Flow and Optimal Difficulty in the Portable EEG: On the Potentiality of using Personalized Frequency Ranges for State Detection

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Abstract: The experience of flow has been centrally linked to peak task performances and heightened well-being. To more effectively elicit these outcomes, flow is increasingly studied using neurophysiological measures. For example, portable EEG is employed to enable automatic state detection required for adaptive system design. However, so far, there is a lack of highly diagnostic findings, and moderately diagnostic ones relate more strongly to a central flow pre-condition – namely optimal task difficulties. Unfortunately, even these metrics might be infeasible in real-world scenarios and for portable EEG systems without midline electrodes. In this work, we discuss how frequency band personalization and separation could provide options to overcome these problems. Results from an experiment with a task manipulated in difficulty highlight that upper Alpha and Beta ranges show differentiating patterns to their lower frequency counterparts (i.e. within bands). These sub-bands could be used to detect instances of higher flow and optimized difficulty using portable EEG.

1 INTRODUCTION

Flow, the experience of effortless attention, peak task performance and heightened well-being is deemed an individually beneficial experience and also a desirable state from an organizational perspective (Ceja and Navarro, 2012). As the requirements for flow are complex, flow facilitation at work is still a central challenge (Ceja and Navarro, 2012). One promising avenue to study flow and to advance the development of flow-adaptive support systems is to use electroencephalographical (EEG) measures (Cheron, 2016; Harris et al., 2017). EEG provides comparatively low cost, high portability (e.g. wireless EEG headsets) and high temporal resolution (Blankertz et al., 2016). Nonetheless, empiric EEG results regarding flow have so far been short and have shown conflicting results. For example, opposing patterns of frontal Alpha activity with increased flow have been reported (e.g. Berta et al., 2013; Léger et al., 2014; Ewing et al., 2016; Katahira et al., 2018). Overall, so far, no robust neural marker of flow has been identified, despite shared conceptions that a distinctive experience like flow ought to have some representative underlying neural configuration (Cheron, 2016; Harris et al., 2017). One of the closest, yet not sufficient approaches to identify intensified flow comes from the detection of situations with moderate task demands. This is derived from research on mental workload and the reverse inference that a task with too low or too high demands is unlikely to elicit flow (Csikszentmihalyi, 1996). The diagnostic potential is given by observations of frontal midline Theta increases with task demands, or by posterior Alpha reductions with increasing task demands (Borghini et al., 2014). Despite these advances, the transferability of laboratory findings – particularly for flow – is still limited, in particular because some of the aforementioned features show limitations through confounds with prolonged task exposure (e.g. Theta power increases with task duration), natural behavior (e.g. posterior Alpha blocking through visual stimulation), and topographical localization (e.g. Theta changes are strongest over midline positions). The latter is important, as portable EEG is often using few electrodes in non-uniformly distributed positions.

To extend the work on unobtrusive, automated flow detection through portable EEG devices, we propose that through a refined frequency separation approach, (1) refined empiric contributions can be made to the research on flow neurophysiology, (2) new avenues to observe the concept of neural efficiency during flow are opened, and (3) alternatives to the prominent Theta and Alpha markers for mental workload can be derived.

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2 THEORETIC BACKGROUND

Flow research has found the state to occur remarkably similar across numerous contexts like arts, gaming, work, or sports (Csikszentmihalyi, 1996; Moller et al., 2010). Flow theory describes the experience along nine dimensions, that are classified in order of occurrence (cf. Csikszentmihalyi, 1996 – Figure 1).

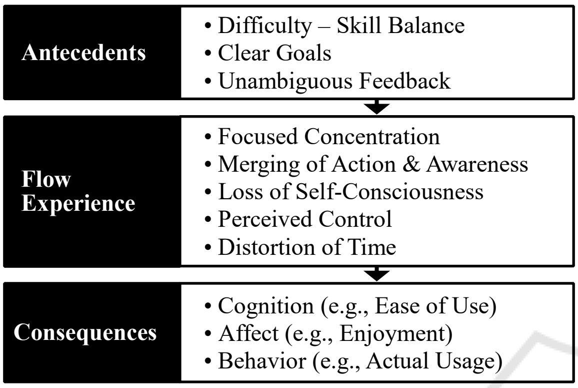

Figure 1: Flow Theory.

