Flow Neurophysiology in Knowledge Work: Electroencephalographic Observations from Two Cognitive Tasks

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Abstract: In an effort to study flow experiences in the context of less structured knowledge work (KW), we explored a paradigm we call controlled experience sampling (cESM). Participants worked on a naturalistic, cognitive task (a personal scientific thesis), and a difficulty-manipulated math task. Results show that the cESM approach elicits a consistent flow experience with intensities as least as high as in the math task flow condition. An interesting finding is that given similar flow intensities, different perceptions of stress arise between the two paradigms. EEG results from both tasks suggest increased frontal upper alpha band (10-12Hz) activity with increased task attention, that has higher temporal stability in flow than in a boredom condition, and that is laterally indifferent. Integrating with the presently available literature, the results further consolidate an understanding of flow as a state of fronto-lateral activation.

1 INTRODUCTION

The experience of flow, where the individual is completely involved in a challenging task (Csikszentmihalyi, 1996), is deemed a beneficial state in the work environment due to its links to improved performance and well-being (Spurlin and Csikszentmihalyi, 2017). As the requirements for flow are complex (e.g. absence of distractions, structure of the task, state of the individual, etc.) (Ceja and Navarro, 2012), flow facilitation at work is still a central challenge (Spurlin and Csikszentmihalyi, 2017). However, the recent advancements on the biological basis of flow (Harris et al., 2017; Knierim et al., 2017) highlight promising avenues for supportive bio-adaptive systems (Rissler et al., 2018). Within the emerging research a central focus lies on highly controlled game tasks (Moller et al., 2010), leaving gaps to understand flow neurophysiology in more unstructured tasks typical to knowledge work (KW). Furthermore, the focus on artificial laboratory tasks has been argued to be a central limitation in studying the (flow) experience of effortless attention (Hommel, 2010). Therefore, in an attempt to increase external validity and naturalistic character of flow laboratory research we propose the adaption of the experience sampling method (ESM) (Csikszentmihalyi and Hunter, 2003) to the laboratory setting. This adaption signifies a controlled approach (cESM) prompting individuals to work on a personalized KW task during observation with neurophysiological sensors and through repeated interruption in order to "catch flow in the act". By comparing observations to a validated flow induction paradigm, the main research question of how well the cESM approach can elicit flow is to be answered. Furthermore, while there have been serious advancements in the field of brain-computer interfaces that keep extending the applicability of real-time neuroimaging to *in situ* phenomena like attention, operator workload and engagement (Blankertz et al., 2016; Ewing et al., 2016; Kosti et al., 2018), the study of neural correlates of flow in more externally valid scenarios is still sparse (Katahira et al., 2018). In general, the knowledge of how flow can be described using neural measures still lacks of repeated insights, which is why this work fills several important gaps. Overall, our work contributes to flow research by: (1) advancing the understanding of flow elicitation in laboratory settings in the context of KW, and by (2) extending flow neurophysiology knowledge by consolidation of related work, across task analysis and study of high interest brain regions.

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2 BACKGROUND

2.1 Flow Theory

Flow research spans contexts like arts (de Manzano et al., 2010), gaming (Moller et al., 2010; Harmat et al., 2015), or writing (Csikszentmihalyi, 1996; Erhard et al., 2014) and has found the state to occur remarkably similar across contexts. The experience is described in nine dimensions, that are classified temporally (see Table 1).

Table 1: Flow Experience Components (cf. Nakamura and Csikszentmihalyi, 2009).

Component	Class
1) Challenge-skill balance 2) Clear Goals 3) Unambiguous Feedback	Antecedents
4) Action-Awareness Merging 5) Sense of Control 6) Loss of Self-Consciousness 7) Transformation of Time 8) High Concentration	During Experience
9) Autotelic experience	Consequences

2.2 Research Paradigms

In the past, primarily self-reports have been used to develop flow descriptions (interviews & surveys) (Moneta, 2012). The ESM was specifically designed for this purpose, in order to surpass interview limitations (e.g. recall bias) and to study flow close to its occurrence through repeated interruption (Csikszentmihalyi and Hunter, 2003). The naissance of experimental flow induction has only later and recently occurred, focusing on the paradigm of difficulty manipulation (DM) (Moneta, 2012). The manipulation of difficulty is used to elicit experiences of boredom, flow, and anxiety (through low/balanced/high difficulty). It has been criticized whether or not the approach can elicit real flow experiences, given the reduced motivation and involvement common in laboratory tasks (Moller et al., 2010), and given the elicitation of effortful attention from novel and artificial tasks (Hommel, 2010). Other approaches have focused on engagement (E) paradigms where participants are for example asked to play a game and report their experience afterwards (e.g. Labonté-Lemoyne et al., 2016). Flow physiology research has extensively used the DM paradigm. Based on a previous survey of 20 studies on the peripheral nervous system (PNS) (Knierim et al., 2017) and three studies published since then (Klarkowski, 2017; Tian et al., 2017; Barros et al., 2018), we found that 13 of 23 studies used this paradigm. Furthermore, 17 of 23 studies used game tasks, a pattern similarly visible in flow neuroimaging research (see next section). This shows a focus with low external validity, that has led to calls for creative laboratory research (Harris et al., 2017).

2.3 Flow Neurophysiology

Given the youth of experimental paradigms, flow research has only recently produced increased amounts of theoretic and empiric research on underlying neurophysiological processes (Peifer, 2012; Harris et al., 2017). One of the first propositions of flow neurophysiology is the reduction of prefrontal cortex activity during flow in favour of more implicit, automated processing of learned behaviour (Transient Hypofrontality = TH) (Dietrich, 2004). Extending this proposition, linear reductions of default mode network activity with flow experience have been put forward that would alternatively explain the experience of automaticity and the absence of self-referential processing (Peifer, 2012; Harris et al., 2017). Furthermore, the proposition of flow as an emergent property of highly synchronized activity in attention and reward networks of the brain has been highlighted (Synchronization Theory = ST) (Weber et al., 2009; Harris et al., 2017).

