eight younger and four older participants were excluded due to the failure of attention checks. One older adult was excluded due to equipment errors. The characteristics of the remaining participants are summarized in Table 1.

Table 1. Exp. 1 participant characteristics

Mean (SD)	Younger adults	Older adults	*t*	*p*
N	36	36	N/A	N/A
Age	19.72 (2.68)	65.61 (3.69)	N/A	N/A
Sex	M: 14, F: 21, Unidentified: 1	M: 16, F: 20	N/A	N/A
BDI-II	5.28 (4.08)	3.17 (3.00)	2.50	.015
PA	35.42 (6.46)	35.53 (7.36)	-0.07	.946
NA	18.28 (4.93)	11.94 (2.83)	6.68	<.001
MMSE	29.11 (1.21)	29.56 (0.70)	-1.91	.061
DSST	61.83 (8.77)	54.94 (14.79)	2.40	.011
WCST	42.14 (10.04)	35.42 (11.83)	-60.38	<.001

Materials

The stimuli consist of 320 three-sentence vignettes divided into 4 conditions, as shown in Table 2: 80 positive topic words in positive contexts, 80 positive topic words in negative contexts, 80 negative topic words in positive contexts, and 80 negative topic words in negative contexts. In each vignette, a topic word appears once in the first sentence and a second time in the third sentence at the subject position. In the second sentence of each vignette, a positive/negative adjective acts as the context word to shift the valence of the topic word.

Table 2. Stimulus example

Conditions	**Positive topic word (underlined)**	**Negative topic word (underlined)**
Positive context (italicized)	The **pianist** had a new performance. Her skills were ***remarkable***. The **pianist** practiced every day.	The **dentist** often worked with children. They found him ***trustworthy***. The **dentist** cared about them.
Negative context (italicized)	The **pianist** had a new performance. Her skills were ***rusty***. The **pianist** practiced every day.	The **dentist** often worked with children. They found him ***formidable***. The **dentist** cared about them.

Topic words were selected from the affective norms for English words (Warriner et al., 2013). In this norm, subjective ratings of valence and arousal are measured with 9-point Likert scales (1 = *unhappy* to 9 = *happy*; 1 = *calm* to 9 = *aroused*). Topic words are all low-arousing nouns (mean ratings < 5), as the positivity bias in older adults impacts low-arousing words more (Ku et al., 2022). No arousal differences were found between positive and negative topic words (p = .24). To avoid age differences, arousal ratings were matched in each condition between younger and older adults (both p values > .22), based on the same norms. On average, positive topic words scored higher on valence ratings than negative ones ($p < .001$). Older adults showed higher valence ratings than younger adults in positive ($p < .01$), but not negative topic words ($p = .08$). Word length ($t(158) = -0.04$, $p = .97$), frequency ($t(158) = 1.41$, $p = .16$), and concreteness ($t(158) = 1.55$, $p = .12$) were matched between conditions for topic words, based on the Corpus of Contemporary American English (Davies, 2009), and the English Lexicon Project database (Balota et al., 2007). The characteristics of the topic words used in the experiment are shown in Table 3A.

Adjectival context words were normed on the same 9-point Likert scales for emotional valence and arousal with a different group of undergraduate participants (N = 34 younger adults). Positive context words showed higher valence ratings than negative ones ($t(159) = 40.87$, $p < .01$). No arousal differences were found between positive and negative context words ($t(159) = 0.73$, p = .46). To rule out the possible confound from adjective context words on the second occurrence of the topic words, word length ($t(159) = 1.76$, $p = .08$), frequency ($t(159) = -0.84$, $p = .40$), concreteness ($t(138) = 0.22$, $p = .83$), and word probability ($t(159) =-1.10$, $p = .27$) of the adjective context words were further matched between the conditions using the same corpora as in Experiment 1 and the gpt-2 (unidirectional) model. The characteristics of the topic and adjective context words used in the experiment are shown in Table 3.

All the 320 vignettes were divided into two lists. Each list consists of 160 topic words with 80 positive/negative contexts. The stimulus order in each list was pseudo-randomized such that no more than four consecutive trials came from the same condition. The list order was counterbalanced with participants' number. Participants read each vignette of the same topic word only once.

Table 3. Stimulus characteristics

Mean (SD)		Negative topic word	Positive topic word	Negative context word	Positive context word
Valence		3.20 (0.49)	7.14 (0.38)	3.33 (0.80)	6.67 (0.85)
	Younger	3.34 (0.60)	7.02 (0.57)	3.33 (0.80)	6.67 (0.85)
	Older	3.09 (0.71)	7.29 (0.52)	N/A	N/A
Arousal		4.13 (0.55)	4.02 (0.61)	4.93 (0.58)	4.98 (0.57)
	Younger	4.13 (0.74)	4.15 (0.86)	4.93 (0.58)	4.98 (0.57)
	Older	4.08 (0.70)	3.90 (0.79)	N/A	N/A
Concreteness		4.05 (0.87)	3.84 (0.81)	2.29 (0.56)	2.28 (0.55)
Length		6.75 (1.93)	6.76 (1.67)	7.99 (2.17)	7.57 (2.39)
Frequency		3.99 (0.72)	3.53 (0.77)	3.82 (0.72)	3.90 (0.73)
Word probability		N/A	N/A	$2.98*10^{-6}$ ($1.97*10^{-5}$)	$5.87*10^{-6}$ ($2.62*10^{-5}$)

Procedure

We conducted a behavioral experiment via Zoom sessions. Participants were first interviewed by an experimenter for the MMSE. Then, participants completed the DSST and WCST via OpenSesame/OSWeb extension (Mathôt et al., 2012) under an experimenter's instructions. For the DSST, in each trial, participants needed to match a symbol to a number based on a key on the top of the screen, by pressing the corresponding number key on their keyboard, as quickly and accurately as possible. The number of the correct responses with the allotted time, i.e., 90 seconds, was recorded. For the WCST, participants matched 64 cards, one at a time, to one of four sample cards on the top of the screen, by either color, shape, or number. The computer would indicate if the matching was correct or not after each response. After participants correctly matched five cards in a row, the computer would automatically change the matching criteria. The total number of the correct matches was recorded.

Next, participants filled out a web-based Qualtric survey on their language background, and the BDI-II/PANAS. Participants were then presented with the topic words in isolation, and rated the valence of each topic word. In the last part of the survey, they read the first two sentences in each vignette, with both the two sentences presented on the screen at once, and rated the valence of each topic word again. We presented the only first two sentences in the vignettes to rule out the confounding of emotional information, if any, in the third sentence of each vignette. Emotional valence was rated on a 1-9 scale (1 = *very negative* to 9 = *very positive*). To avoid fatigue, participants rated six or seven items at most as a chunk each time on the screen. The entire experiment lasted for about 75-90 minutes.

Data analysis

To examine the update of affective representations of the topic words, and to rule out the confound of age differences on the valence ratings in pre-experiment norming, valence ratings of each topic word in isolation were subtracted from those ratings of the same topic word embedded in the first two sentences of each vignette, for each item and each participant. To account for by-participant and by-item random variances, we entered these difference ratings into a linear mixed effect regression model, as the dependent variable, using R (R Core Team, 2022; version 4.2) in RStudio (RStudio Team, 2022; version 2022.07) with the lme4 package (Bates et al., 2015). The fixed effects in the model included the categorical variables of Topic (negative vs. positive), Context (negative vs. positive), Age (younger vs. older), and their interaction effects. The random effects included by-participant and by-item random intercepts. We also included Topic, Context, and their interaction as by-participant random slopes, along with Context as by-item random slopes (Barr et al., 2013).

Independent variables were dummy-coded (Topic/Context word valence: negative = 0, positive = 1; Age: younger = 0, older = 1). A Box–Cox transformation test was conducted to identify an optimal transformation to improve normality of the distribution of the dependent variable (Box & Cox, 1964). Only significant coefficient t-statistics and p-values associated with the fixed effects were reported, via Satterthwaite's degrees of freedom method with the lmerTest package (Kuznetsova et al., 2017). Single contrasts were further conducted if an interaction effect was found, via the least-squares means method with the lsmean package (Lenth, 2016).

To explore participants' cognitive and affective characteristics on the valence evaluation of topic words in context, we further performed four multiple linear regression models, with participants' age, DSST scores, WCST scores, PA scores, and NA scores as independent variables/predictors, and the mean valence ratings from each of the four conditions as the dependent variables. Each dependent variable and the predictors were entered simultaneously in the model to determine which predictor could significantly account for the variance in the dependent variable, when holding other predictors constant.

Results

Based on the Box–Cox transformation test, no transformation was needed for the difference ratings, so the original difference ratings were entered into the model. Consistent with our design, the analysis showed a significant main effect of Context (β = 1.52, t(72.67) = 4.01, p < .001).

Regardless of topic word valence, topic words with positive contexts (*M* = 0.78, *SD* = 2.17) were rated as more positive than those with negative contexts (*M* = -1.1, *SD* = 2.69), compared with topic words in isolation. The main effect of Topic was also significant (β = -1.44, *t*(76.83) = -3.65, *p* < .001). Irrespective of context word valence, positive topic words in context (*M* = -0.91, *SD* = 2.65) were rated as less positive than negative topic words in context (*M* = 0.59, *SD* = 2.36), compared with topic words in isolation. In addition, there was a marginal interaction of Topic and Context (β = 0.31, *t*(99.18) = 1.83, *p* = .07): The rating differences were larger when negative topic words were followed by positive (*M* = 1.41, *SD* = 2.59) vs. negative context (*M* = -0.24, *SD* =1.74; *Z* = -6.13, *p* < .001). Similarly, the rating differences were larger when positive topic words were followed by negative (*M* = -1.96, *SD* = 3.16) vs. positive context (*M* = 0.15, *SD* = 1.36; *Z* = -6.14, *p* < .001). This marginal interaction also indicated that the influence of negative contexts on positive topic words tended to be stronger than that of positive contexts on negative topic words (Fig. 1A; the difference between black and gray bar was larger than that between red and pink bar). Due to null effect or interaction involving Age (all *p* values > .18), and high multicollinearity between Age and other independent variables, we fitted a reduced model by removing Age from the fixed effects. The reduced model showed the same results as described above, with a significant interaction of Topic and Context (β = 0.45, *t*(118.10) = 3.48, *p* < .001). The model comparison suggested no difference between the reduced and full model (χ^2 = 6.54, *p* = .16).

In the multiple regression models, age and positive affect significantly predicted the mean valence ratings of positive topic words in positive contexts (adjusted R-square = 15.4%, *F*(5,66) = 3.58, *p* = .01). Older age (β = 0.39, *t* = 2.49, *p* = .02) and higher positive affect (β = 0.33, *t* = 2.61, *p* = .01) were associated with more positive ratings of positive topic words in positive contexts (Fig. 1B). These two predictors showed low multicollinearity (both variance inflation factors <

2.10), suggesting separate contribution for accounting for the variance in the valence ratings. No other significant models were found.

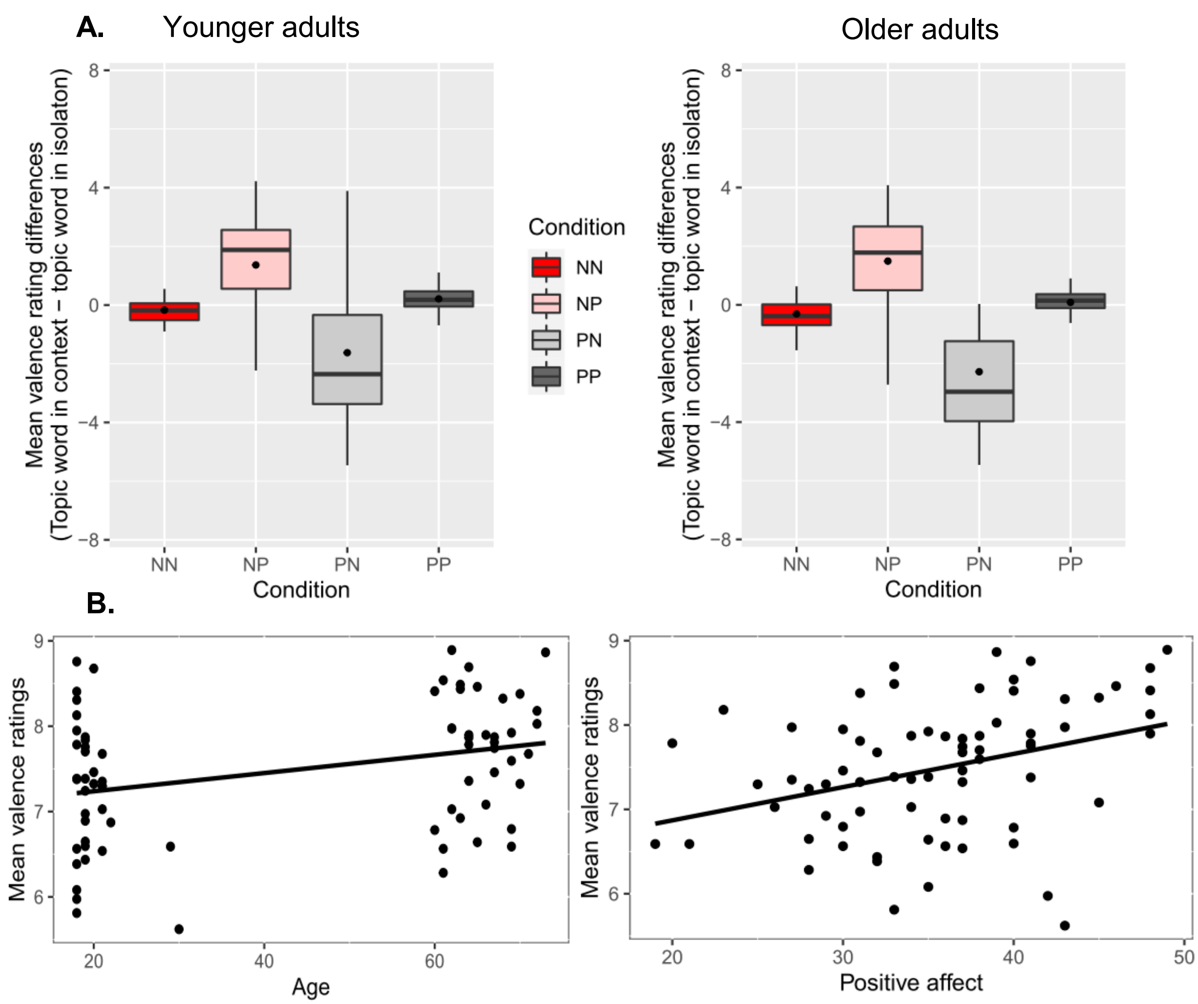

Fig. 1. (A) Boxplots for the Exp. 1 mean valence rating differences (subtracted from topic words in isolation) for positive topic words in positive contexts (PP), positive topic words in negative contexts (PN), negative topic words in positive contexts (NP), and negative topic words in negative contexts (NN), in younger adults (left panel) and older adults (right panel). Black dots and horizontal lines in the boxes denote the means and medians, respectively. **(B)** Correlation plots of mean valence rating differences for positive topic words in positive context and age (left panel)/positive affect (right panel)

Discussion

Our rating results revealed that in both the age groups, for positive topic words, negative contexts led to more negative evaluations than positive contexts. For negative topic words, positive contexts led to more positive evaluations than negative contexts. Also, the observed effect of negative contexts seemed to be stronger than that of the positive contexts across the two age groups, as indicated by the interaction (i.e., slope differences) of Topic and Context word valence in the linear mixed regression models. These data suggested that the context effect on the valence evaluation of the topic words depends on topic word valence, but not age: In both younger and older adults, topic words and contexts with opposite valence (i.e., when there was an emotional shift) influenced participants' evaluation more than those with the same valence.