Among the antecedents, the optimal balance between perceived difficulty and an individuals' skills has played a major role in explaining how experiences might range from boredom in very easy tasks to anxiety in very hard tasks (Csikszentmihalyi, 1996). Due to its central place in flow theory, the manipulation of a task's difficulty, has been primarily employed for the experimental flow elicitation (Moller et al., 2010), as it has been in workload contexts, albeit not with a focus on optimal difficulties. Markers from workload research have already been employed in flow research and have for example led to conclusions of increased frontal Theta levels in flow (Katahira et al., 2018), potentially even with a maximum in higher flow (Ewing et al., 2016).

A second stream in neurophysiology research has focused on elucidating whether or not flow is represented by neural activity reductions. In one theoretic instance, it has been proposed that during flow, neural activity in frontal brain regions might be downregulated to shift explicit demand processing in frontal regions to implicit and automated processing of learned behaviours in posterior regions (Transient Hypofrontality – Dietrich, 2004). While this approach has been criticized to be overly simplistic (Harris et al., 2017), extensions of a reductionist understanding have proposed that still, some brain regions would show reduced activation during flow, as only areas crucially necessary to meet the task demands would be activated. Such an optimization could make a way to experience highly automated and error-free task processing (Neural Efficiency Hypothesis – (Cheron, 2016; Harris et al., 2017). Following both propositions, in the EEG Alpha band activity, as the prototypical inhibitory rhythm during wakefulness, could be the measure of choice to identify neural configurations during flow (Cheron, 2016). In relation to this, while some studies find increased Alpha power with higher flow self-reports (Léger et al., 2014), within the difficulty manipulation (DM) group comparison studies, results point more to Alpha activity decreases with increasing task difficulty (Ewing et al., 2016; Katahira et al., 2018 report the inverse relationship, but use amplitudes as unit of analysis). This highlights that there is still much to uncover to explain Alpha patterns in flow.

In this article it is argued, that the refined specification of frequency band ranges might explain some of the previous differences and could open new avenues with additional explanatory potential and higher robustness of findings. Often in EEG research and in flow EEG research in particular, frequency band ranges are extracted using generalized, broad ranges (e.g. Theta 4-7.5 Hz or Alpha 7.5-12.5 Hz), despite evidence, that such generalized ranges can mask frequency specific changes (Klimesch, 1999). Importantly, evidence from laboratory experiments has highlighted that Alpha band components can show different and even sometimes opposing patterns (Klimesch, 1999). For example, by segmentation of personalized Alpha bands into three 2 Hz wide subcomponents, lower Alpha bands (Lo1 and Lo2) have been found to relate to general attentional demands and alertness (over the whole scalp) and the upper Alpha has been found to react to changes in task-specific processes (in topographically restricted regions) (Klimesch, 1999).

As flow is not only repeatedly associated with cognitive demands in the form of working memory recruitment (i.e. Theta range activity), but also often in relation with attentional processes (Harris et al., 2017), it would seem of high interest to employ Alpha band segmentation to not only identify regions of reduced neural activity, but perhaps even identify changes in global changes in attentional demands, and task-specific pattern changes. The need for band personalization has already been acknowledged in flow research (Berta et al., 2013; Ewing et al., 2016), yet no extensive evaluations have been completed, for example studying personalized, narrow, and multiple sub-bands. Such approaches would seem however to cover several conceptually related processes of flow like workload, attention and neural efficiency.

3 METHOD

In the herein presented study, the adaptation of a mental arithmetic DM task was chosen due to its pre-validated nature in flow research (Katahira et al., 2018). In this math task, the DM can be easily achieved by increasing or decreasing the number of digits that have to be summed in a fixed time frame (here 28s per trial – with 4s breaks between trials). The final result is in all cases a three-digit number, yet the number of digits is adapted based on performance (cf. Table 1). In the EASY condition, very simple equations are shown, that could only have the result 303 or 304. In the HARD condition, very hard equations are shown that always are at minimum 9 levels higher (i.e. 9 digits more) than the level that is calibrated to have the optimal difficulty for each participant. Finally, in the OPTIMAL-Calc. condition, the equations are of a moderate difficulty as determined by an early calibration phase. Lastly, in the OPTIMAL-Chos. condition, participants can select the optimal task difficulty themselves.