Extending the aforementioned literature review corpus, several peer-reviewed studies of flow neurophysiology were identified. Much of this research has focused on hemodynamic imaging (e.g. Ulrich et al., 2014; Harmat et al., 2015; Barros et al., 2018). Also, there has of late been an increase in electroencephalographic (EEG) flow research (Wolf et al., 2015; Ewing et al., 2016; Katahira et al., 2018). Yet there has been little consolidation of these lines of work. For this report we decided to focus on results on frontal brain regions, as the study of frontal regions has been preferred often based on the early TH account. (Dietrich, 2004). So far, for TH's main hypothesis of overall frontal activity reduction during flow, little support has been found in fMRI (Ulrich et al., 2014) and fNIRS (Harmat et al., 2015; Barros et al., 2018) imaging studies. Instead, it appears parts of the prefrontal cortex (PFC), specifically lateral parts, are highly active during flow, yet the medial PFC shows activity decreases during flow, and boredom conditions show a more general PFC reduction (Harris et al., 2017; Barros et al., 2018).

Frontal activity has also been reported on in most of the related flow EEG studies, with repeated results supporting the region as a location of interest. While two of these studies (Chanel et al., 2011; Berta et al., 2013) report on the relevance of frontal activity for the machine-learning (ML) based classification of flow states, six other studies describe activity in more detail (see Table 2). Aggregating the results of these studies that primarily focused on frequency band activity across difficulty-manipulated conditions, we conclude several results that have not been integrated:

(1) One of the more clear findings is a difference in frontal theta band activity in flow conditions, with increases compared to boredom task conditions, and either similarity between flow and overload conditions (Soltész et al., 2014; Katahira et al., 2018) or decreases from flow to overload conditions indicating an inverted U-shaped relationship between frontal theta activity and task demands (Ewing et al., 2016). Support for theta band differentiation has also been noted in ML research on flow classification (Chanel et al., 2011).

(2) Repeated observations have been made for frontal alpha activity. While some find increased alpha power with higher flow self-reports (Léger et al., 2014; Labonté-Lemoyne et al., 2016), within the DM group comparison studies, findings point more to decreases in alpha activity with increasing task difficulty (Ewing, Fairclough and Gilleade, 2016; Katahira et al., 2018 report the inverse relationship, but use amplitudes as unit of analysis). ML research also finds frontal alpha activity to be a differentiating feature (Berta et al., 2013).

(3) Lastly, a few observations have also been made regarding frontal beta band activity in flow, with ML reports demonstrating differentiation potential alone (Chanel et al., 2011; Berta et al., 2013), left frontal beta band reductions correlated with higher flow self-reports (Léger et al., 2014), but also right frontal beta band increases with task difficulty (Klarkowski, 2017).

Within this body of research, additional interesting EEG observations have been mentioned that are lateral differences, specifically frontal alpha asymmetry (FAA) (Wolf et al., 2015; Labonté-Lemoyne et al., 2016), frequency band separation, (e.g. individualized theta, alpha band and beta band splits) (Berta et al., 2013; Soltész et al., 2014; Ewing et al., 2016), and also temporal differences of frequency band activity within task conditions (Soltész et al., 2014). In this study, we followed up on several of these in favor of an in-depth analysis of frontal activity patterns.

3 METHOD

3.1 Materials & Procedure

Overall, 12 students (3 female) ages 21-30 participated voluntarily in our laboratory study. Each participant worked on (1) writing for a scientific thesis, and on (2) solving math equations in manipulated difficulties. Scientific writing was chosen for its challenging and frequent task nature for scholars and students (exemplary KW). Also, writing (scientific or literary) has previously been related to engaging experiences in general and flow in particular (Csikszentmihalyi, 1996; Erhard et al., 2014; Galluch et al., 2015).

Table 2: Frontal EEG results in related work (Legend: Par. = Paradigm, Anal. = Type of analysis, (Q-)Com. = (Quasi-) Condition comparison, Regr. = Regression EEG & self-reports, Un. = Unit of analysis, μ = Frequency amplitude, μ^2 = Frequency power. Exemplary explanation of symbols: • = No significant differences, = Boredom condition significantly different from flow & overload condition, = Positive, linear relation of frequency band and self-report).

Reference	Par.	Anal.	Un.	Frontal Electrodes: Left	Mid	Right	θ	lo-α	hi-α	α	lo-β	hi-β	βa
Katahira et al., 2018	DM	Com.	μ	(AF3,F3, F7,FC3)	(Afz,F z,FCz)	(AF4,F4, F8,FC4)	4-7		10-13				14-30 •
Ewing et al., 2016	DM	Com.	μ^2	F3		F4	4-7	7,5-10 •	10,5-13				
Klarkowski, 2017	DM	Com.	μ^2			AF4	4-8 •			8-13 •			13-30
Soltész et al., 2014	DM	Com.	μ^2	(Fp1,Fp2,F3,F4,F7,F8,Fz)			4-8	8-11 •	11-13 •		13-25 •	25-35 •	
Labonté-Lemoyne et al., 2016	E	Q-Com.	μ^2			(F4,F8)	4-7 •			8-12			13-30 •
Léger et al., 2014	DM	Regr.	μ^2	F3						8-12			12-22

Participants brought their own, active thesis project (bachelor or master level) to work on for a session of 20-25 minutes. Initially they were given time to inspect the state of their document and to define a challenging, yet achievable goal for a writing session. To standardize the goal setting approach the SMART mnemonic was used (Doran, 1981). This approach was also considered to facilitate the flow experience. For example, setting a goal that is specific (S) (i.e. less abstract) has been found to facilitate high quality writing outcomes (Flower and Hayes, 1981), and should further provide on one of the flow pre-requisites of having a clear goal. Deriving a goal attainment measure (M), was considered to be helpful in fulfilling the second flow pre-requisite of unambiguous feedback. Lastly, the focus on a relevant (R) and achievable (A) goal, was considered to further enhance the optimality of a task challenge. The thesis writing software was standardized to Microsoft Word in full-screen mode.