In addition, the multiple regression models showed that age and positive affect predicts the valence ratings of positive topic words in positive contexts, partially supporting a positivity bias in older adults. We did not find a correlation between age and positive affect (p = .251), suggesting a separate contribution of age and positive affective trait in explaining the variance in the valence ratings of positive topic words in positive contexts. However, these results could be further confounded by the difference in the pre-experiment ratings of topic words in isolation: Older adults rated the positive topic words in isolation as being more positive than younger adults did. Therefore, caution should be exercised when interpreting these results.

There are several points to consider in terms of the null age-dependent context effect, which led us to the Experiment 2. First, the behavioral ratings only provide us a coarse picture of post-lexical evaluations of valence features. In our survey, each valence rating could take up to seconds. As negative content often leads to delayed disengagement of attention (Kauschke et al., 2019), it is possible that we observed a stronger negativity bias in both the age groups from the survey ratings. Second, according to the SST, older adults' positivity bias is related to their prosocial motivations. In our Experiment 1, older adults were mainly recruited from the Prolific platform, and took the survey possibly due to financial reasons, just as the younger adults who participated for course credits. This is in contrast to other lab-based or in-person studies showing age-related positivity bias, in which older adults may participate to fulfill their prosocial engagement. This could possibly smear out the age effects. Lastly, the behavioral ratings did not inform us how contexts affect the processing of affective neural representations of a word, during or before the lexical-semantic stage.

Experiment 2

Experiment 2 examined how affective-neural representations of a word change depending on emotional valence of contexts, across younger and older adults. We recorded the scalp EEG from the first and second occurrence of the topic words in the three-sentence vignettes. This provided us a track of neural representations of valence features in the topic words. We predicted that based on the AVH, negative (vs. positive) contexts would lead to more negative evaluations of the topic words, regardless of topic word valence, in younger adults. This would be reflected by an enhanced N400 and/or late positivity, as they were linked to the depth of semantic processing/integration and the update of mental affective representations. For older adults, based on the SST, positive (vs. negative) contexts would lead to more positive evaluations of the topic words, irrespective of topic word valence. This would be linked to an increased N400 and/or late positivity to topic words in positive contexts. We did not predict any EPN/P2 effects specifically, as no studies showed context-based emotion effects on the EPN, and the very few findings on the P2 were mixed (Chou et al., 2020; Lai & Huettig, 2016).

Participants

Forty-eight younger (29 females, 1 non-binary, 1 unspecified sex, mean age ± SD = 18.8 ± 1.5 years, range = 18-25 years) and 35 older (23 females, mean age ± SD = 68.4 ± 4.2 years, range = 60-77 years) adults participated in the experiment. The younger participants were undergraduate students recruited from the psychology subject pool for course credits. The older participants were recruited from senior community centers and online/newspaper advertisements, and received $25. All the participants were right-handed, native English speakers, with normal or corrected-to-normal vision. None had language-related disorders, neurological/psychological illness, and were on psychoactive medications likely to modulate emotional processes, based on self-report. All gave informed consents in accordance with the local ethics committee prior to participation.

We collected the same affective and cognitive measures from the participants, including the BDI-II, PANAS, MMSE, DSST, and WCST, as in Experiment 1. We excluded two younger participants due to a high BDI-II score of larger than 14. Eighteen younger and 7 older participants were excluded due to insufficient trials (< 60%) after artifact rejection of the EEG data, possibly due to the mask requirement during COVID-19. The characteristics of the remaining participants are summarized in Table 4.

Table 4. Exp. 2 participant characteristics

Mean (SD)	Younger adults	Older adults	*t*	*p*
N	28	28	N/A	N/A
Age	18.82 (1.47)	68.43 (4.25)	N/A	N/A
Sex	M: 7, F: 21	M: 11, F: 17	N/A	N/A
BDI-II	2.61 (2.62)	3.96 (3.00)	-1.80	.077
PA	37.50 (4.27)	35.32 (7.72)	1.31	.197
NA	16.32 (5.06)	12.82 (1.98)	3.41	.002
MMSE	29.61 (0.83)	28.32 (5.64)	1.19	.238
DSST	58.04 (7.08)	39.69 (7.25)	9.40	< .001
WCST	42.32 (6.06)	37.15 (7.04)	2.90	.005

Materials

The materials were identical as in Experiment 1.

Procedure

Participants first completed a questionnaire about their language use and health condition. An elastic cap mounted with 32-channel Ag/AgCl electrodes was then fitted on the participant's head. After the EEG capping procedure, the participant was taken to a sound-proofed booth and seated at a desk facing a computer screen 80-100 cm in front of them. The stimuli were presented visually in a white font (Font: Courier New; Point size: 20) against a black background via E-prime 3.0 software (Psychology Software Tools, Inc.).

An example trial is illustrated in Fig. 2. Each trial started with a central fixation cross for 500 ms, followed by a blank screen for 200 ms. Then, each vignette was presented word-by-word in a rapid serial presentation paradigm (topic words and adjective context words: 260-420 ms depending on the word length, other words: 300 ms, interstimulus interval: 200 ms). Participants were instructed to read each word carefully and silently. A rating scale then came up on the center of the screen after a 700-ms blank in the end of each vignette. When cued by the scale, participants needed to judge how they felt about the topic word in the vignette, as quickly as possible, by pressing a button (-1 = negative, 0 = neutral, 1 = positive) on a response box. After the response, a "blink or continue" screen would appear following a 300-ms blank so that participants could rest their eyes or take a quick break in a self-paced way.

Before the formal experiment, participants did eight practice trials to familiarize themselves with the procedure. The session of the experiment were divided into four blocks, with a short break between blocks. Each block lasted for 10 minutes, and the entire EEG session lasted for about 50 minutes.

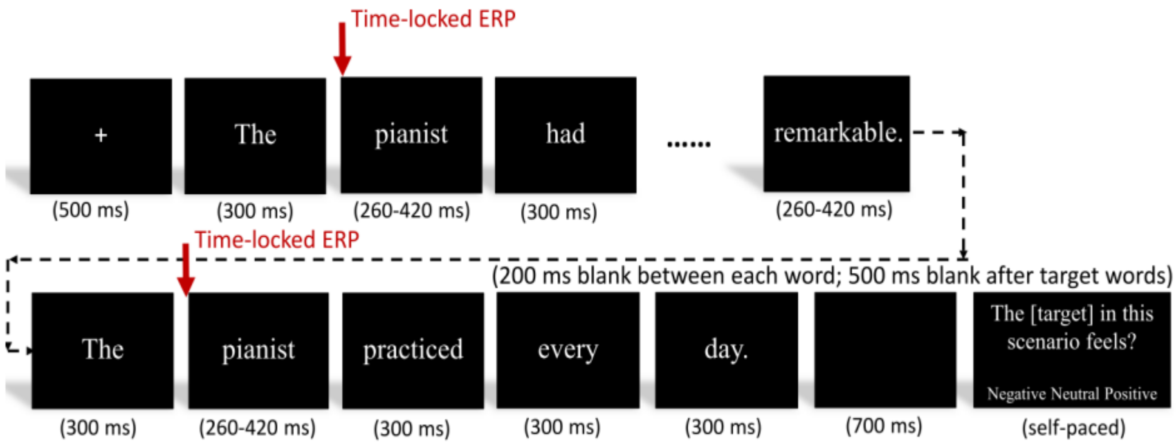

Fig. 2. An example trial in the valence judgment task

EEG acquisition

The electroencephalogram (EEG) was recorded from 32 electrodes placed on an electrode cap arranged in the 10-10 system (actiCAP, Brain Products GmBH). The scalp EEGs were recorded with a sampling rate of 500 Hz and referenced to Cz during online recording (actiCHamp, Brain Products GmBH). A forehead electrode served as the ground. To avoid impulse artifacts, the online low pass filter was set to 140Hz and the high pass filter was set as DC recording. The electrode impedance was kept below 10 kΩ.

ERP analysis

EEG recordings were processed offline with the EEGLAB toolbox (Delorme & Makeig, 2004) and the ERPLAB plugins (Lopez-Calderon & Luck, 2014) implemented in Matlab (Mathwork Inc.). For the ERP analysis, the EEG data were first bandpass filtered with frequency values set as 0.1-30 Hz. Data were re-referenced to the average of both mastoids (i.e. TP9 and TP10). Then, the continuous EEG data were epoched by setting the interval as 200 ms before and 1000 ms after the stimulus onset, using the pre-stimulus interval of -200 to 0 ms as the baseline correction. An independent component analysis (ICA) with the runica algorithm implemented in EEGLAB was used to identify eye and muscle artifacts. Those components which had more than 90% probability of being the muscle or eye artifacts, as automatically labelled by using ICLabel plugin in EEGLAB, were removed from the data. Trials contaminated with artifacts due to peak deflections exceeding ±75 mV, or excessive noises due to fatigue were rejected. The average trial acceptance rates were 73.91% for younger adults and 73.46% for older adults. No difference was found for the number of trials included between groups ($t(54) = 0.21$, $p = .83$). Finally, the ERP data were averaged for each condition in the younger and older participants.

Statistical analysis

For the behavioral data, valence ratings with response times more than 3 standard deviations above/below all the participant's mean were excluded (1.95% of total responses). As in Experiment 1, we entered the valence ratings into a linear mixed effect regression model, as the dependent variable. The fixed effects in the model included Topic (negative vs. positive), Context (negative vs. positive), Age (younger, older), and their interaction effects. To reach the model convergence, the random structure only included by-participant and by-item random intercepts and Context as by-participant random slopes.

For the ERP data, to examine the change in the affective representations of the topic words, we subtracted the mean ERP amplitudes of the first occurrence of the topic words from those of the second occurrence of the topic words. The mean ERP amplitudes of the difference waves were exported from 180-300 ms, 300-500 ms, and 600-800 ms after the topic word onsets, based on visual inspection of the waveforms and past literature (Chou et al., 2020; Delaney-Busch et al., 2016; Delaney-Busch & Kuperberg, 2013). To characterize the spatial distribution of the ERP effects, a repeated-measures ANOVA (RM-ANOVA) of Age (younger, older) x Topic (negative, positive) x Context (negative, positive) x Region (anterior, central, posterior) was conducted in each time window, using the difference wave amplitudes. Guided by visual inspection of the ERP waveforms and past literature on emotion word processing (e.g., Ku et al., 2022), ERP difference wave amplitudes were averaged over three electrodes from each of the three regions of interest: anterior (F3, Fz, F4), central (C3, Cz, C4), and posterior (P3, Pz, P4) sites. When the sphericity assumption was violated, the Greenhouse-Geisser correction was applied. The alpha levels were set as 0.05 for all statistic tests. To correct multiple comparisons, the Bonferroni correction was applied.

To further compare ERP effects across the age groups, we adopted a two-fold strategy. First, we focused on the Region of Interest (ROI) analysis guided by the above omnibus analysis, which led us to collapse over (1) all the nine electrodes for the N400 effect, and (2) the posterior electrodes (P3, Pz, P4) for the P2 and LPC effect. We then entered the mean difference wave amplitudes in the P2, N400, and LPC time windows into a three-way RM-ANOVA with Topic and Context as within-subjects factors and Age as a between-subjects factor. Second, we conducted ROI-based regression analyses with difference wave amplitudes of Topic (negative minus positive topic words) and Context effects (negative minus positive contexts) in the P2, N400 and LPC windows as dependent variables. Predictor variables included participants' age, PA scores, NA scores, DSST scores, and WCST scores.

Results

Behavioral results

Based on the Box–Cox transformation test, no transformation was needed for the mean valence ratings. The linear mixed effect model analysis showed a significant effect of Topic (β = 0.34, t(93.38) = 5.57, p < .001). Regardless of context word valence, positive topic words (M = 0.17, SD = 0.85) were rated as being more positive than negative topic words (M = -0.07, SD = 0.83). There were also an interaction of Topic x Age (β = -0.20, t(8514.31) = -5.57, p < .001), and of Topic x Context x Age (β = 0.20, t(8514.91) = 4.94, p < .001). Due to the three-way interaction and high multicolineairty between Age and Context, we further fitted a reduced model in each age group separately, with only Topic, Context, and their interaction as the fixed effects and the same random structure described above. These reduced models showed only a significant effect of Topic in both younger (β = 0.34, t(155.97) = 5.29, p < .001) and older adults (β = 0.14, t(155.67) = 2.21, p = .03). Irrespective of context word valence, positive topic words (Younger adults: M = 0.19, SD = 0.85; Older adults: M = 0.16, SD = 0.86) were rated as being more positive than negative words (M = -0.1, SD = 0.82; Older adults: M = -0.04, SD = 0.84; Fig. 3).