Table 1: Examples of the Math task Difficulties.

EASY (Level = 0)	OPTIMAL (Level = 2)	HARD (Level = 16)
100 + 1 + 100 + 1 + 100 + 2	100 + 13 + 100 + 22 + 100 + 3	100 + 35 + 22 + 16 + 2 + 100 + 64 + 45 + 26 + 100 + 25 + 51 + 31

Study participants were sampled from a public student pool and received a compensation of 22 Euro. After a preparation phase (consent, sensor attachment, 5min eyes open resting and 1min eyes closed resting), an introduction to the math task was shown and participants could practice the task using the EASY condition. Afterwards, the task was shown in the OPTIMAL condition starting at level 1 in order to calibrate the optimal difficulty. Next, all four math task conditions were presented in randomized order (Williams Design). The preparatory and all following task conditions lasted for ca. 5 minutes. After each condition, self-reports were collected for perceived difficulty (1 item) and flow (10 item flow short scale – FKS – both instruments by Engeser and Rheinberg, 2008). EEG data was collected with a saline-based 14-channel Emotiv Epoc+ headset (256Hz sampling).

Data was collected for 41 participants. Data from two participants who repeatedly failed control questions in the surveys were removed. For all self-report variables, outliers were removed (>2 standard deviations – SD – from the construct mean). Next, Cronbach's Alpha coefficients were inspected for the flow construct and found acceptable after one item was removed (0.80). The distribution normality was assessed (univariate Shapiro-Wilk tests) and supported for all conditions.

Table 2: EEG Data Pre-processing Pipeline.

Step	Parameters	Ref.
Data Preparation (R)		
Data Extraction	Baseline & Task Phases	–
Channel Centering	Channel Mean Subtraction	–
Signal Processing (Matlab)		
Step	**Parameters**	**Ref.**
Line Noise Removal	50 Hz & 100 Hz	Bigdely-Shamlo et al., 2015
Re-Referencing	Robust Common Average Reference	Bigdely-Shamlo et al., 2015
Detrending	1 Hz High-Pass	–
Trim Outliers	800mV / 250ms	–
Channel & Paroxysmal Artefact Removal	Artefact Subspace Reconstruction (ASR) - Burst Criterion 10 SD	Mullen et al., 2015
Stationary Artefact Removal (Independent Components)	AMICA - ICs: [Horizontal & Vertical Eye Movement, Blinks, Discontinuities]	Mognon et al., 2011
Feature Extraction (R)		
Step	**Parameters**	**Ref.**
Processing Inspection	Visual Comparison of Input & Output	–
Frequency Power Extraction (Morlet Wavelets)	55 Frequencies, Range [3, 60], Wavelet Cycle Range [3,10] log. spaced with frequencies	Cohen, 2014
dB Power Conversion	10*log10(mV^2/Hz)	–
Frequency Band Extraction	Theta, Alpha & Beta Bands from IAF Peak	Klimesch, 1999
Change Score Computation	Δ = Task – Eyes Open Baseline	–

EEG data was processed primarily along the guidelines of Cohen (2014). 7 data sets had to be excluded due to recording errors, insufficient data quality, or lack of survey report data. The retained, complete sample for EEG analysis comprised 34 participants. Data preparation, feature extraction, and analysis were conducted in R, signal processing and artefact removal in Matlab (EEGLab). The automated EEG data preparation process is outlined in detail in Table 2. Signal data was additionally screened before and after signal processing to ensure no critical errors occurred in the pipeline. Parameters for the processing steps were tuned for the Epoc+ headset. For almost all feature aggregation steps median averaging was used to reduce the impact of outliers in the data (Cohen, 2014).