The math task was chosen as reference to a validated DM task (Ulrich et al., 2014; Katahira et al., 2018). Replicating the design by Ulrich et al., (2014), participants sum two or more numbers. Two adjustments were made to the design as task difficulty was found to be too high in previous tests. The boredom condition was adjusted so that, subjects solved randomly drawn equations in one of three forms (101 + 1, + 2, or + 3). The flow condition was altered so that, difficulty was increased/decreased when three sequential responses were correct/incorrect. There was a constant waiting period between trials of four seconds. The math and writing task order was randomized. Also, the three math task conditions were ordered randomly, which resulted in a total count of 12 procedure variations (2 * 3! combinations). All variations were executed once. At the start of the experiment, participants completed eyes-open and eyes-closed baseline phases in which they were asked to “let their mind wander to wherever it takes them”, to keep their eyes focused on a black fixation cross on a white screen (in the eyes-open phase), and to avoid unnecessary movements. The same message and fixation cross were shown for the washout screens prior to each math task condition and between math and writing task. The complete procedure is outlined in Figure 1. In the recruitment survey participants reported mean thesis challenge levels of 4.3 (SD: 0.98) and Wilcoxon comparisons showed no difference in preference for writing or math tasks (measured using three questions from Ulrich et al., 2014).

3.2 Measures

Round questionnaires contained scales on flow and task demand (ten item Flow Short Scale (FKS) and one additional task demand question all by Engeser and Rheinberg, 2008), stress (five item construct by Tams et al,. 2014), and affect (single question arousal SAM scale by Bradley and Lang, 1994), amongst others. Between-task surveys included scales on task importance (Engeser and Rheinberg, 2008). Almost all questions used 7-p Likert scales (SAM arousal used 9-p). Additionally, ECG data was collected in Lead II configuration using gelled electrodes. EDA data was collected using gold cup electrodes on the left foot. However, we focus in this report on the analysis of EEG data only. EEG data was collected with an Emotiv Epoc+ headset. This 14-channel wireless headset uses saline-based electrodes, collecting data at a sampling rate of 256Hz. Electrode sites are: AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4, AF4 (10-20 system). Two reference electrodes, the ‘‘common mode sense’’ (CMS) and ‘‘driven right leg’’ (DRL) are placed on the left and right mastoids. While the headset comes with downside regarding data quality, it has been found to deliver adequate data for our type of study (Barham et al., 2017) and has been used in previous studies related to the KW context (Kosti et al., 2018), and to

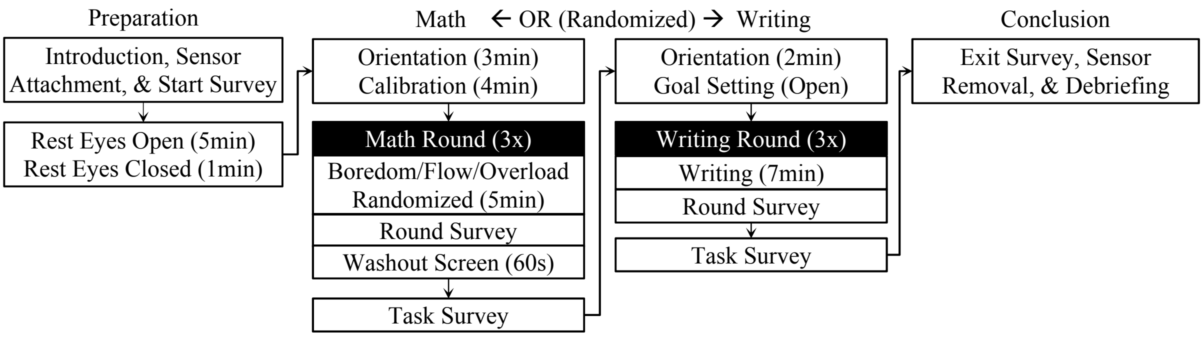

Figure 1: Experiment procedure.

flow experiences (Klarkowski, 2017). Prior to application of the headset, the felt-pad electrodes were moistened with a standard 0,9%-NaCl saline solution. After application, acceptable contact quality was controlled for all electrode sites using the proprietary impedance information supplied by the manufacturer's API.

3.3 Psychometric Data Preparation

Outliers were removed for all psychometric variables (>2 SD from the construct mean). Distribution normality (Shapiro-Wilk test) and homogeneity of variances (Fligner-Killen test) did not hold for many samples ($p < 0.05$), prompting non-parametric test use. Removing one item from the stress construct improved Cronbach's Alpha in the math boredom condition. Further item removal did not improve Alpha values, which left the stress construct Alpha level bordering a critical value of 0.6 that is deemed acceptable in some cases (Hair et al., 2011). Given the high internal consistency across phases (see Table 3), and corroborating results from the arousal item, the stress construct was retained.