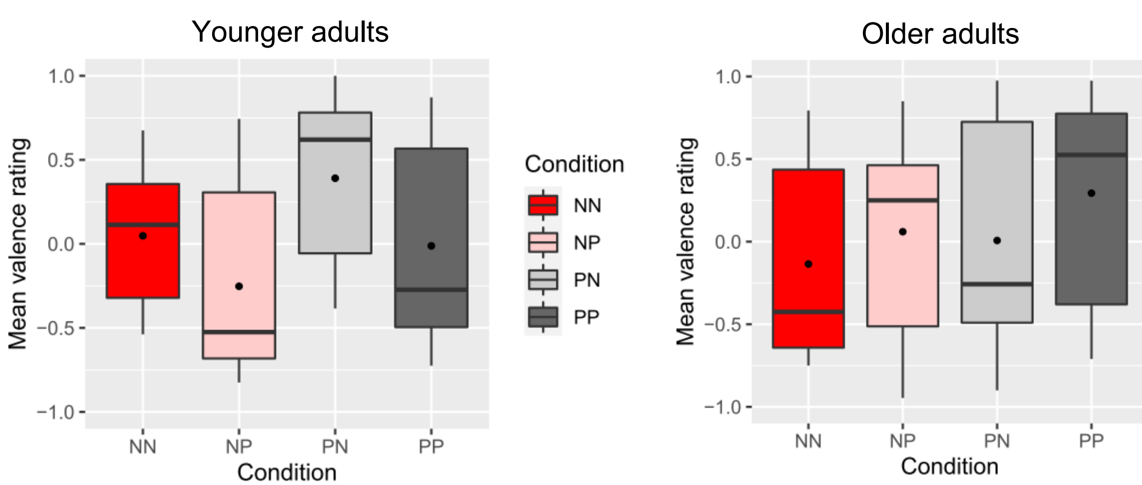

Fig. 3. Boxplots for the Exp. 2 mean valence ratings for positive topic words in positive context (PP), positive topic words in negative context (PN), negative topic words in positive context (NP), and negative topic words in negative context (NN), in younger adults (left panel) and older adults

(right panel). Black dots and horizontal lines in the boxes denote the means and medians, respectively.

ERP results

The grand averaged ERP waveforms for the first and second occurrence of the topic words based on 28 subjects each group are shown in Fig. 4A and 4B. For both the occurrences of the topic word, all the participants showed clear visual N1 and P2 complexes, indicating normal early visual processing. Additionally, in younger adults, all the conditions showed ERP amplitude deflections starting from ~180 ms, identified as P2, N400s, and LPC. Consistent with Ku et al. (2022), in older adults, the first occurrence of negative topic words elicited a smaller N400 at ~350 ms and a larger LPC at ~ 600 ms than that of positive topic words, regardless of context word valence. In older adults, negative topic words, when presented the second time after positive context, also elicied a larger negativity starting slightly earlier from ~180 ms, compared with the other conditions. To capture the change of affective representations of the topic words, difference waves between the first and second occurrence of the topic words were calculated, and are shown in Fig. 5A.

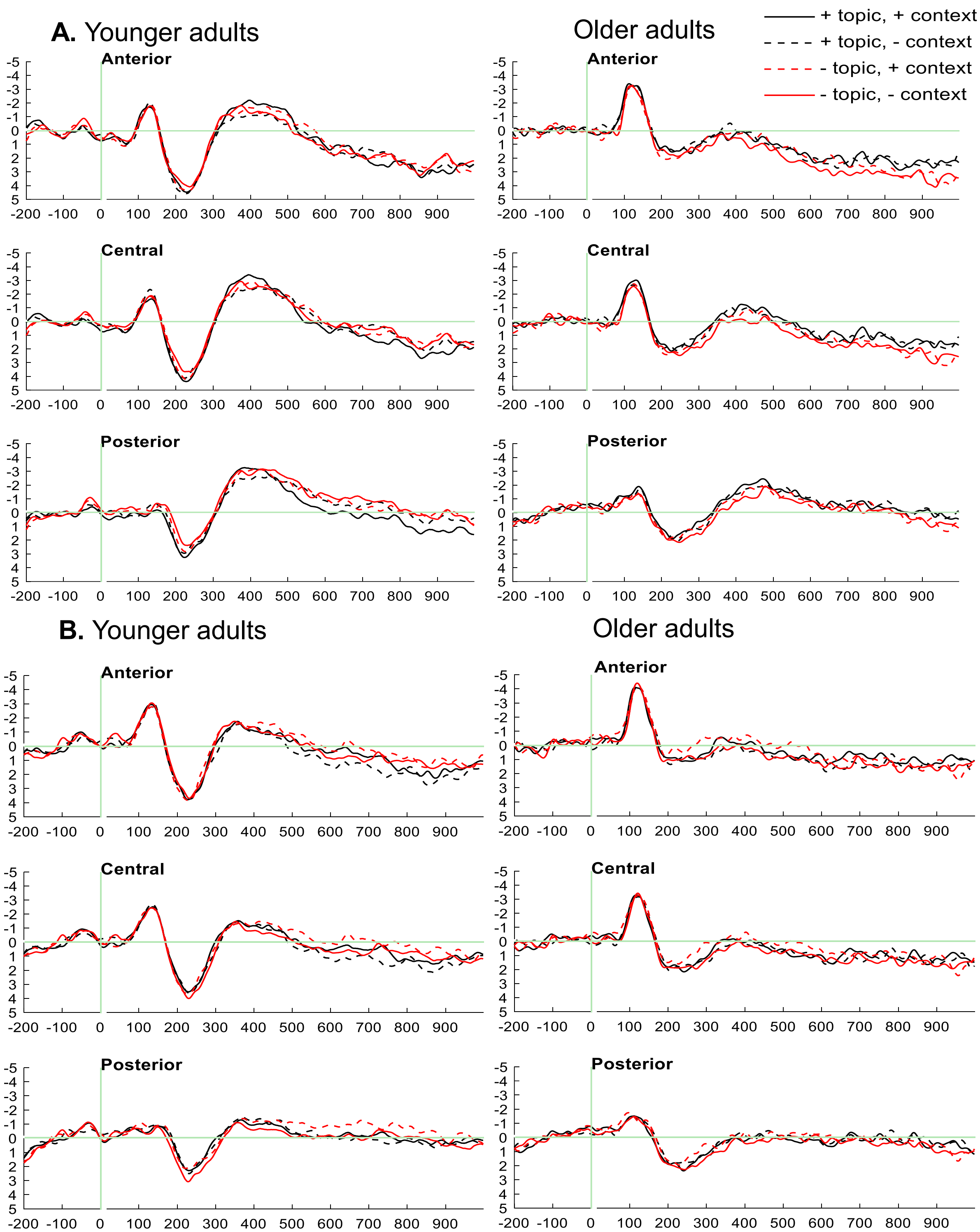

Fig. 4. Grand averaged ERP waveforms (N = 28 each group) for the first (panel A) and second (panel B) occurrence of the topic words for positive topic words in positive context (+ topic, + context), positive topic words in negative context (+ topic, - context), negative topic words in positive context (- topic, + context), and negative topic words in negative context (- topic, -

context), at anterior, central, and posterior scalp regions, in younger adults (left panel) and older adults (right panel).

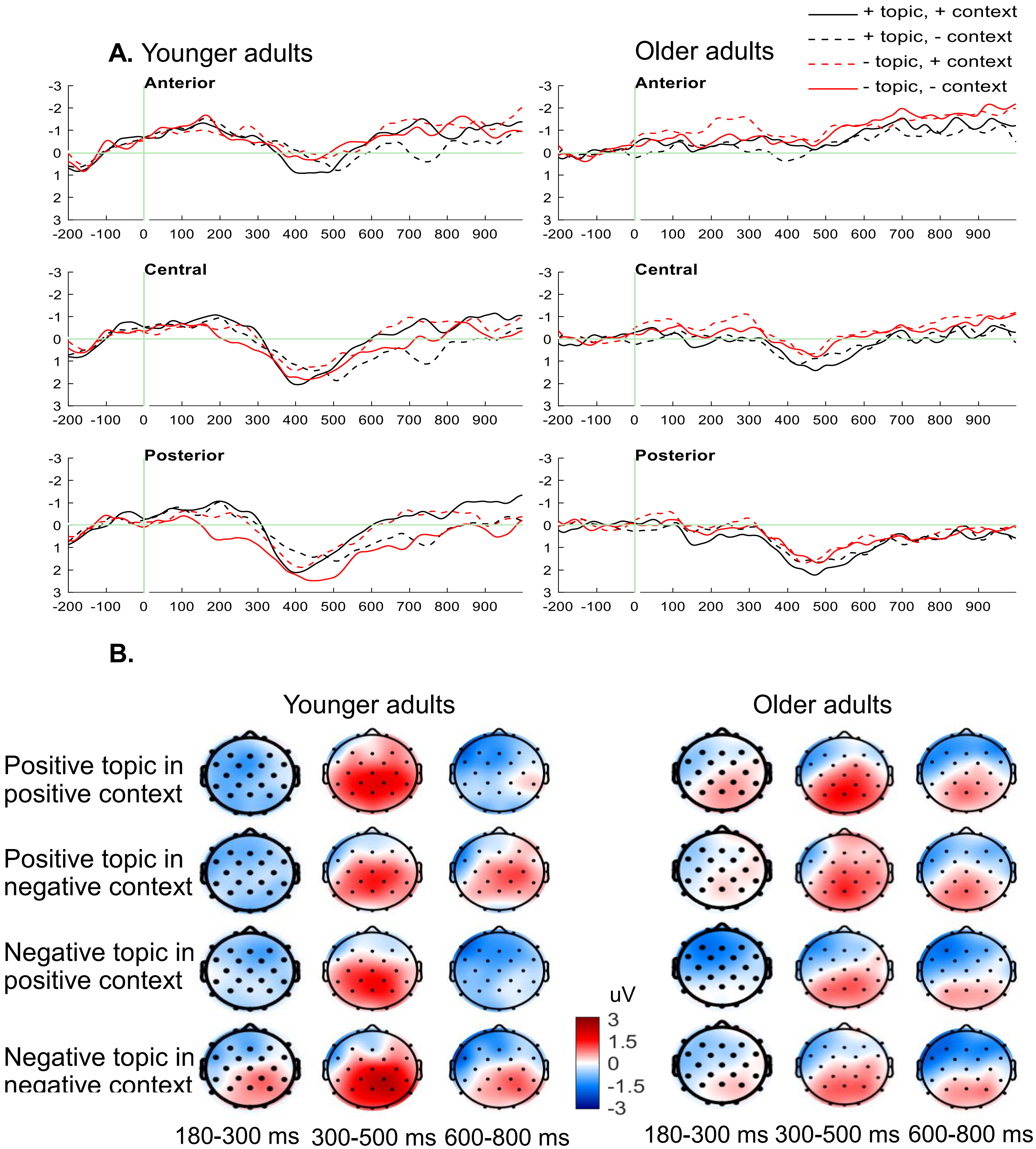

Fig. 5. (A) Grand averaged ERP waveforms (N = 28 each group, low-pass filetered at 10 Hz for the visualization) for the difference waves of the 2nd minus 1st occurrence of the topic words for positive topic words in positive context (+ topic, + context), positive topic words in negative context (+ topic, - context), negative topic words in positive context (- topic, + context), and negative topic words in negative context (- topic, - context), at anterior, central, and posterior scalp

regions in younger adults (left panel) and older adults (right panel). **(B)** The scalp topographies of the P2, N400 and LPC effects from the difference waves in each condition, in younger and older adults. Note that for the N400 effects, the red area indicated a reduced N400 at the 2nd occurrence of the topic words, compared with the 1st occurrence of the same words.

P2 (180-300 ms)

In the 180-300 ms time window, the RM-ANOVA showed a Topic x Age interaction (F(1, 54) = 4.13, p = .05, η^2 = 0.07). In older adults, positive topic words (M = 0.01, SD = 1.37), regardless of context valence, tended to increase the P2 more than negative words (M = -0.54, SD = 1.64; uncorrected p = .04, p = .09), whereas no Topic effect was found in younger adults. There was also a Topic x Region interaction (F(2, 108) = 6.88, p = .01, η^2 = 0.11). Negative topic words, regardless of context valence and age, increased the P2 more in the posterior than central sites, with the smallest increase in the anterior sites (anterior: M = -0.94, SD = 1.79, central: M = -0.39, SD = 1.68, posterior: M = 0.12, SD = 1.55; all p values < .001). Additionally, there was an interaction of Context, Region, and Age (F(2, 108) = 4.27, p = .03, η^2 = 0.07). However, follow-up comparisons revealed no effects or interaction involving Context in each age group. No other significant effects or interactions involving the factors of Topic, Context, and/or Age were found.

N400 (300-500 ms)

The RM-ANOVA in the 300-500 ms time window revealed no significant main effects or interactions involving the factors of Topic, Context, and/or Age (all F values < 2.76, all p values > .1).

LPC (600-800 ms)

The RM-ANOVA in the 600-800 ms time window showed a main Context effect ($F(1, 54) = 4.62$, $p = .04$, $\eta^2 = 0.08$), and a Topic x Region interaction ($F(2, 108) = 4.05$, $p = .04$, $\eta^2 = 0.07$). Negative contexts ($M = 0.07$, $SD = 1.86$) increased the LPC more than positive context ($M = -0.57$, $SD = 1.66$), regardless of topic word valence and age. Positive topic words, irrespective of context word valence and age, increased the LPC more in both the central and posterior region than the anterior region (anterior: $M = -0.77$, $SD = 2.21$, central: $M = 0.09$, $SD = 1.98$, posterior: $M = 0.41$, $SD = 1.84$; both p values < .01). Similarly, negative topic words increased the LPC more in the posterior than central region, with the anterior region showing the smallest increase (anterior: $M = -1.33$, $SD = 2.09$, central: $M = -0.33$, $SD = 1.92$, posterior: $M = 0.43$, $SD = 2.06$; all p values < .001).

Age comparisons

To compare age differences on the change of affective representations, separate ROI analyses were conducted based on the omnibus RM-ANOVA results above. In the P2 time window, mean difference amplitudes were collapsed over the posterior (P3, Pz, P4) electrodes, and entered into an RM-ANOVA with the factors of Topic, Context, and Age. The results showed a Topic x Age interaction ($F(1, 54) = 6.17$, $p = .02$, $\eta^2 = 0.1$). Positive topic words, regardless of context valence, increased the P2 more in older adults ($M = 0.32$, $SD = 1.52$) than in younger adults ($M = -0.81$, $SD = 1.53$; $p = .03$, Fig. 5). Within younger adults, these positive topic words also showed a decreased P2 compared with negative topic words in all the contexts ($M = 0.17$, $SD = 1.35$), despite failing to achieve significance after multiple corrections (uncorrected $p = .03$, $p = .12$).

In the N400 time window, mean difference amplitudes were collapsed over all the nine electrodes and entered into the same RM-ANOVA. No significant effects or interactions were found for any factors (all F values < 1.58, $p > .21$). In the LPC time window, mean difference amplitudes were collapsed over the posterior (P3, Pz, P4) electrodes, and entered into the same RM-ANOVA. The results revealed a main Context effect ($F(1, 54) = 5.78$, $p = .02$, $\eta^2 = 0.10$), and a marginal Context x Age interaction ($F(1, 54) = 3.07$, $p = .07$, $\eta^2 = 0.06$). In younger (but not older) adults, negative contexts ($M = 0.71$, $SD = 1.76$) increased the LPC more than positive contexts ($M = -0.42$, $SD = 1.61$; $p = .02$), regardless of topic word valence (Fig. 5). In addition, older adults ($M = 0.62$, $SD = 1.86$) tended to show a larger LPC increase in response to all the topic words in positive contexts, irrespective of topic word valence, compared with younger adults ($M = -0.42$, $SD = 1.61$; uncorrected $p = .03$, $p = .12$).