Frequency bands were extracted following Klimesch (1999). To account for inter-individual differences, individualized Alpha frequency (IAF) peaks were identified. As Alpha is known to also vary regionally (being slower at anterior sites), yet as not all participants showed such clear peaks for all sites, a global IAF maximum was determined as lying 0.5 Hz below the occipital Alpha maximum during an eyes-closed resting phase (cf. Figure 2).

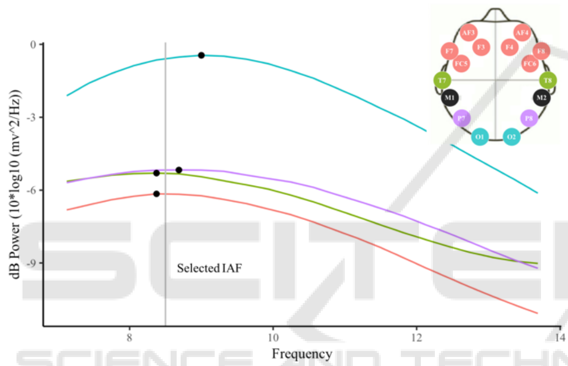

Figure 2: PSDs for one participant during an eyes-closed resting phase with pooled anterior (AF3, AF4, F3, F4, F7, F8, FC5, FC6), temporal (T7, T8), parietal (P7, P8), and occipital electrodes (O1, O2). Dots show regional peaks.

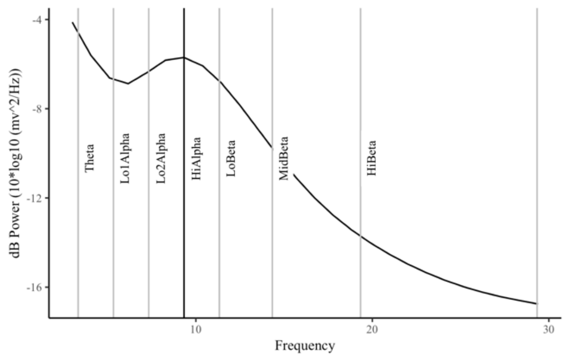

Figure 3: Grand Average PSD for all participants during an eyes-closed resting phase with all 14 electrodes pooled, demonstrating the frequency band decomposition into narrow Theta, Alpha and Beta bands.

Based on this IAF, 2 Hz Theta and Alpha sub-bands were extracted (cf. Figure 3). To extend the personalized and band-refined approach, the Beta band was similarly decomposed. In line with previous research that has extracted low, mid, and upper Beta bands with 3 Hz, 5 Hz, and 10 Hz ranges respectively (Berta et al., 2013), the previous IAF-based decomposition was continued using these ranges.

4 RESULTS

In the following analyses, one-way repeated measures analyses of variance (ANOVA) with Greenhouse-Geisser (GG) correction were used to assess main effects, followed up by pairwise Welch's t-Tests with Benjamini-Hochberg (BH) correction. Error bars in all figures show standard errors. To check the manipulation success, perceptions of task difficulty and flow are evaluated. For task difficulty, a difference between the conditions is found ($F(3, 102) = 161.81$, $p < .01$, $\eta^2_G = .71$) with stepwise increases in perceived task difficulty per condition ($p < .01$). Also, for flow, a main effect for condition is found ($F(3, 99) = 29.63$, $p < .01$, $\eta^2_G = .30$). Follow-up tests show a stepwise increase in flow from the EASY to the OPTIMAL conditions, with OPTIMAL-Cal. being increased from EASY at trend level ($p = .085$), and OPTIMAL-Chos. being increased to both former conditions (i.e. maximal) ($p < .01$). In the HARD condition, flow is decreased compared to all other conditions ($p < .01$), showing the expected inverted U-shape pattern of flow with increasing difficulties (cf. Figure 4). Together, the findings lead to the assumption, that flow is increased in the OPTIMAL conditions, with a maximum in OPTIMAL-Chos.