Table 3: Cronbach's Alpha levels per experiment phase (m-B/F/O/All = Math Boredom/Flow/Overload/All conditions, w1-3/All = Writing round 1-3/All rounds).

	mB	mF	mO	mAll	w1	w2	w3	wAll
Flow	0.68	0.88	0.89	0.80	0.77	0.98	0.93	0.95
Stress	0.84	0.58	0.78	0.84	0.84	0.78	0.90	0.82

3.4 EEG Data Pre-Processing

EEG data was processed along the guidelines of Cohen (2014) and Picton et al. (2000). Data was processed only for a homogenized sub-sample (three female participants were excluded) (Picton et al., 2000). Also, two data sets had to be excluded due to recording failure. The retained sample for EEG analysis comprised 7 right-handed males. Data preparation, feature extraction, and analysis were conducted in R, signal processing and artefact removal in EEGLab (Ver. 14.1.1). Initially, experiment phases of interest were extracted for each participant (eyes open baseline, all three math task conditions, all three writing task rounds). Channels were first centred through mean subtraction. Afterwards, the extracted data was loaded into EEGLab where a 0.5-45Hz bandpass, and a 50Hz notch filter were applied. Signal data was then visually inspected for artefact removal. First, channels that had failed to collect data were removed. Then, paroxysmal artefacts were removed manually. Afterwards, using the infomax algorithm, an independent component analysis (ICA) was performed to identify and remove components of the data related to eye blinks and sideway saccades (EOG artefacts). Next, data was re-imported in R in order to extract frequency band information for the frontal electrodes (AF3, F3, F7, FC5, FC6, F8, F4, AF4) similar to (Ewing et al., 2016) on the basis of 2s long epochs with 50% overlap and tapered using a Hann windowing function. Average band power (μV^2) was extracted using the Fast Fourier Transformation (FFT). Only artefact-free and complete epochs were used for feature extraction (epochs containing more than 95% of required samples, i.e. > 2s * 256Hz = 512 samples). Extracted frequency bands are: Theta (4-8Hz), Alpha (8-12Hz), and Beta (12-30Hz). Also, for the Alpha and Beta band additional sub-segments were extracted that are low Alpha (8-10Hz), high Alpha (10-12Hz), low Beta (12-15Hz), mid Beta (15-20Hz), and high Beta (20-30Hz). Afterwards, frequency band data was normalized (Ln transformation). Electrodes were pooled by computing the mean for three regions of interest that are all frontal sites (AF3, F3, F7, FC5, FC6, F8, F4, AF4), left frontal sites (AF3, F3, F7, FC5), and right frontal sites (FC6, F8, F4, AF4) for each epoch. Next, feature epochs were aggregated temporally by computing the median over each experiment phase. Median use was preferred as a way of conservative data interpretation, taking care of potential outliers. Finally, to facilitate comparisons between experiment phases, change scores were computed by subtracting the eyes open baseline phase mean from each experiment phase (e.g. $\Delta theta = theta_{Task} - theta_{Baseline}$). For an additional analysis of temporal segments of each experiment phase, the same procedure outlined above was repeated on 30s-long epochs within each phase. The window length of 30s was chosen based on the report by Soltész et al. (2014) who argue that at the start of phases temporal differences could occur in this interval already. Distribution tests indicated that assumption of normality was violated for many groups (Shapiro-Wilk on the temporally and spatially aggregated data sets for each condition and frequency band, $p < 0.05$), which is why non-parametric tests were used afterwards. Fligner-Killeen tests showed no violation of variance homogeneity assumptions.

4 RESULTS

We report on four psychometric (flow, task demand, stress, arousal) measures together with multiple EEG features compared across six experiment phases (three math conditions, three writing rounds). Beyond statistical comparisons, the reduced number of samples in the EEG data prompted us to include additional descriptive analyses. We believe this approach also has merit in light of the young age of the research on flow neurophysiology. The descriptive approach has more of a case study character, a format that has previously been employed for flow PNS measures (Harmat et al., 2011).

4.1 Psychometric Data

Friedman tests indicated the presence of main effects in psychometric variables at significant levels ($p < 0.01$). Variable means and standard deviations are shown in Table 4, and post-hoc pairwise Wilcoxon comparisons of experiment phases in Table 5.

The task demand variable was inspected for a manipulation check (cf. Keller et al., 2011; Tozman et al., 2015). Between all math conditions significant differences were found, displaying increasing task demand from boredom to overload conditions. DM success was thereby confirmed. Within the writing samples task demand levels lay continuously between the math boredom and overload condition. Possibly task demand in writing was also lower than in the math flow condition (trend level indication). No differences were found within the writing task for task demand, with the exception of one trend level difference between writing round 1 and 3. Also, no differences were found in all other psychometric variables across writing rounds and are therefore not reported further.

Within the math task, flow report (FKS) comparisons show significant differences between the math flow and overload condition. Also, repeated significant differences between the math boredom and overload conditions with the writing rounds are found. Lastly, a trend level indication is visible for higher reported flow in writing round 1 compared to the math flow condition. As there are no significant differences within the writing task, flow was reported as high in writing as in the math flow condition in all writing rounds. Support for this consistency is also visible in the range of flow reports per participant (mean range = 1.13, SD = 0.62, writing task only).

The stress report comparison showed significant differences between all math task conditions, increasing with difficulty at every step. In the writing task, stress levels were consistently below the math flow and overload conditions. Comparisons of the arousal reports reveal a similar pattern, with increasing arousal from math boredom to overload conditions. Albeit only with a significant difference for the boredom condition with the other two. Like stress, arousal was consistently reported lower in writing than in math flow and overload conditions.