In the P2 time window, regression analyses showed a significant model only for the Topic effect (adjusted R-square = 16.8%, $F(5, 45) = 3.02$, $p = .02$). In this model, age ($\beta = -0.80$, $t = -3.3$, $p < .01$) and negative affect ($\beta = -0.36$, $t = -2.34$, $p = .02$) separately predicted the size of the P2 of Topic effect. Older age and higher negative affect were associated with smaller P2 differences between negative and positive topic words (Figs. 5 and 6). In the LPC time window, the model only approached significance (adjusted R-square = 11.8%, $F(5, 45) = 2.34$, $p = .06$) for the Context effect. In this model, age ($\beta = -0.53$, $t = -2.17$, $p = .04$) and negative affect ($\beta = -0.39$, $t = -2.47$, $p = .02$) separately predicted the size of the LPC of Context effect. Older age and higher negative affect were associated with smaller LPC differences between the topic words in negative and positive contexts (Figs. 5 and 6). In both the time windows, negative affect acted as a partial mediator between the relationship of age and its corresponding ERP effect. No significant models were found in the N400 time window.

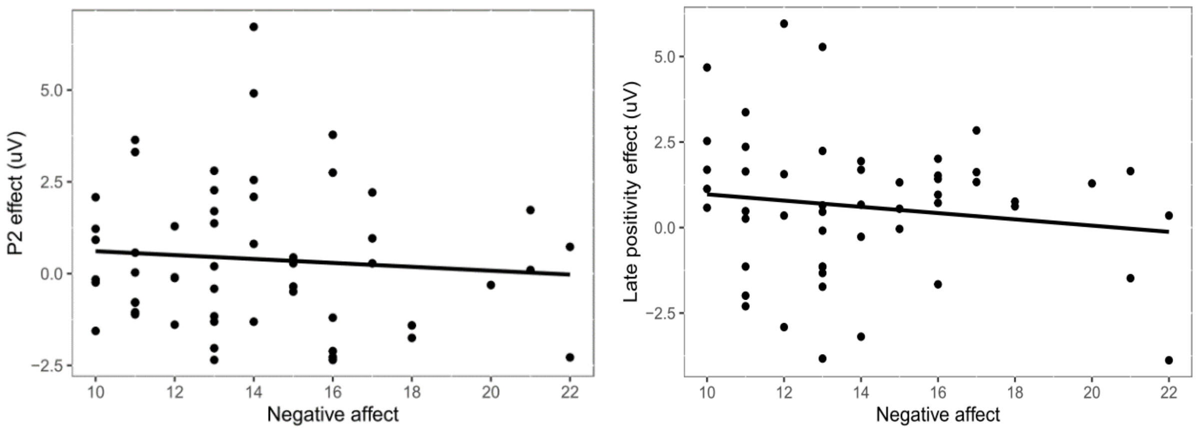

Fig. 6. Correlation plots of negative affect scores and ERP amplitude differences in posterior sites between negative and positive topic words in the P2 time window (Left panel), and between negative and positive contexts in the LPC time window (Right panel).

Discussion

The behavioral ratings in Experiment 2 showed a topic word valence effect across younger and older adults, confirming our manipulation of topic word valence. However, we did not find a context effect, or any age differences across the experimental conditions. One possible reason is that participants were asked to rate the valence of the topic word in context, after reading the whole three-sentence vignette, due to the constraint during the EEG recording. Therefore, the emotional content in the third sentence of each vignette may influence the valence evaluation. However, a post-experiment analysis using Stanford sentiment analysis (Socher et al., 2013) showed that there was no significant difference of valence between the third sentences with positive topic words ($M \pm SD = 2 \pm 0.69$ out of a 0 (very negative) to 4 (very positive) scale) and those with negative topic words ($M \pm SD = 1.84 \pm 0.6$; $t(158) = 1.51$, $p = 0.13$). On one hand, this ruled out the confounding of valence features in the third sentence of each vignette. On the other hand, it suggests that any context effects we built up in the second sentence of each vignette may be overridden by the following neutral sentence during the valence judgment. We thus refrained from further interpretation of these ratings.

In our ERP data, younger adults showed an enhanced LPC to all the topic words in negative (vs. positive) contexts, regardless of topic word valence, supporting the AVH and a negativity bias of Context effects in younger adults. Compared with younger adults, older adults tended to show a larger LPC increase in response to all the topic words in positive contexts, irrespective of topic word valence, indicating an increasing positivity bias based on contexts in aging. Within older adults, this increasing positivity bias balanced out the negativity bias from the Context effects, as shown by the same LPC increase across all the conditions and the ROI-based regression analysis. These results supported a weak version of the SST and a positivity bias in older adults. Apart from the age-dependent Context effects on the LPC, we also found Topic effects modulated by age in the early P2 time window. Regardless of context valence, older adults showed an increased P2 to positive topic words, compared with younger adults. Within younger adults, these positive topic words showed a decreased P2 compared with negative topic words, in all the contexts. Like the LPC effects, these results suggest that (1) younger adults displayed a negativity bias in processing all the topic words in contexts, and (2) this negativity bias shifted to a positivity bias in older adults, as evidenced by the ROI-based RM-ANOVA and regression analysis.

Crucially, the regression analyses revealed that these age-dependent Context and Topic effects were mediated by participants' negative affect. However, a closer look at these relationships suggested that the age-dependent Context and Topic effects we found was not likely totally due to participants' negative affect. Our older adults had lower negative affect than younger adults, yet older age and higher, rather than lower, negative affect both predicted a smaller Context and Topic effect, on the LPC and P2 respectively. Nevertheless, the negative association between the negative affect and each of the ERP effects is consistent with the past literature that showed attenuated reactivity to both pleasant and unpleasant stimuli, in depressed or neurotic individuals who often show higher negative affect (Foti et al., 2010; Speed et al., 2015).

General Discussion

The current study investigated (1) whether younger and older adults update affective representations of an emotional word in the same affective context differently, and (2) how affective neural representations of a word change before and after emotional contexts. In a web-based and an EEG experiment, participants read and judged the valence of the topic words embedded in positive and negative contexts in the three-sentence vignettes. In Experiment 1 (web-based), we found that compared with the topic words in isolation, positive contexts biased the topic word evaluation toward stronger positive ratings, whereas negative contexts led to stronger negative ratings. This modulation effect was the strongest when the context was negative and the to-be-evaluated topic words was positive. This was supported by the significant interaction of Topic and Context word valence in the linear mixed regression model, and counterintuitively, the Topic word valence effect where positive topic words in all the contexts were rated as less positive than negative topic words, compared with isolated topic words. In Experiment 2 (EEG), compared with the topic words in isolation, positive topic words in all the contexts increased the P2 more in older adults than younger adults. In younger adults, positive topic words in all the contexts tended to reduce P2 more, compared with negative topic words. We also found LPC effects of Context modulated by age: Younger adults elicited a larger LPC in response to all the topic words in negative contexts vs. positive contexts, whereas older adults showed a similar LPC increase to all the topic words in negative contexts and positive contexts.

Empirical integration

From the aspect of valence evaluation, younger and older adults in our Experiment 1 both showed a negativity bias in evaluating the topic words in the emotional contexts, supporting the AVH in the decision stage of valence evaluation after the affective/valence representations of a word are retrieved. This is consistent with Lüdtke and Jacobs' (2015) behavioral study showing that compared with positive and neutral adjectives, negative adjectives in a simple sentence (i.e., subject + auxiliary verb + adjective) have a stronger influence on evaluation processes of their nominal subjects, in younger adults. Also, Kuhlmann and colleagues (2016) found that compared with non-bivalent noun-noun-compounds in German, bivalent compounds (e.g., *bomb-sex*) led to a strong tendency towards a negative rating whenever one of the constituents in the compound was negative. Unlike the above studies, our data showed that this general negativity bias in the evaluation processes not only exerts over a longer context, i.e., across constituents and a single sentence, but also extends to older adults. Across the age groups, negative information in contexts attracted more attention than positive ones during participants' decision of response/rating outputs. It is noted that the strength of the negativity bias grows more rapidly than that of the positivity bias, when the goal (e.g., external stimuli) is close in space or time (Cacioppo et al., 1997; Rozin & Royzman, 2001). As the position of our adjective context words were often near the end of the second sentence in the vignettes, their temporal proximity with valence ratings may lead to a (similar) negativity bias in younger and older adults.

As for affective neural representations, our ERP findings indicated an age-dependent effect of topic word valence on the P2: While younger adults showed a negativity bias, older adults showed a positivity bias, on the P2. Chou et al. (2020) found a larger P2 to the neutral target words preceded by emotional than neutral contexts. The authors linked this P2 to the update of affective representations in the neutral target words, similar to the combinatorics account (Neufeld et al., 2016). Other language studies associated the P2 to context-driven prediction, attention, and/or emotional salience (Donahoo et al., 2022; Fritz & Baggio, 2020; Lai & Huettig, 2016). We argued that our P2 effects may reflect both an enhanced attention to emotional salience and the update of affective representations of the topic words in contexts possibly via combinatorial processes, both modulated by age-related emotional bias. This is because there were P2 differences both at the first and second occurrence of the topic words (see Fig. 4A and 4B), suggesting both a word-level and context effect.

Importantly, we found an age-dependent effect of context word valence on the LPC. Similar to the P2 effect, younger adults showed a negativity bias, whereas older adults showed a reduced negativity bias, on the LPC. As most of the studies associated the LPC to the update of word-level or discourse level representations due to prior contexts (c.f., Introduction), we suggested that our LPC effects reflect the update of the affective representations of our topic words in contexts, based on our design in contrasting the first and occurrence of the topic words. Notably, we did not find any N400 effect. Past studies reported that the N400 effect of context congruency could be reduced when the context and the target word were both emotional, possibly because the affective processing was prioritized over semantic processing (Chou et al., 2020; Delaney-Busch & Kuperberg, 2013). In addition, N400 effects were mostly found in studies using emotional sentences that are implausible or with semantic violation/anomaly (León et al., 2010; Martín-Loeches et al., 2012). We therefore linked our null N400 effect to the plausible emotional contexts and topic words used in our stimuli.

Theoretical implications

In terms of affective semantic processing, our data from valence ratings suggest that the update of valence representations of a word does not base on a linear combination of the valence values of each constituent in the sentence. This is indicated by (1) nearly no change of the valence values for emotionally-consistent conditions (i.e., positive topic words in positive contexts, negative topic words in negative contexts), compared with a prominent change of valence values in emotionally-inconsistent conditions, and (2) the negativity bias in valence evaluation, as discussed in Experiment 1. This is in contrast to the view of general semantic combinatorics which posit that the meaning of a sentence is determined by the meanings of its parts and their syntactical combination. Instead, our rating data indicate that the "appraisal" of valence representations of a word can be influenced by dimensions including stimulus-based intrinsic valence (positive or negative) and motivational valence (a relation among the stimulus, speaker goals, and the perceiver's concerns) (Martin &White, 2003). Our study suggests that the motivational valence of a word depends on age, consistent with the SST. This is not in contradiction with the constructionists' view of emotion (c.f., Introduction, and also Barrett, 2011; Barrett, 2017), where there exists many instances of core affect of a certain emotion concept (e.g., anger) that can be combined in diverse and flexible ways, and the categorization of the core affect depends on the to-be-evaluated situation, the prior experience, and the stimuli.

In terms of affective processing in aging, our ERP findings support the strength and vulnerability integration (SAVI) model of aging: Based on the SAVI model, older adults' positivity bias can be modulated by the stages of emotional experiences (i.e., before, during, or after the event) (Charles, 2010). Due to reduced physiological flexibility, older adults have greater and/or more sustained emotional responses when experiencing emotional events, especially high-arousing ones, whereas they have more positive appraisal or better emotion regulation for low-arousing events, especially before or after the event, compared with younger adults. Our emotional contexts in the vignettes could be viewed as emotional events. The ERP results suggest that older adults did attend to positive content in the contexts more than younger adults, after the affective representations of the topic words were retrieved. This possibly indicates older adults' increased positive appraisal or up-regulating of positive emotions.

There are some limitations and future directions in the current study. First, the general negativity bias found in our Experiment 1 could result from the positions of the adjective context words. Future studies can explore the role of different positions and word categories (e.g., verbs or nouns) of the critical context words on the affective evaluations of a word. Second, based on the pre-experiment norming data, we estimated the accuracy of the valence evaluation (based on only the emotionally-consistent conditions) in Experiment 2. We found younger adults showed a mean accuracy rate of 64.7%, whereas older adults, 74.5%. While these accuracy rates were well above the chance level (33.3%), future studies could adopt a stricter strategy for attention checks (e.g., by inserting filler vignettes). Also, meta-reviews suggested that task types can modulate emotional bias (Reed et al., 2014; Yuan et al., 2019): Explicit emotion tasks often led to a negativity bias, while implicit emotion tasks often led to no emotional or positive bias. Future studies can manipulate and compare different tasks in investigating the age-dependent emotional bias on affective representations of a word.

Conclusions

In the current study, we investigated whether and how age-dependent emotional bias influences the update of affective representations of a word in emotionally loaded contexts. Across the two experiments, we demonstrated that younger and older adults update affective neural representations of an emotional word in the same affective context differently. Supporting the AVH, younger adults quickly disengage from positive topic words and attend to negative topic words in all emotional contexts. Later on, they attend to negative contexts more. In contrast, older adults quickly attend to positive topics in all emotional contexts, and at a later stage, both the positive and negative contexts, which suggests a weak version of the positivity bias. These results are in contrast to participants' valence evaluation, where younger and older adults show similar valence ratings of an emotional word in the same affective context. Our study thus indicates that age could influence affective neural representations of a word and the valence decision in a different way.

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Appendix C.

A reduced negativity bias in older adults: Predicting affective features of a word in emotionally ambiguous sentences

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Abstract

Readers pre-activate linguistic features prior to encountering each word in a sentence. Language prediction studies usually examined concrete semantic features, such as animacy, but little focused on abstract features, such as emotional valence. The present study examined whether and how younger and older readers predict positive and negative features of a word in emotionally ambiguous sentences, using electroencephalogram (EEG). Participants first read the sentence primes that could have either a positive or a negative continuation, and actively predicted an outcome or explanation of the scenario described in the sentence prime. Then, participants made a similarity judgment between the target words (positive or negative) and their prior prediction. Younger readers showed a larger N400 for positive than negative target words, suggesting a greater mismatch between their internally predicted negative features and the externally presented positive features. This N400 effect was not present in older readers. Additionally, in both younger and older readers, negative target words elicited a larger late positivity than positive words. Such effect started earlier in older readers (~350 ms) and later in younger readers (~550 ms). This suggests that both younger and older readers made more efforts in processing negative features of the target words. Overall, our study supported a negativity bias in younger adults, and a reduced negativity bias in older adults during affective meaning prediction, which is consistent with the strength and vulnerability integration model of aging.