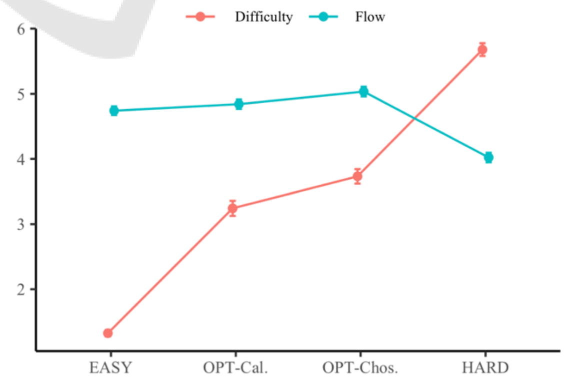

Figure 4: Perceived difficulty & flow reports.

To assess the changes in frequency band activity over several scalp locations, separate one-way repeated measures ANOVAs (GG corrected) were conducted for each available electrode pair (i.e. data were pooled for electrodes at AF3 & AF4 (= AF), F3 & F4 (= F-M), F7 & F8 (= F-L), FC5 & FC6 (= FC), T7 & T8 (= T), P7 & P8 (= P), O1 & O2 (= O) (cf. Table 3). All ANOVA significance levels were BH-adjusted, as were the significance levels in the follow-up pairwise Welch's t-tests.

Table 3: EEG Frequency Power ANOVAs – Only showing significant results. Exact p-values when $p > .01$.

Site	Test Result
Theta (IAF-6 to IAF-4)	
T	$F(3, 75) = 3.72$, $p = .0686$, $\eta^2_G = .02$
Lo2Alpha (IAF-2 to IAF)	
P	$F(3, 87) = 11.69$, $p < .01$, $\eta^2_G = .04$
O	$F(3, 90) = 9.24$, $p < .01$, $\eta^2_G = .02$
HiAlpha (IAF to IAF+2)	
F-M	$F(3, 87) = 7.04$, $p < .01$, $\eta^2_G = .03$
P	$F(3, 84) = 12.86$, $p < .01$, $\eta^2_G = .04$
O	$F(3, 87) = 14.16$, $p < .01$, $\eta^2_G = .04$
Alpha (IAF-4 to IAF+2)	
P	$F(3, 87) = 11.52$, $p < .01$, $\eta^2_G = .04$
O	$F(3, 90) = 8.89$, $p < .01$, $\eta^2_G = .02$
LoBeta (IAF+2 to IAF+5)	
F-M	$F(3, 87) = 10.65$, $p < .01$, $\eta^2_G = .05$
P	$F(3, 90) = 7.70$, $p < .01$, $\eta^2_G = .03$
O	$F(3, 93) = 11.55$, $p < .01$, $\eta^2_G = .03$
MidBeta (IAF+5 to IAF+10)	
F-M	$F(3, 84) = 3.34$, $p = .0840$, $\eta^2_G = .03$
HiBeta (IAF+10 to IAF+20)	
AF	$F(3, 81) = 5.97$, $p = .0213$, $\eta^2_G = .08$
F-M	$F(3, 81) = 4.03$, $p = .0524$, $\eta^2_G = .05$
F-L	$F(3, 78) = 7.00$, $p < .01$, $\eta^2_G = .06$
FC	$F(3, 75) = 5.39$, $p = .0196$, $\eta^2_G = .05$
T	$F(3, 75) = 10.14$, $p < .01$, $\eta^2_G = .09$
P	$F(3, 84) = 5.96$, $p = .0152$, $\eta^2_G = .06$
O	$F(3, 87) = 5.65$, $p = .0193$, $\eta^2_G = .04$

Altogether, Theta power shows almost no difference across the conditions, with only a trend level effect being present at temporal locations. For this location, post-hoc tests showed trend level increases of OPTIMAL-Cal. ($p = .0537$) and OPTIMAL-Chos. ($p = .0952$) from EASY as the only differences. To complete this assessment, the neighbouring Lo1Alpha band did not show changes at any site, and neither did the Theta band when extracted for a more traditional and non-individualized 4-7.5 Hz range (all $p > .1$).