Finally, after both tasks, participants rated the importance of the task. No significant differences were found (Means: math = 3.82, writing = 4).

4.2 EEG Data

4.2.1 Results Between-Phase Comparisons

Friedman tests were computed for each feature (pooled sites) and frequency band to detect main effects across experiment phases. A main effect was found only for the hiAlpha band ($p < 0.05$). No different effects were found for either the left side or right side alone, which is why the analysis of hemispheric differences was not pursued further.

Table 4: Psychometric variable means & standard deviations (in parentheses) across experiment phases.

	mB	mF	mO	w1	w2	w3
Flow	4.03 (0.80)	4.53 (1.16)	4.02 (1.21)	5.43 (0.59)	4.93 (1.55)	5.09 (1.14)
Stress	2.96 (1.32)	4.18 (0.74)	4.75 (1.18)	2.81 (1.26)	2.79 (1.02)	2.64 (1.07)
Arousal	2.73 (1.19)	6.18 (0.98)	6.27 (1.27)	3.33 (1.50)	2.82 (1.08)	3.91 (1.64)
Demand	1.45 (0.93)	5.18 (0.60)	6.09 (0.70)	4.42 (0.90)	4.17 (1.19)	3.73 (1.01)

Table 5: P-values psychometric & EEG data pairwise Wilcoxon tests across experiment phases.

	Demand			Flow			Stress			Arousal			ΔhiAlpha		
	mB	mF	mO	mB	mF	mO	mB	mF	mO	mB	mF	mO	mB	mF	mO
mF	<.01			>.1			<.05			<.01			<.1		
mO	<.01	<.05		>.1	<.05		<.01	<.05		<.01	>.1		<.05	>.1	
w1	<.01	<.1	<.01	<.01	<.1	<.01	>.1	<.05	<.01	>.1	<.01	<.01	<.05	<.1	<.1
w2	<.01	<.1	<.01	>.1	>.1	<.05	>.1	<.01	<.01	>.1	<.01	<.01	<.1	>.1	>.1
w3	<.01	<.05	<.01	<.05	>.1	<.1	>.1	<.01	<.01	<.1	<.01	<.01	<.05	>.1	<.1

Post-hoc pairwise Wilcoxon tests were conducted on the remaining “all frontal” feature hiAlpha frequency band (see Table 5). Within the math task, the hiAlpha band shows significantly higher levels in the boredom condition than in the overload condition, and the flow condition indicated on trend level, and no difference between flow and overload condition. Across tasks, the hiAlpha band activity in the math boredom condition is significantly higher than in writing rounds 1 and 3, and also higher than in writing round 2, indicated at trend level. For the hiAlpha band, trend level differences also indicate lower hiAlpha in writing round 1 than in the math flow condition, and lower hiAlpha in writing rounds 1 and 3 than in the math boredom condition.

To further deepen the analysis, phase medians were descriptively compared. Difference thresholds were defined conservatively by ascertaining that classified results fit the previously described Wilcoxon tests as medium to larger differences (e.g. the significant hiAlpha difference between the math boredom and math flow condition has a median difference of 0.493). Therefore, differences between 0.15 and 0.30 are considered as smaller, between 0.30 and 0.45 as moderate, and above 0.45 as larger differences. This process lead to 33.3% of math comparisons, 0% of writing comparisons, and 37.5% of across task comparisons being subject of descriptive interpretation. Within the writing task, no differences are found, indicating a consistent experience. Within the math task, median comparisons show higher hiAlpha in math boredom compared to math flow and overload conditions (mB-mF = 0.493, mB-mO = 0.356), a contrast that is similarly visible in the broad alpha band, although with smaller differences (mB-mF = 0.284, mB-mO = 0.277). Furthermore, the descriptive comparison points to higher theta in the math flow than the math boredom condition (mB-mF = 0.171), also to higher hiBeta in math overload compared to math boredom (mB-mO = 0.154) and also to higher beta in the math overload condition compared to both boredom and flow conditions (mO-mB = 0.2, mO-mF = 0.231), all with smaller differences. Across tasks, the descriptive data again shows increased hiAlpha in the math boredom condition compared to all three writing rounds (mB-w1 = 0.564, mB-w2 = 0.488, mB-w3 = 0.548) with larger differences. The same pattern is visible for the broad alpha band (mB-w1 = 0.356, mB-w2 = 0.332, mB-w3 = 0.394), albeit with moderate differences, and the loAlpha band (mB-w1 = 0.231, mB-w2 = 0.175, mB-w3 = 0.186) with smaller differences. Furthermore, the median differences point to lower hiAlpha in writing rounds 1 and 3 than in the math overload condition (mO-w1 = 0.208, mO-w3 = 0.192) with smaller differences. Also, hiBeta shows higher levels in writing round 1 than in math boredom and flow conditions (mB-w1 = 0.2, mF-w1 = 0.157), as does the broad beta band (mB-w1 = 0.233, mF-w1 = 0.265), all with smaller differences. Both the median levels and group significance differences are visualized in Figure 2.

4.2.2 Results within-Phase Comparisons

To analyse the potential of temporal variation in frequency band activity during flow (Soltész et al., 2014), within experiment phase effects were investigated. Friedman tests on 30s-based segments of each experiment phase were computed (10/14 segments for each math/writing task phase).