Keywords: Emotional ambiguity, aging, meaning pre-activation, ERP, N400

1. Introduction

Imagine you read a sentence "*This pizza has a very unique flavor.*" What is a possible explanation you would predict for the scenario described in the sentence? Is this pizza "*delicious*" or "*disgusting*"? The prediction based on this emotionally ambiguous scenario may be influenced by different factors, such as age and affective disorders (e.g., depression and anxiety; Mikels & Shuster, 2016; Moser et al., 2008, 2012). For example, a recent study found that most people, when growing older, show a reduced tendency in making negative interpretations under ambiguous scenarios (Mikels & Shuster, 2016), suggesting a reduced negativity bias in information processing. In the present study, we investigated whether readers predict positive and negative features of a word in emotionally ambiguous sentences, and how age influences the prediction of these emotional features of an upcoming word, using electroencephalogram (EEG).

When compared with younger populations, healthy older adults tend to prioritize positive information over negative ones, in an attempt to maximize their emotional satisfaction in the late life (Carstensen, 2006; Mather & Carstensen, 2005). This "positivity bias" in older adults could be modulated by the intensity of emotion (i.e., arousal), task demands, and stimulus modality. For instance, recent meta-reviews have reported that older adults' positivity bias could be attenuated *when* processing high-arousing (vs. low-arousing) stimuli, explicit (vs. implicit) emotion tasks, or pictorial (vs. linguistic) stimuli (Reed et al., 2014; Yuan et al., 2019). However, one less explored topic is whether the age-dependent positivity bias holds in different stages of emotional experiences, e.g., *before* an emotional event or stimulus appears. According to the strength and vulnerability integration (SAVI) model of aging (Charles, 2010), when processing an emotional stimulus, older adults have greater and/or more sustained emotional responses due to their reduced physiological flexibility (e.g., slower returning to the baseline activity in physiological responses).

In contrast, older adults show strengths in using attentional, appraisal, and/or behavioral strategies to avoid negative emotions and approach positive ones, before or after an emotional stimulus occurs. Empirical evidence supporting the SAVI model mostly came from behavioral studies using facial and pictorial stimuli (Charles et al., 2003; Isaacowitz, 2006; Mather & Carstensen, 2005). These studies may not truly reflect the impact of the age-related bias on language comprehension: Compared with pictures, the same words and/or sentences can evoke different emotional representations across individuals, suggesting a malleable affective mental representations of linguistic stimuli (Ku et al., 2022; Ku & Lai, in prep.). This could in turn influence how one processes emotional features of linguistic stimuli before they actually appear.

Studies on language comprehension have shown that readers or listeners rely on predictive processing (Altmann & Kamide, 1999; Dikker & Pylkkänen, 2013). During sentence processing, comprehenders actively anticipate upcoming linguistic information based on their prior experiences and contextual information. One of the earliest studies to examine the effect of language prediction in younger adults was conducted by Altmann and colleagues, who tracked participants' eye fixations while they followed instructions and moved objects on the computer screen (Altmann & Kamide, 1999; Altmann & Mirković, 2009). In their experiments, participants heard a sentence in which the verbs impose different semantic constraints on the object nouns (e.g., high constraint: "*The boy will eat the cake*" vs. low-constraint: "*The boy will move the cake*"). It is found that participants tended to move their eyes towards the referent of the object noun (*cake*), before hearing the actual object noun, in the high constraint condition. This was not the case for the low constraint condition. The authors argued that the verb "*eat*" generates an expectation of edible objects, leading to more anticipatory eye-movements. However, language prediction may not only refer to all-or-none processes of activating a particular word in advance of the bottom-up input (DeLong et al., 2014; Luke & Christianson, 2016), it may occur in all levels of language, including visual features of words (Kim & Lai, 2012; Kuperberg & Jaeger, 2016), morpho-syntactic structures (Otten & Van Berkum, 2009), and lexical semantics of the upcoming words (Szewczyk & Schriefers, 2013). For instance, in terms of semantic features, Szewczyk and Schriefers (2013) manipulated sentential context such that it predicts the animacy feature of the sentence-final nouns. They found that even before the target nouns appeared, prediction-inconsistent adjectives elicited a larger N400 than prediction-consistent ones. The authors associated the N400 effect to the detection of the failed prediction, and argued that language prediction could be based on semantically defined categories. These results motivate the current study, as past studies usually examined concrete semantic categories or features, e.g., animacy. Little was done on the prediction of abstract features in the upcoming words, such as emotional valence.

In event-related potential (ERP) studies, predictive processing of emotional features in language is usually associated with the effect of cloze probability (CP) of the sentence-final words during reading, in younger adults. The CP of a word is defined as the number of the participants using that word to continue a sentence divided by the number of total participants. For instance, Moreno and colleagues (2011, 2014) manipulated the sentence frames (positively biased, negatively biased, and emotionally neutral) and target word expectancy (emotionally expected and emotionally unexpected/opposite), based on target word CPs. They found a lager N400 and a post-N400 frontal negativity (PNP) to emotionally unexpected/opposite target words (i.e., low-CP sentence-final words), compared with emotionally expected target words (i.e., high-CP sentence-final words; e.g., *There was nothing special about the episode and it turned out to be very…*<u>*interesting/boring*</u>). Among those emotionally expected target words, the N400 effect was larger for highly expected positive target words than negative ones. The authors argued that from the integration view, the N400 effect may suggest an ease to integrate negative words into prior context, compared with positive words. Alternatively, from the prediction view, readers may more likely to generate predictions using negative (vs. positive) contexts. Notably, the PNP effect was only found in emotional (vs. neutral) contexts, and associated with the effort needed to override a lexical prediction due to the affective content of the sentence being processed. Recently, Chou et al. (2020) also examined language prediction by manipulating the sentence frames (emotionally biased vs. unbiased/neutral) and target word type (emotional vs. neutral). They found that emotional target words attenuated N400s when embedded in emotionally biased (predicted) contexts, compared with emotionally unbiased (unpredicted) contexts. The N400 effect was associated with a facilitation of semantic processing due to contextually-driven pre-activation of emotional features. Furthermore, in contrast to Moreno et al. (2014)'s findings, emotionally unexpected yet plausible target words elicited a larger PNP than emotionally expected ones, following both the emotionally biased and unbiased/neutral contexts. The authors argued that the PNP effect reflected neural demands to override anticipated representations and/or to update message-level representations.

Taken together, the above studies suggested that failed prediction of an upcoming word based on emotional contexts increases the N400 effect, whereas the updating of affective mental representations for such failed prediction sometimes increases the PNP effect. Additionally, younger readers seem to process the upcoming negative information more easily than positive ones. However, several questions still remain. First, past studies mostly manipulated emotional expectancy by sentential contexts. It is unclear if readers' tendency can also shift emotional expectancy. Second, these studies did not probe whether participants really predict the actual target word or not. This could render multiple interpretations of the observed ERP components, e.g., the N400 may reflect lexical prediction itself, or other processes such as semantic integration and association, or discourse processing. More importantly, if younger readers do predict emotional (e.g., valence) features of an incoming word, would older readers predict these features differently? As prior work examined lexical prediction of emotional features in language in older adults is scant, we reviewed studies on context-based language prediction in general below.

There are at least two theoretical positions for aging in language prediction. First, older adults seem to show reductions in context-based predictive processing (DeLong et al., 2014; Federmeier et al., 2010; Payne & Federmeier, 2017; Wlotko et al., 2012). For instance, Wlotko et al. (2012) manipulated sentence constraints (strong, weak) and expectedness (expected, unexpected) of the sentence-final target words. Younger adults had a larger PNP for weakly-constraining unexpected (e.g., "*I was impressed by how much she <u>published</u>.*") versus strongly-constraining unexpected target words (e.g., "*Sam could not believe her story was <u>published</u>.*"). Like above, this PNP effect was linked to neural demands to override or suppress anticipated semantic representations and/or to update message-level representations following prediction violations. By contrast, older adults did not show such prediction-related PNP effects. There are a couple of speculative interpretations for this null effect. First, older adults might not experience similar costs as younger adults did when the prediction was violated. Second, older adults may not pre-activate semantic features of the upcoming words in contexts. This is consistent with findings from the same research group showing that older adults had reduced semantic processing (Federmeier et al., 2002, 2010; Federmeier & Kutas, 1999). In one study, participants read two-sentence vignettes such as "*He caught the pass and scored another touchdown. There was nothing he enjoyed more than a good game of ...*", which ended either with a plausible ending ("*football*"), an implausible ending of within-category violations ("*baseball*"), or an implausible ending of between-category violations ("*monopoly*"). In younger adults, between-category violations elicited a larger N400 than within-category ones. But in older adults, the two types of violations had similar N400s. These results suggest that older adults may have a prediction deficit, which the authors argued possibly results from cognitive decline.

A second position suggests that language predictions in older adults may depend on language experience and/or cognitive abilities, rather than showing an overall decline due to age. For instance, Dave et al. (2018) found that older adults with higher verbal fluency showed preserved predictive processing as younger adults. Participants read moderately-constraining two-sentence contexts such as "*Debbie wanted a long crunchy vegetable to dip into the ranch dressing. She decided to buy some …*", and weakly-constraining contexts such as "*At the checkout, Debbie needed a treat that would quiet her fussy children. She decided to buy some…*". They were asked to actively form a mental prediction of the upcoming word (e.g., "*celery*" or "*carrots*" in the former case, but "*candies/cookies*" in the latter) based on the context, and read the same target word across conditions on the screen (e.g., "*celery*" in this case). Although older adults showed a reduced prediction N400 effect, they showed a bilateral PNP effect (600-900 ms) for unpredicted yet plausible upcoming words, compared with predicted ones in the moderately-constraining sentences. Moreover, older adults' verbal fluency performance contributed to the context PNP effect between the unpredicted yet plausible target words in moderately-constraining sentences vs. implausible target words in low-constraining sentences. The authors argued that the verbal fluency task requires top-down mechanisms that are also important for language prediction, such as generating the lexical items, monitoring verbal outputs, and inhibiting the task-irrelevant semantic information.

To summarize, past literature on language prediction suggested that older adults may rely less on context-based prediction. Instead, they could shift neural resources from processes related to meaning facilitation (i.e., N400s) based on contexts to those reflecting mental representation updating (i.e., PNPs) due to the incoming features of the stimuli. No studies, to our knowledge, examined how affective prediction based on readers' age is impacted in language comprehension.

The current study investigated (1) whether younger and older readers predict affective representations of an upcoming word, and (2) how age-related positivity bias influences meaning prediction, in emotionally ambiguous sentences. We employed an ambiguous scenario paradigm to probe the predictive processing in emotional language. This paradigm has been primarily used in examining interpretation bias in depressive and/or socially anxious people in social situations, and showed sensitivity to prediction effects based on readers' tendency (e.g., *As you give a speech, you see a person in the crowd smiling, which means that your speech is stupid/funny*.; Bisson & Sears, 2007; Moser et al., 2008, 2012). For instance, Moser and colleagues found that younger readers with low anxiety showed a larger N400 (400-500 ms) and/or late positivity (500-700 ms) to negative endings of these ambiguous scenarios than positive ones. Both ERP components were linked to expectancy violation, and taken as evidence to support a positive interpretation bias in low anxious people. We then constructed emotionally ambiguous sentence primes that can have both positive and negative interpretations, paired up with positive and negative target words. We also matched the semantic relatedness of sentences and words between conditions to rule out confounding from semantic association. These sentence-word pairs were moderately related across conditions such that the sentence primes would allow for both positive and negative meaning interpretation equally likely. To differentiate actual lexical prediction from other processes such as semantic integration, and to address the possible decline in context-based prediction in older adults, we adapted an active prediction decision task based on Dave et al. (2018): Participants were instructed to read the emotionally ambiguous sentence and come up with a possible outcome or explanation for the scenario described in the sentence. Then, to evaluate participants' actual lexical prediction, they made a similarity judgment between the target words presented on the screen and their prior prediction. Moreover, neutral sentences paired with both highly semantically related and unrelated target words were constructed as control stimuli, to make sure that older adults do show typical semantic relatedness effect as younger adults, in neutral contexts.

Based on the SAVI model, older adults' tendency to engage in positive meanings and to disengage from negative meanings could influence their lexical predictions before the emotional word actually appears, suggesting a positivity bias. We therefore hypothesized that older adults would actively anticipate positive meanings in our emotionally ambiguous sentences, whereas younger adults are more likely to predict negative meanings. Specifically, we expected to observe an interaction between age and target word valence on the N400 and/or PNP effect. Older adults with their positive bias would find negative meanings unexpected yet still plausible, which means a larger N400 and/or PNP for negative target words than positive target words. In contrast, younger adults with their negative bias would find positive meanings unexpected yet still plausible, which means a larger N400 and/or PNP for positive target words than negative target words. It is possible that we would only observe N400 effects often associated with emotional expectancy violation, as the PNP effect in the previous literature were mixed under emotionally unbiased/neutral contexts (Chou et al., 2020; Moreno & Rivera, 2014). Behaviorally, we expected that older adults would show higher similarity ratings for positive than negative target words, whereas younger adults would show a reversed pattern. Alternatively, older adults could show a reduced negativity bias (Mikels & Shuster, 2016), i.e., anticipating negative meanings just as much as positive meanings in emotionally ambiguous sentences. This means that we would observe no N400 and/or PNP effect and no rating differences between target word types in older adults. Finally, for the control stimuli, we expected to replicate the classic N400 semantic relatedness effect to guide our analyses of experimental stimuli (Kutas & Federmeier, 2011; Tiedt et al., 2020). That is, semantically related target words would reduce the N400s, compared with semantically unrelated ones, regardless of age.

2. Method

2.1. Participants

Forty-one younger (28 females, mean age ± SD = 18.9 ± 0.9 years, range = 18-22 years) and 31 older (19 females, mean age ± SD = 68.0 ± 4.9 years, range = 60-76 years) adults participated in the experiment. The younger participants were undergraduate students recruited from the psychology subject pool for course credits. The older participants were recruited from local newspaper advertisements and received $30 for compensation. All the participants were right-handed, native English speakers, with normal or corrected-to-normal vision. None had language, neurological, or psychological disorders, and were on psychoactive medications likely to modulate emotional processes, based on self-report. All gave informed consents in accordance with the local ethics committee prior to participation.