While no effects were found in the lowest Alpha range (Lo1Alpha), both Lo2Alpha and HiAlpha showed Alpha suppression at posterior regions (both at P & O) with similar effects. Namely, a decrease in Alpha from EASY, with all other conditions being on the same level (all $p < .01$). For Lo2Alpha at occipital sites ($p = .0247$) and HiAlpha at occipital sites ($p = .0513$ - trend level), there was also a lower level in HARD than OPTIMAL-Cal. indicating that occipital alpha suppression was somewhat in line with perceived difficulty increases. In relation, for LoBeta at posterior sites, power reductions are found. At parietal sites LoBeta power drops from EASY to OPTIMAL-Cal. ($p < .01$) and OPTIMAL-Chos. ($p = .0321$). At occipital sites, LoBeta power drops from EASY compared to all other conditions (all $p < .01$) (cf. Figure 5).

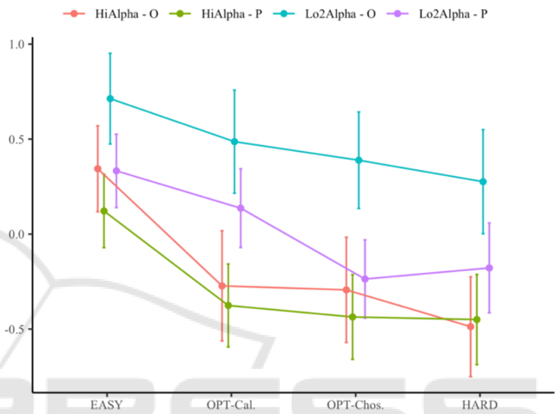

Figure 5: Posterior Alpha decreases from EASY are visible in all Alpha frequencies. Occipital sites show more sensitivity to difficulty changes.

While the same pattern of posterior Alpha reductions is also generally visible in the broad 6 Hz Alpha band (also here with occipital Alpha being slightly higher at OPTIMAL-Cal. than HARD – $p = .0174$), the most noticeable difference revealed through the Alpha split is a reduction of frontal Alpha power at sites closer to the midline (F-M), that is visible in HiAlpha, but not in the lower Alpha bands, nor the broad 6 Hz Alpha band. HiAlpha at F-M is suppressed in all other conditions when compared to EASY (all $p < .05$) (cf. Figure 6). This effect is identically found in the adjacent LoBeta band (and in MidBeta at trend level – here the post-hoc contrast is visible for EASY compared to OPTIMAL only – and HiBeta at trend level, $p = .0893$ and $p = .0701$ – also, for F-M HiBeta a minimum in OPTIMAL is visible due to an increase in HARD compared to OPTIMAL-Cal. $p = .0302$ and OPTIMAL-Chos. $p = .0185$).

Furthermore, the (almost complete) absence of effects in the MidBeta range further highlights the utility of the narrower frequency inspection. In particular, HiBeta is found to be increased at AF sites in HARD compared to EASY ($p = .0411$), and

OPTIMAL-Cal. compared to EASY at trend level (p = .0721), at F-L sites in HARD compared to EASY (p < .01), to OPTIMAL-Cal. (p = .0744 – trend level), and to OPTIMAL-Chos. (p = .0150), with EASY showing lower power than the OPTIMAL conditions at trend level (p = .0608 and p = .0.798). At FC sites, HiBeta is found to be increased in HARD compared to all other conditions (all p < .05). At T sites, HiBeta shows an increase from EASY to OPTIMAL-Chos. (p = .0335) and from there an increase to HARD (p = .0385). HARD is also higher compared to EASY (p < .01) and OPTIMAL-Cal. (p = .0335). OPTIMAL Chos. is found to be higher than OPTIMAL-Cal. at trend level (p = .0778), which means that temporal HiBeta slightly indicates a stepwise increase in power that would be in line with difficulty perception changes. HiBeta is also elevated in HARD at parietal and occipital sites when compared to all other conditions (all p < .05), with the other conditions being equal. Altogether, this means that HiBeta mostly reveals maxima during HARD task conditions over the whole scalp (cf. Figure 7), which represents a useful contrast to the lower frequency effects, in particular the Alpha increase at posterior and fronto-medial sites during the EASY condition.