Results show main effects for the alpha and hiAlpha band in the math boredom condition and writing round 3 (all $p < 0.05$), and for the beta and midBeta band in writing round 1 (both $p < 0.01$). For writing round 3 post-hoc pairwise Wilcoxon tests revealed only a single significant difference in the hiAlpha band (out of 91 comparisons), which is why this finding is considered an anomaly. For writing round 1 on the other hand, multiple significant differences are found for midBeta (19/25) and beta (20/23) ($p < 0.05/0.1$), with the most pronounced differences for early vs. late segments, pointing to a beta activity increase in the first minutes of writing round 1. For the math boredom condition, multiple significant differences are found for alpha (5/11) and hiAlpha (11/14) ($p < 0.05/0.1$) (out of 45 comparisons). This pattern is more volatile with alpha showing a difference of the first 30s to the mid part of the boredom task round (alpha appears to peak slightly in the first 1-3min), but hiAlpha shows repeated differences between segment 1 and 3-6, then again, a difference of segment 3 to segments 7-9, and segment 6 to 7-9, indicating an early and late peak (and a mid-part valley). No repeated start or end effects were found in all bands and experiment phases. Also, besides the beta pattern in writing round 1, the phases showing higher flow reports are more strongly marked by consistency than volatility. Significant differences are shown in Figures 3 & 4.

5 DISCUSSION

5.1 Psychometrics Findings

Within the writing task, all variables indicate experience consistency, despite repeated interruption.

This is an important finding as interruptions are often considered a central flow hindrance (Rissler et al., 2017), which is why we anticipated more experiential variance. Possibly, some factors in the writing task design (like the goal setting procedure) dampened such interruption impacts by providing structure.

Within the math task, our results show DM success with results comparable to previous research, showing that flow is reported most strongly when task demands are balanced (Keller et al., 2011; Tozman et al., 2015; Klarkowski, 2017).

The results are taken as first support that the cESM approach (with this scientific writing design) can be used to elicit flow, with at least similar intensities compared to a standard DM paradigm (the math task). However, a clear difference between the two paradigms appears as writing is perceived to be less stressful and demanding than the math task in flow and overload conditions. A key reason for the stress difference could be that per design multiple stress factors present in the math task and typical DM designs (task demand overload, social-evaluative threat, lack of control) (Tozman et al., 2017) were not present in the writing task. In the past, these stressors have been purposefully introduced to DM designs in order to elicit motivated task performances (Ulrich et al., 2014; Tozman et al., 2015, 2017). At the same time, in these approaches repeated sightings of psychometric reports that point to increased stress/arousal in balance and overload conditions compared to boredom conditions have been made, even in contexts where threat experiences could be less likely (e.g. in gaming) (Harmat et al., 2015; Tozman et al., 2015, 2017; Klarkowski, 2017). Our results indicate, that a naturally important task lacking these stressors, results in similar reported flow intensities without perceptions of strain. It would appear that the critique on the applicability of the DM paradigm to elicit real flow could therefore receive some support (Moller et al., 2010), as could the proposition that naturalistic tasks are perceived as less effortful (Hommel, 2010). However, these results could also indicate a central limitation to how flow is collected psychometrically.

5.2 EEG Findings

Within the writing task, EEG results mostly support the view of a consistent experience across writing trials. The only effect that shows variation is the initial beta increase within the first part of writing task round 1 (temporal analysis). Given that this variation is not apparent in later phases, we believe it to be most likely attributable to a type of task initiation activity.

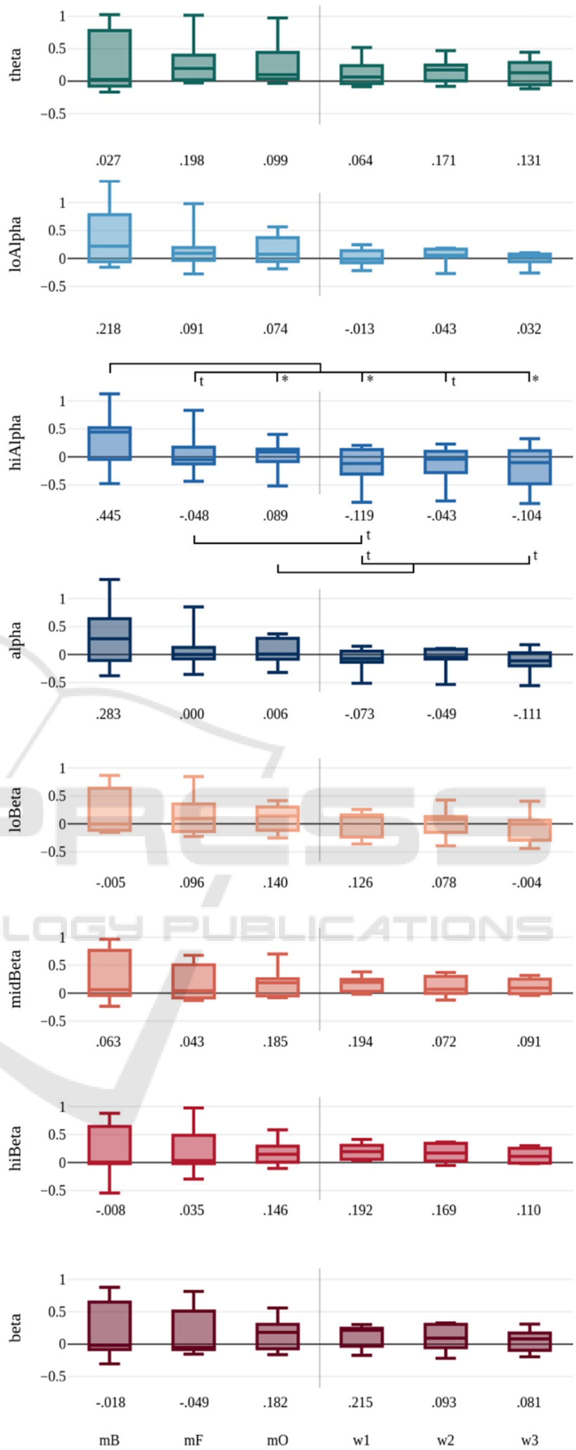

Figure 2: Experiment phase frequency band activity over all frontal electrodes pooled (y-axis = change scores of ln-transformed avg. frequency band power). Median values of each phase are listed beneath. Bars show Wilcoxon test results with p < 0.05 (*) and p < 0.1 (t).

