Investigating the Emotion-Cognition Interaction: Effects of Affective Distractors on Working Memory Load

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Motivation and Aim: In the past decade, theoretical models of modular architectures with cold cognitive and hot affective-emotional systems have been progressively revised [1-3]. Nowadays, these mechanisms are suggested to be interwoven [4-5] and even processed in shared underlying neurocircuitry (e.g., [1,3]). Particularly in naturalistic environments, we are confronted with complex, (socio-)emotional stimuli claiming attentional and working memory resources (e.g., a crying baby during home office or laughter in open-plan offices). However, the precise nature of emotion-cognition interactions is still subject to research [5-8]. Previous studies revealed detrimental effects of emotional distraction on cognitive processes [9-11] with strongest interference when cognitive load is low and distractors' valence deviates from neutral [1,12]. Electroencephalography (EEG) is a technique that provides separable brain correlates for emotional and cognitive states. EEG research suggested the frontal alpha asymmetry (FAA) as a suitable correlate indicating emotional states [13-15] and the ratio of frontal theta (4 – 7 Hz) and parietal alpha (8 – 12 Hz) power to index cognitive load (workload (WL); [16-17]). Here, we investigate whether these correlates can capture interactions between cognitive control and affective-emotional distraction processes. More precisely, we are interested in how auditory distractors and their affective valence influence neurophysiological indices associated with valence and cognitive load (here working memory load, WML). We assume stronger detrimental effects (i) under low WML because of sufficient available resources to process emotional distractors fully, and (ii) for (potentially harming) stimuli with low valence due to a higher salience and relevance (cf., [1,18]).

Methods: We analyzed EEG data from 12 participants (5 female; 1 diverse; M = 24; SD = 2.6 years). Participants performed a series of elementary arithmetic additions either with 1-digit numbers (low WML, LWML) or 2-digit numbers (high WML, HWML), presented visually (cf., [19-20]). Concurrently, we presented auditory distractions using negatively (low valence, LV), neutrally (neutral valence, NV), and positively (high valence, HV) associated sounds of the International Affective Digitized Sounds (IADS) database [21] resulting in a two-factorial 2(LWML-HWML)×3(LV-NV-HV)-levels within-subject design. EEG were recorded from 20 channels using a mobile, dry-EEG system at a sampling rate of 500 Hz (Cognionics Inc.). Signals were de-trended, zero-padded, and re-referenced to mathematically linked mastoids [22]. We applied a notch filter and zero-phase lag finite impulse response (FIR) bandpass filter (cut-off frequencies: 0.5 and 45 Hz). Afterward, signal was cut into epochs starting at stimulus onset and lasting for 4 s. Artefacts were removed via amplitude rejection (above 250 µV in frontal electrodes) and independent component analysis ([23-25] implemented in mne [26]). We calculated power spectral measures via Welch's method of the Fast Fourier Transformation (FFT). The WL index indicating WML was calculated by log-transforming the ratio of theta-band at Fz and alpha-band power at Pz [16-17]. The FAA index was computed by subtracting and log-transforming alpha-band power in F3 (left hemisphere) from F4 (right hemisphere; [15]). To increase interpretability, we reversed the FAA and scaled both indices between 0 and 1. For the FAA, low values are associated with negative and high values with positive experiences. For the WL, low values indicate low and high values high WML. Grand averages and confidence intervals (CIs; Bonferroni-corrected to adjust for multiple comparisons) were calculated via 5000-fold bootstrapping for each condition (Figure 1A). Next, we determined nine contrasts by computing the difference between conditions' mean participant-wise for each contrast and computed the grand average mean and Bonferroni-corrected CIs (Figure 1B). For conditions, no overlap between CIs indicates a statistical significance of $p < .01$ and a partial overlap without including means a statistical significance of $p < .05$ [27], whereas for contrasts, those with CIs not including zero can be considered as significant (Figure 1 and Table 1).