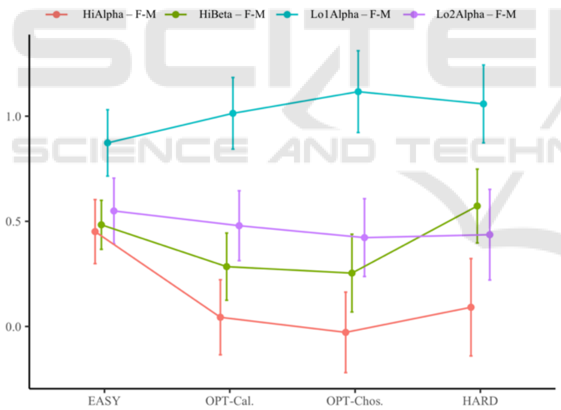

Figure 6: Fronto-Medial Alpha and HiBeta progressions.

This points to an interesting potential of combining (Hi-)Alpha and (Hi-)Beta powers, to identify states of OPTIMAL difficulty. Such approaches have been previously undertaken on the Workload Index (Berka et al., 2007), that have also been employed in flow research (Chanel et al., 2011) and are traditionally either used for pooled electrodes over the whole scalp or for central midline electrodes. For the sake of comparison this Workload Index (WI = Beta / (Theta + Alpha)) was also computed for pooled electrodes here using non-individualized broad bands (Theta = 4-7.5 Hz, Alpha = 7.5-12.5 Hz, Beta = 12.5-30 Hz). No significant effect was found in a one-way repeated measures ANOVA using the difficulty conditions as within-subjects factor.

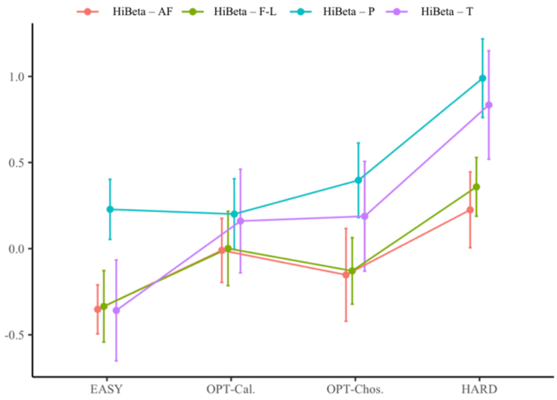

Figure 7: Whole Scalp HiBeta progressions – for better visibility only the most distinctive patterns are shown (O was very similar to P and FC very similar to F-L).

5 DISCUSSION AND CONCLUSIONS

Of particular importance is the finding that through frequency band separation, HiAlpha suppression in frontal medial sites emerged independent of LoAlpha frequencies, similarly to the work by Ewing et al. (2016). This is an interesting finding that not only points to the utility of frequency band separation, but might provide an alternative to detection of increased task demands in real-world scenarios where posterior Alpha blocking has been named as a prominent confounding factor (Blankertz et al., 2016). Furthermore, through segmentation of the Beta band it was also found that while a larger similarity is visible between HiAlpha and LoBeta ranges, the MidBeta range showed mostly no variation across conditions, and the HiBeta range primarily showed increases with very high task demands.

Using the refined approach, we did not find features that clearly reflect the variation in reported flow. This is not completely surprising given that related work has not uncovered such markers using frequency power comparisons in DM tasks. Although, here, two observations tentatively indicate such reactivity, namely temporal Theta and frontal medial HiBeta activity at trend levels. Both are in line with previous findings of increased Theta activity during moderate to high task difficulty (Ewing et al., 2016), and with documentations of negative correlations between frontal Beta and flow self-reports (Léger et al., 2014). Therefore, these results would appear to warrant further investigation. As an initial proposition, it would be plausible to consider simultaneous, localized HiAlpha suppression together with HiBeta reductions as a sign of neural efficiency. The reasoning behind this thought builds on the proposition of HiAlpha reflecting task-specific information processing (Klimesch, 1999), and Beta reflecting increased local communication (Buzsáki and Draguhn, 2004). Therefore, HiAlpha suppression could be indicative of a cortical region being recruited to process a particular task, while at the same time a reduction in local Beta would reflect a reduction in communication among local neuron populations. In a similar manner as frontal Theta and widespread Beta increases are considered as coping mechanisms during (too) hard tasks (Sauseng et al., 2005), a reduction of local Beta might be indicative of the fact that local regions are coping well and only recruit absolutely required neuron groups.