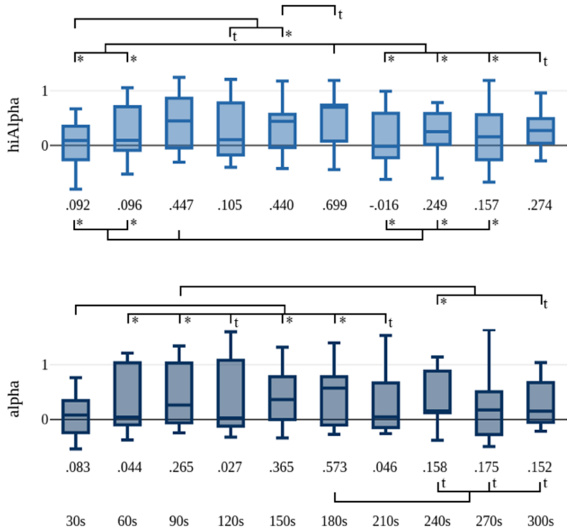

Figure 3: Temporal variation math boredom condition.

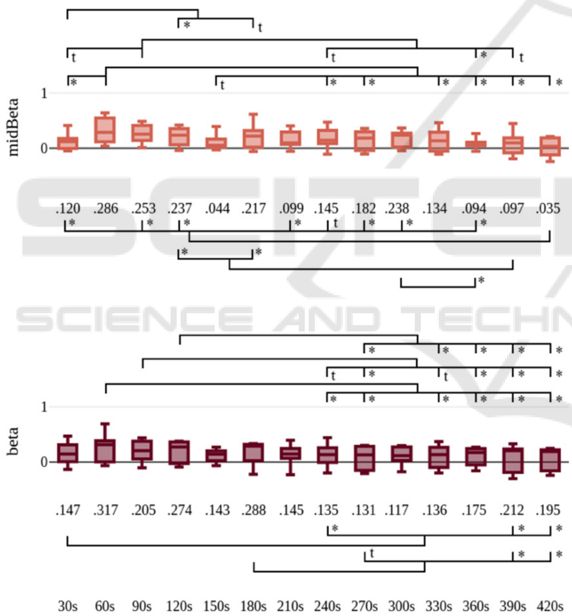

Figure 4: Temporal variation writing round 1.

It has been reported in flow and writing research (Flower and Hayes, 1981; Csikszentmihalyi, 1996), that initiation of a writing session takes additional effort to structure the task that may be required less at later stages. Given that beta activity is often related to increased excitatory cognitive activity, we believe this findings shows an initially increase in cognitive effort that dissipates after a while, and that is not specifically related to flow experience or neural correlates thereof, as something similar is not visible in the math flow condition either.

Within the math task, EEG results integrate in several ways with previous work. The finding of frontal theta activity changes (descriptive analysis) with difficulty increases is supported, yet only weakly. This could be a spurious effect caused by our small sample or point to a need to further specify theta band activity (like Ewing et al., 2016 who select individualized theta band activity from the 4-7Hz range). The finding of lower hiAlpha activity with increasing task difficulty (statistical & descriptive analyses) is interesting in multiple ways. First, the separation of the alpha band shows that hiAlpha is more of a differentiating feature between math task conditions, a finding that has not been outlined as such in previous work, yet would explain why some of the work that includes separation does find frontal alpha to contribute valuable diagnostic information between difficulty conditions (Ewing et al., 2016; Katahira et al., 2018), while others that work with the broad alpha band do not (Chanel et al., 2011; Klarkowski, 2017). Whether or not the hiAlpha band provides diagnostic potential for flow observation beyond indication of a difference to boredom, remains a subject of future work. Presently it appears that flow and overload conditions show a similar level of hiAlpha, that is lower than in the boredom phase (thus showing a potentially reduced activity in frontal brain regions in the boredom phase). The results of frontal theta and alpha increases with sustained attention and increased task difficulty are in line with previous EEG research on mental workload (Borghini et al., 2014). The results are also fairly similar to a recent fNIRS-based study that finds frontal brain activity to be reduced in easy/boredom conditions and to increase when task difficulty increases (Barros et al., 2018). The aforementioned authors attribute this activity to attention on the task, which we find plausibly transferrable given the volatile hiAlpha signature only present in the math boredom phase (temporal analysis), specifically as mind wandering during this condition was noted explicitly by one participant in the final experiment survey comment section. However, it needs to be noted that the frontal alpha reduction is not a unanimous finding in the related work. While it is also inferred from the amplitude-based results of Katahira et al. (2018), the results by Léger et al. (2014) and Labonté-Lemoyne et al. (2016) point in the opposite direction. Mainly, this might stem from the difference in experimental approaches and analyses. Labonté-Lemoyne et al. (2016) for example observe two interacting participants and don't manipulate difficulty externally. A last finding with potential implications is the increase of beta activity in the math overload condition compared to the boredom and flow conditions (descriptive analysis). As previously outlined, such beta band activity might be indicative of a threshold when cognitive effort increases strongly. Lower beta activity has been found to be linked to higher flow experience self-reports (Léger et al., 2014), yet again has also been found to increase with task difficulty increases from boredom levels (Klarkowski, 2017). It appears frontal beta can increase at a certain level of difficulty. We would expect this phenomenon to be visible when the perceived stress levels increase, yet find no such pattern. However, other studies have also found no beta difference at all on frontal sites (Soltész et al., 2014; Katahira et al., 2018).