Participants completed the Depression, Anxiety, and Stress Scales (DASS, 21-item version; Henry & Crawford, 2005), and the Positive and Negative Affect Schedule (PANAS – trait version; Watson et al., 1988), as affective states and traits could modulate emotional bias in generating expectation in ambiguous scenarios (Moser et al., 2008, 2012). The DASS contains three self-report subscales to measure the levels of depression, anxiety and stress. Each subscale includes 7 questions, with each of the questions answered on a 4-point scale ranging from 0 to 3, based on how much the statement in each question applied to the participant over the past week. The cutoff scores for mild depression, anxiety, and stress are 10, 8, and 15 respectively. The PANA includes two self-reported subscales for positive affect (PA) and negative affect (NA), respectively. Each participant indicated the level one generally feels this way to 20 items, on a 5-point scale (1 = not at all to 5 = extremely). The older participants also completed the Geriatric Depression Scale (GDS; Sheikh & Yesavage, 1986), a 15-item yes/no questions to specifically measure depression levels in the elderly. Eight younger participants were excluded due to a high DASS – depression score (i.e., > 10), while no older participants were excluded based on the cutoff GDS score (i.e., > 5) for depression.

Additionally, all the participants had Mini-Mental State Examination (MMSE; Folstein et al., 1975) scores of greater than 26, suggesting no cognitive impairment. As a general assessment of cognitive functions (Jaeger, 2018), participants completed the Digit Symbol Substitution Task (DSST; Wechsler, 1997). Participants needed to match symbols to numbers according to a key located on the top of the page, and the number of correct responses within 90 seconds, is the total score. Participants also completed a Verbal Fluency Test (VFT; Benton, 1968), which includes both a letter and category sub-test, as past literature suggested that language prediction may involve language production/verbal cognitive control processes (Dave et al., 2018; Federmeier et al., 2010). In the letter VFT, participants named as many words as possible that begin with a particular letter (i.e., F, A, S) within 60 seconds, whereas in the category VFT, participants named as many words as possible that belong to a semantic category (i.e., fruits, animals, non-fruit items in a supermarket). We added up the total correct response within the letter and category VFT, separately.

Three younger and 1 older participants were excluded due to insufficient trials (< 60%) after artifact rejection of the EEG data in the experiment. The characteristics of the remaining participants are summarized in Table 1.

Table 1. Participant characteristics

Mean (SD)	Younger adults	Older adults	*t*	*p*
N	30	30	N/A	N/A
Age	18.8 (0.93)	68.17 (4.86)	N/A	N/A
Sex	M: 10, F: 20	M: 11, F: 19	N/A	N/A
DASS_Depression	3.87 (3.28)	1.53 (2.21)	3.23	.002
DASS_Anxiety	4.47 (4.19)	1.60 (1.92)	3.41	.001
DASS_Stress	8.00 (6.67)	3.67 (3.41)	3.17	.003
PA	30.80 (6.41)	33.73 (7.65)	-1.61	.113
NA	16.57 (4.14)	12.07 (2.24)	5.23	< .001
GDS	N/A	0.90 (1.06)	N/A	N/A
MMSE	29.30 (0.92)	29.47 (0.97)	-0.68	.500
DSST	63.57 (15.19)	52.31 (10.92)	3.28	.002
VFT_Letter	46.10 (9.75)	53.67 (15.75)	-2.24	.029
VFT_Category	63.27 (11.92)	64.90 (13.92)	-0.49	.627

2.2. Materials

The stimuli consist of 120 sentence primes, paired with both a positive and a negative target word that are semantically related to its sentence prime. Sentence primes and target words were adapted from Bisson and Sears (2007)'s study. Each of these sentence primes described an emotionally ambiguous scenario, and allowed for both a positive and a negative interpretation. For example, the sentence "*Joan was stunned by her final exam result.*" was paired with a positively related target word "*success*", and a negatively related target "*distress*".

To rule out the confounding from semantic relations, we normed the strength of the semantic relation between sentence primes and target words. Forty-six undergraduate participants who did not participate in the EEG experiment rated semantic relatedness between the sentence primes and target words. These participants were asked to judge whether the sentence and the target word in each pair was related in meaning, on a 4-point Likert scale (0 = *unrelated*, 3 = *strongly related*). The mean semantic relatedness were matched between positive target words ($M = 1.99$, $SD = 0.50$) and negative ones ($M = 1.93$, $SD = 0.48$; $t(119) = .85$, $p = .40$). These ratings indicated that the semantic relatedness between sentence primes and target words were similarly moderate across conditions, which suggests no dominant emotional interpretations of the ambiguous scenarios described in the sentence primes. We excluded low related sentence-word pairs as weak contextual support may likely attenuate older adults' prediction effect (Federmeier et al., 2010).

Target words were selected based on the affective norms for English words (Warriner et al., 2013). In this norm, subjective ratings of valence and arousal are measured with 9-point Likert scales (1 = *unhappy* to 9 = *happy*; 1 = *calm* to 9 = *aroused*). We chose moderate-arousing target words, as the positivity bias in older adults impacts low-arousing words more (Ku et al., 2022). No arousal differences were found between positive and negative target words ($p = .16$). On average, positive target words scored higher on valence ratings than negative ones ($p < .001$). Based on the same norm, older adults rated negative target words as being slightly more arousing ($p < .01$), and more negative ($p = .04$) than younger adults. Word length ($t(119) = 0.92$, $p = .36$), frequency ($t(116) = 0.47$, $p = .64$), and concreteness ($t(116) = -0.82$, $p = .41$) were matched between conditions for target words, based on the South Carolina psycholinguistic metabase (Gao et al., 2022). Target words spanned across different part-of-speech (i.e., nouns, verbs, and adjectives). The characteristics of the topic words used in the experiment are shown in Table 3.

To make sure that older adults process semantic relatedness similarly as younger adults, we also created 80 control sentences that are unambiguous (e.g., "*The judge sentenced her to six months in jail.*"), paired with target words that are related ("*jury*") and unrelated ("*glass*"). These sentence-word pairs were adapted from Peelle et al. (2020) and Rodd et al. (2013). The semantic relatedness between the sentence primes and the target words were normed (N = 46), using the same 4 point Likert scale described above. Related target words ($M = 2.63$, $SD = 0.44$) were more semantically related to the primes, compared with unrelated target words ($M = 0.14$, $SD = 0.19$; $t(79) = -48.95$, $p < .001$). Word length ($t(79) = 0.51$, $p = .61$), frequency ($t(79) = -1.92$, $p = .06$), and concreteness ($t(79) = 1.24$, $p = .22$) were matched between related and unrelated target words (Table 2).

All the 240 sentence-word pairs were divided into two lists. Each list consists of 120 sentences with 60 positive and 60 negative target words. Control sentence-word pairs were also divided into two lists, with 80 sentences paired with 40 unrelated and 40 related target words in each list. The stimulus order in each list was randomized for each participant. The list order was counterbalanced with participants' number. Participants read the same sentence prime only once.

Table 2. Stimulus characteristics

Mean (SD)	negative	positive	unrelated	related
Length	6.68 (2.15)	6.91 (2.32)	6.09 (1.92)	5.91 (2.00)
Frequency	2.96 (0.67)	3.00 (0.67)	2.80 (0.69)	3.00 (0.63)
Concreteness	3.03 (0.92)	2.96 (0.92)	4.21 (0.99)	4.01 (0.87)
Valence	2.93 (0.77)	7.03 (0.79)	-	-
Younger	3.09 (0.93)	6.96 (0.78)	-	-
Older	2.79 (0.82)	7.15 (0.97)	-	-
Arousal	5.05 (0.83)	4.89 (1.04)	-	-

Younger	4.81 (0.93)	5.01 (1.21)	-	-
Older	5.25 (1.02)	4.83 (1.16)	-	-

2.3. Procedure

Participants first completed a questionnaire about their language use and health condition. An elastic cap mounted with 32-channel Ag/AgCl electrodes was then fitted on the participant's head. After the EEG capping procedure, the participant was taken to a sound-proofed booth and seated at a desk facing a computer screen 80-100 cm in front of them. The stimuli were presented visually in a white font (Font: Courier New; Point size: 20) against a black background via E-prime 3.0 software (Psychology Software Tools, Inc.).

The EEG recording session was separated into experimental and control blocks. In experimental blocks (Fig. 1), each trial started with a central fixation cross for 500 ms. Then, a sentence prime appeared on the screen in full. Participants had to read the sentence carefully and silently, and press any button on a response box once they comprehended the sentence. After that, a central arrow appeared for 500 ms to orient participants' attention, followed by a 1500 ms blank, during which participants were instructed to actively predict a possible explanation or outcome based on the sentence prime. Participants were told that there was no "correct" answer for the prediction. Then, a target word came up on the center of the screen for 260-420 ms depending on the word length. When cued by the target word, participants needed to compare how similar the presented target word was to the prior prediction on their mind. Afterwards, participants made their similarity judgment on a 0 (not similar at all)-3 (very similar) scale shown on the screen, by pressing a button on a response box, after a 2000 ms blank. The button configuration was counterbalanced across participants. After the response, a "blink or continue" screen would appear so that participants could rest their eyes or take a quick break in a self-paced way.

Control blocks followed the same trial procedure as in experimental blocks (Fig. 1), except that participants were not asked to actively predict a possible explanation based on the sentence prime. Also, instead of the similarity judgment, they needed to judge whether the presented target word and the sentence prime was related in meaning or not, by pressing a “Related” or “Unrelated” button on the response box as accurately and quickly as possible.

The session of the experiment contained three experimental blocks and two control blocks. Participants completed all the experimental blocks first, and then the control blocks, with a short break between blocks. Prior to the first experimental and control block, participants did six practice trials to familiarize themselves with the procedure and task. Each block lasted for 10 minutes, and the entire EEG session lasted for about 50 minutes.

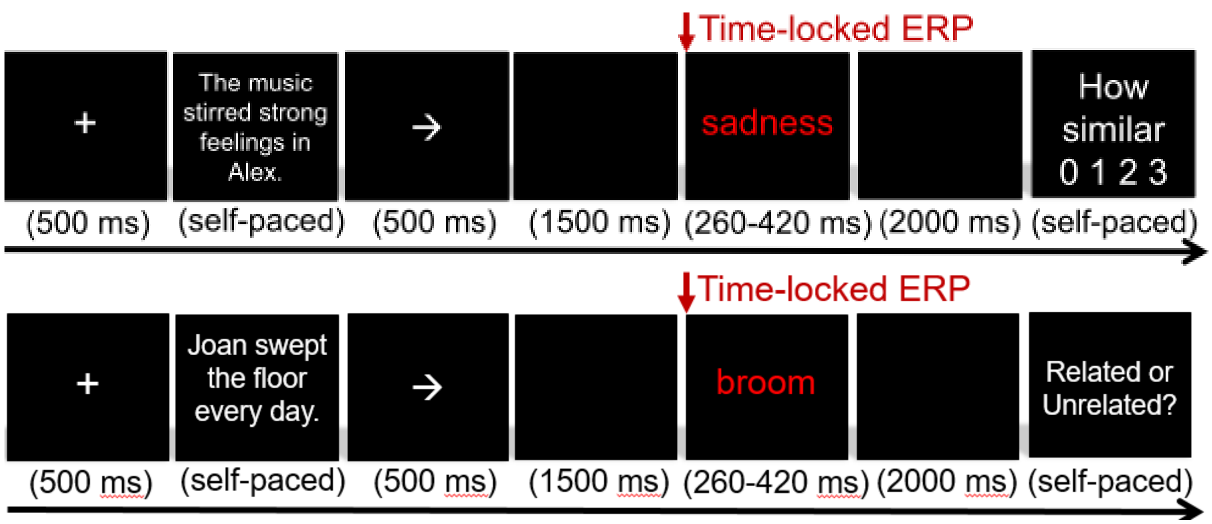

Figure 1. An example trial in the experimental block (top) and the control block (bottom)

2.4. EEG acquisition

The electroencephalogram (EEG) was recorded from 32 electrodes placed on an electrode cap arranged in the 10-10 system (actiCAP, Brain Products GmBH). The scalp EEGs were recorded with a sampling rate of 500 Hz and referenced to Cz during online recording (actiCHamp, Brain Products GmBH). A forehead electrode served as the ground. To avoid impulse artifacts, the online low pass filter was set to 140Hz and the high pass filter was set as DC recording. The electrode impedance was kept below 10 kΩ.

2.5. ERP analysis

EEG recordings were processed offline with the EEGLAB toolbox (Delorme & Makeig, 2004) and the ERPLAB plugins (Lopez-Calderon & Luck, 2014) implemented in Matlab (Mathwork Inc.). For the ERP analysis, the EEG data were first bandpass filtered with frequency values set as 0.1-30 Hz. Data were re-referenced to the average of both mastoids (i.e. TP9 and TP10). Then, the continuous EEG data were epoched by setting the interval as 200 ms before and 1000 ms after the stimulus onset, using the pre-stimulus interval of -200 to 0 ms as the baseline correction. An independent component analysis (ICA) with the runica algorithm implemented in EEGLAB was used to identify eye and muscle artifacts. Those components which had more than 90% probability of being in the muscle or eye artifacts, as automatically labelled by using ICLabel plugin in EEGLAB, were removed from the data. Trials contaminated with artifacts due to peak deflection exceeding ±75 mV, or excessive noises due to fatigue were rejected. For experimental blocks, the mean trial acceptance rates were 84.58% (i.e., an average of 51 out of 60 trials) for younger adults and 86.05% (i.e., an average of 52 out of 60 trials) for older adults. For control blocks, the mean trial acceptance rates were 79.79% (i.e., an average of 32 out of 40 trials) for younger adults and 82.38% (i.e., an average of 33 out of 40 trials) for older adults. No difference was found between age groups (both F values < .52, p values > .47). Finally, the ERP data were averaged for each condition in the younger and older participants.

2.6. Statistical analysis

For the behavioral data, data with response times more than 3 standard deviations above/below all the participant's mean were excluded (1.96% of total responses for the similarity ratings and 2.12% of total responses for the relatedness judgment). For the experimental blocks, the mean similarity ratings for each target word type were entered into a repeated-measures ANOVA (RM-ANOVA) with the factors of Age (younger, older) and Target (negative vs. positive). For the control blocks, the mean accuracy rates for each target word type were entered into a RM-ANOVA with the factors of Age (younger, older) and Target (unrelated vs. related). We did not analyze reaction times, as a delayed response of the similarity/relatedness judgment was adopted to avoid motor artifacts caused by button pressing.