Results: After scaling, the FAA boundary was set to 0.699 (previously at zero). Our results revealed higher alpha power in the left compared to the right hemisphere in all conditions. We observed a significant difference in the FAA for HV distractors under LWML compared to HWML with higher values in the LWML condition (HV HWML-

LWML). Interestingly, there was a trend that HV distractors evoked lower FAA compared to NV (HV-NV HWML) and LV (HV-LV HWML) under HWML (n.s.). Regarding the WL index, there is a trend indicating higher WL in the NV HWML compared to the HV HWML and LV HWML as well as in the NV LWML compared to LV LWML condition (n.s.).

Discussion: Investigating effects of emotional auditory distractors on WML, we observed higher alpha power in the left hemisphere in all conditions suggesting negative emotional processing and an avoidance tendency [13-15]. This might be explained by the arithmetic task probably inducing tension and negative emotions as well as task-irrelevance of the auditory stimuli. Hence, the simultaneous working memory task altered emotional evaluation with strongest effects for HV stimuli. The significant difference in the FAA for HV distractors between LWML and HWML and effect of reduced positivity for HV in comparison to NV or LV distractors under HWML contribute to this explanation. Generally, we observed a trend for decreased FAA and increased WL under HWML compared to LWML independent of stimulus valence (n.s.). Hence, the WML level affected the neuronal correlates stronger than emotional manipulation. Contrary to our assumptions, LV distractors did not show stronger detrimental effects. NV distractors, however, seem to have stronger detrimental effects than HV and LV distractors, especially, under HWML (n.s.). This finding suggests stronger claims of cognitive resources when processing neutral distractors. Interestingly, a meta-analysis concluded that neutral stimuli are processed as rather mild negatively when compared to emotional stimuli [18]. Our study highlights the necessity to further investigate emotion-cognition interactions using a larger sample since inconsistencies between findings and uncertainty regarding precise underlying processes remain. We further point out difficulties when investigating strongly intertwined processes. There is a great need for suitable experimental paradigms and methods to isolate interacting effects and components. For instance, potential suppression mechanisms of emotional content to prioritize the cognitive task. Possible implications of this research include a higher context sensitivity and holistic evaluation of identified mental states in safety-critical environments, e.g., during driving or in human-computer interactions.