Besides these theoretical potentials, the remaining present findings show an alternative practical potential to differentiate levels of perceived difficulty (and thereby indirectly flow) through feature combination. In this regard, it should be pointed out first, that barely any significant changes were detected in the Theta band. This was an unexpected finding, as a large amount of literature is available documenting frontal Theta increases with increasing task demands (Klimesch, 1999; Borghini et al., 2014). As to why such a pattern is here only reflected in trend level temporal Theta power changes, several explanations are possible. Theta changes have been documented to occur strongly with prolonged task exposure (e.g. in studies with airplane simulators – Borghini et al., 2014). By adding the first task round (the task introduction using the EASY treatment), to a one-way repeated-measures ANOVA we do find a difference for frontal Theta at F3 & F4 (F-M) ($F(4, 104) = 4.33$, $p < .01$, $\eta^2_G = .05$), with the lowest Theta power in the introduction phase. This points to the fact that time might have acted as a confounding effect on Theta power changes. Further, frontal Theta effects are typically identified in midline positions (e.g. Fz – see Ewing et al., 2016). Thus, as these electrodes are missing for the Epoc+ headset, it might not be possible to find Theta effects in some EEG devices. This is a limitation that could easily occur in real-world measurement scenarios using portable EEG systems with few electrodes.

However, employing the frequency separation approach, an interesting pattern emerged in that some narrow frequency features showed significant reaction to changes in perceived difficulty, with some indicating stepwise, monotonous increases, some indicating increases with moderate level plateaus for OPTIMAL conditions and some indicating maxima for either the EASY or the HARD condition when compared to all other conditions. The functional explanation of these patterns should be the subject of future work as would be the development of sensitive and robust compound indices, ideally based on more than one task type (see e.g. Berka et al., 2007). Presently, it is primarily argued that these patterns allow to discuss flow related changes in a refined manner and that they pose interesting alternatives for the detection of situations of optimal difficulty, especially in scenarios where less information might be available than typically is in laboratory setups (e.g. fewer and unevenly distributed electrodes). When considering how for example neuro-adaptive systems employ thresholds to inform adaptation rules (cf. e.g. Ewing et al., 2016), features indicating maxima during EASY or HARD conditions could be valuable indicators, given that they would be subject to lower variation except in the boundary cases. In this regard they could firstly be employed to robustly identify when difficulty is unbalanced and flow unlikely.

In conclusion, this study posits that flow research could benefit from nuanced frequency power analyses, in general by identifying Alpha and Beta power changes that could relate to neural efficiency (in a local form), and in particular when (portable) EEG systems are used that lack midline electrodes. In line with previous research (Klimesch, 1999), the herein presented initial analyses support the understanding that a personalized and narrow frequency power analysis helps to avoid to miss frequency specific effects. Specifically, this research contributes to the literature on flow by highlighting that frontal medial HiAlpha decreases in increased task difficulty (and HiBeta decreases during optimally balanced task difficulties) as well as widespread HiBeta increases in very hard task conditions provide additional avenues to automatically and unobtrusively detect boundary situations to flow. Thus, these metrics, indirectly allow to improve the identification of situations with optimal preconditions for flow to emerge. Importantly, the frequency segmentation approach would appear to be a valuable alternative when portable EEG systems are used that don't include midline electrodes. As an additional effect, Alpha and Beta bands appear unaffected by influences from task exposure durations providing an interesting alternative to the more established metric of frontal midline Theta power increases with higher task demands (e.g. Ewing et al., 2016). Ideally by taking narrow frequency power analysis into account, future flow research will thus move closer to identifying robust concomitants and markers of flow that can be employed in neuro-adaptive systems using portable EEG in real-world scenarios. Eventually, systems able to adapt to flow intensities could then reduce flow interruptions (e.g. by blocking incoming messages) or provide feedback information to improve flow self-regulation (e.g. by self-adjusting task difficulty, or by optimizing arousal levels and catalysing task focus through EEG-neurofeedback).

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