Considered across tasks, beta increases would not necessarily appear to be detrimental to flow, or related to it for that matter, at least as the first writing round that shows beta increases (descriptive & temporal analyses), does not show differences in flow experience reports (compared to the math flow condition). Other comparisons across tasks further support the potential relation of the hiAlpha band to flow experience, or at least an expected corollary of it that is attention on the task. Whether or not there is an actually realized decrease in hiAlpha in the writing task compared to the math overload condition (statistical & descriptive analyses) could be an interesting additional support of the relation of flow experience to increased voluntary task attention.

In summary of the different frontal EEG features investigated it can be noted, that a role of theta band activity across tasks is in this data not supported, pointing again to a reduced role in flow experience. Overall, alpha band separation shows the most useful diagnostic extension. For the beta band, this seems less so to be the case, although a few results point to potentially higher diagnostic properties of the midBeta and hiBeta band. While frontal hemispheric differences would intuitively appear to be related to flow (e.g. as FAA is related to task approach motivation) (Wolf et al., 2015; Labonté-Lemoyne et al., 2016), our findings show no such pattern. Lastly, the temporal sub-segmentation of experiment phases indicates that at least for frontal sites, flow experiences could be rather marked by consistency than volatility. The findings of lower hiAlpha activity in flow-related experiment phases point to further support of frontal brain activity in flow experience. This finding is in contrast to initial TH reasoning (Dietrich, 2004), but in line with both previous EEG work (Ewing et al., 2016), and other neuroimaging studies indicating a more nuanced frontal activation picture (Ulrich et al., 2014; Harmat et al., 2015; Barros et al., 2018). Given the lack of midline frontal electrode positions for the herein used headset and a neglect of such dedicated differentiation of lateral and medial frontal sites in related work (see Table 2), it appears that the differentiating potential of frontal EEG could be dependent on capturing more spatial nuances (which might be difficult to attain) or have to be accompanied by other sensors. Whether or not frontal EEG activity alone can differentiate flow experience from other experiential states has yet to be explored further. Regardless of frontal activity, what might perhaps be most interesting in the context of this research approach, is that given the psychometric differences in stress perceptions, it might be possible to study a difference between the experience of flow as a state of effortless (cESM) or effortful (DM) attention (Hommel, 2010), if this perceptual difference is confirmed in future work to be present and relevant.

5.3 Study Limitations

The small sample size is a main limitation of this study, which is why the results can only be treated as preliminary. Through integration with related work we have tried to somewhat overcome this limitation. Considering the experiment design, future work should increase experiential variance in the writing task (e.g. by including a controlled, writing boredom phase), and employ more psychometric scales (involvement, effort, effortlessness, etc.) to enable more detailed insights. Similarly, the integration of a more self-determined difficulty adjustment as in Barros et al. (2018), could provide additional comparability between the two paradigms. Physiologically, the work is limited to frontal sites in favor of a more detailed inspection. We did not take into account that there are other topographical regions of interest that could be providing interesting information on what differentiates flow from other experiences. Some research for example points to the explicit role of central (Katahira et al., 2018), temporal (Wolf et al., 2015), or parietal and occipital brain regions (Chanel et al., 2011).

6 CONCLUSIONS

We took an extensive look at psychometric and physiological data in two flow induction paradigms and compared data to unintegrated results of related EEG studies. The summarized contributions are:

(1) We provide evidence for the applicability and utility of the cESM approach to study flow in more

unstructured tasks in the context of KW. The writing task design appears to elicit a constant flow experience that is at least as high in intensity as in an established DM paradigm. At the same time the cESM approaches elicits lower perceptions of stress, which makes the approach an interesting, perhaps qualitatively different option for flow research.

(2) We provide further evidence for neural activity in flow experience, specifically in the form of outlining the role of frontal EEG results, first by consolidating related work, then by analysis across two cognitive tasks. The results point to further refusal of the hypofrontality hypothesis and instead point to frontal activation that is visible through split of the alpha band over averaged frontal sites (likely indicating increased task attention). Furthermore, temporal physiological and experiential volatility is in this alpha band only indicated for a boredom condition. This could support the hypothesis that flow is actually experienced as fairly stable (Léger et al., 2014) at least within these short time segments (5-7min), and that volatility might be either visible in different brain regions or over longer periods.

In future work, frontal alpha activity together with heart rate variability (HRV) data could be a fruitful approach to flow detection, given the observed HRV decreases in autonomous flow experiences (Barros et al., 2018). HRV reductions beyond what is expected in higher task difficulties together with stable, frontal hiAlpha activity could be a marker of flow experience or at least its corollary of increased task attention, that is explained by shared regulatory mechanisms (Peifer, 2012; Barros et al., 2018). Although this might not characterize flow neurophysiology uniquely, it could show sufficient diagnosticity to infer flow (vs. boredom or overload) experiences whilst they are occurring automatically, thus enabling the utilization of flow-facilitating bio-adaptive systems in KW. Further detection performance might then be achieved by inclusion of higher spatial resolution on frontal brain activity, as the recent fNIRS work by Barros et al. (2018) proposes flow to be marked by activation of lateral frontal areas and deactivation of medial frontal areas. Whether or not this can be achieved using EEG data could be an interesting avenue for future work, as would be the search for neurophysiological differences that could explain the stress perception difference and with it the potential difference of flow experience as a state of effortless attention (Hommel, 2010).

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