For the ERP data in the experimental blocks, the mean ERP amplitudes were exported from 350-550 ms and 550-900 ms after the target word onsets to capture the N400 and late positivity effect in younger adults, and from 350-900 ms after the target word onsets to capture the sustained positivity in older adults, based on visual inspection of the waveforms and past literature on lexical prediction (Federmeier et al., 2010; Payne & Federmeier, 2017; Szewczyk & Schriefers, 2013). To characterize the spatial distribution of the ERP effects, a RM-ANOVA of Target (negative, positive) x Region (anterior, central, posterior) was conducted in the 350-550 ms and 550-900 ms time window respectively in younger adults, and in the 350-900 ms time window in older adults. Guided by visual inspection of the ERP waveforms and past studies on predictive processing in aging (Brothers et al., 2015; Dave et al., 2018), ERP amplitudes were averaged over electrodes from each of the three regions of interest: anterior (Fz, F3/4, FC1/2, FC5/6), central (C3, Cz, C4), and posterior (CP1/2, CP5/6, P3/4, Pz) sites.

To further compare ERP effects across the age groups, we adopted a two-fold strategy. First, three non-parametric cluster-based permutation tests were used to compare the two target word types across age groups, using the factorial mass univariate ERP toolbox (Fields, 2017; Groppe et al., 2011; Maris & Oostenveld, 2007): One was performed to test ERP amplitude differences between positive and negative target words for both groups (i.e., Target main effect). Another was conducted to test ERP amplitude differences between the two age groups for both target word types (i.e., Age main effect). Finally, the other test was performed on ERP amplitude differences in positive and negative target words between the two age groups (i.e., Age x Target interaction). All the tests were carried out with the ERP data down-sampled to 250 Hz using a boxcar filter, and in a restricted time window of 350-900 ms guided by past literature (Federmeier et al., 2010), both to increase the statistic power (Fields & Kuperberg, 2020). For each test, to start with, a one-way ANOVA was performed at each time point and channel. A cluster was formed when significant F-values were found close in space (i.e., electrodes within 7.86 cm of each other) and time, and summed together. A null distribution was then created, which assumes no amplitude difference between the contrasts of interests. The previous two steps were repeated for 2500 times by randomly assigning the conditions in subjects, and an F-statistic was computed for each randomization. Finally, the F-statistics of the observed data were compared to the null distribution, and the observed clusters exceeding the 95% percentile of the distribution are considered significant. This way, it made sure that the family-wise error was controlled below 5%. Second, we conducted ROI-based regression analyses by entering ERP difference wave amplitudes (i.e., positive minus negative target words) in the 350-550 ms and 550-900 ms time window as dependent variables. Predictor variables included participants' age, PA score, NA score, DASS_Depression scores, DASS_Anxiety scores, DASS_Stress scores, DSST scores, VFT_Letter, and VFT_Category scores.

For the ERP data in the control blocks, the mean ERP amplitudes were exported from 300-600 ms after the target word onsets, based on visual inspection of the waveforms and past literature (Kutas & Federmeier, 2011). With the same regions of interest described above, an RM-ANOVA of Age (younger, older) x Target (unrelated, related) x Region (anterior, central, posterior) was conducted. For all the parametric ANOVA tests, when the sphericity assumption was violated, the Greenhouse-Geisser correction was applied. The alpha levels were set as 0.05, and the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995) was applied by setting a false discovery rate as 0.05 to correct multiple comparisons, if needed. Only the main effects and interactions involving Target, and the corrected p values were reported below.

3. Results

3.1. Behavioral results

The RM-ANOVA on the similarity ratings showed a significant interaction of Age x Topic ($F(1, 58) = 6.69$, $p = .01$, $\eta^2 = .10$). Older adults tended to rate positive target words ($M = 1.49$, $SD = 0.40$) as more similar to their prior prediction than negative target words ($M = 1.34$, $SD = 0.40$; $p = .06$). Numerically, younger adults rated negative target words ($M = 1.43$, $SD = 0.25$) as more similar to their prior prediction than positive target words ($M = 1.34$, $SD = 0.33$), albeit not statistically significant ($p = .18$). No main effect of Age or Target was found (both F values < .58, p values > .45).

The RM-ANOVA on the relatedness judgment revealed a main Age effect ($F(1, 58) = 15.02$, $p < .001$, $\eta^2 = .21$), and an interaction of Age x Target, albeit only approaching significance ($F(1, 58) = 4.09$, $p = .05$, $\eta^2 = .07$). A follow-up comparison showed no significant differences of mean accuracy rates between related vs. unrelated target words in either younger ($M = 95.76\%$, *SD* = 0.05 for related targets; *M* = 92.61%, *SD* = 0.08 for unrelated targets) or older adults (*M* = 96.81%, *SD* = 0.04 for related targets; *M* = 97.89%, *SD* = 0.03 for unrelated targets). Generally, older adults (*M* = 97.35%, *SD* = 0.04) showed a higher mean accuracy rate of relatedness judgment than younger adults (*M* = 94.18%, *SD* = 0.02), regardless of target words.

3.2. ERP results

The grand averaged ERP waveforms for the target words in the experimental blocks based on 30 subjects each group are shown in Fig. 2A. All the participants showed visual N1 and P2 complexes, indicating normal early visual processing. Additionally, in younger adults, there was a deflection across target word types starting from ~350 ms, identified as N400s, while no such N400 effect was observed in older adults. For both younger and older adults, negative target words tended to elicit a larger late positivity than positive target words, with this late positivity starting at ~550 ms in younger adults, yet earlier at ~350 ms in older adults. The grand averaged ERP waveforms for the target words in the control blocks based on the same 30 subjects per group are shown in Fig. 2B. In consistent with past literature, unrelated target words showed a larger N400 than related words at ~300-600 ms in both age groups, with a larger effect in younger than older adults.

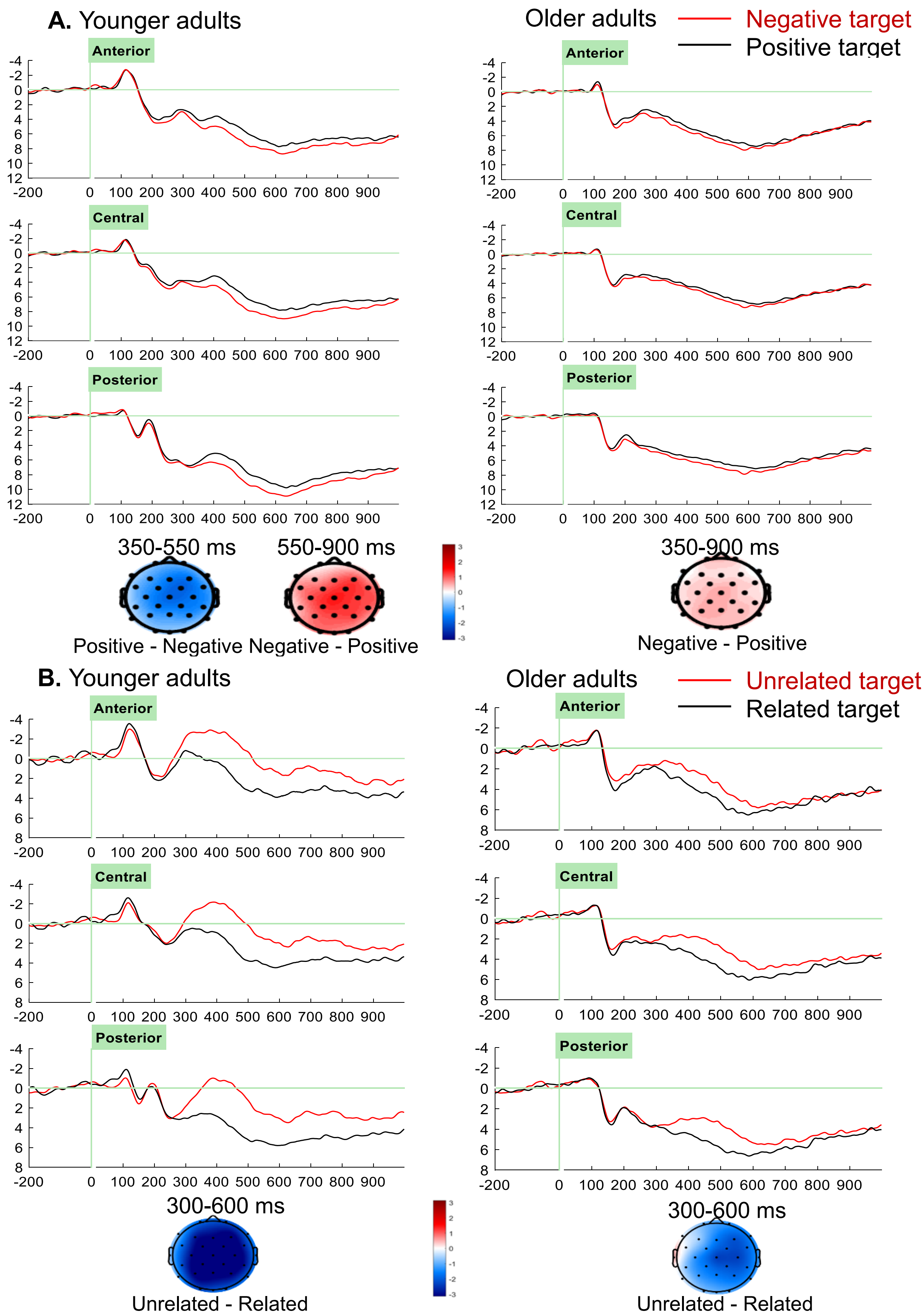
A. Younger adults
Older adults
Negative target
Positive target
Anterior
Central
Posterior
350-550 ms
550-900 ms
350-900 ms
Positive - Negative
Negative - Positive
Negative - Positive
B. Younger adults
Older adults
Unrelated target
Related target
Anterior
Central
Posterior
300-600 ms
300-600 ms
Unrelated - Related
Unrelated - Related

Fig. 2. Grand averaged ERP waveforms (N = 30 each group) for the positive (black lines) and negative (red lines) target words in experimental blocks (panel A) and for the related (black lines) and unrelated (red lines) target words in the control blocks (panel B), at anterior, central, and posterior scalp regions, in younger adults (left) and older adults (right), along with the corresponding scalp topographies of the N400 and late positivity effects.

3.2.1. Experimental blocks

3.2.1.1. N400 (350-550 ms)

The RM-ANOVA in the 350-550 ms time window in younger adults showed a Target main effect ($F(1, 29) = 11.06$, $p < .01$, $\eta^2 = 0.28$). In younger adults, positive target words ($M = 5.77$, $SD = 5.27$) elicited a larger N400 than negative target words ($M = 7.30$, $SD = 5.49$). No Target x Region interaction ($F(2, 58) = 2.45$, $p = .12$) was found.

3.2.1.2. Late positivity (550-900 ms)

The RM-ANOVA in the 550-900 ms time window in younger adults showed a Target main effect ($F(1, 29) = 9.03$, $p = .01$, $\eta^2 = 0.24$). In younger adults, negative target words ($M = 9.34$, $SD = 4.27$) elicited a larger late positivity than positive target words ($M = 8.20$, $SD = 3.88$). No Target x Region interaction ($F(2, 58) = 1.30$, $p = .28$) was found.

3.2.1.3. Sustained positivity (350-900 ms)

The RM-ANOVA in the 350-900 ms time window in older adults showed a marginal effect of Target ($F(1, 29) = 4.56$, $p = .06$, $\eta^2 = 0.14$). In older adults, negative target words ($M = 6.81$, $SD = 3.23$) tended to elicit a larger sustained positivity than positive target words ($M = 6.33$, $SD = 2.92$). No Target x Region interaction ($F(2, 58) = 0.13$, $p = .77$) was found.

3.2.2. Cluster-based permutation tests and regression analyses

As a data-driven approach to detect possible age differences, in addition to the above traditional mean amplitude-based analyses, separate two-tailed cluster-based permutation tests were conducted on all the 4-ms time bins between 350-900 ms and all 30 channels (i.e., excluding the reference sites TP9 and TP10). The permutation tests revealed a significant difference between negative and positive target words in the 350-898 ms time window, in the form of a widespread cluster (cluster-stat = 23,927, $p < .001$; Fig. 3). Additionally, there was a significant cluster difference between younger and older adults in the 502-898 ms time window, distributed over most centro-parietal sites and extending to left anterior sites (cluster-stat = 10,285, $p = .01$; Fig. 3). No significant differences were found on ERP amplitude differences in positive and negative target words between the two age groups (i.e., Age x Target interaction; all p values > .34), which is consistent with the mean amplitude-based analyses.

To rule out the impact of the cognitive and affective measure differences between younger and older adults, two regression models were further performed in the 350-550 ms and 550-900 ms time window, by entering the mean difference amplitudes between positive and negative target words, from the 17 electrodes (c.f., Section 2.6. Statistical analysis) at the anterior, central, and posterior sites, as dependent variables. No significant models were found in both the time windows (both F values < 1.52, p values > .17).

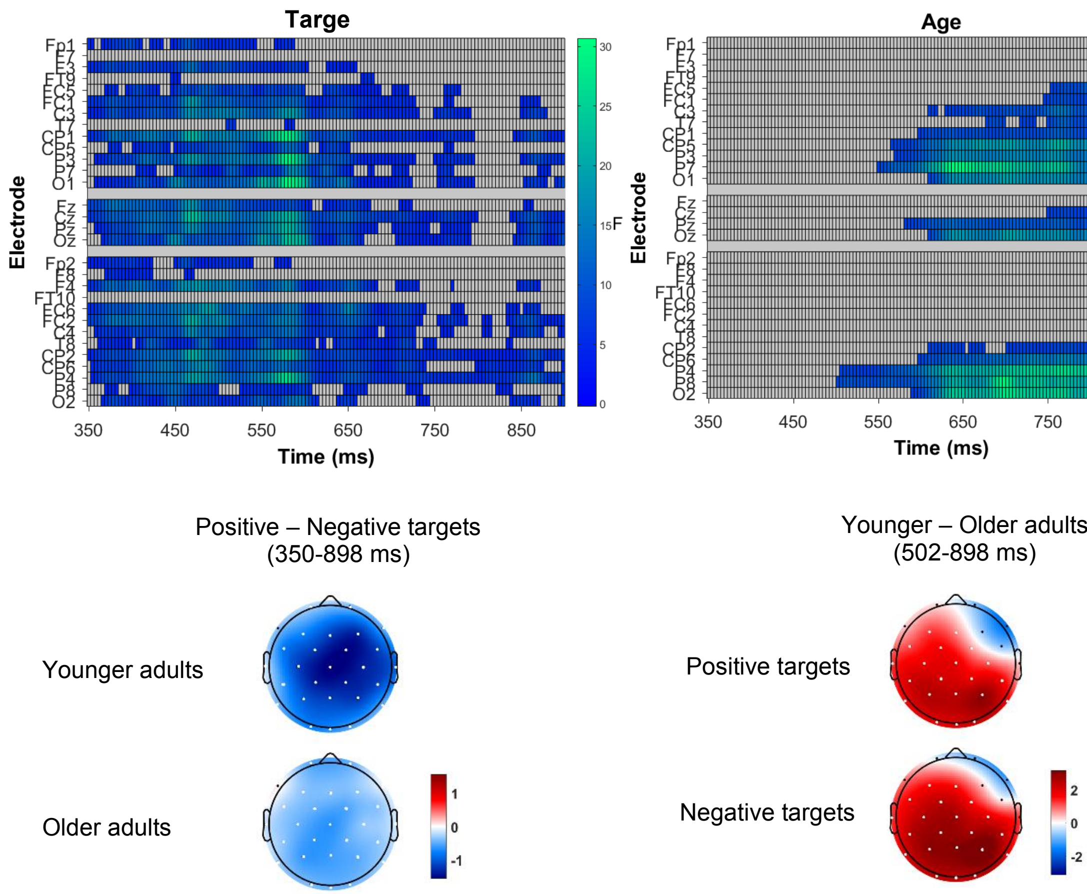

Fig. 3. Raster diagrams of the permutation test results for the Target main effect (top left panel) and Age main effect (top right panel). Each bin represents 4 ms intervals between 350 and 900 ms. The colored (blue/green) rectangles indicate the electrodes and time points that emerge as a significant cluster. Scalp topographies for the difference between positive and negative target words in 350-898 ms, in younger and older adults (bottom left panel), and for the age difference in 502-898 ms, in positive and negative target words (bottom right panel). White dots represent electrodes that form a significant cluster from the permutation test.