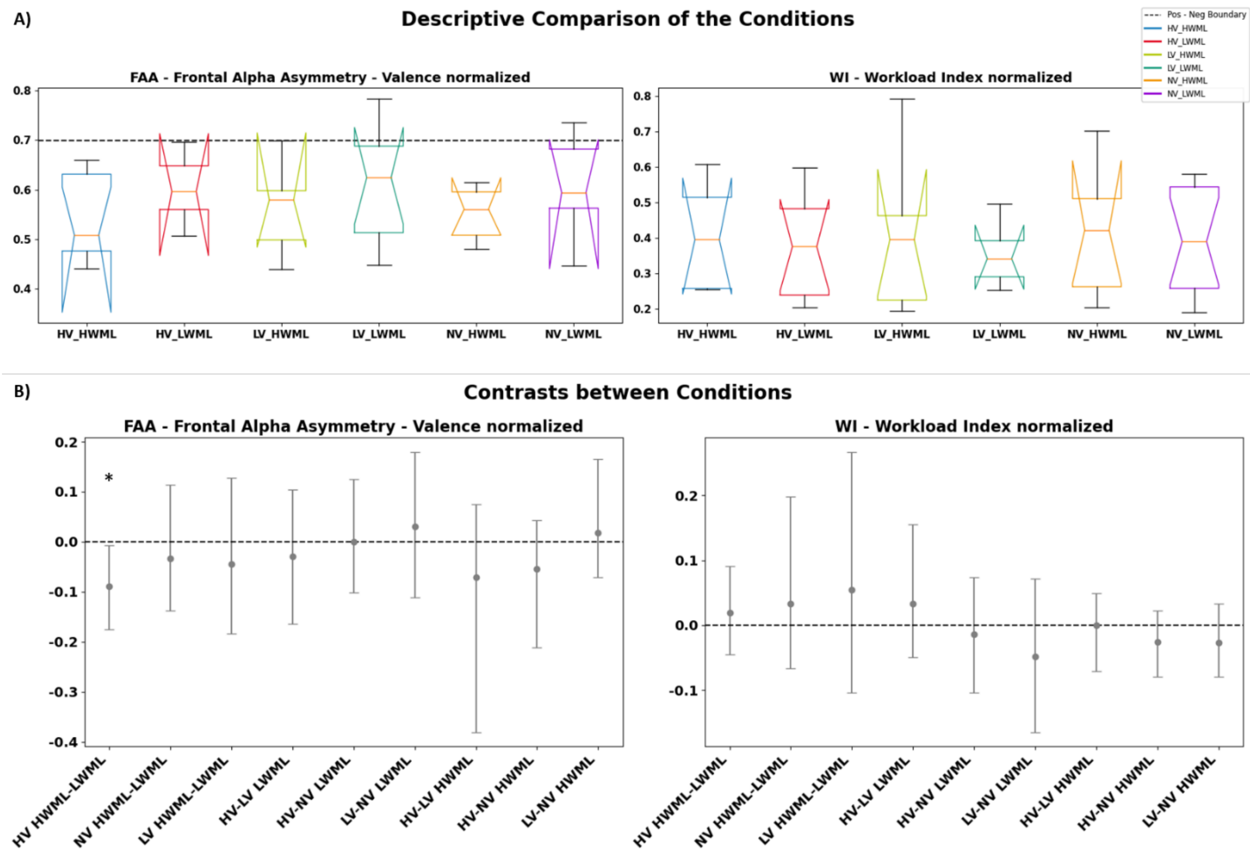

Figure 1. Bootstrapped grand average means and Bonferroni-corrected confidence intervals with 5000 iterations per condition (A) and contrast (B) of the reversed and normalized frontal alpha asymmetry (FAA) index (left; scale: 0 – 1) with low values indicating low valence and high values high valence and normalized workload (WL) index (right; scale: 0 – 1) with higher values indicating a higher WL. HV: high valence; NV: neutral valence; LV: low valence; HWML: high working memory load; LWML: low working memory load.

Table 1.

Bootstrapped grand average means and 95 % confidence intervals with 5000 iterations per condition (upper part) and contrast (lower part) of the reversed and normalized frontal alpha asymmetry (FAA; left) and normalized workload (WL; right) index.

	Reversed and Normalized Frontal Alpha Asymmetry (FAA)			**Normalized Workload (WL)**		
Condition	*Lower CI*	*Mean*	*Upper CI*	*Lower CI*	*Mean*	*Upper CI*
HV HWML	0.353	0.509	0.605	0.242	0.395	0.568
HV LWML	0.468	0.597	0.713	0.252	0.375	0.508
LV HWML	0.484	0.579	0.715	0.236	0.395	0.593
LV LWML	0.531	0.625	0.726	0.255	0.341	0.436
NV HWML	0.509	0.561	0.624	0.271	0.422	0.617
NV LWML	0.441s	0.595	0.701	0.267	0.390	0.513
Contrast	*Lower CI*	*Mean*	*Upper CI*	*Lower CI*	*Mean*	*Upper CI*
HV HWML-LWML	-0.175	-0.090	-0.007	-0.045	0.019	0.091
NV HWML-LWML	-0.138	-0.034	0.114	-0.067	0.033	0.198
LV HWML-LWML	-0.184	-0.044	0.128	-0.104	0.054	0.267
HV-LV LWML	-0.164	-0.030	0.105	-0.050	0.034	0.156
HV-NV LWML	-0.102	0.001	0.125	-0.104	-0.014	0.074
LV-NV LWML	-0.111	0.031	0.180	-0.165	-0.048	0.072
HV-LV HWML	-0.381	-0.071	0.075	-0.070	0.000	0.049
HV-NV HWML	-0.211	-0.054	0.044	-0.080	-0.026	0.022
LV-NV HWML	-0.071	0.019	0.166	-0.079	-0.027	0.033

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