3.2.3. Control blocks

3.2.3.1. N400 (300-600 ms)

The three-way RM-ANOVA revealed significant interactions of Age x Target ($F(1, 58) = 10.07$, $p < .01$, $\eta^2 = 0.15$), and of Target x Region ($F(2, 116) = 9.88$, $p < .001$, $\eta^2 = 0.15$). In both the age groups, unrelated target words (Younger adults: $M = -0.28$, $SD = 3.90$; Older adults: $M = 3.19$, $SD = 3.02$) elicited a larger N400 than related target words (Younger adults: $M = 2.81$, $SD = 4.18$; Older adults: $M = 4.73$, $SD = 3.08$; both p values < .001). However, when further examining the N400 effect size (i.e., Unrelated – Related target words), younger adults (*M* = -3.09, *SD* = 2.28) showed a larger N400 relatedness effect, compared with older adults (*M* = -1.53, *SD* = 1.24; $t(44.83) = -3.29$, $p < .01$). Also, regardless of age and across regions, unrelated target words (Anterior: *M* = 0.74, *SD* = 4.24; Central: *M* = 1.30, *SD* = 4.54; Posterior: *M* = 2.17, *SD* = 3.83) elicited a larger N400 than related target words (Anterior: *M* = 2.97, *SD* = 4.06; Central: *M* = 4.16, *SD* = 4.33; Posterior: *M* = 4.57, *SD* = 3.88; all *p* values < .001).

Additionally, there were main effects of Target ($F(1, 58) = 102.62$, $p < .001$, $\eta^2 = 0.64$), and of Age ($F(1, 58) = 9.21$, $p < .01$, $\eta^2 = 0.14$). Irrespective of age, unrelated target words (*M* = 1.40, *SD* = 4.09) elicited a larger N400 than related target words (*M* = 3.90, *SD* = 3.95). Also, younger adults (*M* = 1.22, *SD* = 4.09) showed a larger N400 than older adults (*M* =4.08, *SD* = 3.12), regardless of target word types.

4. Discussion

The current study investigated (1) whether readers predict positive and negative features of a word in emotionally ambiguous sentences, and (2) how age influences the prediction of these emotional features of an upcoming word. We asked participants to first make active prediction about a possible explanation or outcome while reading emotional ambiguous sentences, and then judge the similarity between the target words they read on the screen and their prior prediction. Our ERP data revealed that in younger adults, positive target words elicited a larger N400 (350-550 ms) than negative target words. This suggested a mismatch between their internally predicted negative features and the externally presented positive features of the target words, consistent with a negativity bias. Notably, this N400 effect was not present in older adults. Instead, in both the younger and older adults, negative target words elicited a larger late positivity than positive target words. Such late positivity started earlier in older adults (~350 ms) but later in younger (~550 ms). Neither the N400 nor the late positivity effect (i.e., positive - negative words) was predicted by the verbal fluency test scores (both letter and category verbal fluency) and the DSST scores. Additionally, within the control blocks, semantic unrelated target words elicited a larger N400 than semantic related ones in both the younger and older adults, with an attenuated effect in older adults.

In consistent with our prediction, younger adults showed larger N400s to positive target words than negative ones, whereas older adults did not show such an N400 effect. These results supported a negativity bias in younger adults yet a reduced negativity bias in older adults in predicting emotional features under emotionally ambiguous scenarios. From the view of prediction, our younger participants were more likely to predict negative features than positive ones in ambiguous scenarios, while older participants just predicted negative features as much likely as positive ones. Therefore, when reading the actual target words on the screen, positive words violated younger adults' prior prediction more, while older adults found both target word types equally plausible. Our N400 findings also added to Moreno and colleagues (2011, 2014)'s studies (c.f., Introduction) on emotional expectation based on contexts: When the contexts were biased to negative emotions, younger participants showed a larger N400 to emotionally unexpected/opposite (i.e., positive) target words. Crucially, this N400 effect was larger than another experimental condition in which negative target words followed the positively biased contexts, suggesting a greater tendency to predict negative (vs. positive) features in younger adults. Unlike the above studies using contexts to manipulate emotional expectancy, we demonstrated that with our emotionally ambiguous/unbiased sentences, younger adults also held a negativity bias in affective prediction during language comprehension, due to their reader tendency.

On the contrary, older adults' null N400 effect is in line with the SAVI model. When growing older, people tend to avoid negative situations and approach positive situations to maintain social well-being, with their accumulating self-knowledge and life experiences. From the account of prediction, it is possible that in our task, older adults predicted fewer negative or more positive features proactively, than younger adults. Alternatively, from the account of emotion regulation, older adults could suppress more negative features by either (1) attending to or (2) appraising positive (vs. negative) features more in their predicted contents, compared with younger adults (Charles, 2010). Although our task with the long prime-target stimulus onset asynchronies (SOAs) does not allow us to determine which account describes our older participants better, both of the accounts supported a reduced negativity bias or even a positivity bias in older adults. This is supported by our behavioral data: Older adults tended to rate positive target words as being more similar to their prior predicted words, whereas younger adults showed a reversed pattern numerically. Importantly, as our data in the control blocks suggested, older adults still showed a relatedness N400 effect in the similar time frame, albeit smaller compared with younger adults, when asked to judge meaning relatedness between sentence primes and target words. Given that semantic relatedness judgment takes *any* relations between our sentence primes and target words into consideration, it was less likely that the null N400 effect in older adults resulted from their insensitivity or decline in judging meaning similarity, a *specific* relation (i.e., meaning commonality) between their predicted contents and the target words.

Our ERP data also showed an enhanced late positivity to negative target words than positive ones, in both the age groups. From the view of prediction, unexpected words often elicited a larger P600, spatially and temporally similar to the late positivity observed in our data, than expected words (e.g., Aurnhammer et al., 2021; Kuperberg et al., 2020; Moser et al., 2008).

Researchers have argued that in addition to semantic expectancy, the P600 can also reflect a variety of similar processes in semantic prediction, including conflict monitoring and resolution of different mental representations (Kuperberg, 2007; Kuperberg et al., 2020), semantic integration of the utterance-level meanings (Aurnhammer et al., 2021; Brouwer et al., 2017), or updating of the mental models at the discourse level (Burkhardt, 2007). We argued that our late positivity was not likely due to the unexpectedness of negative features in younger adults, as it was incongruent with their reduced N400s to negative target words. Instead, it is possible that in our active prediction task, participants, regardless of age, made more attempts or found it more difficult to update/integrate negative (vs. positive) meanings in the presented target words with their mental representations based on the prior prediction. This is in congruent with the affect-as-information theory (Schrauf & Sanchez, 2004), which posits that emotion can reflect how one processes information. Specifically, Schrauf and Sanchez (2004) found that there are universally more negative words than positive ones, and argued that there are in turn more diverse negative emotions. In this case, more neural resources may be needed for processing negative information in our task.

Alternatively, our similarity judgment task required participants to compare the meaning commonality between the presented target words and their prior prediction. In this case, we argued that as positive target words and younger adults' prediction were dissimilar enough, the comparison process was simple, which reduced the late positivity. By contrast, negative target words could show properties somewhat similar to younger adults' mental prediction that required additional efforts or attention for discrimination during the comparison process, as negative features are naturally more diverse as described above. In older adults, the late positivity effect was attenuated. This may result from: (1) negative target words and older adults' prediction were dissimilar enough, so the comparison process was simple, and/or (2) positive target words and older adults' prediction were somewhat similar, but as positive features are naturally less diverse, the comparison process was still comparably simple. A third explanation of the late positivity to negative (vs. positive) target words in both the age groups is from the account of emotion processing. In single word or sentence studies, negative words of moderate or low arousal often elicited a larger late positivity compared with positive words of matched arousal, in younger and/or older adults (e.g., Delaney-Busch & Kuperberg, 2013; Ku et al., 2020). It has been argued that the late positivity reflects sustained attention to or elaborative processing of negative meanings, compared with positive ones. It is thus possible that negative features in our moderately arousing target words (mean arousal: 4.89-5.05 out of a 9 point scale) simply attracted more sustained attention than positive features, regardless of age. Consistent with the SAVI model, this account suggests that negative emotions elicit greater or sustained emotional responses (e.g., higher physiological arousal) when processing the emotional event or stimulus.

Due to the overlapping of the N400 and late positivity effect in younger adults, it is noted that the late positivity effect we observed may actually be a sustained negativity to positive target words in younger and older adults. This is supported by our non-parametric permutation test in which negative target words showed a more positive ERP amplitude compared with positive target words, irrespective of age, with only a significant cluster distributed widely over the scalp in the long 350-900 ms time frame. Based on Brown, Hagoort, and Chwilla (2000)'s study, the sustained negativity was associated with the processing load to establish a link between primes and targets, such as building up an integrated mental representation between word pairs. This suggests that our younger adults continued retrieving positive features from the presented target words, due to fewer predicted positive (vs. negative) features in their prior prediction.

Finally, our regression analysis showed that neither affective states (PA/NA scores, DASS scores) nor cognitive abilities/control (DSST scores, VFT scores) predicted the observed N400 or late positivity effects. For one thing, this suggested that our ERP effects were unlikely to be confounded by the differences of negative affective states or general cognitive abilities between younger and older adults, congruent with past studies on language prediction in older adults (Cheimariou et al., 2019; Federmeier et al., 2002). For another thing, recent studies on language prediction have shown that the prediction-related or context-related effects were predicted by participants' category fluency, the ability to name as many words as possible that belong to a semantic category, rather than letter fluency (Dave et al., 2018; Federmeier et al., 2010). It is possible that as our task was to examine the prediction of category-specific information (i.e., negative or positive information), any individual difference on the prediction-related ERP effects could be smeared out by the matched category verbal fluency scores between younger and older adults.

Overall, our data supported the SAVI model in that *before* an emotional word appears, older adults predict negative meanings less or positive meanings more in the upcoming word under ambiguous scenarios, compared with younger adults. From the aspect of emotion processing, based on the constructionists' view, emotions are events constructed by core affect (e.g., sadness) and categorization, with language serving as contexts (Barrett, 2011; Barrett, 2017). There can be many instances of a core affect to be combined into an emotional concept in different ways. People use their different prior emotional episodes or knowledge to categorize their affective states. Our N400 findings suggested that in emotionally ambiguous scenarios, older adults may tend to select positive features and avoid negative features to conceptualize their emotions during the active prediction, based on their emotional episodes or life experiences. Alternatively, according to the appraisal theories of emotion, emotions are elicited as a result of a cognitive process of appraisal between a person and the situation (Ellsworth & Scherer, 2003; Marsella & Gratch, 2009; Roseman & Smith, 2001). Based on this view, our older adults could make more positive (re-)appraisal of the given ambiguous scenarios based on their emotional memory, and update their mental representations accordingly during the active prediction. From the aspect of language processing/prediction, our data provided evidence that positive and negative features can be differently predicted and such process is modulated by age. This also answers the call for future directions in the review paper by Huettig (2015) in which he asked what other types of representations can be predicted, and what is the possible mediating factors.

There are still some limitations and future directions in the current study. First, to examine lexical prediction directly and address possible age-related declines in using contexts for prediction, we adopted an active prediction task to probe participants' language prediction. To reflect how prediction works in natural language in a more comprehensive way, future studies can examine affective prediction across the lifespan by using different paradigms, such as manipulating the cloze probability (i.e., predictability) of the sentence-final emotional words in a passive reading task. Second, constrained by the active prediction task, we used a long SOA between the sentence primes and the target words. We therefore attributed our results to more strategic or controlled processes of meaning prediction/pre-activation in participants. Future studies can shorten the lengths of SOAs, e.g., 300 ms, to investigate whether current results can still be observed in meaning prediction/pre-activation via automatic spreading activation. Finally, we contrasted only positive and negative target words in the current study, and hence it may be difficult to pinpoint the absolute driving force of the observed ERP effects, e.g., whether the N400 effect was due to an increased N400 to positive target words or a reduced N400 to negative target words. One way to solve the result ambiguity is to construct emotionally ambiguous primes more carefully such that they can be paired up with not only positive and negative target words, but also neutral target words as the baseline, with each of the three conditions matched for semantic relatedness.

5. Conclusions

In the current study, we investigated whether readers predict affective representations of an upcoming word, and how age-related positivity bias influences meaning prediction, in emotionally ambiguous sentences. Our study shows that younger readers predict more negative features of a word in an emotionally ambiguous sentence, as reflected by the reduced N400. Older readers predict fewer negative features and more positive features of a word in an emotionally ambiguous sentence, as shown by the null N400 effect and their higher similarity ratings to positive (vs. negative) words. Later on, both younger and older readers made more efforts in processing negative (vs. positive) features of a word, either due to the emotional salience or the complexity of negative features. Our data thus support a negativity bias in younger adults, and a reduced negativity bias in older adults in predicting emotional features of the upcoming word in emotionally ambiguous sentences. By contrast, after emotional features of a target word are retrieved, both the younger and older adults show a negativity bias. Overall, the present study supported the SAVI model in meaning prediction during language comprehension.

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